STOCK MARKET CORRELATION AND INVESTOR ATTENTION

by

Efthymia Symitsi

A thesis submitted in fulfilment of the

requirements for the degree of

Doctor of Philosophy

Norwich Business School

University of East Anglia

July 2017

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Signed:

Date:

To my late grandfather for his inspiration...

Abstract

This thesis deals with three separate problems in finance related to covariance. First, I assess the forecasting performance of popular multivariate GARCH, hybrid implied and realised covariance models in terms of statistical and economic criteria. I perform a rigorous analysis across major equity indices using different forecasting horizons, market regimes, loss functions and tests. A Vector Heterogeneous Autoregressive specification is the best among competing models. Less complex models that rely on high-frequency data yield superior forecasts and reduce the portfolio risk. Hybrid estimators that combine option-implied and high-frequency information also have merit when option-implied volatilities are corrected for the volatility risk-premium. During financial turmoil the ranking does not change significantly but forecast accuracy deteriorates.

Second, I investigate comovement in investor attention as a determinant of excess stock market comovement proposing a novel proxy, "co-attention". Co-attention is estimated as the correlation in demand for market-wide information across stock markets approximated by the Google Search Volume Index (SVI). My results reveal significant co-attention driven to some extent by correlated news and fundamentals. Most importantly, I find that co-attention is positively related to excess comovement. This effect is more pronounced in developed economies and during recessions. I fail to document significant effects of correlated news supply on stock markets, lending support to the idea that information demand governs investing decisions. Co-attention is not only induced through international investors, but domestic investors as well. My results provide evidence of attention-induced financial contagion in unrelated economies. However, international investors' co-attention appears to facilitate volatility transmission indirectly across markets.

Third, I solve the optimal budget allocation problem across keywords for paid search advertising accounting for the risk induced by maintaining a portfolio of volatile and correlated keywords. In a mean-variance context, I maximise the growth rates in keyword popularities. Advertising costs and conversion rates are shown to be irrelevant. I demonstrate practical implementation using readily available data from Google Trends database estimating averages, variances and co-variances as growth rates in SVIs. Based on keyword sets for major sectors, I form efficient frontiers consisting of optimal combinations of keywords. Optimal keyword portfolios offer statistically higher risk-adjusted performance against portfolios constructed using popular heuristics. A proposed heuristic based on risk-adjusted performance reduces the computational cost and provides competing results.

Acknowledgements

Pursuing a PhD has been a life-changing experience. However, this was not a lonely journey. I would like to thank everyone who accompanied me and provided me with their guidance and support.

Firstly, I would like to express my profound gratitude to my supervisory team. I am indebted to Professor Raphael Markellos for continuously supporting me throughout my doctoral studies. He has been my mentor since my undergraduate studies enlightening me the first sparking of research. Without his patience and advice, the stimulating discussions and the immense knowledge the completion of this thesis would not have been possible. I will never forget that for Raphael this 3-year course was not only about the preparation of this thesis but the development of an academician and an independent researcher. I am grateful to my second supervisor Dr Apostolos Kourtis who was always available for challenging discussion and support in professional and personal level. Over the course of this PhD, I gained valuable knowledge during our meetings that developed further my critical thinking and reasoning. My sincere thanks also go to my third supervisor, Dr Xiaojing Song, for providing me with useful advice, feedback, and encouragement all these years.

I will never forget the generous support of my colleague and friend Dr Lazaros Symeonidis. I have been impressed by his deep knowledge and passion for research. I have learned a lot through our long discussions, and his valuable comments on my work and I am really indebted. His professional attitude and incomparable ethos will always inspire me. I especially thank Dr Nikolaos Korfiatis for valuable advice and guidance, for providing me with unique data for a part of this thesis, and for being there in good and bad times. Through our cooperation, I did not only find a great mind and colleague, but I also gained from his academic experience in several aspects such as doing interdisciplinary research, performing reproducible analysis with programming, and pursuing an academic career. I would like to express my gratitude to Professor Peter Moffat for his reflection on my work at the first year of this PhD that improved the content of this thesis substantially. I also thank Dr George Daskalakis, Dr Anastasiya Shamshur, Dr Francesca Cuomo, Dr Nikolaos Korfiatis, Dr Aris Nikoloulopoulos and Professor Elena Kulinskaya for trusting me to teach undergraduate and postgraduate students and sharing with me their best advice to develop further my teaching skills.

It has been an honour to be a PhD student at Norwich Business School of UEA and a member of the Finance Group. I wholeheartedly thank the UEA and the NBS particularly for the financial support to accomplish my dissertation, for the doctoral training and all the provisions. I am also grateful to all the NBS and PGR Office Staff for always being kind and willing to help. My life was easier from various perspectives. Many thanks to all the faculty members and PhD Students who shared their knowledge and communicated their research that introduced me to other research areas in and beyond finance. I appreciate the valuable feedback I have received during my presentations at the Finance Group and the Doctoral NBS Colloquia from the participants and discussants.

I feel the need to thank Vanya and Raphael, Georgia and Apostolos, Katerina and Nikos, Katerina and Lazaros separately for supporting me and my family during tough personal times. Their reassurance gave me strength to continue working for this outcome. Special thanks to Katerina Anthi who was always available to take care of my son all the times I had to work on this thesis.

I have no words to express my gratitude to my colleague, friend, and husband, Panagiotis. You believed in me from the fist moment we met to the moments I lost faith in myself. Last, without the love and continuous support of my parents, my brother and sister all these years, the academic course would have remained a dream.

Stock Market Correlation and Investor Attention

Efthymia Symitsi

July 2017

Contents

List of Figures

List of Tables

Abbreviations

A-CCC .... Asymmetric Constant Conditional Correlation

A-DiagBEKK ...... Asymmetric Diagonal BEKK

ADF .... Augmented Dickey-Fuller

Adj-HICOV .... Adjusted Hybrid Implied Covariance

AdjHAR-HICOV .. Adjusted Heterogeneous Autoregressive Hybrid Implied Covariance

AMS .... Average Monthly Searches

A-OGARCH .... Asymmetric Orthogonal GARCH

A-ScBEKK .... Asymmetric Scalar BEKK

ASVI .... Abnormal Search Volume Index

BEKK .... Baba Engle Kraft and Kroner

CCC .... Constant Conditional Correlation

CD .... Cultural Distance

CIV .... Corrected Implied Volatility

CoAtt .... Co-Attention

CoBord .... Common Border

COL .... Common Official Language

CoNews .... News Comovement

CoRet .... Return Comovement

CPC .... Cost-Per-Click

CTR .... Click-Through-Rate

DCC .... Dynamic Conditional Correlation

DEV .... Developed (Countries)

DiagBEKK .... Diagonal BEKK

DM .... Diebold-Mariano

EMG .... Emerging (Countries)

EMT .... Efficient Market Theory

EWMA .... Exponentially Weighted Moving Average

FDI .... Foreign Direct Investment

GARCH .... Generalized Autoregressive Conditional Heteroscedasticity

GJR .... Glosten-Jagannathan-Runkle

GW .... Giacomini-White

HAC .... Heteroscedasticity Autocorrelation Consistent

HAR .... Heterogeneously Autoregressive

HICOV .... Hybrid Implied Covariance

IV .... Implied Volatility

JKM .... Jobson - Korkie - Memmel

KPSS .... Kwiatkowski–Phillips–Schmidt–Shin

LRCOV .... Lagged Realised Covariance

LogDist .... Logarithmic Distance

LogFL .... Logarithmic Flows

MC .... Market Capitalisation

MCS .... Model Confidence Set

MIX .... Mixed (Developed and Emerging Countries)

MPT .... Modern Portfolio Theory

OGARCH .... Orthogonal Generalized Autoregressive Conditional Heteroscedasticity

OLS .... Ordinary Least Squares

OTM .... On-The-Money

QML .... Quasi Maximum Likelihood

RCOV .... Realised Covariance

RC .... Realised Correlation

ScBEKK .... Scalar BEKK

SVI .... Search Volume Index

UTC .... Coordinated Universal Time

VHAR .... Vector Heterogeneous Autoregressive

VIF .... Variance Inflation Factor

VRP .... Variance Risk Premium

WWW .... World Wide Web

" Finance is not merely about making money. It's about achieving our deep goals and protecting the fruits of our labor. It's about stewardship and therefore about achieving the good society."

- Robert Shiller, Nobel Prize Laureate 2013 (Interview, January 11, 2011) -

Chapter 1

Introduction

The central paradigm of finance entails that the optimal investing decisions account for risk in addition to reward. Covariance between asset returns is a key component of risk in many financial applications, such as portfolio selection, risk management, hedging and asset pricing. In particular, covariance determines the overall portfolio risk and asset allocation decisions. Important regulatory implications also arise from Basel III, as covariance is a significant input in risk measurement models, such as Value-at-Risk. The recent global financial crisis reveals only some of the serious consequences of highly dependent markets and increased systemic risk. Furthermore, hedging effectiveness depends on the covariance forecasts between the returns of the underlying asset and the instrument used for hedging, while factor asset pricing models, such as the CAPM, rely on the accurate estimation of covariance between asset and market returns. Motivated by the impact of covariance on various aspects of finance, this thesis presents three essays addressing three separate problems in the extant literature.

A plethora of academic papers have devoted substantial effort to capture the dynamics of market volatilities and co-volatilities proposing various multivariate models. However, the extension of univariate models for covariance modelling and forecasting is accompanied with significant challenges. More specifically, the positive definiteness of covariance matrix is guaranteed by heavy restrictions to parameters that increase the computational complexity substantially, especially in large-scale systems. This is more apparent in traditional covariance forecasting approaches that are widely based on multivariate GARCH models most of which involve a large number of parameters that add a significant computational burden. Thus, more recent approaches focus on obtaining covariance estimates and forecasts employing simpler and more parsimonious specifications. For instance, many studies search for superior models based on high-frequency data. Option-implied information is also useful for volatility modelling, but employing it for covariance forecasting is neither technically straightforward nor clearly justified. Despite the importance of the problem, there is no consensus in the existing literature for the best model among the various alternatives. A synthesis of conclusions from different empirical studies is difficult due to the diversity in terms of covariance proxies, information, assets, liquidity, sampling frequencies, time periods, market phases, time zones, model specifications and performance evaluation measures.

The first essay of this thesis addresses these limitations in the literature by undertaking an extensive empirical comparison of several popular alternatives to identify the best covariance forecasting model. Unlike other studies that focus on specific families, such as the horse race of multivariate GARCH models in Laurent et al. (2012), I also include recently proposed specifications that rely on different information sets (i.e., daily, high-frequency and option-implied data). In addition to popular multivariate GARCH approaches, less parametrized models that use intraday data are considered, such as the multivariate extension of the Heterogeneous Autoregressive (HAR) model of Corsi (2009), implemented by Bauer and Vorkink (2011) and Chiriac and Voev (2011). This is very important given the success of the univariate counterpart of Vector HAR in volatility forecasting (Kourtis et al., 2016). Moreover, to the best of my knowledge, I am the first to explore the forecasting performance of a parameter-free "hybrid implied covariance" estimator that combines realised correlations with forward-looking option-implied volatilities. Previous studies have employed mixing approaches of historical correlations with option-implied volatilities to estimate option-implied betas (e.g., Buss and Vilkov, 2012). Motivated by theoretical and empirical results indicating that implied volatility is a biased predictor of future realised volatility due to the existence of a volatility risk-premium (Chernov, 2007), I also apply an adjustment to the hybrid model similar to that of DeMiguel et al. (2013). Thus, I investigate, for the first time, the importance of this adjustment in the context of covariance forecasting.

In my empirical analysis, I perform a comprehensive comparison employing different forecast horizons, loss functions, statistical tests and market regimes across 5 major European equity markets namely Germany, France, Netherlands, Switzerland, and UK based on an extensive dataset that covers the period between January 1, 2000, and April 19, 2016. More specifically, I investigate the performance of 16 models covering the full spectrum from heavy parametric to very parsimonious or non-parametric specifications in daily, weekly and monthly horizons using five different loss functions widely used in empirical studies. In line with standard practice, the realised covariance obtained from 5-minute intraday returns is employed as a proxy of the unobserved covariance (Andersen et al., 2003; Barndorff-Nielsen and Shephard, 2004). Then, I apply the Giacomini and White (2006) test to perform pairwise comparisons across models. I also jointly compare models based on the Model Confidence Set (MCS) of Hansen et al. (2011). Additionally, I explore for differences in model performance across several economically important periods including the 2007-2009 global financial crisis and the Eurozone debt crisis. Most importantly, I study whether more accurate covariance forecasts are translated to significant economic gains and yield higher diversification benefits for an international investor who allocates her wealth across the markets under consideration.

The results of this study provide new insights. I conclude that high-frequency data are particularly valuable for covariance forecasting. Specifically, the Vector Heterogeneous Autoregressive (VHAR) model is shown to outperform the various alternatives in terms of both statistical and economic criteria. In addition to the advantage offered by high-frequency data, VHAR is able to capture short and long-term memory in a parsimonious manner by modelling lagged daily, weekly and monthly realised covariances. My results also indicate that simple, parsimonious and easy to estimate models that rely on high-frequency information yield superior forecasts. Models from the celebrated GARCH family use daily observations and so have fewer data requirements, but are far less accurate and carry substantial computational costs. Although there is no consistently better model from the multivariate GARCH family, specifications that incorporate asymmetries appear to perform slightly better compared to their symmetric counterparts, especially during periods of high volatility. The results are not conclusive towards the exploitation of option-implied information for covariance forecasting in the hybrid covariance estimators. However, I show that the proposed non-parametric hybrid specifications that correct for the volatility risk-premium offer relatively lower forecast errors than the unadjusted version. The risk-premium adjusted approaches have comparable performance to that of the VHAR model. However, both are more demanding in terms of data, since they require high-frequency and option-implied information.

The recent economic recession provides an ideal ground to test the hypothesis of changing predictive ability of covariance models across different market regimes (e.g., see Brownlees et al., 2011 and Kourtis et al., 2016 who suggest that the volatility forecasting accuracy varies with market conditions). My results reveal little change in the order of models during turmoil periods, yet forecast errors are generally higher. In particular, most models produce the least accurate forecasts during the 2007-2009 period following the collapse of Northern Rock and the propagation of the crisis to other economies.

My results also indicate that VHAR clearly outperforms the other models on the basis of economic criteria. Simpler models, in general, reduce portfolio risk substantially compared to an equally-weighted benchmark alternative at daily and weekly horizons. For instance, a portfolio allocation based on the VHAR leads to a 29% (10%) reduction in portfolio variance assuming daily (weekly) rebalancing. While most GARCH models offer comparable reduction in portfolio risk on a daily basis, these benefits vanish with weekly rebalancing.

Altogether, the first essay adds to the literature in several ways. First, I undertake an extensive comparison between diverse models from different families employing several statistical tests. Second, I include models that involve various data sets, including daily, high-frequency, and option-implied information. Third, I investigate the hybrid implied covariance model in covariance forecasting and the importance of volatility risk-premium to implied volatility at the multivariate level. Fourth, I perform an extensive comparison of the multivariate HAR model with popular specifications in the extant literature. Fifth, I investigate the predictive accuracy of covariance models within an international context. Finally, I assess the covariance forecasts across models with economic criteria, such as the minimum variance portfolio risk and portfolio stability.

Another stream of the literature investigates the covariance between stock market returns as a measure of asset comovement. While it is well documented that correlations vary over time (e.g., see Bollerslev et al., 1988; King et al., 1994; Longin and Solnik, 1995; Boyer et al., 2006; Israelsen, 2016) and present asymmetric reactions to negative vs. positive shocks (e.g., see Longin and Solnik, 2001), there is still high disagreement among scholars on the drivers of this comovement. This focus is particularly motivated after the seminal papers of Robert Shiller[1] (1981; 1989) that reveal excess volatility and co-volatility in prices compared to fundamentals. The work of King et al. (1994) also shows that only a small portion of the covariation between markets is explained by economic variables. Thus, alternative theories try to interpret the excess comovement anomaly focusing on correlated investor sentiment and irrational behaviour (Barberis et al., 2005).

A more rational approach advocates the role of limited investor attention to financial information as a source of excess comovement (e.g., see Veldkamp, 2006*a*,*b*; Peng and Xiong, 2006; Mondria, 2010; Andrei and Hasler, 2014). Peng and Xiong (2006) lay the groundwork for market consequences related to increasing comovement when investors trade based on market-wide than firm-specific news. This type of information distracts investors from the true value of their assets and lead to correlated inferences for their fundamentals. However, restrictions in measuring the information that is truly seen by investors lead to limitations in the empirical examination of this explanation. Previously used measures of attention, such as absolute returns, trading volume, advertising expenses, and information supply proxies such as headlines and analysts' coverage are heavily dependent on the assumption that investors should have paid attention to them (e.g., see Grullon et al., 2004; Barber and Odean, 2008; Corwin and Coughenour, 2008; Hou et al., 2009; Chemmanur and Yan, 2010; Mondria and Quintana-Domeque, 2013; Lou, 2014; Yuan, 2015; Israelsen, 2016; Dang et al., 2015). For instance, if a stock is mentioned on the news, then investors should have read

[1]Robert Shiller is the winner of the 2013 Nobel Prize Award in Economic Sciences, jointly with Eugene Fama and Lars Peter Hansen.

this information. However, the over-abundance of information, along with limited cognitive constraints suggest that information demand reflects more accurately what attracts investor interests and updates their beliefs than information supply (Barber and Odean, 2008).

Motivated by the above considerations, the second essay deals with the investigation of correlated investor attention as a determinant of excess comovement across stock markets based on a direct proxy that aggregates the information demand of millions of investors worldwide. In particular, I employ the Google Search Volume Index (SVI), a well-established measure of the search intensity for specific topics in the Google search engine (e.g., see Da et al., 2011; Vosen and Schmidt, 2011; Choi and Varian, 2012; Vlastakis and Markellos, 2012; Kristoufek, 2013; Dugas et al., 2013; Wu and Brynjolfsson, 2015; Da et al., 2015). I introduce "co-attention" to capture the correlated investor attention to market-wide news by searches for stock market indices and stock exchanges. The intuition behind co-attention is based on the theoretical framework of Peng and Xiong (2006). Concurrent focus on market-related news is associated with concurrent distraction of investors from idiosyncratic news leading to correlated inferences for fundamentals and similar price pressures on stock markets.

For a number of reasons, investors are likely to coordinate their attention on similar information. For instance, international investors follow the news on multiple economies to evaluate the interrelations between markets. In periods of high volatility, investors focus more on general information across economies to resolve their uncertainty, explaining why different investors follow the same news concurrently (Peng and Xiong, 2006). This means that co-attention does not refer necessarily to the case of one investor who shares her attention between two markets. It may also reflect a simultaneous interest of different investors for general stock market news. Another possible explanation is related to the social contacts between investors which motivate similar trends in information discovery. The above rationale is also in line with psychological theories which support that the learning process of individuals is facilitated through common observation and interaction (e.g., see Gibson and Rader, 1979; Mundy and Newell, 2007; Seemann, 2011). Barberis et al. (2005) offer a similar explanation on how investors simplify their trading decisions and investing choices, devising rules and heuristics to group assets together. This process creates linkages between assets. Parallel reference of two stock markets in news articles can also trigger further research for them. This idea agrees with Mondria (2010) who suggests that when investors observe correlated signals for different assets, they make similar inferences that impose common stock market dynamics.

I attempt to answer the following questions. Is there significant co-attention on stock market news between financial markets? What are the determinants of co-attention? Does co-attention explain the excess comovement in financial markets? Is the effect of co-attention on stock market comovement more pronounced in developed countries and during highly volatile periods? Is co-attention a channel of financial contagion and crises propagation? These are some of the questions, I address in the third chapter of this thesis. More specifically, I compute co-attention as the simple pairwise correlation of abnormal searches for general news across 33 developed and emerging countries, covering the period from January 1, 2004, to December 31, 2016.

My contributions are as follows. Primarily, I explore co-attention of investors on market-related news and shed some light on the information flows that lead trading decisions. Second, I extend the understanding of co-attention by investigating the factors that explain the common information demand. This is an issue of paramount importance given the consensus reached in Peng and Xiong (2006) that there are serious market implications when investors absorb more market-wide information. To this end, I investigate trading and capital flows, cultural and geographical proximity, and news linkages as potential factors that may explain co-attention. Third, I study the consequences of co-attention on stock market comovement across countries. A positive association indicates that co-attention creates linkages between different economies and imposes similar price dynamics.

Fourth, I connect co-attention to stylised facts in stock market comovement related to stronger correlation in developed economies and crises. Fifth, for the first time I examine jointly the distinct patterns of information demand and supply and their impact on stock market comovement as no empirical study to date conducts a comprehensive evaluation of the "produced" and "consumed" information flows. Given that information is a core component of financial decisions, understanding how investors process it is a major task. Sixth, I study co-attention as a channel of volatility transmission between unrelated economies. The serious by-products of crises and the growing systemic risk between markets attract the interest of many scholars. However, there is still high disagreement on the mechanism that drives the financial contagiousness. To this end, I also attempt to isolate the effect of international and local investors.

My findings exhibit significant cross country co-attention suggesting that investors on aggregate exhibit common information demand across stock markets. My findings also suggest that correlated news explains a part of the variability in co-attention. Surprisingly, financial flows between countries have a less significant role in determining co-attention. However, much of the variation is not explained by the model suggesting that unobservable factors be also decisive for common patterns in attention. I also find that co-attention is positively related to comovement beyond fundamentals. This means that demanding more general news, in the presence of limited time and cognitive resources, imposes constraints on the process of firm news and increases the correlated inferences for the expected value of fundamentals. Additionally, this outcome supports the theory of Peng and Xiong (2006) for a distinct impact of market-wide information on market phenomena.

My empirical analysis reveals that this effect is more prominent for developed economies and recessionary periods. The former is explained by the differences in the environment of developed countries with better infrastructures, coverage and more abundant sources of information (e.g., see Dang et al., 2015, for an extensive analysis of the differences in the information production across countries related to the institutional environment). Moreover, large economies are more open and are in the spotlight not only for investing but also for evaluating the general economic trends. The latter is explained by the attitude of investors to become more concerned about the general market activity during periods of high volatility. Thus, less effort is spent on analysing news related to the fundamentals of the assets in their portfolios. On the same basis, analysts offer broader coverage of financial markets. I also show that co-attention can create linkages between unrelated economies. Distinguishing the co-attention of local investors, I demonstrate that crises are disseminated through international investor co-attention.

The last essay of this thesis deals with an empirical application of portfolio theory in paid search or sponsored advertising. In this type of advertising offered by internet giants such as Google, Baidu and Yahoo!, advertisers bid for keywords through competitive auctions in order to display text ads on the search results page (for a description see Edelman et al., 2005; Abou Nabout et al., 2014). The advertisers are charged every time a user clicks on the ad. This connection of the cost to the performance has increased the popularity of sponsored advertising. As a result, paid search campaigns are the largest component of online advertising since companies worldwide spent over $50 billion in 2014 on advertisements targeted to match keywords searched online by potential customers and are expected to reach $85 billion by 2019.[2] However, companies manage an extensive portfolio of keywords together since there are many typing options and a unique keyword may generate only a few click-to-sale conversions. The performance and the cost of each keyword depend highly on its popularity. But how do companies decide on which keywords to choose and how much to spend on each one in return for uncertain publicity and sales?

There is no consensus in the academic literature or real-world practice, and existing approaches rely on ad hoc measures to assess the performance of individual keywords. As noted by Rutz et al. (2011), these approaches include: (i) "direct marketing strategies" in which for each keyword a cost-benefit analysis is employed to compare advertising-related profits and costs per sale (e.g., see Rusmevichientong and Williamson, 2006), (ii) "model free-strategies" which look at the aggregate sales performance of alternative keyword sets (e.g., the "long tail" or popular keyword strategies, see Skiera et al., 2010 and Jerath et al., 2014), and, (iii) "conversion model-based strategies" which employ keyword characteristics to estimate conditional performance metrics for individual keywords (e.g., Ghose and Yang, 2009; Rutz et al., 2011). All the aforementioned heuristics are performance-based and ignore

[2] *Global Entertainment and Media Outlook 2016 -– 2020*, Price Waterhouse Coopers.

the risk of volatile popularity and the significant covariance between searches. Additionally, despite the huge amounts spent on advertising, there is no effort to find an optimal solution to the budget allocation problem leading to waste of scarce resources and high opportunity costs.

Drawing upon these considerations, in the third essay, I propose the mean-variance portfolio theory of Markowitz (1952; 1968; 2010) solving the optimal allocation of search advertising spend across alternative keywords. This approach is used to assess the performance of individual keywords and, more importantly, of their combinations in a portfolio. A key result that I obtain is the relative amount that has to be invested across keywords in order to maintain optimal performance at an aggregate level. Contrary to existing methods, the proposed approach is well grounded in theory and is consistent with wider firm objectives of profit maximisation. Additionally, it is well-suited for both practical applications and academic research as it can be implemented using readily available data.

The use of portfolio theory in advertising was first proposed by Holthausen Jr and Assmus (1982) for optimal budget allocation when sales responses are uncertain across different market segments. A number of subsequent studies apply a similar approach to problems in advertising and, more generally, to marketing (e.g., Cardozo and Smith Jr, 1983; Devinney et al., 1985; Cardozo and Smith Jr, 1985; Ryals et al., 2007; Borgs et al., 2007; Zhang and Lu, 2009). Dhar and Ghose (2010) draw direct analogies between search advertising markets and financial markets. Specifically, the authors note that search advertising decisions could be solved as portfolio optimisation problems for maximising risk-adjusted returns.

I make three contributions in addition to proposing a new framework for determining budget allocation in paid online search advertising. First, I consider a novel representation of the advertising objective in terms of maximising the growth in firm profits at a given level of risk. This is consistent with the application of the mean-variance approach in finance where portfolio stock growth rates or returns, rather than price levels are used. This representation is different from existing approaches in marketing which focus on maximising levels of sales or profits (e.g., see Holthausen Jr and Assmus, 1982). Beyond issues of consistency, the use of levels is problematic in practice as calculations and comparisons across investments and time are not straightforward. Under mild assumptions, my representation has also the advantage of not depending on sales response functions, click-through-rates, conversion rates and advertising costs.

My second contribution concerns the practical implementation of this methodology. Existing studies of the mean-variance approach in marketing are severely limited by the availability of sales data in relation to advertising. Obtaining reliable sales covariance estimates is particularly challenging as they require not only a sufficient sample size but also synchronous sampling. An additional problem is related to attribution, since it is not always possible to draw a direct link between online advertising and sales for individual consumers. This is because advertising may have a delayed impact on sales or an impact through a non-online channel. I overcome these problems by using a new broad proxy of sales activity in the context of search advertising. This proxy is based on variations in online search intensity for various keywords using data drawn from the Google Trends database. The underlying assumption is that an increase in keyword popularity is associated with an increase in sales. As Google is the leading search advertising provider and the source of the search intensity data, consistency is ensured. Moreover, Google Trends offers a reliable and openly available source of high-quality historical data at monthly, weekly and daily sampling frequencies. The fact that I do not rely on sales data means that I can draw inferences also for new products and services.

Finally, I undertake the first comprehensive empirical application of the mean–variance approach in advertising and marketing. The goal is to test the validity of the approach and to assess its performance against alternative heuristic rules that are currently used by practitioners. Specifically, I estimate the so-called "efficient frontiers" of search advertising spend for 15 major sectors. Each point on the frontier represents an optimal portfolio of keywords that maximises the expected overall growth in search intensity for a given level of risk. Data are drawn from Google Ad Words and Google Trends. Google Ad Words penalises irrelevant advertisers and provides a separate population of keywords available to bid for each sector. This means that each sector has its own separate efficient frontier.

My first major finding is that for all sectors there is a strong positive relationship between average historical growth in keyword popularity and standard deviation. This adds validity to the selected approach as Markowitz theory posits that riskier investments should have higher expected returns. The second major empirical finding is that for all sectors mean-variance optimal portfolios of keywords offer statistically significant improvements in performance over popular alternatives. The alternatives are based on heuristic rules that rank keywords by click-through-rates, popularities and cost-per-reservation ratios, respectively. Finally, I propose a simplification of the proposed approach for practitioners which has few requirements in terms of data and computational complexity and produces comparable results.

Chapter 2

Modelling and Forecasting Stock Market Covariance

2.1 Introduction and Background Information

Accurate estimation of common risk factors is a core task in portfolio allocation, asset pricing, risk management and hedging. Covariance is the most prominent measure of the risk generating from the joint variability between financial assets, and has received much attention in the literature. This effort among scholars has increased substantially after a number of papers revealed time-varying covariance between financial time series (see Bollerslev, 1990; Longin and Solnik, 2001). As a result, a plethora of more complex and heavily parametrized multivariate GARCH models attempt to capture these dynamics precisely, replacing simple covariance alternatives.[1]

It comes as no surprise, though, that the industry has difficulty with adopting computationally demanding models especially in large-scale systems. During the last decade many academic studies focus on modelling the covariance using more parsimonious structures (e.g., see Gouriéroux et al., 2009; Bauer and Vorkink, 2011; Chiriac and Voev, 2011; Jin and Maheu, 2012; Halbleib and Voev, 2016). Additionally, recent approaches present more efficient ways to obtain covariance estimates and forecasts using information from high-frequency data. Despite the importance of accurate covariance forecasting, the existing literature

[1]Engle and Colacito (2006) underline the importance of dynamically modelling correlations and show that they contribute to return from 60 to 100 basis points.

comes with limitations as the predictive performance of various multivariate models has not been examined to the same extent as the univariate models due to high complexity.

I fill this gap in the literature by comparing covariance forecasts across several popular models in the context of five major European equity markets, namely France, Germany, Netherlands, Switzerland, and the UK.[2] Employing an extensive dataset of daily and intraday prices and corresponding option-implied volatilities from January 1, 2000, to April 19, 2016, I contribute to the extant literature in several ways. First, I perform a rigorous comparison using models not only from the widely used GARCH family but also across simpler parametric and non-parametric specifications. I analyse whether they exhibit different forecasting ability in short, medium and long-run horizon forecasts and various market conditions including the recent 2007-2009 global financial crisis as well as the Eurozone debt crisis. Using the realised covariance as a well-established proxy of the latent covariance obtained from 5-minute intraday returns (see Andersen et al., 2003; Barndorff-Nielsen and Shephard, 2004), I measure their forecast accuracy based on five loss functions and two statistical tests.

Second, unlike other studies that compare covariance forecasting techniques based mostly on historical data (high- and low-frequency), I accommodate models that rely on different information sets, including (forward-looking) option-implied information. This is extremely important given the findings of various studies on the higher informativeness of high-frequency and option-implied data for variance and covariance forecasting (e.g., see Bollerslev and Zhang, 2003; Fleming et al., 2003; Busch et al., 2011; Maheu and McCurdy, 2011; Chang et al., 2012; Hollstein and Prokopczuk, 2016; Halbleib and Voev, 2016). Third, I examine hybrid option-implied models adjusted for the volatility risk-premium bias (Chernov, 2007) in the spirit of DeMiguel et al. (2013). This is particularly important following the findings of Prokopczuk and Simen (2014) which reveal superior univariate forecasts by adjusting option-implied volatility for the volatility risk-premium. To the best of my knowledge, this is the first study that investigates the importance of this adjustment in the context

[2]See International Monetary Fund, World Economic Outlook, 2016. I do not include Italy and Spain, because there are no implied volatility indices or a long enough history of intraday prices.

of covariance forecasting.

Fourth, I study the forecasting accuracy of the multivariate extension of the recently proposed Heterogeneous Autoregressive (HAR) of Corsi and Audrino (2007) and Corsi (2009), proposed and applied by Bauer and Vorkink (2011) and Chiriac and Voev (2011). Despite the fact that the univariate HAR model significantly outperforms a broad range of popular volatility models (Kourtis et al., 2016), there is scarce evidence of its performance among important covariance models. Fifth, I investigate the performance of models in an international context. Given that financial markets become more integrated and the systemic risk increases substantially in highly correlated economies, it is essential for financial institutions to measure covariances accurately. To account for non-synchronicity issues and alleviate concerns about microstructure noise, I select major countries within the same geographic region.[3] Concentrating on stock market indices rather than individual stocks also ensures that my analysis is unaffected by illiquidity, which is always an issue with individual equities. Last and most important, I measure the economic benefits of accurate covariance forecasts for international investors who allocate their wealth across the five European equity markets under consideration.

In my empirical analysis, I employ the most popular models from the GARCH family. In particular, I consider the scalar and the diagonal BEKK models of Ding and Engle (2001) and Kroner and Ng (1998) respectively, to overcome the difficulties of the fully parametrized version for more than three assets. I examine the Constant Conditional Correlation model (Bollerslev, 1990) and the extension of Engle (2002) to the Dynamic Conditional Correlation. These estimation methods follow a two-step process. The first step involves the modelling of GARCH(1,1) univariate volatilities, while the second step extends them to the multivariate

[3]Most studies focus on stocks from the same stock market. There is little consensus in literature on which covariance model is the best using data on international markets. Ledoit et al. (2003) present the flexible multivariate GARCH model in an application on international equity markets but their purpose is to demonstrate its superiority with respect to other GARCH alternatives. Colacito et al. (2011) employ international indices but they focus on testing the performance of the DCC-MIDAS within a portfolio allocation framework.

level. I also study the orthogonal GARCH model (Alexander and Chibumba, 1997; Alexander, 2001) which reduces the number of parameters with the use of principal components. To incorporate asymmetries from negative shocks, I use the asymmetric versions of all these models.

The multivariate GARCH models are well established in literature providing flexibility in modelling covariances as a function of past shocks and covariances (see Bauwens et al., 2006, for an extensive review). However, their complexity when the number of assets increases dictates many computational constraints ("curse of dimensionality"). As a result, the industry is reluctant to adopt burdensome covariance techniques, compromising on less demanding, yet less efficient solutions. Such trade-off, though, can be a source of suboptimal capital investment and higher portfolio risk that arise when the predicted covariance deviates from the true covariance. My purpose is to test the accuracy of these models covering the full spectrum from heavy parametric to very parsimonious alternatives. To this end, I also employ the parsimonious Exponentially Weighted Moving Average estimator of RiskMetrics.

All the previous methods use daily data to estimate the model parameters. Given that other sources of information can be easily obtained, I attempt to answer whether models based on intraday or option-implied information outperform the established covariance techniques. The aforementioned Vector Heterogeneous Autoregressive model (VHAR) is a simple parametric model which estimates covariance forecasts using 5-minute returns. This model captures the persistence through a panel regression on past daily, weekly and monthly realisations of covariance. I also employ non-parametric models based on high-frequency data. From this family, I consider the naive lagged realised covariance (LRCOV), assuming that past realisations of covariance are informative about future covariance.

I also assess the performance of the hybrid implied covariance model. I am the first to combine option-implied volatility with realised correlation in covariance forecasting as a solution to the lack of implied correlation data. This approach follows Buss and Vilkov (2012) who present a similar approach for the estimation of implied betas when it is not possible to obtain option-implied data directly. In the same spirit, I investigate whether the combination of historical intraday information with (forward-looking) option data improves the precision of covariance forecasts. Potential benefits from mixing different information sets towards more accurate covariance are also examined in recent papers. However, they rely on daily historical information. For instance, Halbleib and Voev (2016) present a covariance model that uses high-frequency information for the estimation of variance and low-frequency for the estimation of covariance. Other papers employ different frequencies of the same information set, such as the work of Colacito et al. (2011). As mentioned above, I also generate covariance forecasts adjusting the implied volatility for the volatility risk-premium using two different specifications to estimate the ex-ante expectation of variance. I use (i) the lagged realised volatility from 5-minute intraday returns and (ii) the HAR model following the findings of Kourtis et al. (2016) which suggest that it offers accurate volatility forecasts.

I compare daily, weekly, and monthly in-sample fit and out-of-sample forecasts on the basis of the Absolute distance, Euclidean distance, Frobenius distance, Stein and Quasi-likelihood loss functions. I, then, identify superior models using the statistical test of Giacomini and White (2006) for pairwise forecast comparisons and the Model Confidence Set of Hansen et al. (2011) for comparisons across all models. In general, the best model is the VHAR. In many cases, this does not differ significantly from the naive lagged realised covariance and the adjusted hybrid models indicating that more parsimonious models that estimate forecasts based on high-frequency and option-implied data are statistically superior to the popular GARCH models. Despite that the results are not as decisive for hybrid models, I document that the volatility risk-premium adjustment improves the predictive performance of the unadjusted hybrid estimator. I further examine how the models are ranked when covariance between markets varies under more or less volatile conditions. I do not report differences in the ranking, but I find that the forecasting accuracy of the models worsens. While the ranking of VHAR is robust across different loss functions and tests, the same does not apply to the rest of models. Two factors explain my findings. First, there is higher information content in high-frequency data. Second, the estimation of a vast number of parameters affects the predictive accuracy of the covariance models significantly.

I move a step further to assess the economic value of investing in the global minimum variance portfolio compared to an $1/N$ benchmark (see DeMiguel et al., 2009; Kourtis et al., 2016), and I find that the VHAR, the LRCOV and the adjusted option-implied models lead to lower portfolio risk compared to the $1/N$ benchmark at the daily and weekly horizons. In addition, their average portfolio turnover indicates that they generate stable allocations with comparable costs of rebalancing with regards to the rest models under consideration, particularly in the longer horizons.

My results have important implications for risk management, asset allocation and hedging. For instance, the contribution of covariance for the determination of the overall portfolio risk increases substantially as the number of assets increases. Thus, inaccurate forecasts may lead to suboptimal asset allocation decisions. This study is important not only for the individual international investors but also for financial institutions which aim at diversification benefits by maintaining international portfolios. My findings also have significant implications to the regulatory frameworks as well in light of Basel III, contributing on how financial institutions should measure the risk and the minimum capital risk requirements (similar to Brooks et al., 2002).[4] Duffie (2008) points out the lack of accurate covariance models for the estimation of default risk and presents the naive techniques used as part of weak risk management in financial institutions. Furthermore, effective hedging depends on accurate covariance forecasts between the returns of the underlying asset and the derivative (Skintzi and Xanthopoulos-Sisinis, 2007; Hsu et al., 2008).

This chapter contributes to two major streams in the literature. Primarily, I add to the extant literature of covariance forecasting. The majority of studies in this area focus on accurate covariance and correlation modelling (e.g., Alexander, 2001; Engle, 2002; Gouriéroux et al., 2009; Bauer and Vorkink, 2011; Chiriac and Voev, 2011; Halbleib and Voev, 2016). However, there is little consensus in the existing literature on the most prominent covariance models among the most dominant alternatives. I, therefore, extend the literature by performing a comprehensive comparison of several popular covariance forecasting models both

[4] http://www.bis.org/publ/bcbs152.pdf

in statistical and economic terms. My study is closely related to the work of Laurent et al. (2012) who demonstrate how models of the multivariate GARCH family perform. However, my research differs from theirs in that I consider models from more families that employ high-frequency and option-implied data. This is an essential difference given that the forecasting performance of these models is not extensively studied in the literature. Also, I do not only explore statistical differences among models as Laurent et al. (2012) do, but I assess whether they are translated into economic gains.

This essay also adds to the growing literature that employs high-frequency data to evaluate portfolio performance. Fleming et al. (2003) report substantial gains from a volatility timing strategy, which uses intraday than daily data for the estimation of the covariance matrix. Hautsch et al. (2015) show that using intraday data lowers portfolio risk substantially. I investigate whether covariance forecasts obtained from intraday data or a mix of intraday with options data lead to superior portfolio performance compared to those based on models that employ daily data.

The remainder of this chapter is organised as follows. Section 2 presents the empirical analysis. In particular, it describes the methodology and the data, the out-of-sample performance of the covariance forecasts under the total period and different market regimes respectively, the in-sample accuracy of the models, the economic gains within a minimum variance portfolio and the robustness checks. Section 3 identifies the limitations and future extensions, and Section 4 presents the main conclusions.

2.2 Empirical Analysis

2.2.1 Methodology

Let r_t be an $N \times 1$ vector of returns on N assets for $t = 1, 2, ..., T$. Also, $\mathcal{F}_{t-1}$ indicates the information set available up to time *t-1*. Assuming a constant conditional mean model, returns r_t are expressed as:

$$r_t = \mu_t + e_t \tag{2.1}$$

where $\mu_t = E(r_t|\mathcal{F}_{t-1})$ is the conditional mean and e_t denotes a vector of innovations satisfying:

$$e_t = H_t^{1/2} z_t \tag{2.2}$$

where H_t is the $N \times N$ positive definite conditional covariance matrix of e_t (i.e., $H_t = E_{t-1}(e_t e_t'))$, and z_t is an i.i.d. vector (standardised residuals) that follows a multivariate standard normal distribution, $z_t \sim N(0, I_N)$. I_N is an $N \times N$ identity matrix. Below, I consider several different ways of modelling H_t in order to obtain forecasts of the latent covariance Σ_t.

Latent Covariance Proxy

As the true covariance, Σ_t, is unobservable, a proxy, $\hat{\Sigma}_t$, is required. The most popular and theoretically justified proxy is the realised covariance computed from intraday returns sampled at equally spaced intervals (e.g., as explained in Andersen et al., 2003, every 5, 15, or 30 minutes). If the prices are observed in $M+1$ intraday intervals at times $t_0, t_1, ..., t_M$ and p_{t_j} is the logarithmic price at time t_j, then the corresponding return, r_{t_j}, for the j^{th} intraday interval of day t is defined as $r_{t_j} = p_{t_j} - p_{t_{j-1}}$. The realised covariance is a non-parametric estimator of Σ_t given by:

$$RCOV_t = \hat{\Sigma}_t = \sum_{j=1}^{M} r_{j,t} \, r'_{j,t} \tag{2.3}$$

It has been shown in Andersen, Bollerslev, Diebold and Ebens (2001) that the above estimator computes consistently the true unobserved covariance as the sampling frequency goes to infinity. Following the standard practice, I use 5-minute returns to calculate 1-day $\hat{\Sigma}_t$. Covariance over τ-day horizons are estimated by the sum of daily realised covariances.

Covariance Forecasting Models

I examine sixteen covariance forecasting models. These alternatives do not belong exclusively to one family of covariance models and they differ in various ways. I study parametric and non-parametric specifications spanning from more complex with a large number of parameters to simpler parameter-free ones. They are also subject to different estimation methods or information sets.

Models using Daily Data

Diagonal BEKK

From the multivariate GARCH family, I consider the Baba-Engle-Kraft-Kroner model (BEKK) as is defined in Engle and Kroner (1995). The BEKK(1,1) model is a multivariate extension of the univariate GARCH model of Bollerslev (1986), specified as follows:

$$H_t = C'C + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B \tag{2.4}$$

where C is an $N \times N$ positive definite upper triangular matrix of $N(N+1)/2$ constant terms, and A and B are $N \times N$ matrices of parameters. A major advantage of the BEKK model is that it guarantees the positive definiteness of matrix H_t. The full version of the model is heavily parametrized in the sense that the number of parameters for estimation increases rapidly with the number of assets.[5] Thus, it cannot be adopted for large dimensions. To this end, similar to Laurent et al. (2012), I estimate the reduced and more parsimonious diagonal version (DiagBEKK). The square matrices A and B are diagonal. Nevertheless, the model still involves a large number of parameters (e.g., for 5 assets, 25 parameters are estimated). An additional drawback of this version is that it ignores spillovers between the assets.

Asymmetric Diagonal BEKK

The DiagBEKK assumes no difference in the impact of positive and negative shocks of

[5] In the full BEKK model $2N^2 + N(N+1)/2$ parameters are estimated. 65 parameters are required for 5 assets.

the same magnitude on conditional covariance. In the presence of extensive evidence of asymmetric comovement in equity markets (Ang and Bekaert, 2002; Cappiello et al., 2006), which tends to be higher following negative return shocks, I allow for leverage effects on multivariate volatility, estimating the asymmetric specification of the diagonal BEKK model (A-DiagBEKK) extending Equation (2.4) as follows:

$$H_t = C'C + A'e_{t-1}e'_{t-1}A + \Gamma' u_{t-1}u'_{t-1}\Gamma + B'H_{t-1}B \tag{2.5}$$

where u_t corresponds to the $N \times 1$ vector of negative shocks defined as $u_t = min(e_t, 0)$, and Γ is a diagonal $N \times N$ matrix of parameters. The rest of the notation is as previously defined.

Scalar BEKK

The scalar BEKK (ScBEKK) reduces the parameters of diagonal BEKK by imposing similar dynamics on all elements in matrices A and B (e.g., for 5 assets, 17 parameters are estimated). Thus, Equation (2.4) is modified to:

$$H_t = C'C + \alpha e_{t-1}e'_{t-1} + \beta H_{t-1} \tag{2.6}$$

where α and β are scalars. The rest of the notation is as previously defined.

Asymmetric Scalar BEKK

The symmetric version of ScBEKK imposes similar dynamics on the leverage effects as well. To account for asymmetries, the asymmetric ScBEKK (A-ScBEKK) is specified as:

$$H_t = C'C + \alpha e_{t-1}e'_{t-1} + \gamma u_{t-1}u'_{t-1} + \beta H_{t-1} \tag{2.7}$$

where γ is a scalar. The rest of the notation is as previously defined.

Constant Conditional Correlation

The Constant Conditional Correlation model (CCC) of Bollerslev (1990) assumes that conditional correlations remain constant, while conditional covariances vary over time and are proportional to conditional volatilities. The model is formally defined as follows:

$$H_t = D_t R D_t \tag{2.8}$$

where $D_t = diag\{\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, ..., \sqrt{h_{NN,t}}\}$ is a diagonal matrix. The diagonal elements are the conditional volatilities (i.e., the square root of conditional variances) of the N assets. The $h_{ii,t}$ are modelled through univariate GARCH(1,1) processes. R is the $N \times N$ unconditional correlation matrix of the standardised residuals from Equation (2.1) given by $z_{it} = e_{it}/\sqrt{h_{ii,t}}$. Positive conditional variances and the positive definite matrix R ensures the positive definiteness of H_t. The CCC model offers the advantage of easier estimation compared to BEKK, as it only requires estimation of N univariate GARCH(1,1) models. Also, the inverse covariance matrix required for the optimisation of the multivariate quasi-likelihood function can be easily computed as it relies on univariate volatility processes and the unconditional correlation matrix, R. However, the non-linearity in Equation (2.8) imposes greater difficulty in the estimation of the unconditional covariances than the unconditional variances. An important disadvantage of this model is the assumption that conditional correlations are time-invariant. This hypothesis is unrealistic based on the empirical findings of many studies which reveal time-varying conditional correlations (e.g., Longin and Solnik, 2001).

Asymmetric Constant Conditional Correlation

Asymmetries in CCC (A-CCC) are imposed through GJR-GARCH(1,1) processes of Glosten et al. (1993) for each diagonal element of D_t. The GJR-GARCH model captures the asymmetries observed in empirical studies related to the stronger impact of negative shocks than positive shocks (see Kroner and Ng, 1998) as follows:

$$h_{ii,t} = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} + \gamma_i u_{i,t-1}^2, \qquad \text{for all } i \tag{2.9}$$

where ω_i, α_i, β_i and γ_i are parameters for estimation. The rest of the notation is as previously defined.

Dynamic Conditional Correlation

To accommodate time-varying conditional correlations, Engle (2002) extend the CCC model in Equation (2.8) to the Dynamic Conditional Correlation (DCC).[6] This is estimated through a two-step process described by:

$$R_t = V_t^{-1} Q_t V_t^{-1} \tag{2.10}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} z_{t-1}' + \beta Q_{t-1} \tag{2.11}$$

where $V_t = diag\{\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, ..., \sqrt{q_{NN,t}}\}$. z_t are the standardised innovations estimated as $z_{ii,t} = e_{it}/h_{ii,t}$, where $h_{ii,t}$ follow a univariate GARCH model. $\bar{Q}$ is the unconditional covariance matrix of the $z's$. The $q_{ij,t}$ elements of matrix Q_t represent quasi-correlations, which are re-scaled within [-1,1] and are used to calculate conditional correlations as $h_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t} q_{jj,t}}$.

There is additional difficulty in ensuring positive definiteness $\forall t$. However, this is imposed assuming that the same dynamics govern the conditional correlations. The necessary

[6] Christodoulakis and Satchell (2002) and Tse and Tsui (2002) also propose dynamic generalisations of the CCC. While the former is easily implemented and Fisher transformation of the conditional correlation matrix guarantees positive definiteness, it is restricted to the bivariate case. The latter is an alternative representation of the model of Engle (2002). A difference between them is that the DCC of Engle formulates the conditional correlations as the bivariate standardised products, while the DCC of Tse and Tsui forms them as the weighted sum of past correlations. Since Tse and Tsui's DCC has not received the same interest in the literature, I calculate the DCC of Engle.

condition to ensure mean-reverting correlations is to impose restrictions on the scalar parameters to satisfy $\alpha + \beta < 1$.

Similar to CCC, DCC is easily estimated through (i) non linear combinations of univariate GARCH models and (ii) estimation of parameters in Equation (2.11). This results in feasible solutions in large systems. A drawback of the standard DCC model is that the scalar parameters impose the same dynamics on all correlations.

Asymmetric Dynamic Conditional Model

The asymmetric extension of the standard DCC model (A-DCC) that allows for leverage effects on dynamic correlation is described by:

$$Q_t = [(1-\alpha-\beta)\bar{Q} - \gamma\bar{N}] + \alpha z_{t-1}z_{t-1}' + \beta Q_{t-1} + \gamma u_{t-1}u_{t-1}' \tag{2.12}$$

where $u_t = I_{\{e_t<0\}} \circ e_t$ is a vector of negative innovations, and $\bar{N}$ is the unconditional covariance matrix of the negative innovations ($u's$). Asymmetries are also estimated on the univariate $h_{ii,t}$ through GJR-GARCH models. The rest of the notation is as defined above.

Orthogonal GARCH

From the GARCH family, I also consider the orthogonal GARCH (OGARCH) model of Alexander and Chibumba (1997) and Alexander (2001). This model belongs to the class of factor models, which are based on the assumption that the observed return series can be expressed as a linear transformation of a few uncorrelated factors. An important advantage of this model is that these factors are simply obtained through univariate GARCH(1,1) models on a few principal components of the full covariance matrix (linear combinations). As a result, it circumvents difficulties in large-scale systems estimating a smaller number of parameters. Empirical evidence has also shown that the model is particularly successful in the context of highly correlated assets (Alexander, 2001).

More specifically, assuming that $z_t = V^{-1/2}e_t$ is the vector of standardised innovations at time t, where V is the $N \times N$ diagonal matrix of the unconditional variances of the innovations e_t. Then, the $p \times 1$ vector of principal components of the correlation matrix of z_t at time t is given by $f_t = \Lambda^{-1/2}P'z_t$ where Λ is the $p \times p$ diagonal matrix of the eigenvalues of the unconditional correlation matrix of the z_t's ranked in decreasing order and P is the $N \times p$ matrix of the corresponding eigenvectors. The diagonal conditional covariance matrix of e_t is approximated as follows [7]:

$$H_t = \tilde{W}_t S_t \tilde{W}_t' + \Omega \tag{2.13}$$

where $\tilde{W}_t$ is an $N \times p$ matrix of normalised factor loadings corresponding to the p principal components, where $\tilde{W}_t = V^{1/2}P\Lambda^{1/2}$. and S_t is a diagonal matrix of conditional covariances of the p principal components obtained through estimation of univariate GARCH(1,1) models on each of the factors. Ω is the unconditional covariance matrix of the approximation error by using p ($p < N$) instead of the full number of principal components.[8] However, the reduced rank of the conditional variance matrix may be a problem in applications that require the inverse of H_t.

The main benefit of this model lies in the parsimony and estimation simplicity. Large covariance matrices are not a problem since the factors reduce the dimensions substantially. In highly correlated systems, a few principal components can explain most of the variation in the data. Moreover, the principal component analysis allows to identify the risk associated with each component (see Alexander, 2008, pp. 171-180, for more details). Given the small dimension of this problem, I set the full set of principal components and therefore Ω in (2.13) is equal to zero.

[7] $H_t = E_{t-1}(e_t e_t^{'}) = E_{t-1}(V^{1/2}z_t z_t^{'}V^{1/2}) = E_{t-1}[V^{1/2}P\Lambda^{1/2}P^{'}(\Lambda^{1/2})^{'}V^{1/2}]$. Given that $S_t = E_{t-1}(f_t f_t^{'})$ and because of the orthogonality of factors $P^{'} = P^{-1}$, I arrive at Equation (2.13).

[8] For $p = N$, $\Omega = 0$.

Asymmetric Orthogonal GARCH

The asymmetric orthogonal GARCH model (A-OGARCH) is constructed using the GJR-GARCH(1,1) to model the conditional variances of the factors f. More specifically, the conditional factor variances in Equation (2.9) become as follows:

$$s_{ii,t} = \omega_i + \alpha_i f_{i,t-1}^2 + \beta_i s_{ii,t-1} + \gamma_i I_{[f_{i,t-1}<0]} f_{i,t-1}^2 \tag{2.14}$$

where I is an indicator variable for negative factors. However, the transformation of the returns to factors complicates the interpretation of the factor asymmetry. The rest of the notation is as defined above.

Exponentially Weighted Moving Average

I employ the exponentially weighted moving average (EWMA) covariance, also known as the "RiskMetrics" estimator, which is the most widely used model for estimation of covariance and VaR (International Monetary Fund, 2007; Danielsson, 2008). The EWMA model assigns exponentially decaying weights for the covariance matrix allocating more weight to more recent information. Similar to BEKK, EWMA is a generalisation of the univariate GARCH(1,1) model describing volatilities as unit root processes. However, EWMA lacks a mean reversion term. Covariance is recursively computed as follows:

$$H_t = (1-\lambda)\, e_t\, e_t' + \lambda\, H_{t-1} \tag{2.15}$$

where the parameter λ determines the rate of decay. Following the standard practice, I adopt $\lambda = 0.94$.

EWMA is very simple to implement in large dimension problems as it does not require any optimization and needs only one parameter. Nevertheless, it is subject to the criticism that parameter λ governs the dynamics of every component. Moreover, the choice of the parameter is based on the estimation of "RiskMetrics", which means that it is not adjusted uniquely to each problem.

Models with High-frequency Data

Lagged Realised Covariance

I consider a naive covariance forecasting method which is based on lagged realised covariance (LRCOV). This model assumes that covariance is a Markov process and therefore last period's covariance is highly informative of future covariance. This is even more pronounced since this is estimated using high-frequency information. Empirical evidence suggests that high-frequency based measures be superior to measures obtained from daily data (e.g., see Bollerslev and Zhang, 2003; Maheu and McCurdy, 2011). The LRCOV is modelled as:

$$H_t = H_{t-\tau} \tag{2.16}$$

Despite the naive approach, LRCOV has the great advantage of being parameter-free, which reduces errors subject to the estimation method.

Vector Heterogeneous AutoRegressive Model

Corsi and Audrino (2007) and Corsi (2009) propose the Heterogeneous Autoregressive (HAR) model to capture the long-memory in volatility, documented by several studies (e.g., see Andersen, Bollerslev, Diebold and Labys, 2001; Andersen et al., 2003). Chiriac and Voev (2011) extend the previous work at a multivariate level proposing the Vector Heterogeneous AutoRegressive model (VHAR), which expresses the realised covariance as a linear combination of daily, weekly and monthly realised covariances as:

$$Y_{t+1} = c + \beta_d Y_t + \beta_w Y_{t-4:t} + \beta_m Y_{t-21:t} + \varepsilon_{t+1} \tag{2.17}$$

where $Y_t = vech(X_t)$ is a $q \times 1$ vector that stacks the $N(N+1)/2$ upper triangular elements of

X_t obtained from the Cholesky decomposition of $H_t = X_t' X_t$ as in Chiriac and Voev (2011). Modelling factors rather than the H_t does not require parameter restrictions on the model since the reverse of the Cholesky transformation is positive definite. c is a constant and β_d, β_w, and β_m represent the slope parameters of daily, weekly, and monthly components obtained through OLS regression. The τ-day covariance terms Y_t (for weekly and monthly covariances) are computed as $Y_{t-\tau:t} = \frac{1}{\tau}\sum_{j=0}^{\tau-1} Y_{t-j}$. Then, I obtain covariance forecasts, H_t, by a reverse transformation of the Y_t's. As pointed out in Chiriac and Voev (2011), modelling the Cholesky factors rather than covariances directly is done to avoid imposing unnecessary restrictions to ensure positive definite covariance matrices. As before, I iteratively produce τ-step ahead covariance forecasts ($H_{t:t+\tau}$) based on day-ahead forecasts obtained from (2.17).

VHAR is a parsimonious model that involves a fixed number of parameters regardless of the number of assets and is easy to estimate through panel OLS. However, all covariances are assumed to obey the same dynamics.

Hybrid Models of High-frequency and Option-implied Data

Hybrid Implied Covariance

I estimate τ-day ahead forecasts using the non-parametric Hybrid Implied Covariance model (HICOV) which combines option-implied and high-frequency information as:

$$H_{t:t+\tau} = IV_t^{(\tau)} RC_{t-\tau:t} IV_t^{(\tau)} \tag{2.18}$$

where $IV_t^{(\tau)}$ is a diagonal matrix with τ-horizon implied volatilities, and RC_t is the realised correlation estimated by high-frequency data. Since in my analysis I employ stock market indices, I cannot extract fully option-implied correlations using existing approaches. For instance, Driessen et al. (2009) rely on implied volatilities of a market index or portfolio of assets and its constituents to approximate implied correlations, which is obviously not applicable in my case. Moreover, the methodology of Chang et al. (2012), that estimates option-implied betas based on risk-neutral volatility, skewness or kurtosis, assumes a linear asset pricing model (e.g., CAPM). This consists of an asset and the market portfolio. This means that it can be implemented in the case of assets, but not in the case of indices. The combination of option-implied and historical data is presented by Buss and Vilkov (2012) to improve the predictive accuracy of realised beta coefficient. As the implied correlations are not observable, they approximate them using daily historical data. On the contrary, I substitute them with high-frequency information. There is ample evidence that the forward-looking information in option prices predicts better future volatilities and betas as implied volatilities represent the current market expectations about future market dynamics (see Busch et al., 2011; Chang et al., 2012; Hollstein and Prokopczuk, 2016). I rescale the annualised implied volatility index for index options with 1-month maturity (IV) to forecast the τ-horizon covariance by setting $IV_t^{(\tau)} = \sqrt{\tau/252}IV_t$ similar to Kourtis et al. (2016).

Adjusted Implied Covariance

Several studies in the literature suggest that implied volatilities are related to biased forecasts of future realised volatility unless the market price of volatility risk is zero (Chernov, 2007). This assumption is rejected by several studies which find a strong negative risk-premium (e.g., Carr and Wu, 2009; Driessen et al., 2009).[9] Thus, I also implement the non-parametric correction of DeMiguel et al. (2013) for the volatility risk-premium. Prokopczuk and Simen (2014) find that this correction improves the performance of univariate volatility models. Thus, the variance risk-premium for each asset from t to $t+\tau$ is estimated as follows:

$$VRP_{t:t+\tau} = \frac{IV_{t:t+\tau}^2}{E(RV_{t:t+\tau}^2)} \tag{2.19}$$

where $VRP_{t:t+\tau}$ is the variance risk-premium between t and $t+\tau$, $IV_{t:t+\tau}$ is the model-free implied volatility and $E(RV_{t:t+\tau}^2)$ is the expected realised variance for the period from t to

[9]A negative risk-premium reflects that investors are averse to increasing volatility and, thus, they are willing to pay a premium to hedge against it.

$t+\tau$. Forecasts of the realised variance are obtained using the LRCOV. Following DeMiguel et al. (2013), the average risk-premium, $\overline{VRP_t}$, over $252-\tau$ days is estimated as:

$$\overline{VRP_t} = \frac{1}{252-\tau} \sum_{j=t-251}^{t-\tau} VRP_{j:j+\tau} \tag{2.20}$$

The risk-premium corrected implied volatility, $\widetilde{IV_t}$, is calculated as follows:

$$\widetilde{IV_t} = \sqrt{\frac{IV^2_{t:t+\tau}}{\overline{VRP_t}}} \tag{2.21}$$

The τ-day ahead covariance forecasts are estimated as:

$$H_{t:t+\tau} = CIV_t \quad RC_{t-\tau:t} \quad CIV_t \tag{2.22}$$

where CIV_t is an $N \times N$ diagonal matrix containing the $\widetilde{IV_t}$ and $RC_{t-\tau:t}$ is the realized correlation from day $t-\tau$ to day t. The rest of the notation is as defined above.

HAR Adjusted Implied Covariance

Last, I estimate the HAR Adjusted Implied Covariance (AdjHAR-HICOV) model substituting the RV in Equation (2.19) with the HAR model forecasts, following the findings of Kourtis et al. (2016) that HAR produces good volatility forecasts.

Table 2.1 presents an overview of these models. Overall, I include models that come from the multivariate GARCH family, conditional either on past variances and covariances (DiagBEKK, A-DiagBEKK, ScBEKK, A-ScBEKK) or past variances and correlations (CCC, A-CCC, DCC, A-DCC), models that simplify the covariance matrix using factors (OGARCH, A-OGARCH), and simpler models that do not require any assumption (VHAR) or parameter estimation (EWMA, LRCOV, HICOV, Adj-HICOV, AdjHAR-HICOV). All parametric

Table 2.1

Description of Models

This table describes the models used for the estimation of covariance forecasts, the data, and the number of parameters for N assets. The hybrid models use option-implied and high-frequency data.

Code	Model	Data	# of Parameters
ScBEKK	Scalar BEKK	Daily	$2 + N(N+1)/2$
A-ScBEKK	Asymmetric Scalar BEKK	Daily	$3 + N(N+1)/2$
DiagBEKK	Diagonal BEKK	Daily	$2N + N(N+1)/2$
A-DiagBEKK	Asymmetric Diagonal BEKK	Daily	$3N + N(N+1)/2$
CCC	Constant Conditional Correlation	Daily	$N(N-1)/2 + 3N$
A-CCC	Asymmetric Constant Conditional Correlation	Daily	$N(N-1)/2 + 4N$
DCC	Dynamic Conditional Correlation	Daily	$3N + N(N-1)/2 + 2$
A-DCC	Asymmetric Dynamic Conditional Correlation	Daily	$4N + 2N(N-1)/2 + 2$
OGARCH	Orthogonal GARCH	Daily	$3N$
A-OGARCH	Asymmetric Orthogonal GARCH	Daily	$4N$
EWMA	Exponentially Weighted Moving Average	Daily	1
LRCOV	Lagged Realised Covariance	High-Frequency	-
HICOV	Hybrid Implied Covariance	Hybrid	-
Adj-HICOV	Adjusted Hybrid Implied Covariance	Hybrid	-
AdjHAR-HICOV	Adjusted HAR Hybrid Implied Covariance	Hybrid	-
VHAR	Vector Heterogeneous AutoRegressive	High-Frequency	4

models are estimated via quasi-maximum likelihood (QML) except for the VHAR and the AdjHAR-HICOV which require the ordinary least square method (OLS).

In this table, I also summarise the models according to the information sets employed (daily, high-frequency, hybrid). The hybrid models involve a combination of high-frequency, and option-implied data. The last column is indicative of the computational requirements and the complexity presenting the number of parameters for an $N-$asset covariance matrix. For 5 assets the GARCH models should estimate 17, 18, 25, 30, 25, 30, 27, 43, 15 and 20 parameters for ScBEKK, A-ScBEKK, DiagBEKK, A-DiagBEKK, CCC, A-CCC, OGARCH[10] and A-OGARCH[11] respectively. EWMA does not require the estimation of the parameter λ since this is suggested by RiskMetrics. LRCOV, HICOV, and Adj-HICOV are parameter-free computations of covariance. The parametric VHAR and AdjHAR-HICOV require the estimation of 4 parameters regardless the number of assets.

[10]The number of parameters for p factors is $p(p-1)/2 + 2p$.

[11]The number of parameters for p factors is $p(p-1)/2 + 3p$.

Model Evaluation Criteria - Loss functions

To evaluate the out-of-sample performance of the multivariate models empirically, I employ five multivariate loss functions that summarise the forecasting accuracy of various covariance forecasting models in a single statistic. Patton (2011) and Laurent et al. (2013) derive the properties of consistent statistical loss functions that are robust to biases induced by noisy proxies of the latent covariance. According to their findings, the widely used absolute deviation, $\mathcal{L}_A$, is not a robust loss function (e.g., see Chan et al., 1999; Clements et al., 2009). However, I include it in the set of loss functions due to its popularity. In doing so, I illustrate how the ranking differs when simpler or more complex models are used.

Also, I employ four robust statistical loss functions. $\mathcal{L}_E$ is the Euclidean quadratic loss function computed by equally weighting all the unique elements of the forecast error matrix. $\mathcal{L}_F$ is the Frobenius quadratic loss function which extends at a multivariate level the mean squared error assigning double weights to the covariance forecast errors. The Stein loss function (also known as Burg divergence), $\mathcal{L}_S$, is scale-invariant as estimates standardised forecast errors. $\mathcal{L}_S$ accounts for asymmetries regarding under-/over-predictions and penalises under-predictions. $\mathcal{L}_Q$ is the quasi-likelihood loss function. The loss functions are presented below:

$$\mathcal{L}_A = \|vech(\Sigma_t - H_t)'\|_1 \tag{2.23}$$

$$\mathcal{L}_E = vech(\Sigma_t - H_t)'vech(\Sigma_t - H_t) \tag{2.24}$$

$$\mathcal{L}_F = Tr[(\Sigma_t - H_t)'(\Sigma_t - H_t)] \tag{2.25}$$

$$\mathcal{L}_S = Tr[H_t^{-1}\Sigma_t] - log|H_t^{-1}\Sigma_t| - N \tag{2.26}$$

$$\mathcal{L}_Q = log|H_t| + Tr[H_t^{-1}\Sigma_t] \tag{2.27}$$

where $\|\cdot\|_1$ is the 1-norm, $vech$ is the operator that stacks to a vector all the lower triangular covariance matrix along with the main diagonal and Tr is the trace of a square matrix defined as the sum of all diagonal elements. I employ these loss functions to compare the differences in the forecasting errors of the various covariance models with two different statistical processes.

Statistical Comparison of Forecasts

Giacomini-White Test

I implement two different tests for the out-of-sample predictive ability of the models, the parametric asymptotic Unconditional Predictive Ability (UPA) test of Giacomini and White (2006) and the non-parametric Model Confidence Set approach (MCS) of Hansen et al. (2011). The UPA test is complement to the tests presented in this literature by Diebold and Mariano (1995) and West (1996), but it is extended to account for nested models and parameter uncertainty. Another major contribution of that work is the generalisation to a conditional predictive ability test (CPA). As I check the average predictive accuracy across models, I implement the UPA (I call this statistical process GW). The null hypothesis of equal predictive ability is described by:

$$H_0 : \overline{\Delta L_{ij}} = 0 \tag{2.28}$$

where $\overline{\Delta L_{ij}} = 1/T \sum_{t=1}^{T} \Delta L_{ij,t}$ is the average loss difference between models i and j across time, stating that the forecasting method i is not more accurate than the forecasting method j. In other words, there is no difference in the average losses between models i and j. The test follows a chi-squared distribution with 1 degree of freedom. To account for serial dependence in multi step-ahead forecasts, I use a Newey-West estimator of the asymptotic variance of the out-of-sample loss differences, with τ lags (where τ indicates the forecast horizon).

Model Confidence Set

The MCS test identifies a set of the best forecasting models within a confidence interval using forecasts under the specified loss functions. Given a level of confidence, for an initial set of forecasting models $\mathcal{M}_0$, the test discards any model with inferior predictive ability until a subset $\mathcal{M}$ with the dominant models is reached. The elimination is based on sequentially testing the following hypothesis:

$$H_0 : E(\Delta L_{ij,t}) = 0, \qquad \text{for all } i, j \in \mathcal{M}. \tag{2.29}$$

Let $\overline{\Delta L}_i = 1/m \sum_{j=1}^{m} \overline{\Delta L}_{ij}$ be the average sample loss of model i relative to average across all other m models that are currently in the set, $\mathcal{M}$. The above null hypothesis is tested at each step, using the following two statistics:

$$T_{SQ} = \sum_{i<j} \frac{(\overline{\Delta L}_{ij})^2}{\widehat{var}(\overline{\Delta L}_{ij})} \tag{2.30}$$

$$T_R = \max_{i,j \in \mathcal{M}} \frac{|\overline{\Delta L}_{ij}|}{\sqrt{\widehat{var}(\overline{\Delta L}_{ij})}}, \tag{2.31}$$

where T_{SQ} is the semi-quadratic statistic, and T_R is the range statistic, respectively.[12] If the null hypothesis is rejected, then the model with the highest value of the statistic $t_i = \overline{\Delta L}_i / \sqrt{\widehat{var}(\overline{\Delta L}_i)}$ is eliminated and the procedure is repeated until the MCS is constructed at the given confidence level (for more technical details refer to Hansen et al., 2011). $\widehat{var}(\overline{\Delta L}_{ij})$ and $\widehat{var}(\overline{\Delta L}_i)$ are estimates of the asymptotic variance of $\overline{\Delta L}_{ij}$ and $\overline{\Delta L}_i$, respectively, computed using a block bootstrap procedure with 10,000 replications and a block length of 2 observations.[13]

2.2.2 Data

My data set consists of tick-by-tick transaction prices from TickData for AEX, CAC 40, DAX 30, FTSE 100, and SMI nominated in local currency. I also use their daily dividend-adjusted closing prices and end-of-day option-implied volatility indices from Datastream. The selection of indices is subject to the availability of intraday data covering the period from January 1, 2000, to April 19, 2016. To avoid any microstructure issues, I use indices within Europe. Since the UK is located in a different time zone compared to the other four

[12] To save space we only report results for the T_{SQ} statistic of Equation (2.30) and present the results for the T_R statistic in Appendix A.

[13] Experimentation with different block lengths (e.g., 4 and 12) has very similar results.

Table 2.2

Realised Correlation of 5-min Returns and Historical Correlation of Daily, Weekly, and Monthly Returns

This table reports in lower triangular matrices the average daily realised correlations using 5-minute intraday returns and the correlation between daily, weekly and monthly returns over the total sample period and three sub-periods (before, during, and after the crisis) in panels A, B, C, and D respectively. * indicate a significant difference between the correlation coefficient of the total sample period and the correlation coefficient of a sub-period at 95% level of confidence.

	1/1/2000-19/04/2016				1/1/2000-31/07/2007				01/08/2007-31/12/2009				1/1/2010-19/04/2016			
	AEX	**CAC**	**DAX**	**FTSE**	**AEX**	**CAC**	**DAX**	**FTSE**	**AEX**	**CAC**	**DAX**	**FTSE**	**AEX**	**CAC**	**DAX**	**FTSE**
Panel A: 5-min Returns																
AEX																
CAC	0.8425				0.7538*				0.8852*				0.8967*			
DAX	0.7919	0.8220			0.7543*	0.7748			0.8135	0.8489*			0.8220*	0.8570*		
FTSE	0.6833	0.6851	0.6574		0.4364*	0.4454*	0.4159*		0.8382*	0.8493*	0.7842*		0.8076*	0.8007*	0.7969*	
SMI	0.6291	0.6439	0.6514	0.5522	0.5272*	0.5397*	0.5592*	0.3138*	0.7324*	0.7534*	0.7572*	0.7300*	0.6887*	0.7016*	0.7000*	0.6916*
Panel B: Daily Returns																
AEX																
CAC	0.8901				0.8775*				0.8846				0.9330*			
DAX	0.8603	0.9141			0.8665	0.9053*			0.8203*	0.9257*			0.9024*	0.9217*		
FTSE	0.7699	0.7808	0.7404		0.6455*	0.6426*	0.6013*		0.8635*	0.9156*	0.8701*		0.8813*	0.8673*	0.8464*	
SMI	0.7741	0.7872	0.7761	0.6997	0.7886	0.7748	0.7758	0.5891*	0.7667	0.8586*	0.8158*	0.8359*	0.7586	0.7473*	0.7398*	0.7406*
Panel C: Weekly Returns																
AEX																
CAC	0.8859				0.8635				0.8941				0.9316*			
DAX	0.8384	0.8861			0.8354	0.8741*			0.8109	0.8964*			0.8956*	0.9071*		
FTSE	0.7863	0.8006	0.7451		0.6795*	0.6707*	0.5940*		0.8608*	0.9352*	0.8892*		0.8715*	0.8350*	0.8131	
SMI	0.7414	0.7416	0.7195	0.6942	0.7622	0.7433	0.7227	0.6001*	0.7423	0.7994	0.7597	0.8027	0.7054	0.6885	0.6672*	0.7222
Panel D: Monthly Returns																
AEX																
CAC	0.8909				0.8984				0.8945				0.9041			
DAX	0.7958	0.8999			0.8536	0.9227*			0.7375	0.9096*			0.8491	0.8875*		
FTSE	0.7899	0.8452	0.7919		0.7360	0.7981	0.7489		0.8610	0.9331*	0.8747		0.8305	0.8065	0.7593	
SMI	0.7586	0.7943	0.7268	0.7604	0.7824	0.7486	0.6803	0.6941	0.7814	0.9077*	0.8426	0.8976*	0.7044	0.7187	0.6827	0.6930

countries, I synchronise all the markets at the Coordinated Universal Time (UTC). While market microstructure issues impact on volatility through the bid/ask bounce, it affects realised covariance in a different way. Non-synchronous trading effects induce a bias toward zero when time series are not contemporaneous and when the fixed time interval is reduced. This bias is also present when there is no trading for one of the time series in an interval. Interpolating the missing values with the previous price produces a zero return for that asset and a zero cross product of returns between the time series.

In empirical studies, 5- or 30-minute return intervals are used to eliminate microstructure effects (e.g., see Andersen, Bollerslev, Diebold and Labys, 2001; Laurent et al., 2012). In this study, I adopt 5-minute intraday returns. I exclude observations across all indices when there is no trading for at least one index. I clear the intraday data sampling prices before 08:15:00 and after 16:15:00 UTC that can introduce distortions from the opening and close procedures. I also exclude from my sample any holidays or days with many missing observations at least at one market (less than 300 1-minute intraday data). For the remaining days, I interpolate the 1-minute prices with the previous price, and I estimate 5-minute logarithmic returns. In the robustness checks, I also use high-frequency data without interpolation.

To be as consistent as possible, I estimate logarithmic daily returns using close-to-open dividend-adjusted prices taken from the high-frequency data for each day.[14] I also use option-implied information.[15] The option-implied volatility indices are based on mid-quote of OTM call and put options with various strike prices and maturities. They are derived following a model-free methodology, as in Britten-Jones and Neuberger (2000), which addresses issues reported in literature related to stochastic volatility and non-normal returns.

Matching the daily, high-frequency and implied volatility data, I end up with a total of 3,942 daily returns. In literature, it is also common to use close-to-close logarithmic returns estimated from daily prices. This estimation includes overnight returns. The lack of 24-hour high-frequency data, however, induces a bias in realised volatility due to price jumps. There

[14] The open price is the price at 08:15:00 and the close price is the price at 16:15:00.

[15] These data are only available in daily frequency.

are three standard procedures in literature to treat this bias. Martens (2002) and Hansen and Lunde (2005) present two constant-adjustment methods, while Bollerslev et al. (2014) use squared open-to-close returns (i.e, from the close price to the open price the next morning). In my robustness checks, I also estimate close-to-close index returns using daily data. I apply the methodologies above to correct the daily returns estimated via high-frequency data for the overnight returns as described in section 2.7.

Model parameters are estimating using $t = 1, \ldots, 1,000$ in-sample observations. For all GARCH models, the in-sample estimation of parameters is based on the Oxford MFE Toolbox provided by Kevin Sheppard.[16] Using these parameters, I generate the $H_{1,001}$ forecast. Then the in-sample data rolls over from $t = 2, 3, ..., 1, 001$ maintaining the same total of 1,000 observations each time and the process is repeated computing the model parameters at each step. I replace any negative definite covariance forecast with the average realised covariance as suggested in the "insanity filter" of Bollerslev et al. (2016). Except for 1-day ahead forecasts, I gauge 5- and 22-day ahead forecasts representing daily, weekly, and monthly forecasts respectively. To this end, by summing up $\tau - 1$ daily forecasts, I compute the τ-day ahead covariance predictions for all but the LRCOV and hybrid models.

Table 2.2 presents the estimation of correlation for the overall sample period between the European market indices using daily, weekly, and monthly data (Panel B-D). Not surprisingly, all correlation coefficients are quite high, indicating the degree of integration between major European equity markets. I also compute average daily realised correlations from 5-minute returns (Panel A). I find that they are lower than the corresponding correlations from daily returns, indicating that their dynamics may differ substantially.

I also present the correlations for three sub-periods to demonstrate differences in the correlation in different market conditions. For this purpose, I split the total sample period into three sub-periods. The tranquil period is defined from the start of my sample to July 31, 2007. I also consider useful to divide the subsequent volatile period further. The highly

[16]https://www.kevinsheppard.com/MFE_Toolbox. Part of the forecasting code for this analysis is also provided by Dr Lazaros Symeonidis.

volatile period of the global financial crisis is taken from August 1, 2007 to December 31, 2009. The period from January 1, 2010 to the end of my sample includes the Eurozone debt crisis. The beginning of the global crisis is not the peak time of Lehman Brothers' collapse, but it is extended to include the period when the subprime crisis took place with the collapse of Northern Rock (similar to Laurent et al., 2012). I perform a z-test[17] to report statistically significant differences in correlation between the total sample period and each sub-period. In general, the results exhibit significantly higher correlations during the global financial crisis and the Eurozone debt crisis. This provides evidence of increased integration of equity markets during bad economic times. However, as the sampling frequency decreases from daily to monthly, less significant differences are reported.

Table 2.3 reports the summary statistics for the time series of daily realised correlations across markets. Every day, I calculate realised correlations between a market and all the other markets and, then, I take the average across the pairwise correlations. This yields a time series of daily average realised cross-correlations. The table contains average values of the sample mean, minimum, maximum, median values, standard deviation, kurtosis and skewness. The average correlation ranges from 0.58 to 0.71 including also negative correlations between the equity indices. Even though more positive than negative correlations are observed, when they are lower than one indicates that there are diversification benefits within a minimum-variance portfolio. Standard deviations show that substantial amount of variation in cross-correlations, which is consistent with the statistics in Panel A of Table 2.2. The distribution of average correlations is negatively skewed with fat tails and sharper peaks. This non-normal feature of the empirical distribution is the outcome of sudden shifts during the highly volatile periods, such as the 2007-2009 global financial crisis.

There is ample evidence in the literature that markets move more together during ex-

[17] The standard process in the literature is to Fisher transform the correlation coefficient before performing a t-test, since correlation coefficients are not normally distributed. The Fisher transformation of a correlation coefficient ρ, is estimated as $z = ln\frac{(1+\rho)}{(1-\rho)}$ with standard error $SE_z = \sqrt{\frac{1}{n-3}}$, where n is the number of observations. To test statistic for the difference between ρ_1 and ρ_2 is computed by dividing the difference by the pooled standard error $SE_z = \sqrt{\frac{1}{n_1-3} + \frac{1}{n_2-3}}$.

treme market conditions (e.g., Longin and Solnik, 2001; Ang and Bekaert, 2002; Aloui et al., 2011; Garcia and Tsafack, 2011). Some suggested explanations for this phenomenon include the commonality in liquidity during periods of market declines (Hameed et al., 2010), trade linkages between countries (Forbes, 2002), comovement in risk-premiums across markets during illiquid times (Vayanos, 2004), investors' correlated sentiment (Barberis et al., 2005), and correlated information (Israelsen, 2016; Dang et al., 2015). Such simultaneous downwards movements of stock markets lead to losses if investors do not also keep other assets such as bonds. Thus, predicting the covariance matrix correctly is an important input in portfolio selection and capital allocation across assets.

Table 2.3

Descriptive Statistics of Realised Correlation

This table presents summary statistics of average daily realised correlations of each equity index with all the other indices. The table shows the mean, minimum, maximum, median, standard deviation, skewness and kurtosis. The sample period is from January 1, 2000, to April 19, 2016.

	Mean	**Min**	**Max**	**Median**	**StDev**	**Skew**	**Kurt**
AEX	0.6944	-0.0973	0.9641	0.7537	0.2089	-1.5405	5.6110
CAC	0.7066	-0.1029	0.9654	0.7644	0.2051	-1.5171	5.5863
DAX	0.6946	-0.1034	0.9541	0.7480	0.1964	-1.4813	5.6024
FTSE	0.5749	-0.2873	0.9577	0.6904	0.3087	-1.0968	2.9008
SMI	0.5847	-0.1812	0.9357	0.6296	0.2081	-0.8749	3.3650

2.2.3 Out-of-Sample Model Evaluation

Table 2.4 reports the average forecast errors for all the models and statistical loss functions. The best model is the one with the lowest losses. I indicate that with an asterisk (*). To conserve space I report the covariance matrix for all the pairwise comparisons for each loss function in the Appendix A (see Tables A.2-A.6), but I summarise herein the main conclusions of the Giacomini-White test as follows. I identify the model with the lowest losses and I mark with a dagger (†) whether the alternative models are not statistically significantly different from that at 5% significance level. This table does not provide information for any other pairwise comparisons with the GW test. Without looking at the 5×5 table with the GW statistics for each pair, it is not possible to draw any conclusion on how each model performs relative to the others. Furthermore, no established technique summarises the results of the GW pairwise comparisons and ranks the models from the best to the worst. I overcome this difficulty by ranking the average losses. This strategy though provides with a rough ranking of the models which is not statistically inferred. Moreover, an inference based on the mean statistic is subject to the effect of outliers.

Using the most recent 1,000 observations (approximately four years of daily returns), I gauge rolling out-of-sample τ-ahead forecasts. I move then one period forward and repeat the process until the end of the sample. For the multivariate GARCH and VHAR models multi-step ahead forecasts are produced summing daily forecasts, while for the implied covariance models and the LRCOV, they are obtained directly. Thus for a total sample length T and R the in-sample period length, I obtain $T-R-\tau+1$ out of sample forecasts, that is, 2,942 daily, 2,938 weekly, and 2,921 monthly forecasts in total. I compare them with the realised covariance calculating the losses and estimate the average losses for each period stacking all the pairs.

The VHAR model yields the most accurate out-of-sample forecasts. Applying the GW test, L_E and L_F also indicate that the parameter-free LRCOV model and the A-OGARCH compute comparable forecasts that are not statistically different from the VHAR at 5% confidence level. Under the same loss functions, in the longer horizon, more models of the GARCH family offer competing forecasts relative to the VHAR model. In the longer horizon, L_S and L_Q indicate LRCOV as the best model, but it does not differ significantly from the VHAR.

Additionally, the adjusted for the volatility risk-premium specifications of the HICOV generate on average lower losses than most burdensome models. The findings also corroborate the basic idea of this paper that high-frequency and option-implied data within less composite and parameter-dependent models are more informative than lower-frequency data for future realisations of covariance. Nonetheless, the ranking is not consistent across all loss functions when it comes to the rest models, but they remain stable over the three forecasting horizons and within the same loss function. The A-DiagBEKK, A-OGARCH, and DCCs

Table 2.4

Giacomini-White Test of Out-of-Sample Covariance Forecasting Performance

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. Model parameters are estimated in each step using in-sample a rolling overlapping window of 1,000 logarithmic close-to-open returns. The best model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Loss Functions**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.1757	0.0167	0.0249	2.1970	−19.2481
A-ScBEKK	0.1681	0.0161	0.0238	2.2292	−19.2159
DiagBEKK	0.1737	0.0167	0.0249	2.2163	−19.2288
A-DiagBEKK	0.1636	0.0155	0.0230	2.1967	−19.2484
CCC	0.2132	0.0231	0.0349	3.3677	−18.0774
A-CCC	0.2096	0.0241	0.0363	5.0957	−16.3495
DCC	0.1732	0.0161	0.0238	1.8735	−19.5716
A-DCC	0.1732	0.0161	0.0238	1.8741	−19.5710
OGARCH	0.1699	0.0150	0.0223	2.2173	−19.2278
A-OGARCH	0.1697	0.0145†	0.0215	2.2273	−19.2178
EWMA	0.1651	0.0156	0.0232	3.1932	−18.2519
LRCOV	0.1532	0.0181†	0.0263†	1.2374	−20.2077
HICOV	0.3817	0.0296	0.0452	2.5211	−18.9240
Adj-HICOV	0.1509	0.0151	0.0225	1.4271	−20.0181
AdjHAR-HICOV	0.2369	0.0181	0.0271	1.8101	−19.6351
VHAR	0.1297*	0.0133*	0.0195*	0.9097*	−20.5354*
	Panel B: Weekly Forecasts				
ScBEKK	0.1563	0.0094	0.0141	1.9004	−19.0945
A-ScBEKK	0.1478	0.0090	0.0134	1.9226	−19.0724
DiagBEKK	0.1536	0.0094	0.0141	1.9062	−19.0888
A-DiagBEKK	0.1453	0.0088	0.0131	1.8871	−19.1079
CCC	0.2016	0.0152	0.0232	3.0028	−17.9922
A-CCC	0.2004	0.0162	0.0247	4.7044	−16.2906
DCC	0.1516	0.0087	0.0129	1.5951	−19.3999
A-DCC	0.1516	0.0087	0.0129	1.5942	−19.4007
OGARCH	0.1522	0.0081†	0.0122†	1.9219	−19.0731
A-OGARCH	0.1552	0.0084	0.0127	1.9384	−19.0566
EWMA	0.1441	0.0085	0.0128	2.9941	−18.0009
LRCOV	0.1278	0.0087†	0.0129†	0.7253†	−20.2697†
HICOV	0.3751	0.0246	0.0381	2.0270	−18.9680
Adj-ICOV	0.2274	0.0156	0.0237	9.2222	−11.7727
AdjHAR-ICOV	0.2358	0.0125	0.0191	1.3901	−19.6049
VHAR	0.1120*	0.0072*	0.0108*	0.7145*	−20.2805*
	Panel C: Monthly Forecasts				
ScBEKK	0.1708	0.0080	0.0121	1.9851	−18.7264
A-ScBEKK	0.1640	0.0081	0.0122†	2.0352	−18.6763
DiagBEKK	0.1652	0.0078	0.0118	2.0201	−18.6914
A-DiagBEKK	0.1604	0.0077†	0.0116†	2.0516	−18.6599
CCC	0.1977	0.0113	0.0173	2.7266	−17.9849
A-CCC	0.1953	0.0124	0.0190	4.2968	−16.4147
DCC	0.1702	0.0081	0.0120†	1.7976	−18.9139
A-DCC	0.1702	0.0081	0.0120†	1.7954	−18.9161
OGARCH	0.1721	0.0075†	0.0115†	2.0338	−18.6777
A-OGARCH	0.1742	0.0083†	0.0127†	2.0752	−18.6364
EWMA	0.1564	0.0076†	0.0115†	3.4101	−17.3014
LRCOV	0.1500	0.0080	0.0119	0.9786*	−19.7329*
HICOV	0.3904	0.0263	0.0404	1.8798	−18.8317
Adj-HICOV	0.2887	0.0171	0.0262	71.1025	50.3910
AdjHAR-HICOV	0.2885	0.0147	0.0227	1.6269	−19.0846
VHAR	0.1258*	0.0066*	0.0100*	0.9893†	−19.7222†

Table 2.5

Model Confidence Set of Relative Covariance Forecasting Performance

This table reports the ranking along with the p-values of the models for each statistical loss function for 1-day, 5-day and 22-day forecasts using the Model Confidence Set test. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.067	12*	0.069	8	0.000	8	0.000
A-ScBEKK	8	0.000	10*	0.075	10*	0.072	9	0.000	9	0.000
DiagBEKK	10	0.000	11*	0.072	11*	0.072	10	0.000	10	0.000
A-DiagBEKK	5	0.000	4*	0.091	4*	0.086	12	0.000	12	0.000
CCC	14	0.000	14	0.050	14	0.044	7	0.000	7	0.000
A-CCC	13	0.000	15	0.044	15	0.031	15	0.000	15	0.000
DCC	11	0.000	8*	0.075	9*	0.072	4	0.000	4	0.000
A-DCC	9	0.000	7*	0.075	8*	0.076	5	0.000	6	0.000
OGARCH	7	0.000	3*	0.091	3*	0.086	13	0.000	13	0.000
A-OGARCH	6	0.000	2*	0.154	2*	0.119	14	0.000	14	0.000
EWMA	4	0.000	6*	0.075	6*	0.085	16	0.000	16	0.000
LRCOV	3	0.000	9*	0.075	7*	0.085	2	0.000	2	0.000
HICOV	16	0.000	16	0.029	16	0.018	11	0.000	11	0.000
Adj-HICOV	2	0.000	5*	0.091	5*	0.086	3	0.000	3	0.000
AdjHAR-HICOV	15	0.000	13*	0.056	13*	0.051	6	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	11	0.000	11*	0.202	11*	0.242	5	0.000	4	0.000
A-ScBEKK	5	0.000	9*	0.230	9*	0.299	4	0.000	5	0.000
DiagBEKK	8	0.000	10*	0.216	10*	0.271	8	0.000	8	0.000
A-DiagBEKK	4	0.000	4*	0.230	4*	0.299	11	0.000	11	0.000
CCC	13	0.000	12*	0.105	12*	0.133	10	0.000	10	0.000
A-CCC	12	0.000	14	0.045	13*	0.081	14	0.000	14	0.000
DCC	9	0.000	7*	0.230	7*	0.299	7	0.000	7	0.000
A-DCC	10	0.000	8*	0.230	8*	0.299	6	0.000	6	0.000
OGARCH	7	0.000	2*	0.230	2*	0.299	12	0.000	12	0.000
A-OGARCH	6	0.000	3*	0.230	3*	0.299	13	0.000	13	0.000
EWMA	3	0.000	5*	0.230	6*	0.299	15	0.000	15	0.000
LRCOV	2	0.000	6*	0.230	5*	0.299	2*	0.603	2*	0.609
HICOV	16	0.000	16	0.026	16	0.026	9	0.000	9	0.000
Adj-HICOV	14	0.000	15	0.037	15	0.045	16	0.000	16	0.000
AdjHAR-HICOV	15	0.000	13*	0.058	14	0.048	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	8	0.000	8*	0.340	10*	0.352	7	0.006	7	0.009
A-ScBEKK	5	0.000	10*	0.340	9*	0.352	4	0.006	4	0.009
DiagBEKK	6	0.000	6*	0.340	6*	0.352	9	0.006	9	0.009
A-DiagBEKK	4	0.000	3*	0.340	3*	0.352	10	0.006	10	0.009
CCC	13	0.000	12*	0.187	12*	0.197	11	0.006	11	0.009
A-CCC	12	0.000	13*	0.090	13*	0.118	14	0.006	14	0.007
DCC	11	0.000	11*	0.340	8*	0.352	8	0.006	8	0.009
A-DCC	10	0.000	9*	0.340	7*	0.352	6	0.006	6	0.009
OGARCH	9	0.000	2*	0.340	2*	0.352	12	0.006	12	0.009
A-OGARCH	7	0.000	7*	0.340	11*	0.338	13	0.006	13	0.009
EWMA	3	0.000	4*	0.340	4*	0.352	15	0.000	15	0.001
LRCOV	2	0.000	5*	0.340	5*	0.352	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.005	16	0.016	5	0.006	5	0.009
Adj-HICOV	15	0.000	14	0.027	15	0.021	16	0.000	16	0.000
AdjHAR-HICOV	14	0.000	15	0.010	14	0.042	3	0.006	3	0.009
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.739	2*	0.739

produce the lower average losses, while the CCCs and EWMA the higher average losses. The best GARCH models of DCC-type in the latter cases is in line with the findings of Laurent et al. (2012). Surprisingly, the inconsistent L_A shows ranking similar to the consistent L_E and L_F.

The results are in line with pairwise comparisons of the models reported in the Appendix A for each loss functions for daily, weekly and monthly forecasts. In particular, I find less significant differences between the average losses the longer the forecasting horizon. CCC and A-CCC models have significantly worse forecasts than BEKK models. They also have worse forecasts than the time-variant counterparts, DCC and A-DCC. EWMA is better than the majority of multivariate GARCH models apart from A-DiagBEKK and A-OGARCH. The Adj-HICOV is significantly better than the AdjHAR-HICOV. However, there is some disagreement across loss functions. In general L_A, L_E, and L_F converge towards similar results. They report that all models with other than daily information but the AdjHAR-HICOV are better than the widely used EWMA model. L_Q and L_S rank EWMA only in better positions than the CCC models. Moreover, the DCC and A-DCC appear to perform better than the rest GARCH models.

However, the GW test does not provide with a clear ranking of the models. To this end, I adopt the Model Confidence Set, which realises comparisons across all models simultaneously. In addition to the probability that a model belongs in the set (e.g., for $p > 0.05$), MCS provides rankings of all the models from the best to the worst, despite the inclusion or exclusion from the set. Bootstrapped standard errors ensure that the statistics do not suffer from autocorrelation and heteroscedasticity. Table 2.5 demonstrates for each loss function the ranking and the probability. The asterisk shows which models are included in the set. I report the classification for the semi-quadratic (SQ) statistic, but the results are robust under the range statistic as well (see Appendix A).

The results differ substantially across loss functions and horizons for the MCS test. In general, the outcomes agree that the VHAR generates more accurate forecasts across loss functions and forecasting horizons. This is the only model that is included in the MCS in all cases. I also examine how the various models are ranked in each loss function over time. VHAR is the only model within L_A. However, the ranking of the rest of the models suggests that more parameter-free models with high-frequency data produce more accurate forecasts. LRCOV performs very well in all cases. While the hybrid Adj-HICOV is ranked after the VHAR in the daily horizon, this is not as effective in longer forecasts, ranked in the worst positions along with the rest HICOV models. From the GARCH models, EWMA and A-DiagBEKK present the highest predicting ability while the CCC models and the ScBEKK the worst. This finding agrees with Laurent et al. (2013) who also report EWMA as the best model under inconsistent loss functions.

In L_E and L_F, the majority of the models are not eliminated from the model confidence set. LRCOV is included in the set for all horizons. However, the OGARCH models and the A-DiagBEKK generate superior forecasts and are ranked in better positions. The CCC models are excluded from the MCS in the short-run, but they are included in longer horizons, though, in adverse positions. Whereas the HICOV is ranked as the worst model the hybrid Adj-HICOV and AdjHAR-HICOV are included in the set for the daily horizon. L_S and L_Q include both VHAR and LRCOV in the MCS. The Adj-HICOV and AdjHAR-HICOV perform well relative to the majority of the GARCH family. Moreover, the DCCs exhibit the best forecasting ability in the short-run and the scalar BEKK models in the longer horizons for the multivariate GARCH, while the orthogonal specifications and EWMA underperform. These results contrast those of the L_A, L_E and L_F. Even though it is not surprising that the EWMA is not the most competing model, the fact that it is widely adopted in practice raises concerns about the serious consequences of misspecified covariance. Additionally, the results vary not only for the ranking of the multivariate GARCH models but also for the implied covariance specifications.

2.2.4 Market Regimes and Model Performance

The central question in this section is whether model performance varies across market regimes. To this end, I repeat the above out-of-sample analysis over three sub-periods of the full sample. Tables 2.6, 2.7 and 2.8 compare the forecasting ability of the models in the calm period before the global financial crisis from January 1, 2000, to July 31, 2007, the peak period of the crisis between August 1, 2007, and December 31, 2009, and the following period from January 1, 2010, to April 19, 2016 that includes the Eurozone debt crisis.

VHAR is the best model in the MCS under various market conditions and forecasting horizons. In L_A, simpler models perform better than more burdensome models for daily forecasts. Adj-HICOV, LRCOV, and EWMA are the best models, and CCCs and DCCs are the worst. However, in longer horizons, models that combine implied and high-frequency information systematically underperform. In extreme market conditions, the A-DiagBEKK and OGARCH specifications produce more accurate forecasts. L_E and L_F cannot exclude models from the MCS except for the last period where in daily forecasts only Adj-HICOV is not in the set. Orthogonal GARCH models perform well compared to GARCH models during the crisis and A-ScBEKK and A-DiagBEKK during more stable periods. In L_S and L_Q, VHAR and LRCOV are in most cases in the set, while Adj-HICOV, and AdjHAR-HICOV are competing models in daily and weekly horizons and HICOV in monthly. The findings are contradictory for the OGARCHs which predict inferior forecasts compared to L_E and L_F.

The ranking of the models is quite sensitive to the specific sub-period. However, the main conclusions are maintained. A slightly better performance of asymmetric specifications during the crisis is quite intuitive as it highlights the importance of accounting for asymmetries during bad economic times,when negative shocks are more frequent and sizeable (see average losses for sub-periods in Appendix A, Tables A.16-A.18). Moreover, this finding is in line with Laurent et al. (2012), who find that during the .com bubble models that incorporate asymmetries are superior to symmetric counterparts. Finally, my results indicate that losses of most models are higher in the post-2007 period that coincides with the global financial crisis and the Eurozone debt crisis. This extends the documented findings of worsening performance of volatility forecasting models during times of market turmoil (Brownlees et al., 2011; Kourtis et al., 2016) to the covariance case. In my robustness checks, I replicate the

Table 2.6

Model Confidence Set for Tranquil and Turmoil Periods: 1-day Forecasts

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day ahead forecasts across calm and turbulent economic conditions. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: 1/1/2000 - 31/7/2007										
ScBEKK	10	0.000	6*	0.131	6*	0.117	9	0.000	9	0.000
A-ScBEKK	5	0.000	5*	0.197	5*	0.185	10	0.000	10	0.000
DiagBEKK	12	0.000	7*	0.119	7*	0.117	11	0.000	11	0.000
A-DiagBEKK	11	0.000	11*	0.118	11*	0.117	14	0.000	14	0.000
CCC	15	0.000	16*	0.076	16*	0.074	4	0.001	4	0.000
A-CCC	13	0.000	14*	0.103	14*	0.109	8	0.000	8	0.000
DCC	7	0.000	13*	0.118	13*	0.117	6	0.000	6	0.000
A-DCC	8	0.000	12*	0.118	12*	0.117	7	0.000	7	0.000
OGARCH	9	0.000	10*	0.119	9*	0.117	13	0.000	13	0.000
A-OGARCH	6	0.000	4*	0.417	4*	0.418	15	0.000	15	0.000
EWMA	4	0.004	9*	0.119	10*	0.117	16	0.000	16	0.000
LRCOV	3	0.004	2*	0.526	2*	0.561	2	0.001	2	0.000
HICOV	16	0.000	15*	0.080	15*	0.076	12	0.000	12	0.000
Adj-HICOV	2	0.032	3*	0.526	3*	0.561	3	0.001	3	0.000
AdjHAR-ICOV	14	0.000	8*	0.119	8*	0.117	5	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: 1/8/2007-31/12/2009										
ScBEKK	12	0.007	12*	0.130	12*	0.136	9	0.004	9	0.007
A-ScBEKK	8	0.012	11*	0.151	11*	0.157	10	0.004	10	0.007
DiagBEKK	9	0.011	10*	0.165	10*	0.164	5	0.004	5	0.007
A-DiagBEKK	2	0.012	4*	0.513	4*	0.519	11	0.004	11	0.007
CCC	13	0.006	14*	0.082	14*	0.078	14	0.004	14	0.007
A-CCC	14	0.004	15*	0.064	15*	0.069	16	0.004	16	0.007
DCC	10	0.009	6*	0.314	6*	0.282	6	0.004	6	0.007
A-DCC	11	0.007	5*	0.382	5*	0.351	7	0.004	7	0.007
OGARCH	5	0.012	3*	0.785	3*	0.770	13	0.004	13	0.007
A-OGARCH	4	0.012	2*	0.785	2*	0.770	12	0.004	12	0.007
EWMA	7	0.012	7*	0.260	7*	0.252	15	0.004	15	0.007
LRCOV	3	0.012	9*	0.218	9*	0.212	2	0.004	2	0.007
HICOV	16	0.000	16*	0.051	16	0.050	8	0.004	8	0.007
Adj-HICOV	6	0.012	8*	0.218	8*	0.212	3	0.004	3	0.007
AdjHAR-ICOV	15	0.002	13*	0.098	13*	0.097	4	0.004	4	0.007
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: 1/1/2010-19/04/2016										
ScBEKK	11	0.000	8	0.028	8	0.030	6	0.000	7	0.000
A-ScBEKK	7	0.000	6	0.028	6	0.032	4	0.000	4	0.000
DiagBEKK	10	0.000	10	0.028	10	0.028	9	0.000	9	0.000
A-DiagBEKK	6	0.000	4	0.028	4	0.032	10	0.000	10	0.000
CCC	8	0.000	14	0.027	14	0.026	11	0.000	11	0.000
A-CCC	5	0.000	15	0.021	15	0.026	15	0.000	14	0.000
DCC	14	0.000	13	0.027	13	0.027	5	0.000	5	0.000
A-DCC	13	0.000	12	0.028	12	0.027	7	0.000	6	0.000
OGARCH	9	0.000	9	0.028	9	0.029	12	0.000	12	0.000
A-OGARCH	12	0.000	3	0.028	3	0.032	13	0.000	13	0.000
EWMA	4	0.000	5	0.028	5	0.032	16	0.000	16	0.000
LRCOV	3	0.000	7	0.028	7	0.032	2	0.000	2	0.000
HICOV	16	0.000	16	0.008	16	0.010	14	0.000	15	0.000
Adj-HICOV	2	0.000	2*	0.456	2*	0.499	3	0.000	3	0.000
AdjHAR-ICOV	15	0.000	11	0.028	11	0.028	8	0.000	8	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

Table 2.7

Model Confidence Set for Tranquil and Turmoil Periods: 5-day Forecasts

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 5-day ahead forecasts across calm and turbulent economic conditions. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: 1/1/2000 - 31/7/2007										
ScBEKK	5	0.003	4*	0.115	3*	0.139	9	0.000	9	0.000
A-ScBEKK	3	0.012	2*	0.115	2*	0.139	10	0.000	10	0.000
DiagBEKK	6	0.003	5*	0.115	5*	0.139	11	0.000	11	0.000
A-DiagBEKK	8	0.003	7*	0.115	7*	0.139	12	0.000	12	0.000
CCC	15	0.000	13*	0.080	13*	0.090	4	0.000	4	0.000
A-CCC	12	0.002	14*	0.074	14*	0.089	8	0.000	8	0.000
DCC	9	0.003	11*	0.115	11*	0.139	5	0.000	5	0.000
A-DCC	10	0.003	10*	0.115	10*	0.139	6	0.000	6	0.000
OGARCH	11	0.003	12*	0.115	12*	0.139	13	0.000	13	0.000
A-OGARCH	7	0.003	3*	0.115	6*	0.139	14	0.000	14	0.000
EWMA	4	0.012	8*	0.115	8*	0.139	15	0.000	15	0.000
LRCOV	2	0.050	9*	0.115	9*	0.139	2*	0.680	2*	0.702
HICOV	16	0.000	15*	0.052	15*	0.065	7	0.000	7	0.000
Adj-HICOV	14	0.000	16	0.038	16*	0.052	16	0.000	16	0.000
AdjHAR-ICOV	13	0.000	6*	0.115	4*	0.139	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: 1/8/2007-31/12/2009										
ScBEKK	12	0.002	11*	0.248	11*	0.257	8	0.015	8	0.022
A-ScBEKK	8	0.006	10*	0.335	10*	0.342	9	0.015	9	0.022
DiagBEKK	6	0.006	9*	0.401	9*	0.409	7	0.015	7	0.022
A-DiagBEKK	3	0.026	7*	0.636	7*	0.675	10	0.015	10	0.022
CCC	11	0.004	14*	0.080	14*	0.072	13	0.015	13	0.021
A-CCC	13	0.002	15*	0.070	15*	0.060	15	0.008	15	0.014
DCC	9	0.006	5*	0.636	5*	0.700	4	0.015	4	0.022
A-DCC	10	0.005	6*	0.636	6*	0.700	5	0.015	5	0.022
OGARCH	5	0.006	2*	0.842	2*	0.838	12	0.015	12	0.022
A-OGARCH	4	0.014	4*	0.636	4*	0.700	11	0.015	11	0.022
EWMA	7	0.006	8*	0.548	8*	0.552	14	0.009	14	0.014
LRCOV	2	0.026	3*	0.715	3*	0.779	1*	1.000	1*	1.000
HICOV	16	0.000	16*	0.052	16	0.050	6	0.015	6	0.022
Adj-HICOV	14	0.002	12*	0.148	12*	0.140	16	0.001	16	0.004
AdjHAR-ICOV	15	0.000	13*	0.090	13*	0.085	3	0.015	3	0.022
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.419	2*	0.379
Panel C: 1/1/2010-19/04/2016										
ScBEKK	8	0.000	6	0.018	6	0.015	5	0.000	5	0.000
A-ScBEKK	5	0.000	4	0.018	4	0.015	3	0.000	3	0.000
DiagBEKK	6	0.000	7	0.018	7	0.015	6	0.000	6	0.000
A-DiagBEKK	4	0.000	2	0.018	2	0.015	9	0.000	9	0.000
CCC	12	0.000	12	0.018	12	0.012	10	0.000	10	0.000
A-CCC	7	0.000	13	0.015	13	0.010	14	0.000	14	0.000
DCC	9	0.000	8	0.018	8	0.015	8	0.000	8	0.000
A-DCC	10	0.000	11	0.018	11	0.015	7	0.000	7	0.000
OGARCH	11	0.000	10	0.018	9	0.015	12	0.000	12	0.000
A-OGARCH	13	0.000	9	0.018	10	0.015	11	0.000	11	0.000
EWMA	3	0.000	3	0.018	3	0.015	15	0.000	15	0.000
LRCOV	2	0.000	5	0.018	5	0.015	2	0.024	2	0.015
HICOV	16	0.000	16	0.002	16	0.000	13	0.000	13	0.000
Adj-HICOV	14	0.000	15	0.007	15	0.007	16	0.000	16	0.000
AdjHAR-HICOV	15	0.000	14	0.012	14	0.010	4	0.000	4	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

Table 2.8

Model Confidence Set for Tranquil and Turmoil Periods: 22-day Forecasts

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day ahead forecasts across calm and turbulent economic conditions. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	Loss Functions									
	L_A		L_E		L_F		L_S		L_Q	
	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value
Panel A: 1/1/2000 - 31/7/2007										
ScBEKK	5	0.040	3*	0.145	3*	0.145	10	0.001	10	0.001
A-ScBEKK	3*	0.076	1*	1.000	1*	1.000	9	0.001	9	0.001
DiagBEKK	6	0.040	4*	0.138	4*	0.145	12	0.001	12	0.001
A-DiagBEKK	7	0.019	5*	0.138	5*	0.145	11	0.001	11	0.001
CCC	13	0.001	13*	0.106	13*	0.099	3	0.001	3	0.001
A-CCC	9	0.018	9*	0.138	9*	0.145	5	0.001	5	0.001
DCC	10	0.018	10*	0.138	10*	0.145	7	0.001	7	0.001
A-DCC	11	0.018	11*	0.138	11*	0.145	8	0.001	8	0.001
OGARCH	12	0.013	12*	0.135	12*	0.131	13	0.001	13	0.001
A-OGARCH	8	0.018	7*	0.138	8*	0.145	14	0.001	14	0.000
EWMA	4*	0.063	8*	0.138	7*	0.145	15	0.000	15	0.000
LRCOV	2*	0.076	6*	0.138	6*	0.145	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.014	16	0.020	6	0.001	6	0.001
Adj-HICOV	15	0.000	15	0.035	15	0.040	16	0.000	16	0.000
AdjHAR-ICOV	14	0.000	14*	0.070	14*	0.070	4	0.001	4	0.001
VHAR	1*	1.000	2*	0.782	2*	0.770	2*	0.161	2*	0.165
Panel B: 1/8/2007-31/12/2009										
ScBEKK	12	0.006	10*	0.382	10*	0.395	8*	0.101	8*	0.102
A-ScBEKK	8	0.020	11*	0.345	11*	0.367	9*	0.091	9*	0.093
DiagBEKK	6	0.020	9*	0.409	9*	0.451	7*	0.101	7*	0.107
A-diagBEKK	2	0.020	4*	0.431	4*	0.501	10*	0.086	10*	0.083
CCC	11	0.011	12*	0.228	12*	0.223	13	0.050	13	0.047
A-CCC	13	0.002	13*	0.125	13*	0.135	15	0.027	15	0.018
DCC	9	0.020	5*	0.431	5*	0.501	5*	0.171	5*	0.163
A-DCC	10	0.013	7*	0.431	6*	0.501	6*	0.121	6*	0.120
OGARCH	5	0.020	2*	0.704	2*	0.625	11*	0.086	11*	0.083
A-OGARCH	7	0.020	8*	0.409	8*	0.451	12*	0.086	12*	0.083
EWMA	4	0.020	3*	0.561	3*	0.625	14	0.037	14	0.025
LRCOV	3	0.020	6*	0.431	7*	0.501	2*	0.357	2*	0.347
HICOV	16	0.000	16	0.023	16	0.029	3*	0.357	3*	0.347
Adj-HICOV	14	0.000	15	0.030	15	0.035	16	0.007	16	0.006
AdjHAR-HICOV	15	0.000	14	0.049	14*	0.053	4*	0.357	4*	0.347
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: 1/1/2010-19/04/2016										
ScBEKK	9	0.001	4*	0.173	6*	0.163	4	0.004	4	0.001
A-ScBEKK	8	0.001	5*	0.173	4*	0.177	3	0.007	3	0.001
DiagBEKK	7	0.002	3*	0.173	3*	0.214	6	0.002	6	0.001
A-DiagBEKK	6	0.004	2*	0.247	2*	0.349	5	0.002	5	0.001
CCC	5	0.004	8*	0.128	8*	0.161	10	0.002	10	0.000
A-CCC	4	0.004	12*	0.064	12*	0.060	14	0.000	14	0.000
DCC	11	0.001	9*	0.097	9*	0.093	9	0.002	9	0.000
A-DCC	10	0.001	10*	0.096	10*	0.078	8	0.002	8	0.000
OGARCH	12	0.001	11*	0.076	11*	0.062	12	0.000	12	0.000
A-OGARCH	13	0.000	13*	0.056	13	0.045	11	0.000	11	0.000
EWMA	3	0.004	7*	0.132	7*	0.163	15	0.000	15	0.000
LRCOV	2	0.004	6*	0.136	5*	0.163	2*	0.577	2*	0.568
HICOV	16	0.000	16	0.003	16	0.002	13	0.000	13	0.000
Adj-HICOV	15	0.000	15	0.008	15	0.009	16	0.000	16	0.000
AdjHAR-HICOV	14	0.000	14	0.016	14	0.024	7	0.002	7	0.001
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

analysis defining the global financial crisis to begin from August 1, 2008, similar to Kourtis et al. (2016).

2.2.5 In-Sample Model Evaluation

I assess the fit of covariance models by estimating the losses that are generated in relation with the proxy for the latent process of the true covariance. Using the whole sample, I estimate the model parameters, wherever it is applicable, and extract the in-sample covariance matrix. Most models build this recursively. I use the same statistical loss functions as in the out-of-sample analysis to compare the covariance matrix of the models with the proxy of the true covariance. Tables 2.9 and 2.10 demonstrate the average losses along with the GW statistical results and the MCS ranking along with the p-values, for all the models for 1-, 5- and 22-day horizons.

The findings are more robust across loss functions for the in-sample estimation, but they differ over horizons. However, in all cases, the VHAR model presents the best fit indicating that a simply parametrized model with high-frequency data outperforms more complex and demanding models. Despite that all the other models are excluded, I compare their performance. The non-parametric LRCOV and Adj-HICOV models exhibit systematically very good parameter fit. These outcomes support the core idea of this paper that high-frequency and option-implied data within less parameter-dependent models can be more informative than lower frequency data. Nevertheless, the results do not distinguish clearly the best multivariate GARCH model. DCCs, DiagBEKK, and OGARCH perform better in some loss functions and horizons and worse in others.

2.2.6 Economic Value of Multivariate Volatility Forecasts

I assess the economic potential of my models in forecasting accurate covariances for international portfolio selection. Within the mean-variance framework, the best forecasts are produced from the model with the minimum portfolio variance (Engle and Colacito, 2006;

Table 2.9

In-Sample Model Fit

This table reports the average errors for each statistical loss function for 1-day, 5-day and 22-day variances-covariances. L_A, L_E, L_F, L_S, and L_Q represent the Mean Absolute distance, Euclidean distance, Frobenius distance, Stein, and Quasi-likelihood loss functions respectively. The best-fitted model is indicated in * format for each panel. † indicates the models that yield as accurate forecasts as the best model at the 5% significance level based the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.1729	0.0156	0.0232	1.9596	−19.4799
A-ScBEKK	0.1682	0.0149	0.0221	1.9362	−19.5034
DiagBEKK	0.1722	0.0156	0.0233	1.9505	−19.4891
A-DiagBEKK	0.1631	0.0148	0.0220	1.8748	−19.5648
CCC	0.1580	0.0144	0.0213	1.5653	−19.8743
A-CCC	0.1511	0.0138	0.0202	1.5328	−19.9067
DCC	0.1624	0.0144	0.0214	1.6622	−19.7773
A-DCC	0.1624	0.0144	0.0214	1.6622	−19.7773
OGARCH	0.1662	0.0145	0.0215	1.9326	−19.5070
A-OGARCH	0.1562	0.0132	0.0196	1.9138	−19.5258
EWMA	0.1641	0.0154	0.0229	3.1971	−18.2425
LRCOV	0.1521	0.0179	0.0259	1.2379	−20.2017
HICOV	0.3802	0.0292	0.0447	2.5279	−18.9117
Adj-HICOV	0.1392	0.0127	0.0188	1.2761	−20.1634
AdjHAR-HICOV	0.2361	0.0178	0.0268	1.8129	−19.6267
VHAR	0.0826*	0.0066*	0.0098*	0.2451*	−21.1944*
	Panel B: Weekly Forecasts				
ScBEKK	0.1376	0.0070	0.0105	1.3601	−19.6289
A-ScBEKK	0.1306	0.0065	0.0096	1.3468	−19.6422
DiagBEKK	0.1370	0.0070	0.0106	1.3557	−19.6333
A-DiagBEKK	0.1254	0.0064	0.0095	1.2960	−19.6929
CCC	0.1147	0.0055	0.0081	0.9735	−20.0155
A-CCC	0.1085	0.0052	0.0076	0.9496	−20.0394
DCC	0.1196	0.0055	0.0082	1.0541	−19.9349
A-DCC	0.1196	0.0055	0.0082	1.0541	−19.9349
OGARCH	0.1259	0.0057	0.0085	1.3613	−19.6276
A-OGARCH	0.1157	0.0049	0.0074	1.3520	−19.6369
EWMA	0.1274	0.0067	0.0101	2.4352	−18.5537
LRCOV	0.1268	0.0086	0.0128	0.7246	−20.2644
HICOV	0.3576	0.0195	0.0302	2.0219	−18.9671
Adj-HICOV	0.1038	0.0055	0.0082	0.5149	−20.4740
AdjHAR-HICOV	0.2022	0.0088	0.0134	1.1707	−19.8182
VHAR	0.0531*	0.0022*	0.0032*	0.0981*	−20.8908*
	Panel C: Monthly Forecasts				
ScBEKK	0.1078	0.0031	0.0047	0.9770	−19.7245
A-ScBEKK	0.1021	0.0028	0.0042	0.9894	−19.7121
DiagBEKK	0.1077	0.0031	0.0047	0.9769	−19.7245
A-DiagBEKK	0.0974	0.0028	0.0041	0.9589	−19.7425
CCC	0.0786	0.0019	0.0028	0.6722	−20.0293
A-CCC	0.0777	0.0019	0.0028	0.6690	−20.0325
DCC	0.0826	0.0019	0.0028	0.7247	−19.9768
A-DCC	0.0826	0.0019	0.0028	0.7247	−19.9768
OGARCH	0.0906	0.0020	0.0031	1.0536	−19.6479
A-OGARCH	0.0856	0.0018	0.0027	1.0556	−19.6459
EWMA	0.0953	0.0029	0.0043	1.8322	−18.8693
LRCOV	0.1448	0.0074	0.0112	0.9108	−19.7907
HICOV	0.3402	0.0161	0.0251	1.8276	−18.8739
Adj-HICOV	0.0871	0.0027	0.0040	0.3337	−20.3678
AdjHAR-HICOV	0.1849	0.0057	0.0087	0.9726	−19.7289
VHAR	0.0360*	0.0008*	0.0011*	0.0559*	−20.6456*

Table 2.10

Model Confidence Set of Relative In-Sample Performance

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-, 5-, and 22-day in-sample fit. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	14	0.000	12	0.050	12	0.048	8	0.000	8	0.000
A-ScBEKK	12	0.000	13	0.050	13	0.048	4	0.000	4	0.000
DiagBEKK	13	0.000	9	0.050	8	0.048	6	0.000	6	0.000
A-DiagBEKK	10	0.000	6	0.050	6	0.048	10	0.000	10	0.000
CCC	7	0.000	7	0.050	7	0.048	7	0.000	7	0.000
A-CCC	5	0.000	5	0.050	5	0.048	5	0.000	5	0.000
DCC	8	0.000	11	0.050	10	0.048	11	0.000	12	0.000
A-DCC	9	0.000	10	0.050	9	0.048	12	0.000	11	0.000
OGARCH	11	0.000	8	0.050	11	0.048	14	0.000	14	0.000
A-OGARCH	4	0.000	3	0.050	3	0.048	13	0.000	13	0.000
EWMA	6	0.000	14	0.046	14	0.042	16	0.000	16	0.000
LRCOV	3	0.000	4	0.050	4	0.048	3	0.000	3	0.000
HICOV	16	0.000	16	0.014	16	0.021	15	0.000	15	0.000
Adj-HICOV	2	0.000	2	0.050	2	0.048	2	0.000	2	0.000
AdjHAR-HICOV	15	0.000	15	0.033	15	0.032	9	0.000	9	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	14	0.000	11	0.033	11	0.026	8	0.000	9	0.000
A-ScBEKK	11	0.000	12	0.033	12	0.026	9	0.000	4	0.000
DiagBEKK	13	0.000	7	0.033	7	0.028	4	0.000	8	0.000
A-DiagBEKK	8	0.000	5	0.033	5	0.028	12	0.000	12	0.000
CCC	6	0.000	6	0.033	6	0.028	7	0.000	7	0.000
A-CCC	3	0.000	2	0.033	2	0.028	5	0.000	5	0.000
DCC	9	0.000	9	0.033	9	0.028	11	0.000	11	0.000
A-DCC	10	0.000	8	0.033	8	0.028	10	0.000	10	0.000
OGARCH	12	0.000	10	0.033	10	0.026	14	0.000	14	0.000
A-OGARCH	5	0.000	4	0.033	4	0.028	13	0.000	13	0.000
EWMA	7	0.000	14	0.026	14	0.020	16	0.000	16	0.000
LRCOV	4	0.000	13	0.026	13	0.021	3	0.000	3	0.000
HICOV	16	0.000	16	0.013	16	0.007	15	0.000	15	0.000
Adj-HICOV	2	0.000	3	0.033	3	0.028	2	0.000	2	0.000
AdjHAR-HICOV	15	0.000	15	0.022	15	0.013	6	0.000	6	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	14	0.000	11	0.032	11	0.021	11	0.000	11	0.000
A-ScBEKK	12	0.000	12	0.032	12	0.021	8	0.000	8	0.000
DiagBEKK	13	0.000	10	0.032	10	0.021	10	0.000	10	0.000
A-DiagBEKK	9	0.000	7	0.035	7	0.022	12	0.000	12	0.000
CCC	4	0.000	4	0.035	3	0.024	5	0.000	5	0.000
A-CCC	3	0.000	2	0.035	2	0.024	4	0.000	4	0.000
DCC	7	0.000	5	0.035	5	0.024	7	0.000	7	0.000
A-DCC	5	0.000	6	0.035	6	0.024	6	0.000	6	0.000
OGARCH	10	0.000	8	0.032	8	0.021	14	0.000	14	0.000
A-OGARCH	6	0.000	3	0.035	4	0.024	13	0.000	13	0.000
EWMA	8	0.000	13	0.032	13	0.021	16	0.000	16	0.000
LRCOV	11	0.000	14	0.026	14	0.017	3	0.000	3	0.000
HICOV	16	0.000	16	0.007	16	0.006	15	0.000	15	0.000
Adj-HICOV	2	0.000	9	0.032	9	0.021	2	0.000	2	0.000
AdjHAR-HICOV	15	0.000	15	0.016	15	0.011	9	0.000	9	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

Table 2.11

Global Minimum Variance Portfolio Performance Against the 1/N Portfolio

This table summarises the performance of the global minimum variance portfolios as measured by annualised out-of-sample portfolio variance, and average turnover constructed using covariance forecasts generated by the models under examination. 1-day, 5-day, and 22-day covariance forecasts are used at each panel, and portfolio rebalancing is performed daily, weekly and monthly respectively. The portfolio variance for every model is tested against the benchmark 1/N portfolio. The test corresponds to the non-parametric methodology of Ledoit and Wolf (2011). ** $p < 0.01$ *$p < 0.05$ denote the level of significance.

	1-day Horizon		**5-day Horizon**		**22-day Horizon**	
	Variance	**Turnover**	**Variance**	**Turnover**	**Variance**	**Turnover**
ScBEKK	0.0160**	0.2269	0.0262	0.5520	0.0203	0.9506
A-ScBEKK	0.0155**	0.2023	0.0266	0.5395	0.0199	0.9816
DiagBEKK	0.0160**	0.2566	0.0267	0.5864	0.0206	0.9392
A-DiagBEKK	0.0161**	0.5125	0.0265	0.7508	0.0201	0.9856
CCC	0.0187	0.5291	0.0269	0.5077	0.0208	0.4566
A-CCC	0.0199	0.5482	0.0299	0.5401	0.0235	0.4318
DCC	0.0154**	0.3451	0.0277	0.8059	0.0197	1.1891
A-DCC	0.0154**	0.3457	0.0278	0.8085	0.0197	1.1903
OGARCH	0.0170**	0.2039	0.0236*	0.4752	0.0190	0.7091
A-OGARCH	0.0177*	0.2968	0.0237*	0.5631	0.0192	0.7976
EWMA	0.0167**	0.3628	0.0302	0.9116	0.0215	1.7165
LRCOV	0.0163**	1.2250	0.0267*	0.7286	0.0206	0.6788
HICOV	0.0162**	0.8029	0.0267*	0.6715	0.0210	0.7020
Adj-HICOV	0.0158**	0.7966	0.0263**	0.6435	0.0207	0.6783
AdjHAR-HICOV	0.0158**	0.7927	0.0254**	0.6458	0.0204	0.6854
VHAR	0.0151**	0.5135	0.0266*	0.5443	0.0213	0.7651
1/N	0.0211	0.0028	0.0297	0.0089	0.0237	0.0219

Patton and Sheppard, 2009). The general mean-variance optimisation problem is described by:

$$min \quad w_t' H_t w_t \quad \text{s.t.} \quad w_t' \hat{r}_t = \mu \quad \text{and} \quad w_t' \iota = 1 \tag{2.32}$$

where w_t is an $N \times 1$ vector of portfolio weights, μ is the expected portfolio return, and ι is an $N \times 1$ unit vector. Portfolio weights sum up to one. To avoid any assumptions regarding the returns r_t, I determine the weights of the global minimum variance portfolio (Chan et al., 1999; Clements et al., 2009; Kourtis et al., 2012) based on the inverse covariance matrix and not on the expected returns as follows:

$$w_t = \frac{H_t^{-1}\iota}{\iota' H_t^{-1}\iota} \tag{2.33}$$

Even though this assumption requires that all returns be identical, Engle and Colacito (2006) show that covariance forecasts are unbiased when they minimise the variance portfolio for every possible vector of expected returns. Since there are restrictions with short-selling for both individual and institutional investors, a non-negativity constraint ($w_t > 0$) is adopted for the weights.[18] The $1/N$ portfolio strategy is a common benchmark portfolio to evaluate the performance of portfolios using different covariance forecasts H_t. This is a typical benchmark in the portfolio choice literature because of its superiority over many sample-based portfolios (DeMiguel et al., 2009). The out-of-sample portfolio performance is gauged for each period using data for the forecasts from a constant size rolling window of in-sample returns.

I use two metrics to evaluate the portfolio performance of each forecasting method m, the out-of-sample variance $\hat{\sigma}_m^2 = \frac{1}{P}\sum_{t=1}^{P}(r_t - \hat{r}_t)$ and the out-of-sample average portfolio turnover $\hat{\tau}_m = \frac{1}{P-1}\sum_{t=1}^{P}\|\hat{w}_{t+1} - \hat{w}_t^+\|_1$, where P is the number of out-of-sample returns, $\|\cdot\|_1$ is the 1-norm, $\hat{w}_{t+1}$ is the desired portfolio weight after rebalancing and $\hat{w}_t^+$ is the portfolio weight before rebalancing that accounts for changes in asset prices between t and

[18]Short-selling is expensive for individual investors and is not always allowed to institutional investors.

$t+1$.[19] The portfolio turnover reflects the portfolio stability. Higher portfolio turnover is associated with higher transaction costs. I assess whether there is significant difference between the portfolio variance of each model and the benchmark strategy testing the null hypothesis $H_0 : \hat{\sigma}^2_m - \hat{\sigma}^2_{benchmark} = 0$, estimating the p-values with the robust non-parametric bootstrap method of Ledoit and Wolf (2011).[20]

Table 2.11 reports these metrics for daily, weekly and monthly portfolio rebalancing. In the daily horizon, all the covariance models but the CCCs offer significantly higher diversification benefits with lower portfolio variance than the naive strategy. The simple parametric VHAR builds less risky portfolio allocations. The portfolio rebalancing, though, incurs more stable variance relative to models that use high-frequency and option-implied information but less stable transaction costs relative to multivariate GARCH models. In the weekly horizon, even though VHAR estimates significantly lower portfolio risk relative to the $1/N$, OGARCH specifications, Adj-HICOV and AdjHAR-HICOV have lower portfolio risk. However, it offers decreased transaction costs.

These results demonstrate the competitive advantage of using high-frequency or option-implied information in daily rebalancing. This advantage is complement to the more accurate covariance estimates of the less computationally demanding VHAR. Such a finding has tremendous implications for mutual fund managers, and financial institutions that trade very often. The regulatory frameworks could also consider these results for the estimation of portfolio covariance using new sources of data and more accurate multivariate volatility models. These findings are in line with studies that consider the performance of various models within the mean-variance portfolio framework (e.g., see Liu, 2009; Chiriac and Voev, 2011; Hautsch et al., 2015). Liu (2009) also finds that high-frequency data offer a competitive advantage with daily rebalancing which vanishes with longer rebalancing horizons. However, this study does not control the performance of simple and composite models that use different information sets. The higher portfolio performance of simpler models relative

[19] $\hat{w}_t$ is the portfolio at time t and differs from the $\hat{w}_t^+$.

[20] I assume an average block size of 10 and 10,000 trials.

to more complicated covariance methods is also in line with Chan et al. (1999).

2.2.7 Robustness Checks

By and large, my findings remain robust under several alternative tests. The main conclusions do not change when I estimate the parameters based on an in-sample window of 1,250 observations instead of 1,000 (see Tables A.7 and A.22). I select later dates than the beginning of my sample to minimise the effect of the dot speculative bubble similar to Laurent et al. (2012), trimming the data set to begin either in 2002 or 2003 instead of 2000 (see Tables A.8-A.9 andA.23-A.24). I find that the results remain qualitatively similar. I also replicate the analysis for the various market conditions on the appropriate estimation of the true covariance proxy, defining the global financial crisis from the Lehman Brothers' collapse, similar to Kourtis et al. (2016). However, this specification reduces the number of months in the global financial crisis period (see Tables A.30-A.32). Despite that the GW test corrects for the autocorrelation in the covariance estimates using overlapping information with the Newey and West (1987) and Andrews (1991) heteroscedasticity and autocorrelation corrected standard errors and covariance matrices, I perform the analysis using non-overlapping predictions as well (see Tables A.10 and A.25). I use the range statistic and different levels of confidence, i.e., 90 percent and 75 percent, for the Model Confidence Set (see Tables A.19-A.21). Additionally, I replicate the analysis without interpolating the high-frequency data with the previous price(see Tables A.14 and A.29). I also use the alternative pairwise test of Diebold and Mariano (1995) (see Table A.15). In all cases, the results do not change significantly.

I also estimate close-to-close daily returns. However, even if the markets are close and no transactions are recorded, these returns concern a 24-hour period since the prices still react to the news. The lack of 24-hour high-frequency data does not allow for the estimation of overnight returns. Martens (2002) and Hansen and Lunde (2005) argue that ignoring the overnight returns as previous studies induces bias in the proxy of the actual volatility. To this end, I follow three standard procedures in literature. First, I estimate overnight squared logarithmic open-to-close returns to adjust for the overnight period. In this case the daily realised covariance, $RC_{ij,d}$ is estimated as:

$$RC_{ij,d} = r_{i,co}r_{j,co} + \sum_{m=1}^{M} r_{i,m}r_{j,m} \tag{2.34}$$

where $m = 1, 2, ..., M$ is the number of 5-minute returns, $r_{i,m}$ and $r_{j,m}$ are intraday returns the m^{th} 5-minute interval, and $r_{i,oc}, r_{j,oc}$ are open-to-close logarithmic returns for assets i and j. Second, I use the constant adjustment of Martens. The daily multivariate volatility scales the intraday product of returns with a constant c as:

$$RC_{ij,d} = (1 + c) \sum_{m=1}^{M} r_{i,m}r_{j,m} \tag{2.35}$$

where $c = (\sigma_{ij,oc} + \sigma_{ij,co})/\sigma_{ij,co}$. Third, I adopt the correction of Hansen and Lunde, who estimate the constant $c = [(r_{i,cc} - \hat{r_{i,cc}})(r_{j,cc} - \hat{r_{j,cc}})]/\sum RCij$. The main conclusions are maintained (see Tables A.11-A.13 and A.26-A.28).

2.3 Limitations and Future Research

Limitations in the study of covariance are generally imposed from non-synchronous trading. As a result, the study is restricted on major markets in the same geographic region and is subject to the availability of long enough history of high-frequency and option-implied information. The analysis could also be extended in further geographic markets including more countries. Additionally, these conclusions are based on findings for developed countries. Findings of different dependence patterns across developed and emerging economies suggest that different dynamics govern the covariances (e.g., see Hamao et al., 1990; Karolyi and Stulz, 1996; Bekaert et al., 2002; Boyer et al., 2006; Boyer, 2011; Bekaert et al., 2014). Thus, this study could also explore the performance of models across more unstable and less liquid markets.

Moreover, the analysis considers the most popular alternatives among multivariate GARCH models. However, more recent studies focus on exploiting high-frequency information within GARCH specifications. For instance, the realised GARCH and multivariate realised GARCH models of Hansen et al. (2012) and Hansen et al. (2014) are not examined in this study. The analysis could be extended in the future to compare the contribution of realised data to the predictive accuracy of GARCH models. Finally, in the spirit of Bauer and Vorkink (2011), who extend the MHAR covariance model to accommodate past volatilities and other factors that predict volatilities such as treasury bill, dividend yield, credit spread, slope of term structure and the scorecard, it would be interesting to investigate the contribution of such variables to covariance forecasting.

2.4 Conclusion

This essay investigates the forecasting performance across 16 GARCH, option-implied and realised covariance models. The intuition behind this study is that no extensive research combines broad classes of covariance models, from simple parametric and non-parametric models to fully parametrized. Inferences are also made regarding the contribution of various information sets, such as daily, high-frequency and option-implied, to the prediction of future covariances.

The empirical analysis is based on 5 European equity indices. The results indicate that simple parametric or non-parametric models which use high-frequency data outperform those of the popular GARCH family. In particular, the Vector Autoregressive Model appears to outperform the other alternatives systematically. The lagged realised covariance model based on high-frequency data also offers competing forecasts. The findings are robust across various forecast horizons, market conditions, loss functions and statistical tests. The research output is not as conclusive for hybrid estimators, presented for the first time in covariance forecasting, that combine high-frequency and option-implied information (HICOV, Adj-HICOV, AdjHAR-HICOV). However, in line with the literature, the adjustment of implied volatilities for the volatility risk-premium bias reduces the forecasting errors, offering in many occasions comparable performance to the best models. In addition to the statistical criteria, I report significant economic gains from the estimation of out-of-sample portfolio performance compared to the $1/N$ portfolio. These findings have important managerial implications as they reduce the computational restrictions of practitioners by proposing simpler yet more accurate models for covariance forecasting.

Chapter 3

Co-Attention and Return Comovement

3.1 Introduction and Background Information

Traditional theory suggests that investing across international stock markets generates greater diversification opportunities. However, these benefits fade as markets move more together and in excess of their fundamentals (Shiller, 1989; Karolyi and Stulz, 1996; Brealey et al., 2010). Several studies examine the determinants of excess comovement in alternative theories of correlated sentiment and irrational behaviour (see, Barberis et al., 2005). Notwithstanding, there is little focus on exploring rational determinants of return comovement, such as information flows. Despite the appealing theoretical explanation of correlated information, measurement restrictions challenge its empirical investigation. Relevant literature overcomes this issue measuring the correlated information in terms of news supply (e.g., see Mondria and Quintana-Domeque, 2013; Israelsen, 2016). Limited attention theory, though, argues that no matter how much information flows to financial markets, the information investors pay attention to, has a stronger impact on financial markets (Barber and Odean, 2008).

This chapter extends the understanding and evidence of limited information or attention-based comovement in several directions. First, I establish that investor attention across stock markets comoves presenting a novel proxy, "co-attention", which is based on the correlated search intensity for market-wide information. Second, I explore the factors that drive co-attention between international stock markets. Third, I investigate the market consequences of co-attention on excess return comovement. Fourth, I extend the analysis to document the asymmetric effect of co-attention on developed economies and during downturn periods. Fifth, I study the co-attention of local and international investors across stock markets providing insights for the flow of information and market implications. Finally, I examine co-attention as a channel of financial contagiousness.

Recent evidence in the literature, based on the popularity of online financial information sources, advocates that investors shift their attention similarly across assets (e.g., see the studies of Leung et al., 2016, Agarwal et al., 2017, and Lee et al., 2015, for co-search in Yahoo!Finance and EDGAR and the study of Oestreicher-Singer and Sundararajan, 2012, for co-purchase). This rationale is behind the first objective that similar searching patterns of financial information between stock markets lead to significant comovement in investor attention. Alternative behavioural theories suggest that investors create linkages between assets when they group them together (e.g., see Hirshleifer and Teoh, 2003; Barberis et al., 2005; Boyer, 2011). As a result, their attention varies similarly when they focus on the assets of the group. Other reasons that explain common patterns in information discovery evolve from psychological research which supports that individuals learn faster when learning is a social process (Mundy and Newell, 2007; Seemann, 2011). This means that during interaction with peers, investors share information and sources explaining similar trends in information demand.

The second objective of this essay investigates further factors that may create linkages between stock markets and increase co-attention. Along with capitalisation and market conditions, economic and trading flows (Cohen and Frazzini, 2008; Anton and Polk, 2014; Bekaert et al., 2014), style or group trading (Barberis et al., 2005; Boyer, 2011), news-linked assets (Mondria and Quintana-Domeque, 2013; Höchstötter et al., 2014; Dang et al., 2015; Israelsen, 2016), ownership (Bartram et al., 2015), culture (Grinblatt and Keloharju, 2001) and negative shocks (Bekaert et al., 2014) are some examples that can trigger similar shifts in attention across markets. I control for changing co-attention with market capitalisation, cash flows, correlated news supply, market regimes, and geographical and cultural proximity.

In my subsequent analysis, I test whether comovement in investor attention leads to similar pressures in stock prices that increase their return comovement. As is explained by Jacobs (2015), *"attention constraints might also force investors to resort to complexity-reducing heuristics, which might eventually induce excessive return comovements among stocks often mentally grouped together"*. Based on a theoretical framework of limited attention, I formalise hypotheses that explore a positive association between co-attention and return comovement. Peng and Xiong (2006) suggest that the market efficiency is reduced if investors read more market-wide news and remove their effort from absorbing stock-specific information due to limited processing capabilities. The authors associate the attention to general stock market information with correlated inferences for fundamentals that impose similar price moves on stock markets.

I form further hypotheses to investigate whether there is a more pronounced effect of co-attention on developed countries' comovement and during highly volatile periods. Developed countries have more efficient information markets that promote the coverage of investor demand offering a plethora of information sources. Given that the openness is a key characteristic of developed economies, international investors who diversify their portfolios across stock markets have also a strong incentive to demand common news related to them. Another possible explanation is that many investors attend news for large economies, either they invest there or not, because they are aware of the dependencies across markets. On the same basis, in periods of high uncertainty investors concentrate more on market-wide news to attend the reaction of markets to negative shocks. Extreme conditions also involve higher coverage of stock market news than firm-specific news. Such interpretations are also in line with theories that support countercyclical information production, affected by the business cycle (Veldkamp, 2006*a*; Brockman et al., 2010).

My research also provides insightful empirical evidence for the information flows of various investors. Aggregate co-attention between two stock markets stems either from international investors, or from domestic investors who focus on their markets independently, or co-attend both markets. Locating the searches of independent local investors, I examine whether co-attention to financial information imposes similar dynamics on their stock markets. Leung et al. (2016), Agarwal et al. (2017) and Lee et al. (2015) focus on correlated searches derived from the same individual. This is the first attempt, to the best of my knowledge, to study the aggregate correlation in the search pattern of individuals who concentrate separately on market-wide news for their respective stock markets. Even if the searches are unrelated and concern different markets, when for some reasons, domestic investors coordinate their search for market information, they both become less attentive to firm news resulting in similar inferences and price dynamics.

Finally, I study the channels of financial contagiousness (e.g., see Kodres and Pritsker, 2002; Forbes and Rigobon, 2002; Chiang et al., 2007; Mondria and Quintana-Domeque, 2013; Bekaert et al., 2014; Hasler and Ornthanalai, 2015). Financial contagion involves the transmission of shocks across stock markets and the propagation of crises. Similar to Hasler and Ornthanalai (2015) who present the fluctuating attention to news as a channel of contagiousness between unrelated industries, I identify unrelated countries in terms of capital flows and news and explore the relationship of co-attention with stock market comovement, as well as, the role of locals and international investors in the dissemination of shocks.

I measure empirically the correlated 'consumed' information or 'co-attention' of investors for stock market news between 33 developed and emerging economies employing the Google Search Volume Index (SVI henceforth) over the period from January 1, 2004, to December 31, 2016. I gather SVIs that measure the market-relevant searches for each country, following Peng and Xiong (2006) who support that this type of information is associated with higher market comovement. Then, co-attention is computed as the simple pairwise correlation between weekly abnormal SVIs for each year. To the best of my knowledge, this is the first study that examines the correlated aggregate searching behaviour of millions of people worldwide using readily available time series data from the most popular search engine provider worldwide.

The accuracy of SVI as a proxy for investor attention is well supported by the pioneering works of Da et al. (2011) and Vlastakis and Markellos (2012), which distinguish the information demand from supply. SVI measures directly shifts of attention to financial information reflecting what grabs investors' interest and updates their beliefs. Alternative proxies of attention based on news supply (e.g., see Corwin and Coughenour, 2008; Mondria and Quintana-Domeque, 2013; Israelsen, 2016) are subject to the criticism that they do not measure whether investors have truly paid attention to them.

My results support my hypotheses. Significant positive cross-country co-attention implies that investors concentrate similarly their demand for stock market news and analyst opinions. Compared to return correlations, co-attention exhibits similar patterns, but it is lower and more volatile. High market frictions induced by non-executed transactions, by restrictions on capital flows or by constraints in arbitrage explain this deviation. In other words, investors can alter their attention rapidly, but stock prices cannot follow with the same speed. I also show that co-attention increases for more linked economies and when information supply is more correlated and decreases with geographical and cultural distance. Altogether, correlated information supply and financial flows appear to explain a small part of the variation in co-attention after controlling for asymmetries across turbulent times and across pairs of countries. This finding justifies further the context of this analysis indicating that correlated information demand is only partially driven by correlated news.

Another major finding of my empirical analysis is the positive relation of co-attention and excess return comovement. Employing asset pricing models, I show that co-attention is a significant determinant of excess return correlation beyond other sources that explain market comovement, such as capital flows, distance, and correlated news. The insignificant beta coefficient for correlated news provides further evidence that correlation in the consumed information affects return comovement more than the correlation of news coverage and is not triggered by common reference to news. I also report a stronger effect of co-attention on developed markets and during periods of financial distress. My results remain robust using weekly return correlation and co-attention from a multivariate GARCH process. A weak but significant effect between fundamentally unrelated markets which are not connected either with capital flows or common reference in news, indicates that co-attention is a channel for the transmission of volatility. This effect, though, is disseminated through the indirect search patterns of international investors and not through domestic information demand. Lastly, to mitigate concerns for endogeneity that is generated if co-attention is triggered by return correlation, I also show that past return correlation does not predict investors' co-attention.

In sum, I make three major contributions to the literature. Primarily, I add to the growing body of the literature that investigates news (Veldkamp, 2006*a*; Höchstötter et al., 2014; Israelsen, 2016; Dang et al., 2015; Drake et al., 2016, etc.) and investor attention as rational determinants of pricing, volatility and correlation in financial markets (Peng and Xiong, 2006; Corwin and Coughenour, 2008; Mondria, 2010; Da et al., 2011; Andrei and Hasler, 2014, etc.). More specifically, I show that there is significant comovement in investor attention on market news. In addition to shedding some light on the way investors absorb information, I perform a rigorous analysis of co-attention and reach important findings about stock market dynamics.

In particular, I extend the literature of excess return comovement (e.g., see Shiller, 1989; Brooks and Del Negro, 2004; Barberis et al., 2005; Kallberg and Pasquariello, 2008; Bekaert et al., 2009; Brealey et al., 2010; Boyer, 2011), showing a significant and positive relationship with co-attention after controlling for alternative sources of comovement, such as correlated fundamentals, distance, and correlated news supply. This outcome indicates that stock prices move more in tandem when investors coordinate their attention on the market-relevant news. Finally, I support the literature that approaches investor attention with measures that reflect information demand than supply (e.g., see Barber and Odean, 2008; Da et al., 2011; Vlastakis and Markellos, 2012; Drake et al., 2016).

3.1.1 Literature Review

Efficient Market Theory and Excess Comovement Anomaly

Information has a prominent role in financial markets. The dominant financial theory of Efficient Markets (Fama, 1965; Malkiel and Fama, 1970) entails that investors have a specific attitude towards risks and rewards. A basic assumption is that they make trading decisions considering the same information at the same time. Thus, prices should change because information updates the expectations about fundamentals. Ross (1989) also links the variation in prices with variation in the flow of information. However, there is ample evidence of systematic deviations from the theoretically efficient level, resulting in a gradual relaxation in the literature of the strict hypotheses of rationality, homogeneity in beliefs, and perfect and synchronous availability of information (Malkiel and Fama, 1970) with the introduction of models of incomplete information (Detemple, 1986; Gennotte, 1986) and heterogeneous beliefs (Detemple and Murthy, 1994; Glosten and Milgrom, 1985; Andersen and Bollerslev, 1997).

Grossman and Stiglitz (1980) indicate the paradox of the Efficient Market Hypotheses and the impossibility of equilibrium in markets under complete information. A number of anomalies provide further evidence against the Efficient Market Theory (EMT). Robert Shiller, in his seminal papers (1981; 1989), identifies higher volatility and co-volatility in prices beyond the variance and covariance in cash flows (i.e., dividends). The minuscule contribution of fundamentals to explain these phenomena defines the excess comovement anomaly.[1] Based on these findings, Shiller casts doubts on the EMT implying that the aim to unify and explain markets is nothing more than an ivory tower with ideal but not realisable perspectives (Shiller, 2003).

This is a turning point in Finance with the introduction of behavioural theory which considers market frictions and investor sentiment. As a result, alternative explanations study the stock market comovement building on investors' irrationality and sentiment. Barberis, Shleifer and Wurgler (2005) found a theory where correlated sentiment and noise trading generate excess comovement.[2] They also demonstrate increasing comovement following the

[1] Additional studies report higher comovement between assets, above and beyond correlated fundamentals, rejecting the traditional hypothesis of rational investors and efficient markets (e.g., see Shiller, 1981, 1989; Pindyck and Rotemberg, 1993; Karolyi and Stulz, 1996; Kallberg and Pasquariello, 2008; Brealey et al., 2010).

[2] This is a novel theory that involves three explanations of excess comovement based on frictions and sentiment. The category view holds that common stylised facts (industry, small capitalisation, junk bonds)

addition of a stock to the Standard & Poor's (S&P) 500 index. Green and Hwang (2009) report further empirical findings with stock splits, and Boyer (2011) with stocks that are reclassified between value and growth indices. Investors that focus on specific groups or mutual fund managers that track an index may also impose similar pressure on prices. Coval and Stafford (2007) and Boyer and Zheng (2009) report abnormal comovement for pairs of stocks held by mutual funds. A positive correlation between mutual fund flows and returns illustrates that liquidity puts similar pressure on their prices.

Comovement Determinants and Stylised Facts

A voluminous literature has been emerged to study the drivers of covariance between assets, markets and countries beyond their fundamentals, building on alternative theoretical frameworks (Barberis et al., 2005; Veldkamp, 2006*a*; Peng and Xiong, 2006; Mondria, 2010). This knowledge should give investors the opportunity to predict more accurately the covariance between assets in their portfolios and take advantage of the diversification opportunities from imperfect correlation. As King et al. (1994) explain, a mistaken estimation of covariance shall lead to suboptimal diversification for worldwide portfolio allocation. In addition to portfolio theory, covariance is an important input in asset pricing models, risk management and hedging. Thus, many empirical studies focus on explaining the patterns in stock market comovement (stylised facts). It is generally accepted among academics that covariance is time-varying and stronger between developed economies and during periods of high uncertainty. There is strong disagreement, though, among different schools of thought on the factors that drive variation in covariance under different conditions. There is also sig-

and asset grouping creates comovement through the action of noise traders. The habitat view interprets comovement as the decision of irrational traders to invest in a subset of assets. These two views are examined empirically providing evidence of higher return correlation between an asset that enters a habitat or category and the assets therein. The third view refers to different information diffusion rates in prices due to market frictions. Stocks with the same rate demonstrate similar price return patterns and comove. However, restrictions in measuring the information flow do not allow for an empirical investigation of this view.

nificant conflict for the impact of globalisation on stock market comovement, the extent of integration in markets, as well as, the financial contagiousness (e.g., see Forbes and Rigobon, 2002; Boyer et al., 2006).

Lessard (1974) provides early evidence of changing correlations between various equally-spaced time windows and suggests that trading and capital flows call for loose or tough relationships among countries over time. Bollerslev et al. (1988) find that covariance matrix changes over time and is explained to some extent by past innovations in returns and information. King et al. (1994) show that observable variables cannot explain an important part of variance and covariance, despite the fact that they seem to Granger cause dividends. They conclude that unobservable factors appear to drive changes in correlations. These results also agree with King and Wadhwani (1990), who expand the work of French and Roll (1986) to study the volatility transmission in the US.[3]

A seminal paper that uncovers unstable covariance and correlation over 30 years for seven developed economies is that of Longin and Solnik (1995). The authors also show that correlation increases in the long-run and advocate that integration and higher volatility in business cycles induce higher interdependence across markets. Asymmetries between good and bad times is another confirmation of time-varying correlations. Longin and Solnik (2001) study this phenomenon and find disproportional increases in correlations with higher effect during recessions than expansions. Based on extreme value analysis, they reject the hypotheses of normally distributed and constant correlations in bear markets, but not for bull markets. Other studies, such as Ang and Bekaert (2002) propose a two-regime switching model to show that volatility is a driver of correlation. However, this model fails to capture correlation asymmetries. Later, Okimoto (2008) uses Markowitz switching models and exhibits strong asymmetries in the US-UK and the US-Canada markets, smaller in the US-Germany and the US-France markets, but no asymmetries in the US-Japan, indicating different degrees of reliance between countries.

[3]Both papers support contagion effects and volatility spillover across US and Japan markets when global factors dominate national factors.

Other studies focus on the lower correlation between emerging and developed economies. Early research in this area explores this deviation as an opportunity for risk reduction, diversification and hedging (e.g, see Grubel, 1968). For instance, Levy and Sarnat (1970) reveal improvements in portfolio's features even for the US market that has very good risk-return trade-off. Other streams in the literature concentrate on the factors that lead to different cross-country comovement patterns (e.g., see Hamao et al., 1990; Karolyi and Stulz, 1996; Bekaert et al., 2002; Boyer et al., 2006; Boyer, 2011; Bekaert et al., 2014), on comovement in emerging markets (e.g., see Calvo, 2004; Morck et al., 2000; Dang et al., 2015), and on financial contagion (e.g., Allen and Gale, 2000; Kyle and Xiong, 2001; Forbes and Rigobon, 2002; Kodres and Pritsker, 2002; Bae et al., 2003; Yuan, 2005; Chiang et al., 2007; Mondria and Quintana-Domeque, 2013; Bekaert et al., 2014; Hasler and Ornthanalai, 2015).

Related Literature

This essay is related to several streams of the literature. The first stream explores alternative explanations for the excess comovement anomaly in stock markets. In addition to behavioral biases, recent studies investigate this phenomenon in a more rational context. Psychological evidence that human beings have limited processing capabilities has questioned the strong assumption of instantaneous information process in the context of the EMT (Kahneman, 1973). Therefore, a more social approach considers that limited attention to information is rational for human beings (Sims, 2003)[4]. This essay builds on the theoretical work of

[4]There is ample research on investors' limited attention to financial markets. For instance, investors can be distracted by weather and temperature (see Hirshleifer and Shumway, 2003; Cao and Wei, 2005, etc.), the anticipation of weekend (DellaVigna and Pollet, 2009), leisure activities (see Edmans et al., 2007; Schmidt, 2013), and moon phase Yuan et al. (2006). Despite the consensus that retail investors are more prone to distraction, as explained in Barber and Odean (2008), there is also evidence that distraction concerns market makers and specialists. For instance, Coval and Shumway (2005) show that market makers are biased and distracted. Corwin and Coughenour (2008) observe that market specialists shift their effort among assets affecting their liquidity, while Hirshleifer et al. (2009) find similar distraction effects on assets with higher analyst coverage or institutional investing.

Peng and Xiong (2006) which relates attention to excess comovement. The latter study maintains that comovement is affected by the resources investors allocate to process market-wide news as well as idiosyncratic news. When investors focus more on general information and become distracted by asset-specific news, assets move more together. Another study in this area is that of Mondria (2010) who suggests that attention reallocation to a composite signal related to more assets generates excess comovement. Changes in one asset lead to similar reactions to the other assets increasing their volatility and comovement. The price of the former reacts to the new information, while the others respond to higher uncertainty. The theoretical connection between volatility and uncertainty is also presented in Andrei and Hasler (2014). Similar implications of changing attention are also shown in Corwin and Coughenour (2008). The authors find that when market specialists focus on specific assets, uncertainty and liquidity premiums increase for assets they ignore.

I also add to the literature that investigates market implications of attention empirically. Papers in this area rely on indirect proxies such as absolute returns and trading volume (Gervais et al., 2001; Corwin and Coughenour, 2008; Hou et al., 2009), extreme returns (Barber and Odean, 2008), news (Barber and Odean, 2008; Mondria and Quintana-Domeque, 2013; Yuan, 2015; Dang et al., 2015), advertising costs (Grullon et al., 2004; Chemmanur and Yan, 2010; Lou, 2014) and analysts' coverage (Israelsen, 2016) under the assumption that they should grab investors' attention. More specifically, Mondria and Quintana-Domeque (2013) measure the relative attention between Asia and Latin America with news for these markets to demonstrate that attention reallocation is a channel through which volatility is transmitted across unrelated economies. They show that when more news is provided for Asian countries and less news for Latin American countries the volatility increases in the latter. In the same spirit, Israelsen (2016) explains that analysts coverage is correlated for some reasons and finds a positive association to excess comovement. Dang et al. (2015) report commonality in the news within countries with weaker institutional environments. They also conclude that higher commonality in the news is associated with higher comovement in returns and liquidity.

I approximate the correlated attention on market-wide information and the impact on stock market comovement based on a different perspective. Information demand captured by the traffic volume for specific keywords is a more direct proxy than information supply (news or analyst coverage). The higher the search intensity, the higher the attention of online users. Da et al. (2011) validates that online searches for specific keywords captures investor attention to financial information and predicts stock returns. Similarly, Vlastakis and Markellos (2012) find an association between online searches for stock returns and market volatility.

My work is closely related to the pioneering paper of Drake et al. (2016). The authors use the methodology of Morck et al. (2000)[5] to explore the relation of investor micro-attention (firm-level) with macro-attention (industry and market level) controlling for firm factors (similar to CAPM of Sharpe, 1964). They also document a positive association between their proxy and return comovement. According to their findings, earnings announcements trigger investor attention for related firms (within an industry) indicating how information flows affect financial markets. My approach deviates from that paper in several ways. First, I measure the co-attention specifically on market news since this type of information is associated with excess comovement. Second, I examine the aggregate co-attention of investors between international stock markets providing new insights for the global flow of information and market consequences controlling for linkages between international economies and other sources of comovement.[6] Third, I employ a different methodology, computing co-attention as the simple pairwise correlation matrix between attention proxies in various stock markets.

Fourth, I control for the distinct impact of correlated news to alleviate any concerns with regards to the relationship with information supply proxies. To this end, I employ a unique dataset from Reuters News Scope and calculate correlated news supply similar to Israelsen (2016). I report positive yet weak relationship between correlated news and co-attention.

[5]This methodology identifies the synchronicity of an asset to an industry or market by transforming the R^2 of their regression.

[6]Long et al., 1990, and Calvo and Mendoza, 2000 rely also on the idea that even individually rational decisions can lead to aggregate excess comovement.

This finding supports that information demand has a different effect On financial markets than information supply. Fifth, I examine asymmetric effects of co-attention on return comovement across markets and market conditions. Sixth, I study co-attention as a channel for volatility transmission and financial contagion. Finally, I distinguish the co-attention of local and international investors providing new evidence on the financial information flows of different types of investors.

Co-attention also adds to the literature that explores coordination in trading patterns. For instance, Scharfstein and Stein (1990) discuss coordination in managers' decisions, while Banerjee (1992) and Bikhchandani et al. (1992) explain excess comovement by coordination in investors' decisions. Feng and Seasholes (2004) find evidence of correlated trading which increases with proximity. In this study, I rely on the idea that investors discover information similarly (co-search). Significantly positive co-attention reflects the fact that market participants attend markets in a similar manner and they process similar information. This finding suggests that investors do not seek for rare information that others ignore, but trade on commonly viewed information, instead. This explains why they make correlated inferences and present similar trading patterns. This literature also agrees with the recent research in informatics that explores the online searching habits (Leung et al., 2016; Lee et al., 2015; Agarwal et al., 2017).

My proposition that investors present similar information search patterns also finds support in the psychological theory of joint attention. Joint attention describes the idea that human beings focus on similar tasks or information to increase their understanding and learning. Even though this term is used to describe the process of infants' learning through common observation, recent psychological research explores this phenomenon as a process of social cognition (Mundy and Newell, 2007; Seemann, 2011). If individuals learn faster reacting simultaneously in stimuli, I expect that people allocate their attention in a similar way to facilitate this process. Thus, when investors are faced with a shock or news, it is possible that through their personal or online interaction (e.g., social media, forums) they jointly observe the nature of this shock. There are papers that study the interaction between investors and the impact on financial markets (e.g., Feng and Seasholes, 2004; Hong et al., 2004).

The hypothesis of correlated attention is also in line with further psychological research of attention. According to Gibson and Rader (1979), humans need to allocate less attention to more familiar tasks, allowing this way to multi-task activities. Similarly, investors do not require the same cognitive resources to evaluate a portfolio of familiar assets. In this case, they prefer to invest in similar assets, assets that are widely covered or assets within the same group. In the same psychological study, the authors explain that when people deal with a task with catastrophic consequences, they allocate most of their attention on that task. This also explains why during global financial crises investors become more attentive supporting our hypothesis of higher co-attention throughout periods of financial distress. In front of the risk of losing their capital, investors remove resources from other tasks and focus their attention on processing information that will save them from a "catastrophe".

This essay also conforms with theories that explain patterns in return comovement. A part of this literature studies the higher synchronicity of stocks with their market index in emerging economies. Morck et al. (2000) show that in emerging markets the lower investor protection does not promote arbitrage and increases synchronisation. According to Dang et al. (2015), this is related to the weaker institutional environment that eliminates the production of firm-specific information. Kodres and Pritsker (2002) argue that higher noise trading and herding is expected in emerging markets due to higher informational asymmetries and portfolio rebalancing constraints. Another part of the literature studies cross-country correlation asymmetries and diversification opportunities, which exhibit higher comovement between stock market indices of developed economies compared to emerging economies (e.g., see Errunza, 1977; Divecha et al., 1992; De Santis, 1993; Bekaert and Harvey, 1995, 1997; Bekaert et al., 2009). Constraints in liberalisations, liquidity, and trading are among the factors that explain lower comovements between developing stock markets. I contribute to this literature presenting co-attention as a new explanation of different comovement patterns across countries.

Higher correlation during volatile market conditions is another stylised fact (Longin and Solnik, 1995). Other papers also report asymmetric reactions between bull and bear markets (e.g., see Erb et al., 1994; Santis and Gerard, 1997; Longin and Solnik, 1995, 2001; Yuan, 2005; Bekaert et al., 2014). Yuan (2005) attributes the higher synchronicity of bear markets to the decreasing capital accessibility of informed investors. In this study, I control for higher comovement due to higher co-attention on market information. The focus of the extant literature on financial contagiousness and transmission of volatility is very important in order to understand the mechanism that destabilises the stock markets globally (Forbes and Rigobon, 2002; Chiang et al., 2007; Mondria and Quintana-Domeque, 2013; Hasler and Ornthanalai, 2015). Thus, I explore the conditions under which co-attention is a channel for crises propagation controlling for lower exposure to the US and global financial factors.

I also provide evidence that excess comovement varies with co-attention beyond prior explanations such as correlated trading flows and distance. Many scholars concentrate on comovement induced by the interrelations between local investors (e.g., see Grinblatt and Keloharju, 2001; Feng and Seasholes, 2004). This is in line with gravity theory employed in other papers to show that proximity captures linkages between markets. Also, distance, according to Portes et al. (2001) and Portes and Rey (2005) can be an indicator of informational asymmetries in international financial markets. The authors suggest that information has limits beyond which its effect on stock markets reduces. Likewise, my findings indicate that comovement reduces with distance. However, the global provider of information (WWW) imposes different dynamics in information flows and eliminates information asymmetries to some extent. Even though the geography of information is beyond the scope of this work, my research lends support to the idea that informational proximity and investor attention do matter more than the distance between economies. Moreover, being able to locate the searches for every country, I test whether co-attention at the aggregate level is generated from distant investors who fluctuate their attention for trading in a specific pair of countries or from locals who concurrently change their attention to their stock markets.

My empirical analysis do not support theories that present excess comovement as a random event with many possible equilibria. For example, Diamond and Dybvig (1983) use a bank runs model to show that an investor's trading pattern is subject to other investors' trading behaviour. As a result, patterns in comovement are random as they are dependent on how investors react in shocks each time. Nevertheless, co-attention that predicts patterns of return comovement reveals that comovement is not subject to random factors.

The remainder of this chapter is organised as follows. Section 2 presents the empirical analysis. In particular, it describes the data and sample, the determinants of co-attention, the testable hypotheses, the results and the robustness checks. Section 3 identifies limitations and future extensions and Section 4 discusses the main conclusions.

3.2 Empirical Analysis

3.2.1 Data and Sample

My empirical analysis requires a proxy for investor attention. I employ the Search Volume Index, published by Google Trends in 2004. This is an indicator of the relative search intensity for specific keywords in the Google search engine.[7] Arguably, the superiority of SVI in relation to other variables used in the extant literature to measure attention lies in the direct and non-financial nature. SVI is a direct proxy because it measures the volume of investors who actually have demanded information for specific keywords. On the contrary, news supply is an indirect proxy assuming that has been seen by investors. Unlike other proxies used in the literature, such as absolute and extreme returns, trading volume and advertising expenses, SVI is not based on financial data.

SVI is validated by Da et al. (2011) and Vlastakis and Markellos (2012) as a measure

[7] The index is estimated each week as the average volume of searches for a specific topic over the volume of the total Google searches. This is also normalised taking values in the [0,100] by dividing the series within a specific date range by the highest point of interest. As a result, this is a relative measure of search intensity and is not comparable or additive across different keywords. However, this is not an issue with changes in the search intensity.

of investor attention, reflecting the demand for information. The authors argue that information demand is a more appropriate proxy for attention than supply, since investors' distraction may impose a delay on the discovery of related analyst reports or media coverage. Additionally, while news provision and processing can vary among different types of investors, limited attention is not subject to investors' sophistication or advanced processing methods (Coval and Shumway, 2005; Corwin and Coughenour, 2008; Hirshleifer et al., 2009).[8] Da et al. (2011) and Vlastakis and Markellos (2012) also present methodologies for appropriate keyword selection. The former use the company ticker to measure the SVI in order to reduce the noise from web users other than investors that may look for company's products. The latter use the firm name instead arguing that keywords for tickers capture only a portion of investors' searches as the majority may not be aware of them.

However, an advancement in Google Trends involves the grouping of keywords used for popular searches in topics. A further benefit from this service is that it aggregates searches in all languages. As a result, there is no need to select specific keywords or restrict searches in English but I use SVI topics instead.[9] Since I approximate the attention on market-wide than firm-specific news, I use topics of the most popular stock index or the name of the stock exchange. Investors may search for popular stock indexes by their name, but for less popular indexes it is highly likely to search by the name of the national stock exchange. Between these two thematic areas, I select the one with the highest average interest. For example, to decide among "Dow Jones", "S&P 500", "NYSE", or "Nasdaq", I use the topic with the highest interest in Google Trends for weekly SVIs over the period 2004-2016 (see figure B.1, Appendix B). The focus on general queries rather than stock-related queries eliminates the noise that comes from users who access the firm for reasons other than updates for its

[8]This means that more sophisticated investors such as mutual fund managers, analysts, institutional investors and market markets have access to advanced tools and additional databases to process financial information.

[9]According to Google Trends, topics "share the same concept, in any language". An example is provided for searches of the topic "London". Either online users type "capital of the UK" or the Spanish "Londres", the searches are conceptualized to the topic "London".

financial activity, such as for its products, services or online purchases.

My sample consists of broad stock market indexes for most developed and emerging economies following the MSCI market classification as of June 2016.[10] I drop from the sample countries that are reclassified during the 2004-2016 period. Given that SVI reflects the relative normalised searches of a particular query for the requested period, an increase in SVI can be interpreted as a higher demand for the specific keyword and not as an increase in Internet use (search volume is divided by the total number of searches). Even though changes in the level of internet use in a country cannot affect the level of attention, a low Google market share could distort the actual behaviour of investors in a country. I retrieve the percent Internet use from the World Bank Open Database based on data from the International Telecommunication Union and the percent Google market share between 2008-2016 from the StatCounter service. In all countries but China and South Korea, Google is the dominant search engine provider. Thus, China with Baidu and South Korea with Navel are excluded from the sample. Other countries, such as India and Indonesia, may exhibit a low percentage of Internet use, but Google search engine still has the largest market share. I include Japan since Yahoo is supported by Google. I also include Russia, as Google competes the local provider Yadex. Last, I exclude countries with missing SVIs.

Table 3.1 presents the final data set consisting of 33 countries, 19 developed and 14 emerging in Panels A and B, respectively. I also present the dominant topic for each stock market marking with an asterisk the countries for which the analysis is based on stock market index topics. However, as a robustness check, I replicate the analysis using stock exchange Google search queries for all of them. The last two columns present the percent Internet use and Google market share in each country. Figure 3.1 shows the internet use times the Google market share against the average annual SVI for each country. There is no evidence of a linear association between them suggesting that the analysis is not driven by the search engine use or the Internet use in a country.

[10] According to MSCI report, 23 countries are classified as developed and 23 countries as emerging. Qatar, UAE, Greece, Morocco, Israel, Argentina, Jordan, and Venezuela are excluded from the sample.

Table 3.1

Description of Countries

This table reports the developed countries in Panel A and emerging countries in Panel B, according to MSCI classification ranked in sub-panels of MSCI geographic regions. All countries that are reclassified between 2004-2016, such as Qatar, UAE, Greece, Morocco, Israel, Argentina, Jordan, and Venezuela, are excluded from the analysis. Column (4) shows the topic used in Google Trends to retrieve the Search Volume Index (SVI). The stock exchange is the most popular topic in most cases, but when a stock index is used instead, this is notified by an asterisk. Column (5) measures the percent Internet use in each country, provided by the World Bank Open Database based on data from the International Telecommunication Union. Column (6) presents the percent Google market share from 2008-2016, provided by StatCounter service.

#	Country	Code	Google Search Query	Internet Use	Google Mkt Share
			Panel A: Developed Countries		
Europe					
1	Austria	AT	WIENER BORSE	78.23	96.50
2	Finland	FI	Helsinki Stock Exchange	88.52	97.32
3	France	FR	CAC 40*	78.65	94.61
4	Germany	DE	DAX PERFORMANCE-INDEX*	82.57	95.48
5	Ireland	IE	ISE	74.06	94.15
6	Italy	IT	Borsa Italiana	55.41	95.48
7	Netherlands	NL	AEX index*	91.53	94.08
8	Norway	NO	Oslo Stock Exchange	94.04	93.31
9	Spain	ES	IBEX 35*	68.97	96.48
10	Sweden	SE	Stockholm Stock Exchange	91.86	95.81
11	Switzerland	CH	SIX Swiss Exchange	84.56	95.94
12	UK	GB	FTSE 100 Index*	86.66	91.16
Pacific					
13	Australia	AU	Australian Securities Exchange	79.05	94.16
14	Hong Kong	HK	Hang Seng Index*	74.03	62.07
15	Japan	JP	Nikkei 225*	82.60	68.91
16	New Zealand	NZ	NZX	81.49	94.89
17	Singapore	SG	Singapore Exchange	74.25	85.81
Americas					
18	Canada	CA	TSX	83.09	90.79
19	USA	US	Dow Jones Industrial Average*	72.51	80.52
			Panel B: Emerging Countries		
Asia					
20	India	IN	BSE	11.53	94.87
21	Indonesia	ID	Indonesia Stock Exchange	13.33	96.32
22	Malaysia	MY	Bursa Malaysia	60.82	84.37
23	Philippines	PH	Philippine Stock Exchange	27.86	82.75
24	Thailand	TH	Stock Exchange of Thailand	26.75	98.87
Americas					
25	Brazil	BR	BM&F Bovespa	46.58	96.73
26	Chile	CL	Santiago Stock Exchange	51.82	97.36
27	Colombia	CO	Colombia Stock Exchange	42.70	96.38
28	Mexico	MX	BMV	37.66	93.60
29	Peru	PE	Lima Stock Exchange	36.41	97.55
Europe, Middle East and Africa					
30	Poland	PL	Warsaw Stock Exchange	62.02	97.40
31	Rusia	RU	Moscow Exchange	27.32	53.82
32	Turkey	TR	Borsa Istanbul	43.73	97.89
33	South Africa	ZA	JSE Limited	33.10	93.77

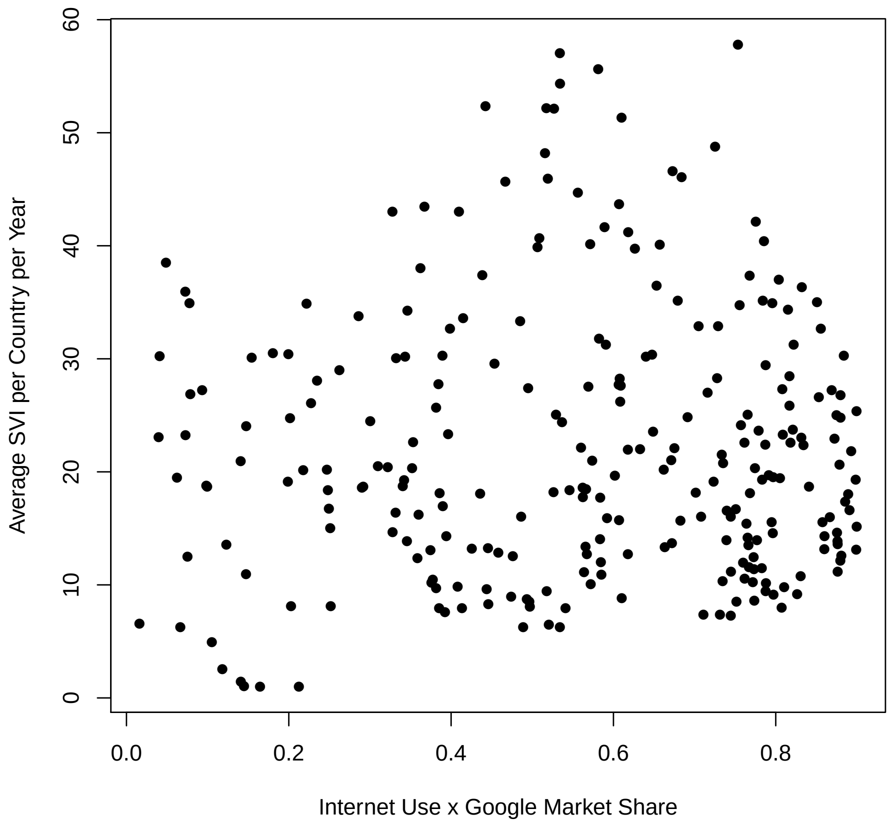


Figure 3.1 Scatter Plot of Internet Use × Google Market Share and Search Volume Index

I also estimate weekly logarithmic returns of country MSCI indices drawn from Datastream (multiplied by 100) denominated in USD. Weekly returns (from the close of Friday to the close of next Friday) do not suffer from non-synchronous trading issues reported in the literature. For SVIs and returns, the sample spans the period from January 1, 2004, until December 31, 2016, yielding 677 weekly observations. Figure 3.2 shows the MSCI Indices for France, United States, Peru, Russia and the MSCI World Index on the top graphs and SVIs for CAC 40, Dow Jones Industrial Average, Lima Stock Exchange, and Moscow Exchange, respectively, on the bottom graphs. Index prices for developed and emerging countries peak and bottom out together. Searches for developed countries have also similar trends. Searches for emerging countries, though, are more volatile and independent but they converge more during periods of high uncertainty. The graphs provide an early indication that the aggregate search patterns of online users for financial information are correlated.

To be consistent with the literature, I calculate the abnormal searches $ASVI_t$, as presented by Da et al. (2011). I subtract from log SVI_t the log median SVI_t of previous 8 weeks (up to two months). The median is a more robust estimator of the normal attention than the mean and is less affected by outliers. Table 3.2 presents the summary statistics namely mean, minimum, maximum, standard deviation, skewness and kurtosis. I also present the results for unit root, stationarity and autocorrelation tests for $ASVI$. The null hypothesis of non-stationarity for the Augmented Dickey-Fuller (ADF) test is rejected under three different specifications ("NC" for a regression with no intercept nor time trend, "C" for a regression with an intercept but no time trend, and "CT" for a regression with an intercept and a time trend). The null hypothesis of stationarity for the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is not rejected under two specifications ("mu" for a constant deterministic part and "tau" for a constant with linear trend). The null hypothesis of independence for the Ljung-Box test, with 8 and 20 lag autocorrelation coefficients respectively, is rejected strongly suggesting the use of autocorrelation robust standard errors.

I also scale each time series with the standard deviation as presented in Da et al. (2011) and in the subsequent study of Da et al. (2015) to account for heteroscedasticity across

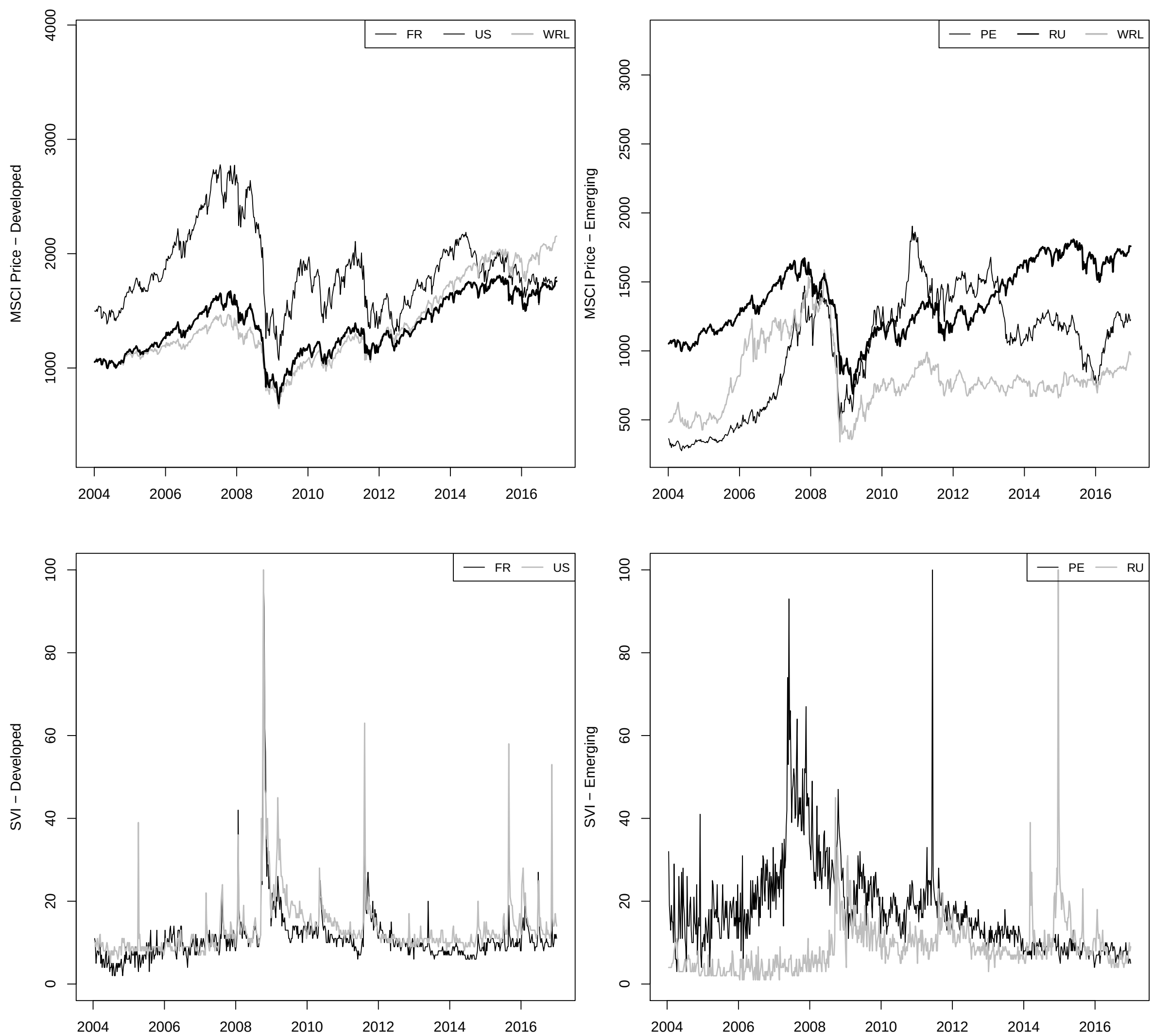


Figure 3.2 MSCI Price Indices and Search Volume Indices The figures display the MSCI Price Indices and SVIs for two developed countries (rightmost), France (black solid line) and United States (grey solid line) and for two emerging emerging markets (leftmost), Peru (black solid line) and Russia (grey solid line). The MSCI World Index is also included on the top figures.

markets. Moreover, to eliminate the outliers and the non-available information, I winsorize the data by 2.5 percent in each tail. In my robustness analysis, I also compute the abnormal searches, *LSVI*, following the methodology of Vlastakis and Markellos (2012). The authors detrend the logarithmic SVIs taking the residuals from a regression of logarithmic SVIs on a time trend and demeaning to remove the seasonality. The correlation between *ASVI* and *LSVI* is 0.7331. Table B.3 in Appendix B provides the summary statistics and the tests for unit root, stationarity and autocorrelation for the *LSVI*.

Proxies for Stock Market Co-Attention and Return Comovement

Co-Attention

Correlated attention assumes that investors synchronise their attention to market-wide information across economies. As SVIs measure the worldwide demand for this type of information, co-attention is generated either from international investors who process market news for both markets, or domestic investors who observe the similar type of information for their corresponding markets, or co-view both markets. Trends in information search are extremely possible for many reasons. First, attention allocation varies over time and across firm and market news (Peng and Xiong, 2006). Second, especially when investors are concerned about market news, they may focus on related economies to resolve their uncertainty. Third, news that involve more economies, may trigger attention and pressure to all of them (Mondria, 2010). Fourth, the world wide web abolishes borders, eliminates the informational asymmetries, and provides access to similar sources. Lee et al. (2015) provide evidence of simultaneous searches for related firms for the users of EDGAR website. Leung et al. (2016) and Agarwal et al. (2017) show similar patterns in searching activity of Yahoo!finance web page.

I estimate co-attention on market-wide news of two economies following similar processes to conditional return correlation, that is, the long-established Pearson product-moment correlation. This measure indicates the existence of dependence between two variables as well

Table 3.2

Summary Statistics for ASVIs

This table shows summary statistics and the results for the Augmented Dickey-Fuller (ADF) unit root test, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity tests and the Ljung-Box autocorrelation test for the abnormal SVIs estimated by the methodology of Da et al. (2011). For the ADF the Null hypothesis is non stationarity ("NC" denotes a regression with no intercept nor time trend, "C" a regression with an intercept but no time trend, and "CT" a regression with an intercept and time trend). For the KPSS test the Null hypothesis is stationarity ("μ" specifies a constant deterministic part and "τ" a constant with linear trend. LB(8) and LB(20) are the test statistics for examining the null hypothesis of no autocorrelation depending on 8 and 20 lag autocorrelation coefficients, respectively. *, †, and ‡ denote significance at 1%, 5% and 10% level of significance respectively.

Country	**Mean**	**Min**	**Max**	**StDev**	**Skew**	**Kurt**	**ADF-NC**	**ADF-C**	**ADF-CT**	**KPSS-μ**	**KPSS-τ**	**LB(8)**	**LB(20)**
Developed													
AT	−0.0172	−1.47	1.31	0.30	0.23	2.85	−13.88†	−13.92†	−13.93†	0.08	0.01	174.40*	214.70*
FI	−0.0379	−1.92	1.82	0.51	−0.35	1.33	−16.07†	−16.16†	−16.19†	0.17	0.03	34.10*	46.30*
FR	0.0034	−0.85	2.16	0.29	1.70	9.91	−11.97†	−11.96†	−11.98†	0.07	0.03	355.60*	401.80*
DE	0.0116	−0.57	1.43	0.19	2.51	14.31	−12.00†	−12.03†	−12.02†	0.04	0.02	357.00*	427.30*
IE	−0.0342	−1.97	1.37	0.40	−0.78	2.97	−15.19†	−15.30†	−15.35†	0.17	0.02	46.40*	73.10*
IT	−0.0037	−1.10	1.37	0.25	0.08	3.82	−11.82†	−11.81†	−11.80†	0.04	0.04	286.00*	427.40*
NL	−0.0031	−1.42	1.88	0.28	1.44	9.66	−11.73†	−11.72†	−11.73†	0.06	0.03	306.30*	334.90*
NO	−0.0280	−2.20	1.13	0.36	−0.66	3.28	−15.28†	−15.38†	−15.44†	0.19	0.01	71.70*	97.30*
ES	0.0009	−0.88	1.36	0.24	0.61	3.58	−11.51†	−11.50†	−11.50†	0.03	0.01	429.90*	539.60*
SE	−0.0051	−1.20	1.43	0.30	0.30	2.52	−15.30†	−15.30†	−15.29†	0.04	0.03	110.90*	128.50*
CH	−0.0297	−1.89	1.87	0.47	−0.25	1.51	−13.97†	−14.03†	−14.02†	0.03	0.04	135.60*	178.20*
GB	0.0080	−0.86	1.97	0.28	2.35	11.95	−11.92†	−11.92†	−11.92†	0.07	0.05	432.90*	494.10*
AU	−0.0070	−2.18	1.61	0.43	−0.41	2.66	−14.38†	−14.37†	−14.38†	0.10	0.04	83.20*	94.70*
HK	0.0002	−1.01	1.08	0.22	0.31	3.19	−13.49†	−13.48†	−13.54†	0.15	0.05	102.10*	118.60*
JP	0.0115	−0.80	2.04	0.24	2.00	10.66	−11.64†	−11.66†	−11.66†	0.05	0.02	366.00*	463.30*
NZ	−0.0177	−1.67	1.26	0.35	−0.50	2.56	−15.11†	−15.15†	−15.15†	0.03	0.01	93.90*	114.90*
SG	−0.0053	−1.58	0.97	0.20	−1.30	11.00	−16.80†	−16.78†	−16.75†	0.10	0.09	59.10*	87.10*
CA	−0.0185	−1.65	1.50	0.46	0.05	1.34	−15.24†	−15.27†	−15.32†	0.11	0.02	76.80*	97.50*
US	0.0237	−0.74	2.16	0.26	3.15	16.27	−10.81†	−10.86†	−10.86†	0.04	0.03	477.00*	566.10*
Emerging													
IN	−0.0045	−0.61	0.74	0.15	0.48	2.25	−12.07†	−12.07†	−12.08†	0.07	0.03	266.10*	304.80*
ID	−0.0239	−1.54	1.47	0.35	−0.36	2.14	−15.37†	−15.42†	−15.41†	0.01	0.01	82.70*	123.70*
MY	−0.0156	−0.98	0.60	0.22	−0.37	1.50	−14.89†	−14.96†	−14.98†	0.10	0.02	125.80*	138.90*
PH	−0.0149	−1.63	1.52	0.35	−0.61	3.55	−16.55†	−16.57†	−16.57†	0.06	0.03	33.30*	82.30*
TH	−0.0025	−0.70	0.64	0.15	−0.18	2.31	−14.42†	−14.41†	−14.40†	0.03	0.03	92.80*	112.30*
BR	0.0111	−1.47	1.39	0.37	−0.01	2.20	−14.50†	−14.50†	−14.49†	0.10	0.10	74.70*	88.70*
CL	−0.0126	−1.67	0.92	0.28	−0.62	3.27	−12.39†	−12.40†	−12.39†	0.02	0.01	205.90*	280.50*
CO	−0.0449	−1.72	1.41	0.41	−0.66	1.96	−14.78†	−14.95†	−14.95†	0.05	0.03	121.80*	158.60*
MX	−0.0433	−2.04	1.37	0.39	−0.66	2.73	−12.87†	−12.98†	−12.96†	0.04	0.02	189.70*	313.60*
PE	−0.0195	−1.79	1.39	0.28	−0.59	6.13	−15.09†	−15.16†	−15.15†	0.04	0.03	73.70*	112.10*
PL	−0.0136	−1.34	0.89	0.25	−0.43	3.78	−14.12†	−14.14†	−14.15†	0.08	0.03	89.30*	100.70*
RU	0.0074	−1.61	1.73	0.42	0.13	1.57	−13.68†	−13.67†	−13.66†	0.04	0.02	129.50*	147.40*
TR	−0.0104	−1.62	1.03	0.26	−0.67	5.31	−13.92†	−13.92†	−13.92†	0.02	0.01	161.40*	174.20*
ZA	−0.0075	−1.09	0.78	0.23	−0.37	1.46	−14.93†	−14.93†	−14.95†	0.08	0.01	80.40*	112.60*

as the degree of their relationship.

I assume normally distributed attention:

$$(\mathrm{a}_t | I_t = I) \sim N(\mu_{\mathrm{a}}, \Sigma_{\mathrm{a}}) \tag{3.1}$$

where a_t is a vector of attention (SVIs) at time t, μ is a vector of expected values, and Σ is the covariance matrix conditional on information I_t. I estimate conditional co-attention, $CoAtt$, as the simple pairwise correlation between a_i and a_j.

$$CoAtt_{ij|I} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii}\sigma_{jj}}}, \tag{3.2}$$

where σ_{ij} is the covariance between i and j and σ_{ii} and σ_{jj} are the variances of i and j, respectively. Boyer, Kumagai and Yuan (2006) follow a similar process to estimate return correlations.

Since correlation coefficients, ρ_{ij}, are bounded within $[-1, +1]$, they cannot be used as dependent variables in a standard regression model (Morck et al., 2000). Fisher transformations to Z-standardised[11] values are widely applied in correlation coefficients. The rescaling is also necessary to transform correlation values into additive values and to average Pearson product-moment coefficients allowing for hypothesis testing and comparisons of average correlations in different groups (e.g., see Rosenthal and Rubin, 1982; Hedges and Vevea, 1998; Field, 2001; Schmidt and Hunter, 2014). I present standard errors following Schmidt and Hunter (2014) because they are straightforward and easily estimated by regression analysis, as well[12]. The results remain qualitatively unchanged, if I compute the standard errors of average correlation coefficients based on alternative well-established methodologies[13], or if

[11] Fisher ρ-to-Z values are calculated as $Z = \frac{1}{2} log_e \left[\frac{1+\rho_{ij}}{1-\rho_{ij}}\right]$ and the standard error as $SE_Z = \sqrt{\frac{1}{n-3}}$. This transformation converts the bounded interval $(-1, +1)$ to the $(-\infty, +\infty)$.

[12] According to Schmidt and Hunter (2014), the standard errors are estimated as $SE_{\bar{Z}_\rho} = \sqrt{\frac{\sum_{i=1}^{\kappa} n_i (Z_i - \bar{Z})^2}{\kappa \sum_{i=1}^{\kappa} n_i}}$, where κ are the number of correlations and n_i weighs the correlations with their sample size. The authors suggest that this method is also applied to untransformed correlations since there is high disagreement for the superiority of Fisher transformation and whether it corrects or inserts bias.

[13] Rosenthal and Rubin (1982) and Hedges and Vevea (1998) compute the standard errors as $SE_{\bar{Z}_\rho} = \sqrt{\frac{1}{\sum_{i=1}^{\kappa}(n_i - 3)}}$.

I assess the p-values of the one-sample non-parametric Wilcoxon sign-rank test[14] similar to Boyer et al. (2006). Finally, another major benefit from using Fisher transformed values in regression coefficients is related to the interpretation of beta coefficients as elasticities. Logging alters the scale of coefficients to percent changes, stabilises the variance, and normalises the data.

Excess Return Comovement

A standard approach in the extant literature for the estimation of excess return comovement, $CoRet_{ij}$, is to extract the residuals (e^{AR1}) from a first order autoregressive (AR(1)) model to account for autocorrelation. A second specification extends the AR(1) model to include a global factor (e^{AR1W}). The MSCI World Index, WRL, is used to approximate the global factor.[15] A third specification is the CAPM model (e^{ERW}). I extract the residuals from a regression of the returns in excess of the risk-free rate on the excess returns of the MSCI World Index. For the risk-free rate, I use the conventional US 3-month T-bill.

$$r_t = b_0 + b_1 r_{t-1} + e_t^{AR1} \tag{3.3}$$

$$r_t = b_0 + b_1 r_{t-1} + b_2 r_{t-1}^{WRL} + e_t^{ARW} \tag{3.4}$$

$$r_t - r_{f,t} = b_0 + b_1 (r_{t-1}^{WRL} - r_{f,t}) + e_t^{ERW} \tag{3.5}$$

Using the residuals, e, from the factor asset pricing models in (3.3), (3.4) and (3.5) respectively, the excess comovement is estimated as:

[14]The null hypothesis requires the number of positive correlation coefficients to be equal to the number of negative correlation coefficients. Simply put, the median should be equal to zero.

[15]Alternatively, the US stock market is used to control for the global factor (e.g., see Chiang et al., 2007; Bekaert et al., 2014).

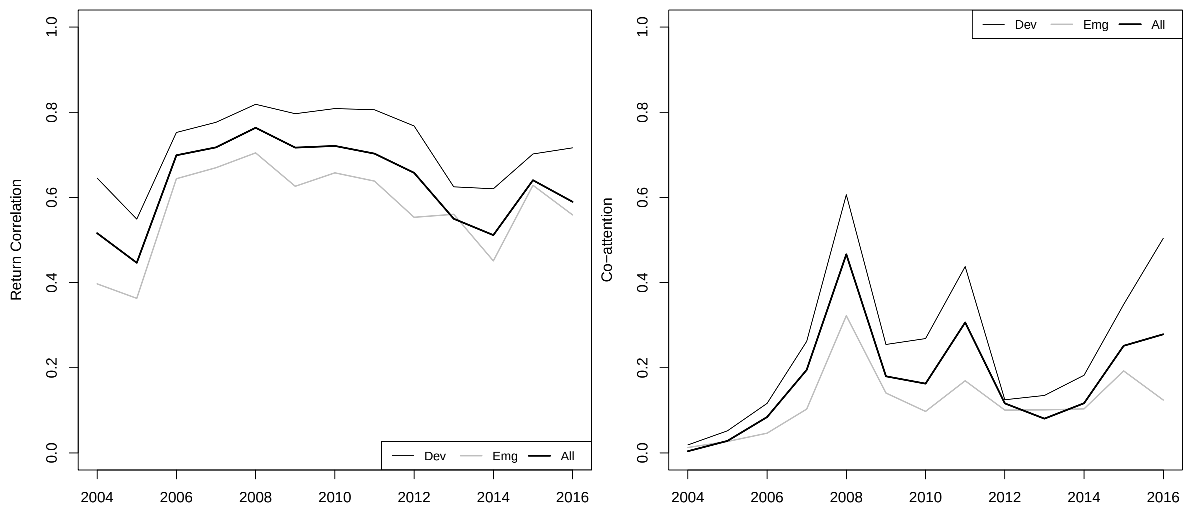


Figure 3.3 Return and Attention Comovement The figures display the average annual return and attention comovement between 33 countries (solid bold line), between developed economies (solid), and between emerging stocks markets. Both are estimated using non-overlapping weekly data.

$$CoRet_{ij} = \frac{\sigma_{e_i,e_j}}{\sqrt{\sigma_{e_i}\sigma_{e_j}}} \tag{3.6}$$

where σ_{e_i,e_j} are the covariances between the residuals from the above models and σ_{e_i} and σ_{e_j} are the variances. This is the comovement in abnormal returns that are not explained with the conventional asset pricing models.

Table 3.3

Summary Statistics of Co-Attention and Return Correlation

This table reports the summary statistics (mean, median, minimum, maximum, standard deviation, skewness and kurtosis) for annual excess correlations in attention and returns estimated with weekly non-overlapping data.

Variable	Mean	Median	Min	Max	StDev	Skew	Kurt
			Co-Attention				
CoAtt^{ASVI}	0.1654	0.1525	-0.5170	0.9462	0.2221	0.3362	0.2241
			Return Correlation				
CoRet^{AR1}	0.6080	0.6257	-0.0725	0.9828	0.1780	-0.4833	-0.1572
CoRet^{AR1W}	0.6081	0.6250	-0.0646	0.9812	0.1776	-0.4923	-0.1244
CoRet^{ERW}	0.6203	0.6394	-0.0925	0.9842	0.1762	-0.5510	-0.0599

Table 3.3 presents the key statistics for annual co-attention and return correlations. They are estimated using non-overlapping weekly data. Return comovement is stronger but

less volatile than attention comovement (see also figure 3.3). The difference in magnitude may be due to the fragmented attention. Investors can be at most totally attentive or at the very least totally distracted from financial markets. Prices, on the other hand, can increase unlimitedly and are only down fragmented as they cannot be negative. The difference in volatility can be explained by the different speed of adjustment for each variable. In other words, investors may switch their attention very rapidly, but prices do not react to trading with the same speed as there are arbitrage restrictions, restrictions on capital flows[16], and orders that are not executed. Moreover, attention is noisy to some extent in that not all individuals that search for stock market information are market participants and not all searches lead to the discovery of information that makes investors alter their portfolio position. However, it consistently measures the general trend in individuals to follow general stock market information. Figure 3.3 also reveals deviations in the average co-attention and return correlations of developed markets from those of emerging.

Co-Attention across Stock Markets

To investigate whether investors allocate their attention for market-wide news similarly across markets, I perform a t-test for the average pairwise co-attention as follows:

$$\begin{cases} H_0 : \overline{CoAtt_{ij}} = 0 \\ H_1 : \overline{CoAtt_{ij}} \neq 0 \end{cases}$$

Panel A in Table 3.4 reports the average pairwise co-attention grouping them in significant and insignificant. Standard errors are presented in parentheses, estimated as explained above (Section 3.2.1). I also provide more details for the significant co-attentions (number and average of significant and negative and significant and positive at 5 percent level of significance). I calculate $CoAtt_{ij,t}$ and $CoRet_{ij,t}$ pairwise correlations with the methodology described above and average them across pairs. From 33 countries, I form 528 $(33 \times (33-1)/2)$ pairwise correlations for the total sample period. The null hypothesis of insignificant average co-attention is rejected. More specifically, an 18.94 percent of them is indistinguishable

[16]For instance, in most markets there are restrictions in foreign ownership.

from zero while only for one pair out of 528 is significant and negative. The majority of pairs indicate significant and positive co-attention with an average of 0.2010. All return correlations are significant and positive with an average of 0.6604, 0.6605, and 0.6966 for e^{AR1}, e^{AR1W}, and e^{ERW}, respectively.

Panel B presents average annual non-overlapping pairwise correlations in both attention and returns from 2004 to 2016 using 52 weekly observations within a year (6,864 correlations). The null hypothesis is not rejected with an average co-attention of 0.1782. For positive and significant pairs the average co-attention is 0.4144, and only an 1.54 percent of them is negative and significant. Return correlations are 0.6426, 0.6424, and 0.6552 for e^{AR1}, e^{AR1W}, and e^{ERW}, respectively.

Investors on average shift their attention in a similar way across markets. This means that when investors in market i become more attentive, investors in market j become more attentive as well and vice versa. The fact that the total investors in both markets co-search for information reflects that they tend to discover information together. At this point, it is not possible to determine whether co-attention is derived from the same investor who co-searches news for i and j, or from the searches of independent investors, international, locals or both.

3.2.2 The Determinants of Co-Attention

I perform an exploratory analysis of the factors that lead to significant co-attention on market news across countries. Barberis et al. (2005) explain that investors form heuristics to group assets together. Limited cognitive resources also force investors to allocate their attention using simple tools. As explained by Chan et al. (2005), familiarity approximated by language, distance, and bilateral trade flows directs investors' preferences towards specific countries. Other studies explore how firm characteristics grab investor attention and create linkages between firms (e.g., see Lee et al., 2015; Leung et al., 2016; Drake et al., 2016; Agarwal et al., 2017). While the analysis in these studies is per INVformed at the firm-level, in this essay, I investigate why investor attention comove across stock markets. This is the

Table 3.4

Average Co-Attention and Return Correlation

This table presents in panel A the number of pairs and the average pairwise attention and return correlations estimated using the total sample weekly data along with standard errors in parentheses. The last four columns present the number of significant pairs of positive and negative correlations and their average. Panel B replicates the analysis for annual correlations computed with 52-week data. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

Variable			**Significant**					
	Total	**Mean**	**Total**	**Mean**	**Positive**	**Mean**	**Negative**	**Mean**
			Panel A: Total-sample-period Correlations					
CoAtt	528	0.1699*** (0.0051)	428	0.2010	427	0.2017	1	-0.1130
CoRet^{AR1}	528	0.6604*** (0.0099)	528	0.6604	528	0.6604	0	—
CoRet^{AR1W}	528	0.6605*** (0.0099)	528	0.6605	528	0.6605	0	—
CoRet^{ERW}	528	0.6966*** (0.0099)	528	0.6966	528	0.6966	0	—
			Panel B: Annual Correlations					
CoAtt	6,864	0.1782*** (0.0031)	2,091	0.4144	1,985	0.4494	106	-0.3506
CoRet^{AR1}	6,864	0.6426*** (0.0038)	6,542	0.6587	6,542	0.6587	0	—
CoRet^{AR1W}	6,864	0.6424*** (0.0038)	6,550	0.6581	6,550	0.6581	0	—
CoRet^{ERW}	6,864	0.6552*** (0.0039)	6,580	0.6694	6,580	0.6694	0	—

first study that offers a rigorous survey of the factors that motivate similar cross-border information searches.

In particular, I expect that investors allocate more attention between more familiar and closely linked economies. To this end, I investigate how co-attention varies with fundamental linkages. *Market Capitalisation* (*MC*) according to MSCI classification is a categorical variable[17] that classifies *developed-developed* (*DEV*), *emerging-emerging* (*EMG*) and *developed-emerging* (*MIX*) pairs. Since the above classification of MSCI summarises the macro factors of the economic development, size and liquidity of firms, openness to foreign ownership and capital flows, financial stability, and efficient operational framework I expect more fundamental linkages (foreign investment and trading relationships) between developed countries.[18]

To be consistent with the literature that studies financial flows and holdings between countries (e.g., see Lipsey et al., 1999; Yeyati et al., 2007; Frenkel et al., 2004), I employ the logarithm of *Foreign Direct Investments Flows*[19] (*LogFL*) from each country to the other countries from the OECD database (in millions) as a measure of fundamental linkages. Since co-attention refers to a pair of countries, I add the bidirectional flows. *LogFL* does not measure only the flows, but also the positions (holdings) because investors are also motivated to attend foreign stock markets if they maintain holdings there.

Distance is widely used in the literature to account for economic linkages and information asymmetries (see Coval and Moskowitz, 1999, 2001; Portes et al., 2001; Portes and Rey, 2005). To put it simply, if two markets are close, it is more likely that news in one country grasps the attention of the other country's investors. Moreover, information asymmetries and cost of discovery are increased with remoteness despite the contribution of the internet. Thus, *LogDist* measures the *logarithmic distance* in kilometres between two stock markets with the Haversine method using their longitudes and latitudes. On the same basis, market neighbouring increases the possibility for attention linkages between markets through com-

[17]However in the analysis I use binary variables for each category to control for differences between them.
[18]https://support.msci.com/documents/10199/e6a49e7c-1b46-424c-8c3c-5b05fd518624
[19]Equity investments.

mon news and higher interest of investors for close economies. To this end, *CoBord* is a dummy variable which indicates the pairs that have *common borders*.

Third, the cultural proximity may also create linkages that attract investor attention. Even though an old-age saying goes "*two nations divided by a common language*", I expect that a shared language can create attention links between countries as it facilitates the information processing and learning. It is very likely that investors attend news for another country with the same language as it is easier to understand and process. Existing literature also treats cultural and linguistic proximities as factors that connect countries. For example, Grinblatt and Keloharju (2001) find that language and culture attract investors in an attempt to reduce information asymmetries. More specifically, they provide evidence that investors have a higher preference for companies with the same language as it is easier to read financial reports. Other studies in this literature deal with these factors in order to explain home and foreign biases.[20] Consequently, I employ a dummy variable for the *Common Official Language* (*COL*) following Beugelsdijk and Frijns (2010). *COL* is provided by Melitz and Toubal (2014) based on data from the CIA World Factbook.

In addition to linguistic similarities, similar collective norms and values can motivate cross-country bonds. Hofstede et al. (2010)'s cultural dimensions across countries dominate in business research. Initially, Hofstede and his team proposed and measured indices of the power distance (*PDI*), the individualism (*IDV*), the masculinity (*MAS*) and the uncertainty avoidance (*UAI*). Two additional indices include the long-term orientation (*LTO*) and indulgence (*IND*)[21]. For a pair of countries, I estimate the *cultural distance* (*CD*) as

[20] Home or domestic bias (e.g., see Brennan and Cao, 1997; Karolyi and Stulz, 2003) refers to the market anomaly related to overweighting of the local assets in a portfolio. Such findings contradict the EMT which suggests that all investors have the same access to information and markets. Foreign bias (see Chan et al., 2005) does not only refer to underweighting of the foreign assets in a portfolio, but it also reflects the preference for particular stock markets.

[21] The power of distance deals with the attitude of individuals towards inequality in the distribution of power. A high index represents people who strive for equal distribution of power while the opposite edge describes people who accept that everyone has a specific and predetermined role in society. The individualism describes societies that emphasize on personal needs in comparison to collectivism where all the members

the deviation along each of the dimensions of the one from the other following the widely applied methodology of Kogut and Singh (1988) to all cultural indices as:

$$CD_{ij} = \frac{1}{6} \sum_{k=1}^{6} \frac{(hofstede_{i,k} - hofstede_{j,k})^2}{var(hofstede_k)} \tag{3.7}$$

where $hofstede_{i,k}$ is the k index for the country i, and $var(hofstede_k)$ is the variance of the k index across all countries in the sample.

I also control for correlated information supply between two economies since co-reference can trigger similar shifts to attention and correlated inferences. I define *CoNews* as an aggregate measure of *correlated news* and I calculate that employing a unique dataset provided by Reuters News Archive as:

$$CoNews_{ij,t} = \frac{News_{ij,t}}{\sqrt{News_{i,t} News_{j,t}}} \tag{3.8}$$

where $News_{ij,t}$ are the number of news articles in Reuters that refer the stock markets i and j simultaneously at a unit of time t, and $News_i$, $News_j$ are the sum of news for i, and j, respectively. This proxy is similar to that of Mondria and Quintana-Domeque (2013) and Israelsen (2016) and gets values within $[0, 1]$. As a measure of information flows, *CoNews* also serves to validate co-attention. Even though *CoAtt* reflects information flows from a different perspective, they should be positively correlated to some extent and the former should contribute to the latter. A weak association of 0.1079, however, indicates differences in how information flows and how is consumed, which further justifies the empirical investigation of co-attention.

take care of each other. The masculinity index measures the more competitive environment with emphasis on effort and rewards as opposed to femininity that shows a preference for cooperation and quality of life. The uncertainty avoidance is related to the attitude of individuals towards risks. A high UAI reflects a lower tolerance for uncertainty. A low score in long-term orientation entails strong linkages with the past and traditions while a high score indicates a more open-minded approach to changes. The indulgence describes societies that emphasize on well-being and happiness while more restraint cultures impose strict norms and personal control.

Panel A in Table 3.5 defines the exploratory variables of co-attention, the sources and the summary statistics (where applicable), while Panel B presents their correlation matrix. Correlations of the categorical variable *MC* with the rest of variables are meaningless. However, significant negative correlation with the *LogFL* shows that there are more flows between developed markets (group 1) than between emerging markets (group 3). As expected, *LogFL* and *LogDist* are negatively correlated supporting the gravity theory which suggests less relationships between more remote markets. This is also apparent from the negative association between *CoNews* and *LogDist*. More flows are related to more correlated news. Surprisingly the correlation of *CoNews* with the *MC* is positive showing that more correlated news are observed in emerging economies. *CoBord* and *LogDist* are negatively related since the former captures the proximity and the latter the remoteness. The same relationship is observed between *COL* and *CD* as the one measures the cultural proximity and the other the distance. Weak to moderate correlations between the exploratory variables mitigate multicollinearity concerns.[22]

I examine how the average co-attention varies with these factors. For the binary variables *MC*, *CoBord*, *COL*, it is straightforward that the intercept of a regression estimates the average for a group in relation to all other groups (regression of co-attention on a constant and the group dummy). For continuous variables, i.e., *LogFL*, *LogDist*, *CD*, and *CoNews*, I form equally spaced quartiles of groups and test how co-attention in quartiles 2-4 (*Q2* - *Q4*), that consist of larger capital flows, geographical and cultural distance, and informational closeness, differ from quartile 1 (*Q1*). The average co-attention is significant for all the reference groups as is shown in Table 3.6. Co-attention is stronger between developed countries. This finding shows that while information supply is more correlated in emerging markets, information demand is more correlated in developed countries revealing a different pattern in the consumption of information. More financial flows between stock markets in-

[22]The Variance Inflation Factor (*VIF*) measures the proportion of variance that each independent variables shares with the rest ($VIF = 1/(R^2 - 1)$). For each explanatory variable X_i in all models, *VIF* is less than 2, which is much lower than most of the rules of thumb generally used in the literature (e.g, critical values of 4 or 10 are widely used as explained in O'brien, 2007).

Table 3.5

Description and Statistics of Explanatory Variables

This table presents a short description and summary statistics of the explanatory variables in panel A and the correlation between them in panel B.

Panel A: Description and Summary Statistics

Variable	Description	Source	Freq	Mean	StDev	Min	Max
MC	A categorical variable that describes the Market Capitalisation with 1 for developed-developed (DEV) countries, 2 for developed-emerging (MIX) and 3 for emerging-emerging (EMG)	MSCI	–	–	–	–	–
LogFL	Logarithm of the sum of capital flows (in billions) between two countries	OECD	Annual	14.3300	47.4500	0.0000	577.2900
LogDist	Logarithm of geographic distance (in 1,000 km) between all pairings given sets of longitude/latitude locations of the stock exchanges using the Haversine method	–	–	8.4300	5.1200	0.2200	19.8000
CoBord	Dummy variable for the cross border country pairings	–	–	–	–	–	–
COL	Dummy variable denoting common official language between two countries	Melitz and Toubal (2014)	–	–	–	–	–
CD	Cultural distance estimated as in Kogut and Singh (1988) using Hofstede's cultural dimensions	Hofstede et al. (2010)	–	2.0000	1.1059	0.0291	6.1703
CoNews	Proxy for the correlation in news for stock markets	Reuters News Archive	Weekly	0.0177	0.0740	0.0000	0.8023
	estimated using a unique dataset	–	Annual	0.0347	0.1038	0.0000	0.8023

Panel B: Correlation Matrix

	MC	LogFL	CoBord	LogDist	COL	CD
LogFL	−0.2961*					
CoBord	−0.0095	0.0551*				
LogDist	0.2648*	−0.1597*	−0.5353*			
COL	−0.1040*	0.0615*	0.0775*	−0.0169		
CD	−0.0122	−0.0348†	−0.1798*	0.2670*	−0.2237*	
CoNews	0.0413*	0.0447*	0.3323*	−0.3128*	−0.0016	−0.1902*

dicate higher attention comovement. Co-attention also increases for neighbouring and less geographically and culturally distant equity markets, that share a language, and have more correlated news.

To examine the determinants of co-attention, I perform the following regression analysis:

$$\begin{aligned} CoAtt_{ij,t} = \beta_0 + \beta_1 LogFL_{ij,t-1} + \beta_2 LogDist + \beta_3 CoBord \\ + \beta_4 COL + \beta_5 CD + \beta_6 CoNews_{ij,t-1} + v_t \end{aligned} \tag{3.9}$$

In an extended version of the model in (3.9), I also control for asymmetries in investor co-attention during downturns (*Recession*), for stronger co-attention between the US and the rest of stock markets (*USIndex*), and in developed than emerging pairs. Such asymmetries are widely established in the literature of return comovement (see Section 3.1.1 for literature review in this area). The extended model is described from the following regression analysis:

$$\begin{aligned} CoAtt_{ij,t} = \gamma_0 + \gamma_1 LogFL_{ij,t-1} + \gamma_2 LogDist + \gamma_3 CoBord \\ + \gamma_4 COL + \gamma_5 CD + \gamma_6 CoNews_{ij,t-1} + \gamma_7 USIndex \\ + \gamma_8 Recession + \gamma_9 EMG + \gamma_{10} MIX + u_t \end{aligned} \tag{3.10}$$

The recent global stock market crash offers a natural experiment to test for asymmetric co-attention during periods of high uncertainty. This period spans from August 1, 2007, to December 31, 2009, according to Laurent et al. (2012) and is triggered by the fall of Northern Rock. This is in line with the smoothed recessionary probabilities for the US economy in Federal Reserve Economic Data (Federal Reserve Bank of St. Louis).[23]

Both models are examined under two different specifications each: a pool regression model that assumes equal dynamics in co-attention between all pairs and a panel model

[23]See Appendix B for the graphs of annual and monthly recessionary probabilities from FRED. The probabilities are derived from the work of Chauvet (1998). Citation:Piger, Jeremy Max and Chauvet, Marcelle, Smoothed U.S. Recession Probabilities [RECPROUSM156N], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RECPROUSM156N, June 13, 2017

Table 3.6

Attention Comovement Across Country Pairs

The table reports differences in average simple pairwise co-attention along with robust standard errors in parentheses in terms of fundamental linkages, geographical proximity, cultural distance, and informational closeness. Fundamental linkages are captured by the MSCI classification of pairs in Developed (*DEV*), emerging (*EMG*), and mixed countries (*MIX*). Quartiles of logarithmic financial flows *LogFL* between economies also control for changes in co-attention that stem from fundamental linkages. Country neighbouring (*CoBord*) and quartiles of logarithmic distance measure differences in co-attention between close and remote economies. Cultural distance in quartiles (*CD*) and common official language (*COL*) explore variations in co-attention due to cultural differences. Quartiles of news commonality (*CoNews*) investigate the impact of information proximity on investors' average co-attention. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

Linkages	Fundamental		Geographical		Cultural		Information
	MC	**Flows**	**Border**	**Distance**	**Language**	**Cultural Distance**	**News Commonality**
DEV	0.2715***						
	(0.0113)						
EMG	−0.1296***						
	(0.0125)						
MIX	−0.1514***						
	(0.0145)						
	0.1183***						
			(0.0446)				
Non-CoBord			0.1708***				
			(0.0052)				
CoBord			0.0907***				
			(0.0274)				
Non -COL					0.0438***		
					(0.0088)		
COL					0.1440***		
					(0.0050)		
Q1		0.1183***		0.3960***		0.1905***	0.1440***
		(0.0350)		(0.0443)		(0.0048)	(0.0101)
Q2		0.0490		−0.1802***		−0.0176	0.0229*
		(0.0351)		(0.0471)		(0.0066)	(0.0126)
Q3		0.0596·		−0.2081***		−0.0013	0.0408***
		(0.0357)		(0.0469)		(0.0106)	(0.0162)
Q4		0.1229**		−0.2380***		−0.0832***	0.0578***
		(0.0382)		(0.0446)		(0.0228)	(0.0246)

regression with fixed and time effects (FE and TE) that impose different dynamics in co-attention across pairs and years (Table 3.7). In all cases, cluster robust standard errors are employed. I expect higher co-attention between more linked stock markets following the literature in this area which suggests that investors due to limited attention be prone to familiar markets. *LogFL* and *CoNews* are lagged to mitigate any objections for endogeneity. Even though none of the variables is estimated with overlapping data, I control for persistence in co-attention using a lagged term of co-attention (Models 3-4 and 7-8).

Based on the adjusted R-squared, fixed and time effects add significantly to the explanation of variability in co-attention (in all cases the adjusted R-squared increases in panel models). They also indicate that co-attention is time-varying and evolves differently for each pair depending on the conditions. A significant finding is the strong effect of information supply on demand. Specifically, a one unit increase in *CoNews* increases co-attention by 24.74 percent (Model 8). However, this does not explain completely the variance in co-attention suggesting that correlated news contributes partially to co-attention. Flows also have a significant but weaker effect on co-attention. An 1 percent increase in *LogFL* is interpreted to a 0.34 percent increase in *CoAtt*. I fail to find significant impact in favour of distance and cultural factors, especially in the panel model indicating that they do not affect the searching pattern of investors.

Similar results are observed in the extended version, where I report a weaker effect in emerging than developed pairs (14.27 percent lower). A complementary finding is that investors tend to follow closely any information related to the US economy. Co-attention is 13.21 percent higher between pairs that include the US. In recessionary conditions, co-attention to market-wide information increases by 11.11 percent on average. This is in line with other studies which imply that during crises investors become more distracted to firm-specific news and resolve their uncertainty following general news (e.g., see Peng and Xiong, 2002; Schmidt, 2013; Andrei and Hasler, 2014). Lagged *CoAtt* is significant at the 99 percent confidence level. It does not add significantly to the variation of current co-attention, but it indicates how fast the dependent variable adjusts to future values (persistence). The inclusion of lagged dependent variable is also a remedy to the omitted variables problem as approximates all other factors that affected $CoAtt_t$ the period $t-1$ and are not included in the model.

Table 3.7

Attention and News Comovement

This tables presents the slope coefficients along with cluster robust standard errors from pooled and panel regressions of co-attention on news comovement controlling for financial flows, geographical distance, market neighbouring, common official language, and cultural distance (Model 1). Model 2 controls for fixed and time effects. Model 3 is a pooled OLS regression controlling for persistent co-attention. Model 4 imposes fixed and time effects in a panel data regression. Models 5-8 control also for market classification, US country, and the global financial crisis. Co-attention and CoNews are estimated using yearly non-overlapping data. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	0.4409***		0.3176***		0.3767***		0.2868***	
	(0.0619)		(0.0453)		(0.0583)		(0.0419)	
CoAtt$_{t-1}$			0.3223***	0.1123***			0.3331***	0.1030***
			(0.0150)	(0.0169)			(0.0153)	(0.0169)
LogFL$_{t-1}$	0.0122***	0.0042**	0.0094***	0.0041**	0.0084***	0.0035*	0.0055***	0.0034**
	(0.0015)	(0.0014)	(0.0011)	(0.0013)	(0.0013)	(0.0014)	(0.0010)	(0.0013)
LogDist	−0.0331***	−0.0200	−0.0240***	−0.0181	−0.0156*	−0.0137	−0.0113*	−0.0127
	(0.0068)	(0.0126)	(0.0050)	(0.0115)	(0.0067)	(0.0136)	(0.0049)	(0.0126)
CoBord	0.0199	0.0424	0.0122	0.0381	0.0333	0.0385	0.0230	0.0349
	(0.0241)	(0.0298)	(0.0174)	(0.0271)	(0.0211)	(0.0284)	(0.0151)	(0.0261)
COL	0.0395**	0.0163	0.0284**	0.0162	0.0136	0.0166	0.0093	0.0163
	(0.0147)	(0.0245)	(0.0108)	(0.0223)	(0.0143)	(0.0240)	(0.0104)	(0.0221)
CD	0.0026	−0.0013	0.0020	−0.0002	0.0045	−0.0036	0.0033	−0.0024
	(0.0043)	(0.0065)	(0.0032)	(0.0059)	(0.0040)	(0.0063)	(0.0029)	(0.0058)
CoNews$_{t-1}$	0.1650*	0.2652***	0.1120·	0.2382***	0.2113**	0.2731***	0.1334**	0.2474***
	(0.0807)	(0.0757)	(0.0571)	(0.0703)	(0.0704)	(0.0751)	(0.0501)	(0.0702)
USIndex					0.0728**	0.1417***	0.0533**	0.1321***
					(0.0237)	(0.0295)	(0.0166)	(0.0276)
Recession					−0.0117·	0.1299***	−0.0842***	0.1111***
					(0.0069)	(0.0330)	(0.0069)	(0.0109)
EMG					−0.1267***	−0.1429*	−0.0966***	−0.1427*
					(0.0107)	(0.0640)	(0.0111)	(0.0596)
MIX					−0.1225***	−0.0581·	−0.0923***	−0.0503
					(0.0107)	(0.0330)	(0.0078)	(0.0308)
Adj-R^2	0.0722	0.2641	0.1617	0.2723	0.1209	0.2724	0.2023	0.2793
Obs	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828
FE	N	Y	N	Y	N	Y	N	Y
TE	N	Y	N	Y	N	Y	N	Y

3.2.3 Testable Hypotheses

As explained earlier, co-attention between country i and j is generated for three reasons. First, international investors are interested in i and j. Second, a local investor who is interested in i and j together. Third, locals in each country who search independently information for their local stock markets. In all cases investors coordinate on the same type of information, that is, market-wide news. Investors that focus simultaneously on general news, even if their attention is not shared between stock markets, are also expected to apply pressure on prices towards similar directions. The allocation of limited cognitive resources on market-wide news prevents investors from evaluating information for the firms and the expected value of their fundamentals. As a result, trading decisions are dominated by similar inferences and prices move together. I form the hypothesis as:

HYPOTHESIS 1 *Higher investor co-attention on stock market information for countries i and j leads to higher return comovement controlling for alternative explanations.*

I perform the following regression:

$$\begin{aligned} CoRet_{ij,t} = \delta_1 CoAtt_{ij,t-1} + \delta_2 CoRet_{ij,t-1} + \delta_3 LogFL_{ij,t-1} \\ + \delta_4 LogDist + \delta_5 CoNews_{ij,t-1} + \epsilon_t \end{aligned} \tag{3.11}$$

Fixed and year effects are also applied in the panel data analysis with robust standard errors.

The next set of hypotheses explore the effect of co-attention on return comovement relative to market capitalisation of countries, the market conditions, and the impact of the US economy. As explained earlier, developed countries have more efficient infrastructures for the supply of information, offering usually several information sources (Dang et al., 2015). Besides, developed countries are more open economies for international investing and diversification with lower market frictions. As a result, international investors in these markets have a strong incentive to share their attention between them. An alternative explanation is that investors may select to follow market news for other strong economies, such as the US. To this end, I also examine whether there is a stronger effect of co-attention on return comovement in pairs that include the US country.

<ins>HYPOTHESIS 2</ins> *There is a stronger effect of co-attention between developed countries on their return comovement controlling for alternative sources of comovement.*

I perform the following regressions:

$$\begin{aligned} CoRet_{ij,t} = {} & \psi_1 CoAtt_{ij,t-1} + \psi_2 CoRet_{ij,t-1} + \psi_3 LogFL_{ij,t-1} \\ & + \psi_4 LogDist + \psi_5 CoNews_{ij,t-1} + \psi_6 EMG \\ & \psi_7 MIX + \psi_8 CoAtt_{ij,t-1} EMG \\ & + \psi_9 CoAtt_{ij,t-1} MIX + \eta_t \end{aligned} \tag{3.12}$$

and

$$\begin{aligned} CoRet_{ij,t} = {} & \omega_1 CoAtt_{ij,t-1} + \omega_2 CoRet_{ij,t-1} + \omega_3 LogFL_{ij,t-1} \\ & + \omega_4 LogDist + \omega_5 CoNews_{ij,t-1} + \omega_6 USIndex \\ & + \psi_7 CoAtt_{ij,t-1} USIndex + z_t \end{aligned} \tag{3.13}$$

Hypothesis 3 and 4 deal with the transmission of volatility across markets. The former explores a higher effect of co-attention on return comovement during crises. The intuition behind this asymmetry stems from the stronger focus of investors and analysts on market information to resolve their uncertainty during recessionary conditions. In addition to Da et al. (2011), Andrei and Hasler (2014) also support that investors tend to be more attentive to financial markets when there are extreme market conditions. They also exhibit that attention is asymmetric to extremely good and bad market states.

The latter hypothesis investigates the effect of co-attention in financial contagiousness. Financial contagion involves the transmission of shocks across economies and the propagation of crises. There is plenty of research for the channels of financial contagiousness due to the high importance of understanding how markets react under conditions of distress and how economies are affected when a shock hits one or more of them (e.g., see Kodres and Pritsker, 2002; Forbes and Rigobon, 2002; Chiang et al., 2007; Mondria and Quintana-Domeque, 2013; Bekaert et al., 2014; Hasler and Ornthanalai, 2015). Mondria and Quintana-Domeque (2013) explore how similarity in investor attention, measured by news supply, increases the financial contagion between fundamentally unrelated markets. A subsequent paper, present the fluctuating attention to news as a channel of contagiousness between unrelated industries (Hasler and Ornthanalai, 2015). I argue that similar trends in information flows may impose similar movements in stock markets even between unrelated economies. Unrelated countries in terms of capital flows or news are the economies without economic flows and without parallel reference in the news.

HYPOTHESIS 3 *Co-attention predicts higher comovement during turmoil periods.*

I address this hypothesis with the following model:

$$\begin{aligned} CoRet_{ij,t} = {} & c_1 CoAtt_{ij,t-1} + c_2 CoRet_{ij,t-1} + c_3 LogFL_{ij,t-1} \\ & c_4 LogDist + c_5 CoNews_{ij,t-1} + c_6 Recession \\ & c_7 CoAtt_{ij,t-1} Recession + \upsilon_t \end{aligned} \tag{3.14}$$

HYPOTHESIS 4 *Co-attention predicts comovement between unrelated markets.*

I examine this hypothesis based on the following regression model:

$$CoRet_{ij,t} = d_1 CoAtt_{ij,t-1} + d_2 CoRet_{ij,t-1} + d_3 LogDist + \zeta_t \tag{3.15}$$

3.2.4 Results

Co-Attention and Return Comovement

Table 3.8 presents the beta coefficients and robust standard errors from the empirical examination of hypotheses 1-3. *ALL*, *MC*, *US*, *MR* return the results of the general model in (3.11), the market capitalisation and US country effect models in (3.12) and (3.13) and the market regime model in (3.14), respectively. As explained earlier, the panel data analysis involves 528 pairs of stock markets for a period of 12 years.[24] *CoRet*, *CoAtt* and *CoNews* are calculated using 52-weekly observations. I also control for the persistence and omitted variables bias using lagged values of the dependent variable as in Chiang et al. (2007). Fixed and time effects capture systematic changes in pairs in the cross-section and over time. Imposing fixed effects in panel data estimation is also a potential solution to endogeneity concerns induced by unobservable heterogeneity. In the next subsection, I examine the conditions under which the fixed effects panel data regression leads to consistent and unbiased estimates.

In all models, I find a statistically significant and positive effect of co-attention on return comovement beyond the effects of fundamentals and distance. The explanatory power of models (1)-(4) is 42 percent and remain robust for excess comovement derived from various risk models (i.e., e^{AR1}, e^{AR1W}, and e^{ERW}).[25] Return comovement rises from 7.42 to 14.80 percent for an 1 percent increase in co-attention. *LogFL* and *LogDist* have a smaller influence. Surprisingly, examining in the same framework co-attention and co-news, I cannot find a significant coefficient of the latter. This finding is also in line with theories which expect deviations between information supply and demand (Barber and Odean, 2008; Da et al., 2011; Vlastakis and Markellos, 2012). Despite the use of non-overlapping data for the estimation

[24]The analysis is for 12 years since I also include lagged values. This yields a total 6,336 observations in the panel data set.

[25]In Appendix B, even though a fixed effect panel data analysis is more appropriate to account for omitted variables and unobservable heterogeneity, I also present the analysis without imposing fixed and time effects and I report a lower explanatory power, indicating that fixed effects are important factors in explaining return comovement.

of correlations, I find that the lagged dependent variable is persistent and has significant power in explaining the contemporaneous values. In Appendix B, I also repeat the analysis omitting the $CoRet_{t-1}$.

All the signs are consistent with theory. More analytically, more flows create higher interrelations between stock markets. As expected, the distance reduces the comovement between countries. However, compared to co-attention, they have a weaker effect on correlation. For emerging economies, I show that correlations are significantly lower (higher dependencies between large stock markets) indicating that the higher integration in financial markets has not eliminated the diversification opportunities. The effect of co-attention also diverges for different type of markets. I interpret this finding similar to Dang et al. (2015), that is, developed countries have more sources and better infrastructures for the search of information.

In addition, even though, I have ruled out the possibility that my results are not driven by the accessibility to Internet and Google, I cannot control for the familiarity and the capabilities of online users to discover information. This means that, in general, users in developed countries have longer experience to use keywords in Google search engine more efficiently. Another interpretation of this finding is that more open and advanced economies are on the spotlight for international investing. Traders, knowing the interdependencies between large economies have the incentive to attend the general news for these economies. This is also apparent from the statistically higher effect of co-attention on the correlation between countries and the world leading US economy (*CoAtt:USIndex*) at 5 percent level of significance. The significant interaction suggests that co-attention explains to some extent the stronger correlations reported in the literature with the US economy.

The coefficient of *Recession* in the *MR* model indicates stronger comovement during periods of excess volatility. The global financial crisis of 2007-2009 has affected the world economy resulting in higher stock market synchronicity. Co-attention has also an increasing effect on stock market comovement. I interpret this result as follows: investors during periods of negative shocks are more likely to focus on market-wide news to resolve their uncertainty.

Concentrating on this type of news leads to correlated inferences for fundamentals and increases comovement between markets. Finite cognitive resources force investors to remove attention from firm news that decreases stocks' synchronicity with the market. An indirect way through which co-attention affects more the return comovement in market turbulence and spreads crises faster across stock markets relies on the uncertainty of domestic investors for the relation of their market with the shock-hit economy. Thus they co-attend market news for both markets leading to parallel inferences for their fundamentals and similar price pressures. This proposition of financial contagion is tested under hypothesis 4 and the results are analysed in section 3.2.4.

Endogeneity and Reverse Causality

Correlated independent variables and error term is defined as endogeneity. This is a major challenge often encountered in business research with serious implications in empirical analyses. Most importantly, biased and inconsistent estimators lead to unreliable inference about the relationship between variable. Omitted variables (unobservable heterogeneity), simultaneity, and measurement error are the three basic sources of endogeneity. In this section, I present how my designing study and econometric techniques target at this issue.

Unobservable heterogeneity is related to the omission of variables that affect both the dependent and the independent variables. These can be unknown factors or known factors that may have an impact but they cannot be measured. For instance, the ability of investors to discover and analyse information or asymmetries and other market frictions are not observable. Ignoring the heterogeneity induced to the dependent variable by unobservable factors raises a cause for concern only when the independent variables are also explained by them. In this case, coefficients and standard errors are inconsistent and inferences based on them are not reliable, especially in a linear regression frameworks which require uncorrelated explanatory variables $X_i s$ with the error term.

Techniques based on instruments are not applicable most of the times due to the lack of observable exogenous variables. Thus, the literature is extensively based on alternative ap-

Table 3.8

Co-Attention and Stock Market Comovement

This table reports the beta coefficients and robust standard errors from panel regressions of return correlation on co-attention controlling for persistent correlation (*CoRet*) and for correlation explained by fundamentals (*LogFL*), geographical distance (*LogDist*), and correlated news (*CoNews*) including year and fixed effects for heterogeneity in each pair and over time. Co-attention and return correlations are derived using yearly non overlapping data. Co-attention is estimated based on ASVI of Da et al. (2011). Model 2-4 explore for differences in the effect of co-attention for developed economies, for pairs including the US, and for different market regimes. Panel A, B and C report the results using return correlations estimated from the residuals of a first order autoregressive model (AR1), the residuals from a first order autoregressive model including the MSCI World Index as a global factor (AR1W), and the residuals from a regression of excess returns (subtracting the riskless rate) on excess MSCI World Index returns (ERW). The US 3-month T-bill is used to approximate the risk free rate. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	Panel A: AR1				Panel B: AR1W				Panel C: ERW			
	ALL	**MC**	**US**	**MR**	**ALL**	**MC**	**US**	**MR**	**ALL**	**MC**	**US**	**MR**
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
CoAtt$_{t-1}$	0.0868***	0.1280***	0.0742***	0.0771***	0.0952***	0.1428***	0.0838***	0.0820***	0.0873***	0.1280***	0.0747***	0.0747***
	(0.0138)	(0.0201)	(0.0147)	(0.0153)	(0.0135)	(0.0189)	(0.0144)	(0.0152)	(0.0139)	(0.0199)	(0.0148)	(0.0154)
RetCom$_{t-1}$	0.1955***	0.1904***	0.1936***	0.1954***	0.1925***	0.1876***	0.1904***	0.1924***	0.1854***	0.1802***	0.1832***	0.1851***
	(0.0175)	(0.0168)	(0.0176)	(0.0175)	(0.0175)	(0.0167)	(0.0176)	(0.0174)	(0.0172)	(0.0164)	(0.0172)	(0.0171)
LogFL$_{t-1}$	0.0038**	0.0029*	0.0036**	0.0039**	0.0037**	0.0028*	0.0035**	0.0037**	0.0039**	0.0030*	0.0037**	0.0040**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0013)
LogDist	−0.0402**	−0.0305*	−0.0400**	−0.0402**	−0.0402**	−0.0307*	−0.0400**	−0.0401**	−0.0426***	−0.0330**	−0.0423***	−0.0425***
	(0.0127)	(0.0122)	(0.0127)	(0.0128)	(0.0126)	(0.0120)	(0.0126)	(0.0126)	(0.0127)	(0.0121)	(0.0127)	(0.0128)
CoNews$_{t-1}$	0.0287	0.0366	0.0326	0.0321	0.0270	0.0337	0.0306	0.0315	0.0158	0.0236	0.0197	0.0201
	(0.0723)	(0.0699)	(0.0728)	(0.0723)	(0.0730)	(0.0707)	(0.0736)	(0.0729)	(0.0739)	(0.0717)	(0.0744)	(0.0738)
EMG		−0.2172***				−0.1997***				−0.2479***		
		(0.0419)				(0.0422)				(0.0428)		
MIX		−0.0980*				−0.0916*				−0.0977*		
		(0.0384)				(0.0389)				(0.0390)		
CoAtt$_{t-1}$**:EMG**		−0.0831**				−0.0934**				−0.0723*		
		(0.0310)				(0.0305)				(0.0310)		
CoAtt$_{t-1}$**:MIX**		−0.0912***				−0.1042***				−0.0935***		
		(0.0236)				(0.0226)				(0.0238)		
USIndex			0.0250				0.0287				0.0328	
			(0.0303)				(0.0301)				(0.0307)	
CoAtt$_{t-1}$**:USIndex**			0.0892*				0.0786*				0.0863*	
			(0.0363)				(0.0356)				(0.0363)	
Recession				0.3320***				0.3235***				0.3007***
				(0.0126)				(0.0125)				(0.0125)
CoAtt$_{t-1}$**:Recession**				0.0409				0.0552*				0.0530·
				(0.0258)				(0.0260)				(0.0272)
Adj-R^2	0.4231	0.4278	0.4243	0.4233	0.4274	0.4325	0.4284	0.4277	0.4236	0.4283	0.4248	0.4239
Obs	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828
FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 3.9

Endogeneity and Reverse Causality

This tables explores for endogeneity issues and reverse causality by regressing co-attention on lagged co-attention and return correlation. Beta coefficients along with robust standard errors are also reported for control variables: financial flows, geographical distance, market neighbouring, common official language, cultural distance, market classification, US country, and the global financial crisis. Co-attention, stock market comovement and CoNews are estimated using annual non-overlapping data. FE and TE are also applied (not reported). *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	AR1	**AR1W**	**ERW**
CoAtt$_{t-1}$	0.1009***	0.1010***	0.1010***
	(0.0170)	(0.0170)	(0.0170)
CoRet$_{t-1}$	0.0208	0.0196	0.0190
	(0.0152)	(0.0152)	(0.0151)
LogFL$_{t-1}$	0.0034**	0.0034**	0.0034**
	(0.0013)	(0.0013)	(0.0013)
LogDist	−0.0122	−0.0122	−0.0123
	(0.0124)	(0.0124)	(0.0124)
CoBord	0.0331	0.0333	0.0332
	(0.0260)	(0.0260)	(0.0260)
COL	0.0164	0.0164	0.0165
	(0.0219)	(0.0219)	(0.0219)
CD	−0.9052	−0.9091	−0.9329
	(2.4296)	(2.4302)	(2.4302)
CoNews$_{t-1}$	0.2480***	0.2480***	0.2483***
	(0.0699)	(0.0699)	(0.0699)
USIndex	0.1320***	0.1319***	0.1319***
	(0.0276)	(0.0276)	(0.0275)
Recession	0.1048***	0.1049***	0.1045***
	(0.0113)	(0.0114)	(0.0115)
EMG	−0.1357*	−0.1363*	−0.1354*
	(0.0594)	(0.0595)	(0.0594)
MIX	−0.0468	−0.0470	−0.0470
	(0.0305)	(0.0305)	(0.0305)
Obs	5,828	5,828	5,828
Adj-R^2	0.2794	0.2794	0.2794
FE	Y	Y	Y
TE	Y	Y	Y

proaches. A common solution to this problem involves the use of time-invariant fixed effects to capture a systematic part of this heterogeneity. Wintoki et al. (2012) explain the conditions for the suitability of fixed effects as a solution to this problem. Fixed-effect estimates would be biased if past return correlations explain current values of co-attention. I examine this reverse relationship between my dependent, *CoRet*, and independent variable, *CoAtt*, by adding a lagged $CoRet_{t-1}$ in model presenting in Equation (3.10). Table 3.9 reports that there is no causal effect of past return comovement on current values of co-attention. Having said that, I show that the fixed-effect panel model addresses the unobservable heterogeneity issue.

Another standard process to confront endogeneity is to use lagged variables instead of contemporaneous values in the models (e.g. see Wintoki et al., 2012; Roberts et al., 2013). Adding lagged covariates rules out endogeneity issues related to omitted variables in time $t-1$ and simultaneity. To control for endogeneity induced by measurement errors since they are generated either from the model or from the proxies used, I employ various specifications (e.g., fixed effects, pool data models, cluster robust standard errors, alternative models for excess returns and abnormal attention). Additionally, my proxy is based on the assumption that online users are potential investors. Thus, searches for financial information reflect the flows of information consumed by them and lead trading decisions. Since SVIs also include the searching behaviour of non-investors, this may be considered as a noisy proxy. However, I argue that even if users do not trade, SVI captures the aggregate trends of investor attention, especially when the search queries are stock-market related instead of asset-specific.

Co-Attention and Return Comovement: International vs. Domestic Investors

$ASVI$ is based on aggregate worldwide searches. Confining the searches within the national borders for each stock market, I estimate the local $ASVI$ ($ASVI_L$). This variable measures the abnormal searches of local online users for their counterpart stock markets. Unfortunately, I cannot estimate local abnormal searches from each country to the rest since SVIs for keywords with a small volume of searches are not available. Yet I investigate whether there are similar trends in the searching activity for the discovery of stock market information of different investors. Panel A in Table 3.10 shows that there is significant co-attention between local search patterns. In other words, there are periods where local users in each country increase or decrease their attention on the same type of information in parallel with local users in other countries. However, this co-attention is significantly lower than the global co-attention.

Table 3.10

Local Investors, Co-Attention and Stock Market Comovement

This table presents in Panel A the attention comovement of local investors in comparison to the co-attention of all investors worldwide. Panel B displays the regression of return comovement on local co-attention and control variables. Co-attention and return comovement is estimated using annual non-overlapping data. FE and TE are also employed (not reported). *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

Panel A: Average International and Local Co-Attention	
ASVI$_L$	0.1624***
	(0.0052)
ASVI$_I$	0.0177*
	(0.0076)

Panel B: Local Co-Attention and Return Comovement	**AR1**	**AR1W**	**ERW**
CoAtt$_{L,t-1}$	0.0444***	0.0477***	0.0463***
	(0.0103)	(0.0101)	(0.0102)
CoRet$_{t-1}$	0.2053***	0.2024***	0.1955***
	(0.0176)	(0.0176)	(0.0173)
LogFL$_{t-1}$	0.0039**	0.0038**	0.0040**
	(0.0013)	(0.0013)	(0.0013)
LogDist	−0.0402**	−0.0403**	−0.0424**
	(0.0129)	(0.0128)	(0.0129)
CoNews$_{t-1}$	0.0489	0.0469	0.0352
	(0.0762)	(0.0768)	(0.0777)
Obs	5,765	5,765	5,765
Adj-R^2	0.4231	0.4270	0.4231
FE	Y	Y	Y
TE	Y	Y	Y

Do similar patterns in local users' attention ($CoAtt_L$) create stock market pressures and increase comovement? This is the question I address in Panel B of Table 3.10. I see that locals' co-attention is positively related to stock market comovement. An 1 percent increase in co-attention increases comovement more than 4 percent units. This effect is significantly lower than the respective coefficients of worldwide co-attention in Table 3.8. The t-statistics of a comparison of the coefficients in ALL models under the three different return specifications are 2.46, 2.82 and 2.38, respectively, which is higher than the critical value at the 1 percent significance level. Despite the difference, this finding confirms that in addition to international investors who have trading interest between two countries, independent investor attention moves in tandem and affects the stock market comovement significantly.

Co-Attention and Financial Contagion

Does attention impact on the correlation between unrelated economies when investors present similar news-searching patterns? To answer this question, I perform panel regression analysis in hypothesis 4 in the cases that news are uncorrelated and there are no economic flows. The results in Panel A of Table 3.11 suggest that co-attention is statistically significant at the 5 percent significance level. The way investors discover online information can affect their trading decisions. More precisely, when investors search for market news they become distracted from firm news and prone to make correlated inferences for stock markets. By isolating data that do not report financial flows between stock markets i and j, I remove from my sample searches triggered by investors in i with holdings in j, and vice versa. In other words, I eliminate from my study those investors in i who have a strong interest to co-attend both markets due to their investments. In essence, the effect of correlated worldwide searches on stock market comovement emerges from the trading behaviour of international users from other countries.

The analysis can go a step further, since this way, I discriminate between locals who concentrate their attention to market news simultaneously (similar search patterns of financial information) from the international investors. Such a specification is extremely important. In addition to investigating two new channels of volatility transmission, it provides insights for the flows of financial information and their impact on stock markets.

To this end, in Panel B, I apply the model in Equation (3.15) for $CoAtt_L$. The local searches, as explained earlier, measure only searches of native users for their own market excluding the residents of the other country. I fail to find significant contagiousness of co-attention when searches are independent. Thus, when a shock hits one financial market, an investor to an unrelated economy who co-searches information for both markets dedicates less cognitive resources to discover idiosyncratic news for her investments and makes correlated inferences. An indirect effect on both economies through international investors is another possible explanation for the significant worldwide impact of co-attention on return comovement.

Table 3.11

Co-Attention and Financial Contagion for Unrelated Markets

Panels A and B report the beta coefficients and robust standard errors of return correlation on international and local co-attention, respectively, between unrelated country pairs (no reported cash flows and correlated news between them). *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	Panel A: Internatiocal Co-Attention			Panel B: Local Co-Attention		
	AR1	**AR1W**	**ERW**	**AR1**	**AR1W**	**ERW**
CoAtt$_{t-1}$	0.0654$^{\cdot}$	0.0730*	0.0575$^{\cdot}$			
	(0.0342)	(0.0340)	(0.0341)			
CoAtt$_{L,t-1}$				0.0365	0.0352	0.0378
				(0.0255)	(0.0250)	(0.0246)
RetCom$_{t-1}$	0.2361***	0.2292***	0.2093***	0.2401***	0.2344***	0.2134***
	(0.0346)	(0.0350)	(0.0347)	(0.0352)	(0.0356)	(0.0351)
LogDist	−0.0665***	−0.0667***	−0.0687***	−0.0660***	−0.0664***	−0.0681***
	(0.0181)	(0.0179)	(0.0180)	(0.0184)	(0.0183)	(0.0182)
Obs	1,261	1,261	1,261	1,256	1,256	1,256
Adj-R^2	0.3999	0.3517	0.3416	0.3423	0.3505	0.3407
FE	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y

Co-Attention and Return Comovement: Evidence using a Multivariate GARCH Model

Accounting for time-varying properties in return correlations based on dynamic multivariate models is widespread in the literature. Based on the insights of key econometric papers in this area and following the results in the second chapter of this thesis, the multivariate GARCH models are more suitable estimators of changing correlations than simple pairwise correlations (e.g., see Bollerslev et al., 1988; Engle and Kroner, 1995; Kroner and Ng, 1998; Silvennoinen and Teräsvirta, 2009). In addition to Da et al. (2011) and Andrei and Hasler (2014) who provide evidence of volatile and asymmetric attention, my previous results illustrate unstable co-attention with varying effect on stock markets over different market states.

Akin to returns, I examine the time-varying properties of co-attention and control for heteroscedasticity employing the BEKK model of Engle and Kroner (1995) as a way to obtain dynamic covariances and correlations .

The specification of BEKK model for returns is described analytically in the previous chapter. The mean equation and the variance-covariance equation for attention are as follows:

$$\mathrm{a}_{\boldsymbol{t}} = \boldsymbol{c} + \boldsymbol{\epsilon_t} \tag{3.16}$$

where $\mathrm{a}_{\boldsymbol{t}} = (\mathrm{a}_{1,t}, ..., \mathrm{a}_{n,t})'$ is a vector of abnormal SVIs, $\boldsymbol{c} = (c_1, ..., c_n)$ is a vector of conditional means, $\boldsymbol{\epsilon_t} = (\epsilon_{1,t}, ..., \epsilon_{n,t})'$ is a vector of innovations in attention that satisfy:

$$e_t = H_{\mathrm{a},t}^{1/2} z_t \tag{3.17}$$

where H_t is an $N \times N$ positive definite conditional covariance matrix at time t of e_t with $\boldsymbol{\epsilon_t}|I_{t-1} \sim N(0, H_t)$. z_t is a vector of standardised residuals that follow a multivariate standard normal distribution with $z_t \sim N(0, I_N)$, where I_N is an $N \times N$ identity matrix. H_t is modelled as:

$$H_t = G^{*'} G^* + V^{*'} \epsilon_{t-1} \epsilon_{t-1}^{'} V^* + W^{*'} H_{t-1} W^* \tag{3.18}$$

G^* is an upper triangular matrix, and V^* and W^* are $N \times N$ matrices with zero off-diagonal elements. The diagonal BEKK model is more parsimonious and is guaranteed to be positive definite compared to the VEC model. Diagonality assumption requires a reduced number of parameters but is more restrictive for the cross-dynamics as the multivariate GARCH depends only on past volatilities and on the cross products of past shocks $\epsilon_{it}\epsilon_{jt}$.

The conditional correlation between i and j is computed with the standard process of dividing the conditional covariance with the product of the conditional variances:

$$CoAtt_{ij,t} = \frac{H_{ij,t}}{\sqrt{H_{ii,t} H_{jj,t}}} \tag{3.19}$$

Table 3.12 reports the coefficients from the mean, variance and covariance equations of BEKK model. I display only the statistically significant coefficients at 5 percent level of significance. Not surprisingly, the majority of constant coefficients in the mean equation are not significant. This is expected since the ASVI represent abnormal (residual) search activity. The coefficients in the variance-covariance equation are highly significant indicating time-varying properties of attention volatility and co-attention and justifying the appropriateness of the BEKK(1,1) specifications. The interpretation of coefficients is not an easy task in multivariate GARCH processes. In the univariate form, the elements in V measure the effect of squared shocks on the conditional variances and in W the effect of past conditional variances on the respective current values. In the multivariate form, the elements in V measure the effect of cross-product shocks on the conditional covariances and in W the effect of past conditional covariances on the respective current values.[26] The three conditions for the parametric structure of dynamic covariance are satisfied. First, all the diagonal elements of G, V and W from Equation (3.18) are positive. Second, the H_t is positive definite.[27] The positive definiteness of the conditional covariance matrix is ensured if the matrices of parameters are all positive definite. Third, the covariance stationary condition, which requires that $v_{ii}^2 + w_{ii}^2 < 1$, is satisfied, as is reported in the last column. Estimates close to unity indicate covariances that are highly persistent.

Return correlations are derived in a similar way using as input the residuals from *AR1*, *AR1W*, and *ERW* risk models. Similar to co-attention the models are well specified and the conditions are satisfied. To conserve space and maintain readability, I present these tables, as well as, tables with alternative variables in Appendix B. Figure 3.4 presents similar trends in the average BEKK-estimated return correlation and co-attention between all pairs, between developed, and between emerging stock markets.

Having estimated weekly co-attention and return correlation through a different estimation method, I replicate the analysis of the previous section. In addition to controlling for time-varying and heteroscedastic correlations, this methodology is superior for three ad-

[26]The off-diagonal elements in the diagonal BEKK are zero. As a result, it does not measure the volatility spillovers across stock markets. Such an estimation is possible in the full parametrised version of the BEKK model. However, for more than 3 assets the estimation is not feasible.

[27]Results are obtained from EVIEWS 8.

Table 3.12

Estimation Results of Co-Attention from the BEKK Model

This table presents the conditional means, c, and the diagonal elements in G, V, and W. Coefficients at higher than 5 percent significance level are not reported. The covariance stationary condition, that is, one of the three conditions for the parametric structure of the diagonal BEKK model and requires $v_{ii}^2 + w_{ii}^2 < 1$, is reported in the last column.

Country	Mean	Variance-Covariance			Stationarity
	c	G	V	W	
AT		0.0343	0.1423	0.9702	0.9616
FI		0.0685	0.0925	0.9605	0.9312
FR	0.0599	0.0129	0.1996	0.9698	0.9803
DE	0.1104	0.0066	0.1571	0.9809	0.9868
IE		0.0463	0.1073	0.9700	0.9524
IT		0.0374	0.2062	0.9555	0.9556
NL		0.0112	0.1758	0.9770	0.9854
NO		0.0398	0.1292	0.9709	0.9593
ES		0.0348	0.2229	0.9527	0.9572
SE		0.0232	0.1194	0.9803	0.9751
CH		0.0629	0.1122	0.9607	0.9355
GB	0.0610	0.0089	0.1642	0.9780	0.9835
AU		0.0358	0.1336	0.9725	0.9636
HK	0.0724	0.0318	0.1558	0.9692	0.9636
JP	0.0653	0.0371	0.2065	0.9568	0.9581
NZ		0.7029	0.3026	0.3757	0.2327
SG		0.0473	0.1823	0.9561	0.9474
CA		0.0664	0.1540	0.9521	0.9302
US	0.1400	0.0140	0.1710	0.9746	0.9791
IN		0.1771	0.2734	0.8526	0.8016
ID	−0.0741	0.9194	0.1631		0.0266
MY	−0.0854	0.1419	0.2294	0.8936	0.8512
PH		0.0607	0.0888	0.9649	0.9389
TH		0.2661	0.2010	0.8266	0.7237
BR		0.0719	0.1501	0.9509	0.9267
CL		0.3804	0.2764	0.7206	0.5957
CO	−0.0819	0.0581	0.1533	0.9572	0.9397
MX	−0.0735	0.0971	0.2474	0.9113	0.8917
PE		0.0578	0.1054	0.9644	0.9412
PL		0.0219	0.1241	0.9806	0.9770
RU		0.2921	0.2191	0.8052	0.6963
TR		0.2878	0.2520	0.7883	0.6848
ZA		0.0204	0.0953	0.9846	0.9784

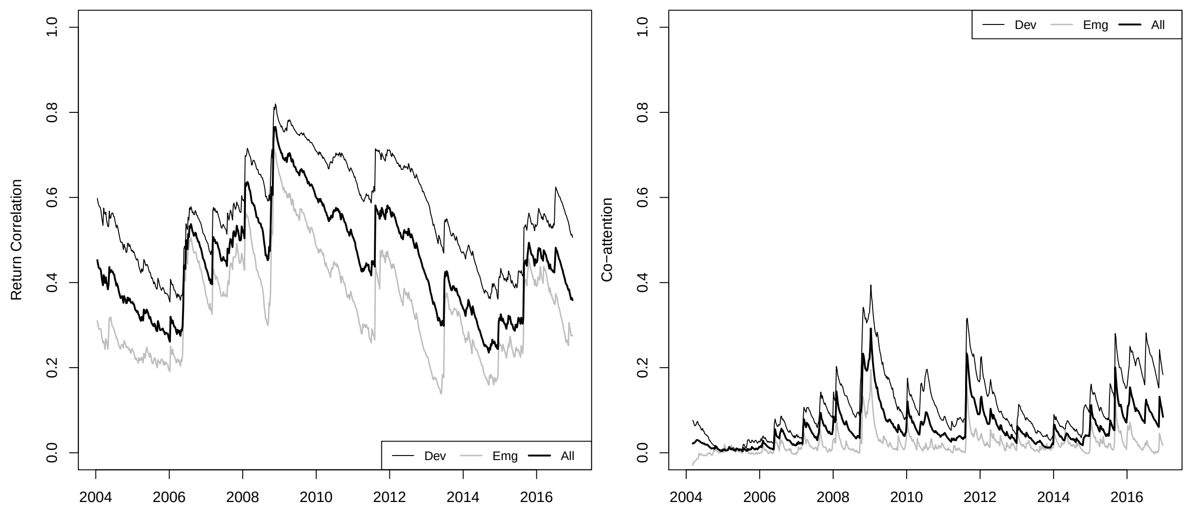


Figure 3.4 Return Correlation and Co-Attention from a Multivariate GARCH Model The leftmost figure displays return correlation and the rightmost figure co-attention estimated using a multivariate GARCH model. The bold solid line averages the return correlation and co-attention between 33 countries, the solid line between pairs of developed countries, the and gray line between pairs of emerging countries.

ditional reasons. First, using weekly than annual time series I examine the short-run effect of co-attention. This should be a more meaningful context for information flows than the annual context. Second, more observations in panel data increase the statistical power of my analysis. Third, I also control for the level and direction of abnormal attention in each market separately. A drawback of this methodology is related to the high dependence of correlation on past values, indicating that the inclusion of a lagged term in the models interprets most of the variation in the regression model yielding very high R-squared coefficients and shrinks the coefficients of other factors. To this end, in Appendix B, I replicate the analysis without the inclusion of $CoRet_{t-1}$. The model in (3.11) is extended as:

$$\begin{aligned} CoRet_{ij,t} = {} & \phi_1 CoAtt_{ij,t-1} + \phi_2 Att_{i,t-1} + \phi_3 Att_{j,t} \\ & + \phi_4 CoRet_{ij,t-1} + \phi_5 LogFL_{ij,t-1} + \phi_6 LogDist \\ & + \phi_7 CoNews_{ij,t-1} + \epsilon_t \end{aligned} \tag{3.20}$$

where $Att_{i,t-1}$ and $Att_{j,t-1}$ are the abnormal attention on stock markets i and j, respectively. A similar approach is adopted for the rest of models in the previous analysis.

Table 3.13 present the coefficients along with robust standard errors to control for autocorrelation and heteroscedasticity. As expected, the effect of lagged dependent variable is strong, driving the adjusted R-squared close to unity and decreasing the coefficients of alternative variables. The results and the directions of the coefficients are consistent with the previous analysis. Yet stronger effects are reported for co-attention during the financial crisis. This indicates that a mGARCH representation captures more accurately the changes in market conditions. Individual shocks of attention also impact significantly on return correlations, though, with a lower effect than co-attention. The effect of *CoNews* remains indistinguishable from zero. Omitting the lagged dependent variable from the covariates yields qualitatively similar results as presented in Appendix B.

3.2.5 Robustness Checks

I conduct several robustness checks in my analysis. I examine whether co-attention is affected by differences in the search topic. Thus, instead of using the most popular topic between stock exchanges and the most important stock market index, I use only search queries on stock exchanges. I show that results are not driven by the selection of keyword and remain qualitatively unchanged (see Table B.10 in Appendix B).[28] Likewise, using returns from popular stock market indices instead of MSCI indices for the estimation of return comovement, I do not find statistically significant differences (t-statistics are extremely low in this case: 0.31, 0.45, and 0.17 - Table B.10). Summary statistics, average pairwise correlations, and correlation matrix between alternative measures lead to similar inferences (see Tables B.1, B.3 and B.4).

I also investigate whether the effect of co-attention on return comovement differs using an alternative proxy for abnormal searches defined as in Vlastakis and Markellos (2012) (see

[28] I perform a t-test for differences in coefficients between popular stock market queries (either stock exchange or stock market index) and stock exchange queries. Coefficients are smaller in the latter case but this difference is not statistically significant at 5 percent level of significance with t-statistics 1.65, 1.79, and 1.58 under the three different return specifications.

Table 3.13

Stock Market Comovement and Co-Attention Estimated using a mGARCH Model

This table reports the beta coefficients and robust standard errors from panel regressions of weekly return correlation on co-attention controlling for persistent correlation (*CoRet*), for attention of each country ($ASVI_i$ and $ASVI_j$) and for correlation explained by fundamentals (*LogFL*), geographical distance (*LogDist*), and correlated news (*CoNews*) including year and fixed effects (not reported) for heterogeneity in each pair and over time. Co-attention and return correlations are derived using weekly data via a multivariate GARCH model (diagonal BEKK). Co-attention is estimated based on *ASVI* of Da et al. (2011). Model 2-4 explore for differences in the effect of co-attention for developed economies, for pairs including the US, and for different market regimes. Panel A, B and C report the results using return correlations estimated from the residuals of a first order autoregressive model (*AR1*), the residuals from a first order autoregressive model including the MSCI World Index as a global factor (*AR1W*), and the residuals from a regression of excess returns (subtracting the riskless rate) on excess MSCI World Index returns (*ERW*). The US 3-month T-bill is used to approximate the risk free rate. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	AR1				ARW				ERW			
	ALL	**MC**	**US**	**MR**	**ALL**	**MC**	**US**	**MR**	**ALL**	**MC**	**US**	**MR**
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
CoAtt$_{t-1}$	0.0101***	0.0101***	0.0098***	0.0071***	0.0101***	0.0101***	0.0098***	0.0071***	0.0100***	0.0079***	0.0100***	0.0073***
	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
ASVI$_{i,t-1}$	0.0022***	0.0022***	0.0022***	0.0022***	0.9759***	0.0022***	0.0022***	0.0022***	0.0023***	0.0012***	0.0022***	0.0023***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ASVI$_{j,t-1}$	0.0018***	0.0018***	0.0018***	0.0018***	0.0022***	0.0018***	0.0018***	0.0018***	0.0019***	0.0010***	0.0019***	0.0019***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CoRet$_{t-1}$	0.9752***	0.975***	0.9752***	0.9781***	0.0018***	0.9757***	0.9758***	0.9788***	0.9750***	0.9753***	0.9747***	0.9791***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0001)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
LogFL$_{t-1}$	0.0001*	0.0000	0.0001*	0.0001***	0.0001*	0.0000	0.0001*	0.0001***	0.000	0.0001*	0.0000	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LogDist	−0.0007**	−0.0006*	−0.0007**	−0.0005*	−0.0006**	−0.0005*	−0.0006**	−0.0004*	−0.0008***	−0.0007**	−0.0007***	−0.0005*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CoNews$_{t-1}$	0.0016	0.0017	0.0016	0.0032*	0.0013	0.0014	0.0013	0.0029*	0.0002	0.0015	0.0002	0.0022
	(0.0017)	(0.0017)	(0.0017)	(0.0014)	(0.0016)	(0.0016)	(0.0016)	(0.0014)	(0.0018)	(0.0017)	(0.0018)	(0.0014)
EMG		−0.0060***				−0.0062***				−0.0078***		
		(0.0009)				(0.0009)				(0.0010)		
MIX		−0.0024**				−0.0024**				−0.0027**		
		(0.0008)				(0.0008)				(0.0009)		
CoAtt$_{t-1}$**:EMG**		−0.0028				−0.0026				−0.0055***		
		(0.0017)				(0.0017)				(0.0011)		
CoAtt$_{t-1}$**:MIX**		0.0002				0.0002				−0.0030***		
		(0.0013)				(0.0012)				(0.0008)		
USIndex			0.0012·				0.0012·				0.0033***	
			(0.0007)				(0.0007)				(0.0007)	
CoAtt$_{t-1}$**:USIndex**			0.0005				0.0008				−0.0024	
			(0.0018)				(0.0018)				(0.0019)	
Recession				0.0057***				0.0056***				0.0058***
				(0.0003)				(0.0003)				(0.0003)
CoAtt$_{t-1}$**:Recession**				0.0428***				0.0535***				0.0395***
				(0.0067)				(0.0067)				(0.0037)
Adj. R-squared	0.9782	0.9782	0.9782	0.9784	0.9789	0.9790	0.979	0.9791	0.9812	0.9812	0.9812	0.9813
Obs	352,704	352,704	352,704	352,704	352,704	352,704	352,704	352,704	352,704	352,704	352,704	352,704
FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Tables B.5 in Appendix B). I do not observe noticeable changes in the coefficients. Thus, I conclude that my results are not driven by a specific procedure for the estimation of abnormal searches. The results do not differ substantially from alternative definitions of the excess returns either.

Finally, I explore for differences in the main effects of co-attention if I use various specifications such as pooled or panel data, with or without fixed and time effects. I find that fixed and time effects increase the efficiency of my models. I also check whether the exclusion of the lagged dependent variable impacts on the importance of co-attention for return comovement, and I do not report significant changes.

3.3 Limitations and Future Research

This essay comes with several limitations. Even though the SVI proxy is widely used in the financial research, it reflects only a part of demanded information flows. There are more channels, on and off line, other than search engines through which investors or analysts seek for information such as major online databases and news platforms. For instance, an investor instead of typing "S&P" in the search engine may look for relevant news directly in Reuters. Measuring and analysing the web traffic of such platforms or the demand for alternative information sources is left for future research.

Another drawback of this proxy is that this is not estimated when the number of searches is relatively low. As a result, the selection of stock markets is subject to the availability of SVIs imposing several limitations for a universal study. The non-availability is more often observed in daily data, especially for less popular searches. Along with the non-synchronous trading issues reported in the literature for cross-country studies of correlation, I cannot examine for a higher impact of information flows in daily horizon. However, the above-mentioned analysis could be extended in the future using a smaller number of countries within the same geographical region (e.g., large European economies). Google Trends has recently released minute SVIs. However, the history of this dataset is restricted to 7-day blocks of data. This means that rescaling is necessary to build longer datasets. Such an extension may seek contributions in market microstructure research. In addition to studying the information discovery from various investors, this also offers a high-frequency context to measure how investors respond to news. An extension of this analysis in the future with more stock markets or assets could also accommodate the economic value of co-attention in a portfolio analysis similar to Israelsen (2016).

3.4 Conclusion

In this chapter, I study the market consequences of correlated attention across international equity indices. In line with theories that associate excess comovement with higher attention to market-wide news, I introduce a proxy that measures investors' correlated information demand directly based on the Google Search Volume Index (SVI). I find that on aggregate investors exhibit similar searching behaviour for general news. Processing less firm-related information results in more coordinated trading decisions and similar pressures on stock prices. Co-attention has a positive effect on return comovement beyond financial flows, distance, and correlated news supply. This effect is more dominant across developed economies and during recession periods.

Examining for the first time news supply and demand in a common framework, I show that the former determines to some extent the latter, but only co-attention seems to have an effect on stock market comovement. My results reveal that time and cognitive constraints force investors to allocate their attention in an easy way. In particular, I provide evidence that they prefer to attend connected markets as familiarity decreases the required resources to process information. I also demonstrate that co-attention is not only generated through international investors. Locals also coordinate independently on market-wide news for their respective markets. However, financial contagion and crisis propagation between unrelated economies are more likely to happen indirectly through investing decisions of international investors.

Chapter 4

Co-Searches and Keyword Portfolio Optimisation

"Risk - calculated risk - is key to success online.", Arthur Ceria, Founder and Chief Creative Officer, CreativeFeed

"The more traffic you have, the more money you get per search.", Gary Flake, Director, Microsoft Live Labs

4.1 Introduction and Background Information

Sponsored search advertising has changed the scenery in online marketing with highly targeted advertisements displayed alongside organic search results - where advertisers pay a fee per click. Advertisements displayed when online users search for relevant information are more efficient for advertisers and less annoying for users, explaining to some extent why paid search advertising is the largest source of income compared to other online advertising forms[1] (Edelman et al., 2005). Companies collectively spend billions each year on advertisements that are targeted to match keywords searched online by potential customers. Paid search advertising is expected to remain the largest constituent of the internet advertising market with revenues growing from US$53.13bn in 2014 to US$85.41bn in 2019. Internet advertising is anticipated to exceed TV and become the largest advertising category by 2019 (Global

[1] Other forms of online advertisement include email marketing, banner advertising and social media advertising.

entertainment and media outlook 2015–2019, PwC). Paid search advertising costs are determined through auctions in competitive markets set up by internet giants such as Google, Baidu and Yahoo! (for a description see Edelman et al., 2005; Abou Nabout et al., 2014). However, there is no consensus on how to allocate the budget optimally across keyword in return for uncertain sales.

Such important decisions are made in practice using ad hoc criteria such as keyword popularity and performance measures. Key findings in research suggest that keyword selection should be based on historical conversion rates, the number of reviews and the involvement of consumers (e.g., Kim et al., 2012*b*). This conclusion is drawn following a positivist approach that shows that these variables have a significant impact on clicks after controlling for the structure of keywords, such as the distance and the correlation between relevant keywords, and characteristics, such as the length, the degree of searching activity, and the categorization to branded or general. There are a plethora of studies toward this direction that investigate the keyword selection problem focusing on their characteristics (e.g., see Ghose and Yang, 2009; Yang and Ghose, 2010; Rutz and Bucklin, 2011; Rutz et al., 2011; Kim et al., 2012*a*). Other papers examine keyword selection on the basis of keyword popularity. Jerath et al. (2014) finds that less popular keywords should be selected as users tend to use highly popular keywords for organic searches and not to respond to sponsored searches.

Thus, the existing academic literature explores the keyword selection problem with less effort to offer a theoretical framework. Besides, most papers study the criteria that impact on various performance measures in paid search advertising without accounting for the risk related to their variability. Also, they do not offer a methodology that determines how the advertising budget should be spent optimally across keywords and, as a result, managers adopt naive strategies that lead to waste of resources.

The present chapter questions the standard practices and proposes an alternative method for keyword selection. Based on the literature that connects marketing decisions to financial markets (Dhar and Ghose, 2010), I employ the Modern Portfolio Theory (MPT) of Markowitz (1952, 1968, 2010) to solve the optimal keyword selection problem under uncertainty. The solution determines the amount that should be spent across keywords accounting for their expected performance and risk. The rationale is similar in that presented in Holthausen Jr and Assmus (1982) where portfolio theory is used as a more appropriate framework to account for uncertain sales across different market segments. However, their model modifies the objective function of MPT to accommodate sales response functions.

Unlike traditional marketing problems, I disengage from sales response functions. This innovation is possible because the spend in keyword advertising is performance-based. In other advertising channels, the performance is not linearly dependent on the cost and managers should estimate the bidirectional effect of increasing budget on performance. However, paid advertising is a special case as the cost is charged only after a successful response to the advertisement. In other words, even if marketers allocate more budget to specific keywords, the number of online users who click on the sponsored link is not affected. This association between search traffic and performance suggests that the"price-taker" hypothesis of MPT, which considers the distribution of returns independent from budget allocation decisions, is not rejected.

Other papers also study the application of MPT on marketing problems (e.g., see Cardozo and Smith Jr, 1983; Devinney et al., 1985; Cardozo and Smith Jr, 1985; Ryals et al., 2007; Borgs et al., 2007; Zhang and Lu, 2009). Nevertheless, there are several issues of particular concern as these papers describe how financial portfolio theory can fit in marketing science without following the financial principles thoroughly. More specifically, the theoretical framework of portfolio theory is in line with the overall objective of the firm, that is, the maximisation of the value for shareholders. On the contrary, these studies focus on performance criteria such as sales or profits rather than on profit growth or returns. Similar to Cardozo and Smith Jr (1983), I argue that there are no individual management decisions across business departments but all business goals should meet the goals of shareholders. Thus, my model maximises the profit growth of keywords for every level of risk, which is consistent with portfolio theory and the overall strategy of a firm.

In particular, I present the conditions under which the problem in paid search advertising is reduced to the solution in Markowitz (1952). The searching interest of online users is a dominant factor that should drive budget decisions in sponsored marketing. Under minor assumptions, I show that the profit growth of advertising for a keyword is simplified to changes in the search traffic for that keyword. This finding suggests that click-through-rates, conversion rates, and costs are irrelevant and what matters in this decision is the average growth in web traffic for keywords, the variances and the covariances. My approach deviates from the existing literature that focuses excessively on the conversion rates, click-through-rates, the popularity of keywords and other key features that could lead to more clicks.

Expressing the advertising returns as a function of web traffic also deals with a major problem in the literature regarding the empirical investigation and practical implementation of this methodology. There are serious limitations that stem from the lack of sales data for online advertising. This constraint is more pronounced for the estimation of covariances since they require a sufficient sample size and synchronous data across keywords. The "attribution" problem is another well-reported challenge which is related to the difficulty to confirm the sales that correspond to each advertising channel (e.g., Swinyard and Ray, 1977; Sparkman Jr and Locander, 1980; Naik and Raman, 2003; Berman, 2016; Sahni, 2016). This means that the current sales may be only a percent of the total sales that are triggered by each keyword. This is because purchases may occur in the future or through a non-online channel. I overcome these issues by using a novel proxy for the wider sales activity in the context of sponsored advertising. This is the Search Volume Index (SVI), launched by Google Trends since 2004, that approximates the relative searches for a query. SVIs are high-quality data provided in long historical time series in daily, weekly and monthly frequencies. In particular, SVI has been extensively used in other sciences such as in finance (e.g., see Da et al., 2011; Vlastakis and Markellos, 2012) to capture investors' attention and in epidemiology to estimate current outbreaks (e.g., see Copeland et al., 2013; Dugas et al., 2013). Another strand in literature uses SVI as an indicator of consumers' behaviour (Goel et al., 2010; Vosen and Schmidt, 2011; Wu and Brynjolfsson, 2015). Regardless of SVI popularity in research and findings that reveal a concurrent increase in Google searches with television ads (Zigmond and Stipp, 2010; Joo et al., 2013), little effort has been made to use this data set in digital advertising. SVI captures online users' attention and co-attention revealing the popularity and the spillovers between advertising hosts. The intuition behind the suitability of SVI is that an increase in searches is associated with an increase in sales. Consistency is maintained as Google is the search engine provider and the source of SVIs. Another advantage of using a broader indicator of expected sales is that inferences are also allowed for new products and services.

Another matter of concern of previous studies for the use of modern portfolio theory in marketing is that they offer little guidance on how marketers can apply this solution in practice. I undertake the first comprehensive empirical application of the mean–variance approach in sponsored advertising. The goal is to test the validity of the approach and to assess its performance against alternative heuristic rules that are currently used by practitioners. My empirical analysis has a strong practical implication for decision making under uncertainty. In addition to the methodological contribution, my approach provides managerial insights for the selection of keywords and the allocation of the budget that is based on the online behaviour of users.

Following the search patterns of keywords, their variation and covariation, managers should invest to keywords that maximise the expected keyword click stream and minimise the risk of investing to volatile or highly positively correlated keywords. Significant correlations between keywords' traffic decrease the diversification benefits in a portfolio of keywords. This results in maximising the profit growth and minimising its uncertainty. My perspective for the optimal allocation of the marketing spend uses a forward-looking method, that is independent of past marketing decisions and other performance measures. Using the same 15 industries as in Abou Nabout et al. (2014), I identify an initial set of relevant keywords for each sector based on Google Ad Words. Since Google Ad Words penalises irrelevant advertisers, I expect different pools of keywords for each sector leading to 15 efficient frontiers. Each point on the so-called efficient frontier represents an optimal portfolio of keyword investments that maximises the expected overall growth in search intensity for a given level of risk. Given that one efficient combination of keywords emerges for every risk target, managers should select the keyword portfolio on the frontier according to the firm's risk tolerance.

In addition to an optimal budget allocation mechanism, I also employ widely used financial techniques to compare my methodology to some commonly used methodologies in industry. These methods are based on simple approaches such as the "do-nothing" strategy, that is, to invest in all relevant keywords, or on performance measures such as the click-through-rates, the popularity, and cost-per-reservation ratio (Rutz and Bucklin, 2007).

A strong positive association between average historical growth in keyword popularity and standard deviation validates the MPT framework which requires that riskier investment choices are rewarded with higher performance. This means that simple practices in industry lead to under diversified portfolios of keywords or over investment in keywords with specific features. A finding of this study is that the minimum variance optimal portfolio of keywords offers statistically significant improvements in performance compared to heuristic rules. Another issue I report is that these practices are very restricted concerning the level of risk that each company is willing to undertake and do not offer them the opportunity to move to more risky levels with higher compensation in performance. Finally, I demonstrate a simplified process of this methodology which is parsimonious in terms of data requirements and computational effort and produces comparable estimates.

Overall, this essay makes three main contributions to the extant literature. First, I approach the keyword selection and budget allocation problem with a new representation that is well ground in MPT. Second, I present the conditions for proper application of the financial principles in paid search advertising and under mild hypotheses, I connect the keyword performance and the objective function to the search traffic for keywords. As a result, I offer a new proxy of search intensity based on readily available data. Third, I provide with managerial implications and insights by demonstrating the solution empirically. In addition to contrasting my solution in terms of efficiency to widely applied alternatives, I also present a simpler keyword selection method that accounts for the risk and the performance.

The remainder of this study is organised as follows. Section 2 presents the empirical analysis. More specifically, it describes the methodology, the data and the empirical findings of keyword optimisation, the managerial implications and the robustness checks. Section 3 discusses the limitations and future research and Section 4 summarises the main conclusions.

4.2 Empirical Analysis

4.2.1 A Portfolio Theory Framework for Paid Search Advertising Decisions

I start with a simple framework in which a firm considers investing an amount x from the total available wealth w in paid search advertising. As first argued by Cardozo and Smith Jr (1983), a utility maximisation objective is adopted for spending on advertising in order to align decisions across the firm with the goals of shareholders. As advertising is a risky activity, I anticipate two states for wealth (W) that result from a "good" return (r_g) or "bad" return (r_b) in sales, respectively:

$$W_g = (w - x) + x(1 + r_g) = w + xr_g \tag{4.1}$$

$$W_b = (w - x) + x(1 + r_b) = w + xr_b \tag{4.2}$$

If the good state occurs with probability p and the bad state with probability $(1 - p)$, the expected utility, $E(U)$, for an investment x is:

$$E[U(x)] = pu(w + xr_g) + (1 - p)u(w + xr_b) \tag{4.3}$$

The derivative of $E(U)$ with respect to x measures the rate at which the expected utility changes with respect to the amount invested in advertising:

$$E[U^{'}(x)] = pu^{'}(w + xr_g)r_g + (1 - p)u^{'}(w + xr_b)r_b \tag{4.4}$$

The second derivative of EU with respect to x implies a concave utility function with $u^{''}(w) < 0$ for every level of wealth:

$$E[U^{''}(x)] = pu^{''}(w + xr_g)r_g^2 + (1 - p)u^{''}(w + xr_b)r_b^2 \tag{4.5}$$

In line with firm risk aversion, the concave utility function means that the level of satisfaction increases with wealth at a diminishing rate. The marginal change in expected utility for the first dollar is found by the first derivative at $x = 0$:

$$E[U^{'}(x)] = pu^{'}(w)r_g + (1 - p)u^{'}(w)r_b \tag{4.6}$$
$$= u^{'}(w)[pr_g + (1 - p)r_b] \tag{4.7}$$

The expression in the brackets is the expected return of the advertising choice and links utility with returns. The firm determines the optimal choice x to invest by setting the first derivative equal to zero. Markowitz, or modern, portfolio theory (MPT) is reconciled with the utility approach by assuming that agents have quadratic utility, or, that investment returns are jointly normally distributed variables. Moving from the level of wealth to the return on a risky portfolio, r_p, in the utility function allows the representation of the mean-variance optimisation problem. The expected utility of the return is given by a second-order Taylor expansion as a function of mean and variance:

$$E[U(r_p)] = E[u(\bar{r_p})] + u^{'}(\bar{r_p})E(r_p - \bar{r_p}) + \frac{1}{2}u^{''}(\bar{r_p})E(r_p - \bar{r_p})^2 \tag{4.8}$$
$$= u(\bar{r_p}) + \frac{1}{2}u^{''}(\bar{r_p})\sigma_p^2 \tag{4.9}$$

where $E(r_p - \bar{r_p})$ is equal to zero.

Having to select the optimal budget allocation across keywords in paid search advertising is a problem similar to the allocation of capital to risky assets. There is a set of possible relevant keywords $i = (1, 2, ..., n)$. I define as N_i the search intensity of online users for keyword i. From each stream of visitors, a proportion of them visits the advertised website with a click-through-rate ϕ_i. From these visitors, a proportion y_i, known as the conversion rate, completes a purchase. Assuming that M_i is the profit of each purchase that is generated through keyword i, the total income is given by the product $M_i \phi_i y_i N_i$.

Online marketing spend in sponsored advertising differs from that in other channels in that the former is a linear function of the number of queries. It also differs from other types of online advertising such as banners that do not have a purely performance-based cost. In the case of paid search advertising, the cost is a function of the number of users who click on the sponsored advertisement that is displayed along with organic results for keyword i. In other words, the total advertising expense is a function of converted visitors to the website of the advertiser given by $c_{i,t} \phi_i N_i$, where $c_{i,t}$ is the Cost Per Click (CPC) for keyword i. The profit that is attributed to each keyword i can be calculated as a function of N_i:

$$\begin{aligned}
\pi_{i,t} &= M_{i,t} \phi_{i,t} y N_{i,t} - c_{i,t} \phi_{i,t} N_{i,t} \\
&= (M_{i,t} \phi_{i,t} y - c_{i,t} \phi_{i,t}) N_{i,t} \\
&= \lambda_{i,t} N_{i,t}
\end{aligned} \tag{4.10}$$

In a discrete time model, I assume that for the same advertiser the parameters in $\lambda_{i,t}$ remain constant for a small change of time from period 0 to period 1. In practical terms, this period would cover a calendar day. Although there is no relevant published evidence, it seems reasonable that these parameters vary significantly only between advertisers, but not across time. I can calculate now the growth in profit as:

$$\begin{aligned}
r_i &= \frac{\lambda_i N_{i,t} - \lambda_i N_{i,t-1}}{\lambda_i N_{i,t-1}} \\
&= \% \Delta N_i
\end{aligned} \tag{4.11}$$

Marketing profit growth (or return) is expressed in this equation as a percentage change in incoming traffic which is approximated by the growth rate in keyword popularity. Since the web traffic for each keyword is a stochastic variable, this growth is risky. Consider the case of allocating a budget across $N > 2$ risky choices which form a portfolio of keywords. Let $w_1, w_2, ..., w_i$ be the percentage allocation of the budget subject to the constraint:

$$w_1 + w_2 + ... + w_N = 1 \tag{4.12}$$

I also impose a non-negativity constraint on weights:

$$w_i \geq 0 \tag{4.13}$$

Under portfolio theory, the expected marketing portfolio return r_p and risk σ_p^2 are given on the basis of the mean and variance:

$$E(r_p) = \mu_p = w_1 E(r_1) + w_2 E(r_2) + ... + w_N E(r_N) \tag{4.14}$$

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j cov(r_i, r_j) \tag{4.15}$$

The efficient frontier of keyword portfolios can be derived with inequality constraints solving a quadratic programming problem:

$$\min_{w_i} \sigma_p = w' \Sigma w$$

$$s.t.$$

$$\mu_p = w' \mu$$

$$w' 1 = 1$$

$$w_i \geq 0 \quad (i = 1, 2, .., N)$$

where μ is a vector of the expected growth in traffic for each keyword and Σ is their variance-covariance matrix.

From this optimisation problem, I deduce that for a portfolio of keywords, advertisers should focus their attention on changes in the incoming traffic to each keyword and their variance-covariance. Under my assumptions, the budget allocation decision is independent of click-through-rates, conversion rates and the advertising cost and it depends solely on the search behaviour of online consumers. Budget allocations that maximise advertising profit without accounting for the variance-covariance may lead to results that are not in line with the objectives of risk-averse shareholders. Within a mean/variance framework, the performance is maximised for a specific level of risk. The risk is reduced when funds are shifted from highly volatile keywords to keywords with more stable variation. This is also reduced when funds are shifted from keywords with positively correlated variation to keywords with weaker or more negatively correlated variation.

4.2.2 Data

In order to demonstrate the application of the proposed framework, I study the problem of selecting the best set of keywords for paid search advertising in 15 different sectors. My choice of sectors follows Abou Nabout et al. (2014) and is representative of a variety of products and services that have an active search advertising market. I draw data from the Google Ad Words and Google Trends databases. As discussed, using openly available data from a single provider facilitates the analysis and ensures consistency.

I first extract the relevant keywords for each sector studied based on the Keyword Planner service of Google Ad Words. Google Ad Words provides advertisers with tools to define sets of keywords that are relevant to their websites. In the Google Ad Words auctions, bidding success also depends on a quality score that increases when the relevancy of the keyword to the landing page of the advertiser is higher. This is a way for Google to optimise its revenue and maximise the probability of clicks for the advertisers limiting bids from irrelevant companies. The implication for my analysis is that the population from which I shall select the keywords and the optimal portfolio will vary between sectors.

Google Ad Words provides advertisers with a variety of metrics which are the basis for heuristic techniques used in practice for keyword selection. These metrics include the average monthly searches (AMS), the expected number of clicks, click-through-rates (CTR) and the cost-per-click (CPC). The AMS reflects the number of times people have searched a keyword over the last 12 months and captures popularity. CTR is the proportion of users who click on the sponsored link. The CPC for each keyword shows the average estimated amount that the advertiser is charged each time a user clicks on the sponsored link and lands on the web page of the advertiser. I only include keywords that have information on these metrics in order to enable a comparison of the keyword selection method proposed in this paper with popular heuristic techniques.

As discussed, in my model the profit growth for each keyword is expressed as a function of variations in incoming traffic. In order to measure the latter, I adopt the Search Volume Index (SVI) time series data produced by Google Trends for each one of the keywords identified in the previous step. Specifically, I estimate the average and variance for the arithmetic changes in SVIs along with their covariance matrix. SVIs have been used in a variety of applications including, for example, finance (Da et al., 2011; Vlastakis and Markellos, 2012), marketing (Goel et al., 2010; Vosen and Schmidt, 2011; Wu and Brynjolfsson, 2015) and epidemiology (Copeland et al., 2013; Dugas et al., 2013). Applications in advertising are limited to studies such as Zigmond and Stipp (2010) and Joo et al. (2013) that report a link between television ads and search activity on Google.

SVI quantifies the search intensity and popularity of specific keywords. The values of SVIs range from 0 to 100 as the absolute number of searches is divided by the maximum number of searches for the period under consideration. However, the search terms need a minimum volume for the estimation of the index. Thus, a zero value reflects either the non-availability of information for a specific term or very weak search interest. I only analyse keywords for which I have a history of at least one year and no missing values. I replicate the analysis using history of 5 years[2] (R1 in Appendix C). Although the highest sampling

[2]Using 5-year history of data (260 observations) alleviates concerns for the use of a small sample for the estimation of the covariance matrix. This follows the literature which suggests that in cases with large

frequency available is daily, I use weekly data in order to increase my coverage in terms of keywords. In line with the literature in finance that omits illiquid assets from empirical analysis, I discard from the dataset keywords with constant SVIs between successive periods for more than 25 percent of the sample. In my robustness checks, I repeat the analysis using a threshold of 10 percent of the sample (R2 in Appendix C).

Table 4.1
Descriptive Statistics for Keywords

This table presents the number of keywords for each industry (No), the average monthly searches (AMS), the expected number of clicks, click-through-rates (CTR) and the cost-per-click (CPC) for sets of relevant keywords in 15 industries provided by Google Ad Words. CPR estimates the cost per reservation, that is, the CPC divided by the CTR.

Industry	Code	No	AMS	Clicks	CTR	CPC	CPR
Advertising Services	ADS	141	945,217	316	0.0306	1.2003	19.67
Beauty	BTY	150	395,431	155	0.0620	0.8186	10.36
Consumer Electronics	CEL	111	232,365	233	0.0246	0.8909	4.52
Fashion & Style	FNS	128	258,391	52	0.0278	0.7252	1.97
Finance	FNC	68	361,157	607	0.0113	0.9728	4.43
Health	HLT	216	307,837	265	0.0282	0.8424	4.96
Hobbies & Leisure	HNL	181	449,210	344	0.0395	0.8690	1003.25
Home Appliances	HAP	323	101,687	206	0.0462	0.9475	26.26
Internet	INR	120	3,986,893	330	0.0404	0.9764	3.19
Internet & Telecom.	TEL	43	788,313	319	0.0230	1.0577	5.98
Management Cons.	MCS	93	87,458	15	0.0256	0.8740	15.20
Motor Vehicles	MVH	223	459,752	326	0.0921	0.8950	135.20
Real Estate	RES	189	841,673	546	0.0579	0.8905	328.09
Social Network	SNT	167	63,572	12	0.0790	0.6546	0.56
Travel & Tourism	TNT	269	384,925	174	0.1284	0.9605	165.44
Average	-	75	962,818	172	0.0315	0.1294	262.14

Some summary statistics about the keywords used and their key metrics for the 15 sectors studied appear in Table 4.1. I also estimate another common measure of keyword performance, the cost-per-reservation (CPR) that is the CPC divided by the CTR (Rutz and Bucklin, 2007). Although the population of keywords suggested by Google Ads can reach up to 800, after filtering across Google Ad Words and Google Trends the number in final dataset ranges between 43 (Internet and Telecommunications) and 323 (Home Appliances) with an average of 75 across sectors. There is a wide variation, and some extreme values in the metrics studied for the keywords in each sector. This suggests that I will test the

number of assets compared to the number of sample, the covariance matrix estimates include significant errors. Shrinkage covariance techniques, such as, the constant covariance estimator of Ledoit and Wolf (2004) are used in such cases as has been shown to reduce the covariance estimation errors. Increasing the sample size in the robust checks, I estimate more stable covariance matrices. In R1 analysis in Appendix C, I show that the findings remain qualitatively unchanged.

merit of various keyword selection methods under various settings. The heterogeneity that is observed across industries in all variables serves to a better understanding of my model and adds to the robustness of the results.

Table 4.2
Descriptive Statistics of Changes in SVIs

This table presents the average mean (μ) and standard deviation (σ) for weekly percentage changes in SVIs. The last column estimates the average correlation (ρ) between all keywords for each sector.

Industry	μ	σ	ρ
Advertising Services	0.0063	0.1185	0.1895
Beauty	0.0079	0.1054	0.0417
Consumer Electronics	0.0073	0.1223	0.1829
Fashion & Style	0.0166	0.1817	0.0207
Finance	0.0108	0.1362	0.2445
Health	0.0079	0.1149	0.2402
Hobbies & Leisure	0.0126	0.1363	0.0254
Home Appliances	0.0116	0.1395	0.1184
Internet	0.0039	0.0906	0.0275
Internet & Telecom.	0.0041	0.1016	0.0212
Management Cons.	0.0125	0.1603	0.1867
Motor Vehicles	0.0061	0.0949	0.0597
Real Estate	0.0072	0.1150	0.2093
Social Network	0.0015	0.1122	0.0301
Travel & Tourism	0.0098	0.1314	0.0960
Average	0.0084	0.1241	0.1138

Table 4.2 presents descriptive statistics for the changes in SVIs for these keywords selected in the previous step. The annualised average changes and standard deviation suggest a significant overall annual growth in the keywords studied of over 43 percent with a volatility of 89.5 percent. In order to get a sense of the correlation between keywords, which in my model may be a significant source of risk, I report in the last column the average correlation. Although the overall correlation is positive with an average of 11.38 percent, a breakdown of these indicates that there is significant scope for diversification as more than one in three correlations have a negative value. In my framework, advertisements in negatively correlated keywords will provide benefits in terms of risk reduction in the overall advertising effectiveness of the portfolio. Yet similar benefits arise with positive and weak correlations.

4.2.3 Keyword Optimisation

A key prediction of MPT is a linear relationship between expected returns and volatility. This is because rational investors will demand higher compensation for assuming additional risk. In order to test this assumption in my dataset I regress average popularity growth against standard deviation for each keyword. The results are summarised in Table 4.3 and confirm a significant positive relationship between the average changes in SVIs and the standard deviation of these changes. The relationship is strong with an average R-squared of over 74 percent across sectors. Keywords with high growth rates, which have strong potential in terms of popularity and advertising, carry also significant uncertainty in terms of this rate being realised.

Table 4.3

Regression of Average SVI Changes against Standard Deviation

This table shows the slope of average weekly percent changes in SVIs regressed on their standard deviation along with the relevant t-statistics estimated using Newey-West robust standard errors. The last column reports the adjusted R-squared of the regression.

Industry	Slope	t-statistic	R^2
Advertising Services	0.1252	8.0163	0.5883
Beauty	0.1558	9.7743	0.8952
Consumer Electronics	0.1194	14.9268	0.8981
Fashion & Style	0.1910	11.5079	0.8922
Finance	0.1980	17.7165	0.9607
Health	0.1444	14.0457	0.8625
Hobbies & Leisure	0.1741	15.6413	0.9662
Home Appliances	0.1339	24.9750	0.8386
Internet	0.1393	5.7099	0.7979
Internet & Telecom.	0.0862	9.7279	0.2576
Management Cons.	0.1436	7.5642	0.6058
Motor Vehicles	0.1331	9.7124	0.7313
Real Estate	0.1353	19.4841	0.7432
Social Network	0.0859	6.8149	0.3676
Travel & Tourism	0.1357	9.2588	0.7422
Average	0.1401	12.3251	0.7432

I now turn to the application of mean-variance optimisation in order to determine for each sector the optimal keyword portfolio weights that will maximise the SVI growth for a given level of risk. The solution to this quadratic programming problem produces points of feasible keyword portfolios with the maximum return at every level of risk, or, equivalently the minimum risk at every level of return. In line with the financial literature, portfolios satisfying these criteria are coined "efficient portfolios" and form curve known as the "efficient frontier". To ease exposition, I produce 100 optimal portfolios for each sector spaced equally in terms of returns. The leftmost edge of the obtained frontier is the minimum variance portfolio, that is, the portfolio with the lowest risk. I also estimate the portfolio with the maximum risk-adjusted performance, that is, the ratio of growth over the standard deviation. Assuming a zero risk-free rate this corresponds to the so-called Sharpe ratio in the financial literature. Advertisers will select a portfolio from the efficient frontier on the basis of their risk preferences. For example, advertisers that are highly risk-averse should prefer solutions with lower risk that lie at the bottom of the frontier close to the minimum variance portfolio.

The next step in the analysis involves the comparison of the proposed approach against alternative benchmark methods that are currently used in practice. I adopt five alternative benchmark methods following the published literature (see Rusmevichientong and Williamson, 2006; Rutz and Bucklin, 2007; Rutz et al., 2011):

- *BP1*: invest equally in the keywords with above average AMS (most popular keywords approach).
- *BP2*: invest equally in the least popular keywords with a below average AMS (least popular keywords or long tail approach).
- *BP3*: invest equally in the keywords with an above average CTR (most effective/expensive keywords approach).
- *BP4*: invest equally in the keywords with a below average CPR (cheapest keywords approach).
- *BP5*: invest equally in all keywords (naive approach).

Table 4.4 presents the number of keywords that are selected under each strategy. *EP* describes the average number of keywords across the 100 optimal portfolios studied. *MVP* is the number of keywords included in the minimum variance portfolio, and *SRP* is the number of keywords in the optimal risky portfolio with the highest Sharpe ratio. The *MPT* approach selects on average a small number of keywords relative to benchmark strategies. However, the number of keywords in the *MVP* and *SRP* portfolios is similar to the number of keywords in *BP1* and *BP3*, respectively.

Figures 4.1, 4.2, and 4.3 plot with a solid line the efficient frontier for each sector. I indicate the minimum variance portfolio with filled circles and the maximum Sharpe ratio portfolio with stars. Triangles depict the mean and standard deviation of the individual keywords, while crosses show the position of the five benchmark keyword portfolios in terms of risk and return. No specific benchmark strategy appears to dominate systematically with regard to return or risk. I observe that the benchmark portfolios lie close to each other in a region that is just below the minimum-variance portfolio. This means that the benchmark methods perhaps suit risk-averse advertisers but not necessarily those with a larger appetite for risk.

Graphically, it appears that portfolios on the efficient frontier dominate benchmark portfolios in that they can provide higher returns for the same level of risk. Moreover, as discussed, they can accommodate higher appetites towards risk. However, the comparison is not straightforward as the estimation of the efficient frontier parameters is based on historical information for a sample of SVIs and the population values are not known. So the differences in performance may be statistically insignificant if sample variation is considered. In order to account for this I test for statistical differences in risk-adjusted performance, as measured by the Sharpe ratio, between benchmark portfolios and the portfolio on the frontier that corresponds to the same level of standard deviation. In other words, I compare the performance at the same level of risk. The parametric JKM test (Jobson and Korkie, 1981; Memmel, 2003) is used to compute the p-values of the difference in Sharpe ratios under the null hypothesis:

Table 4.4
Keyword Portfolio Sizes

This table exhibits the number of keywords in which each strategy invests the budget. *EP* averages the number of keywords across 100 portfolios on the efficient frontier. *MVP* is the minimum variance portfolio, SRP is the portfolio with the maximum Sharpe Ratio, *BP1* and *BP2* are the benchmark portfolios 1 and 2 that invest equally in the most and the least popular keywords respectively (short head vs. long tail), *BP3* and *BP4* are the benchmark portfolios 3 and 4 that invest equally in the keywords with the highest CTRs and the lowest CPRs respectively, and *BP5* is the portfolio that invests equally in all keywords in the dataset.

Industries	EP	MVP	SRP	BP1	BP2	BP3	BP4	BP5
Advertising Services	21	33	34	18	123	45	115	141
Beauty	13	41	39	39	111	33	129	150
Consumer Electronics	11	32	31	25	86	39	89	111
Fashion & Style	13	45	48	31	97	39	87	128
Finance	9	16	16	18	50	30	58	68
Health	13	44	45	69	147	55	168	216
Hobbies & Leisure	13	48	46	33	148	59	180	181
Home Appliances	38	24	50	71	252	96	276	323
Internet	12	42	38	21	99	28	89	120
Internet & Telecom.	9	26	23	12	31	17	33	43
Management Cons.	9	26	27	19	74	30	77	93
Motor Vehicles	11	43	46	41	182	41	214	223
Real Estate	21	37	35	27	162	52	185	189
Social Network	17	77	45	54	113	45	129	167
Travel & Tourism	20	31	36	58	211	47	263	269
Average	15	38	37	36	126	44	139	161

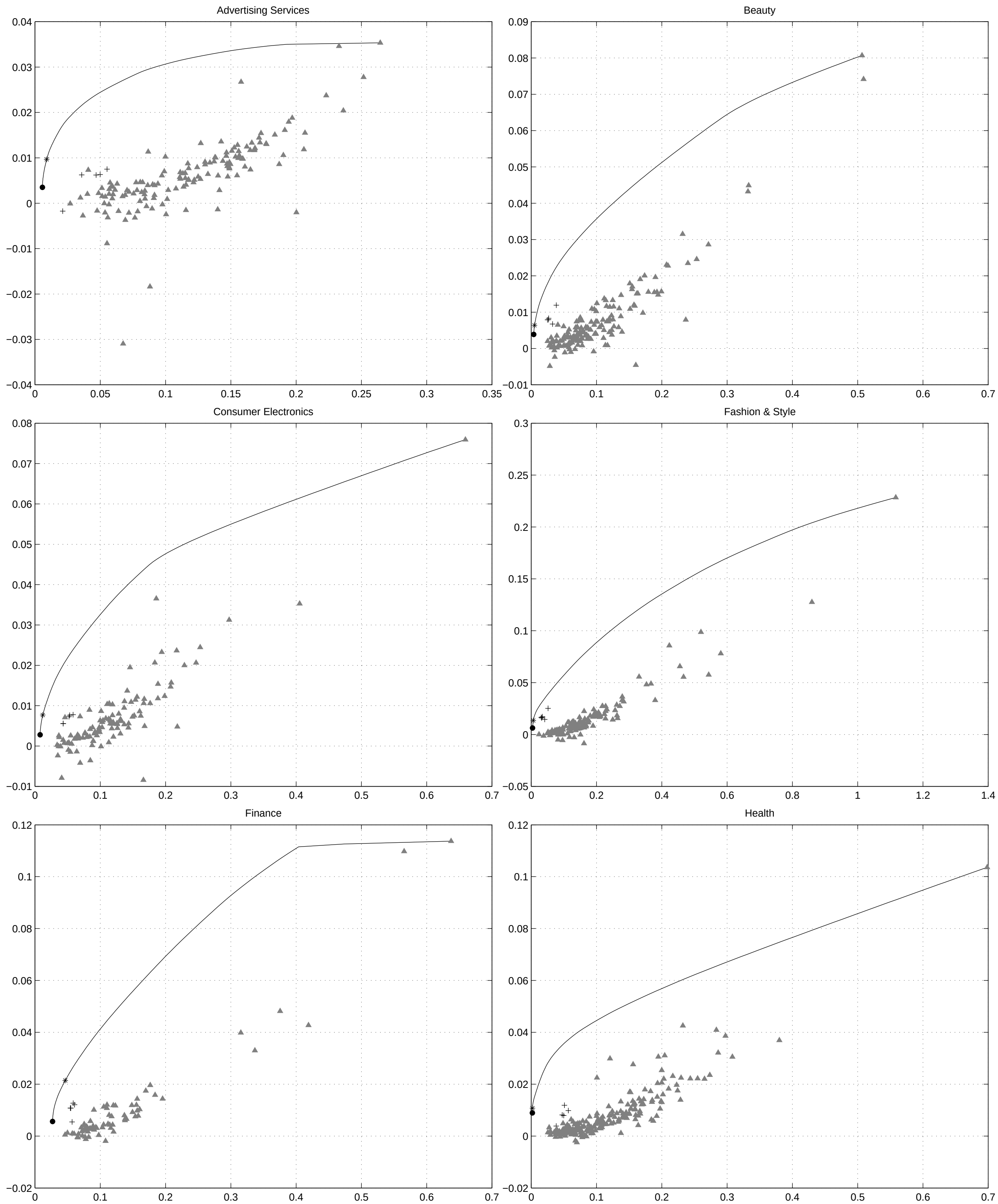


Figure 4.1 Efficient Keyword Frontiers for Industries 1-6 The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

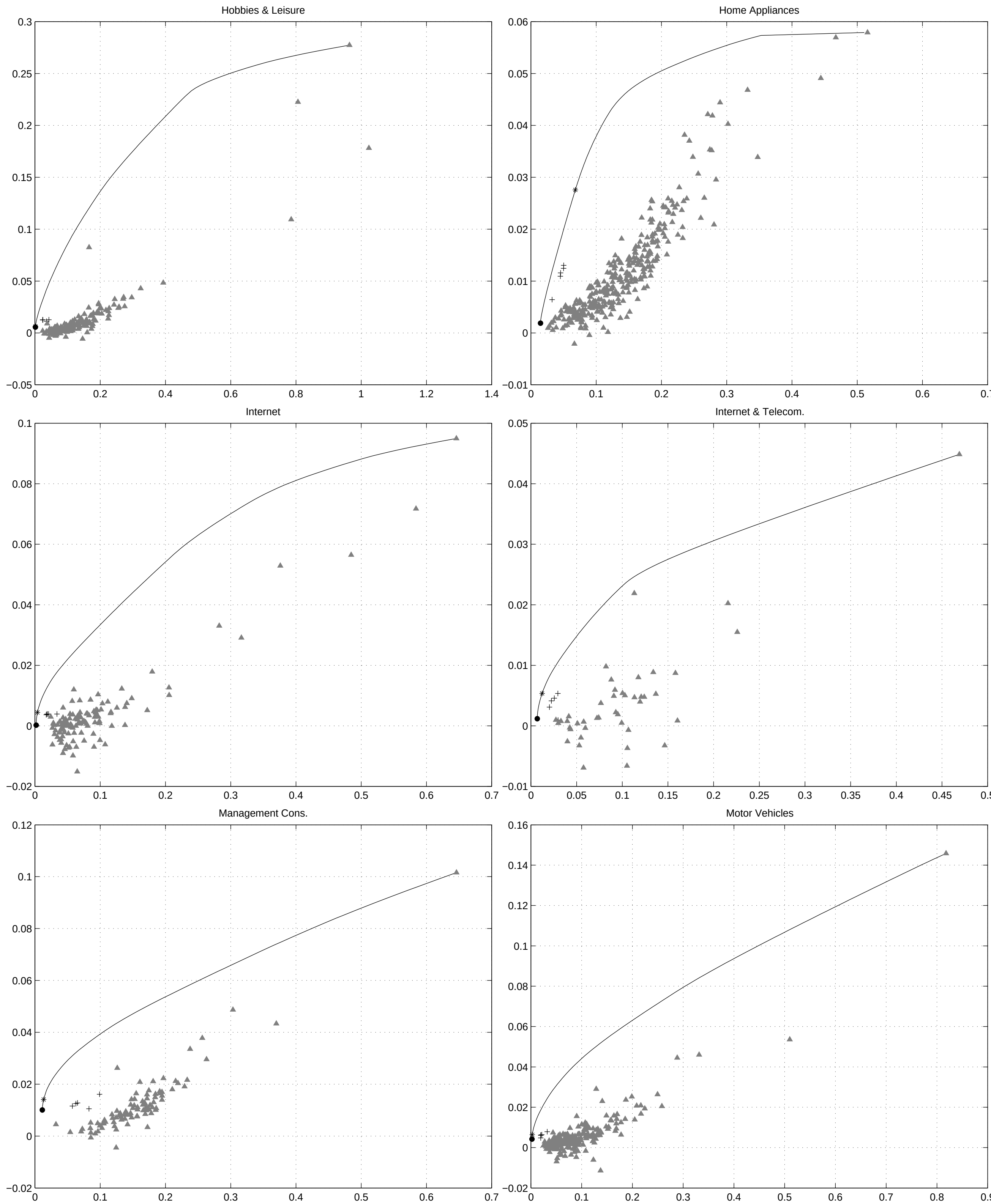


Figure 4.2 Efficient Keyword Frontiers for Industries 7-12 The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

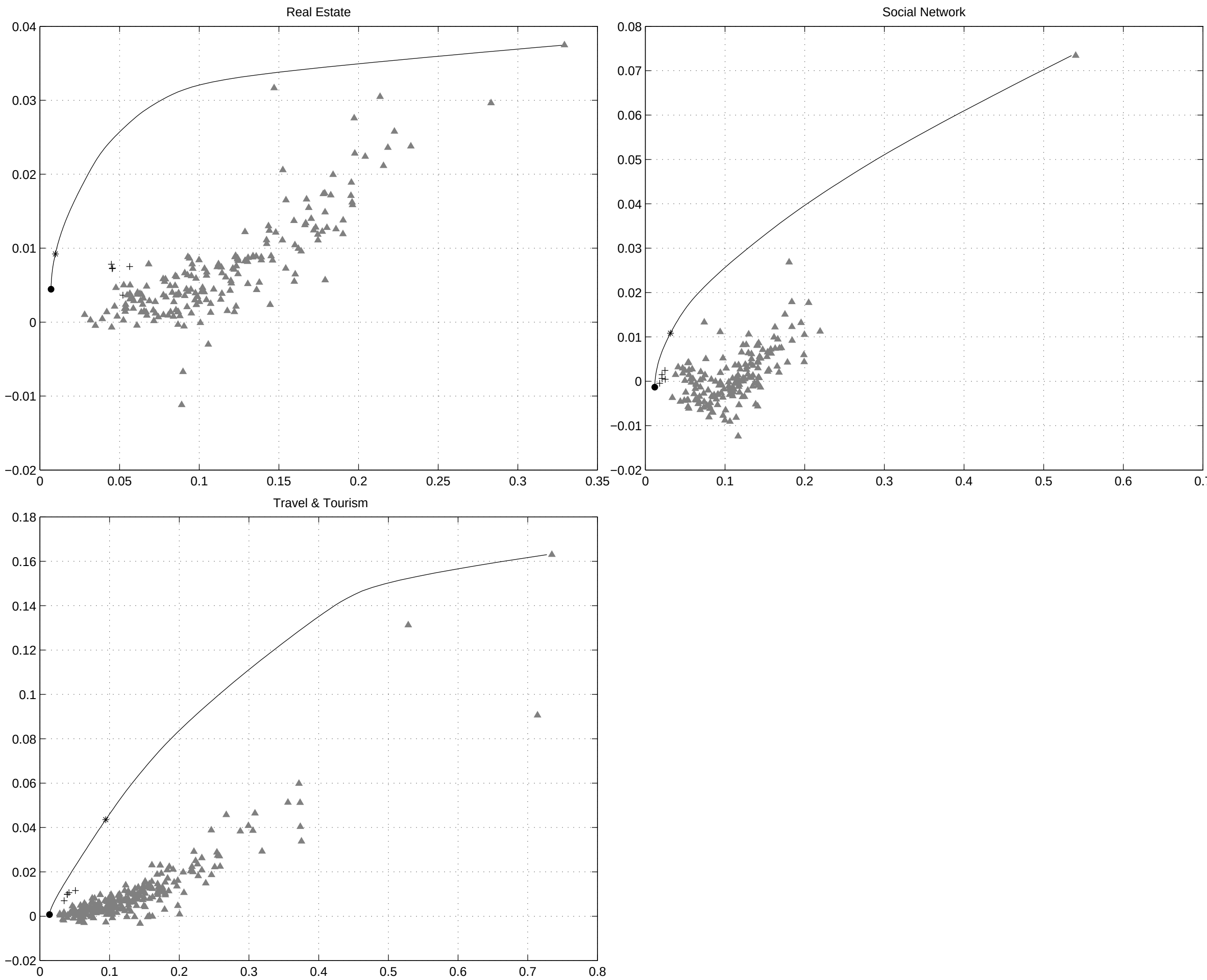


Figure 4.3 Efficient Keyword Frontiers for Industries 13-15 The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

$$H_0 : \frac{\hat{\mu}_i}{\hat{\sigma}_i} - \frac{\hat{\mu}_n}{\hat{\sigma}_n} = 0 \tag{4.16}$$

where i is the portfolio on the efficient frontier and n is the benchmark portfolio.

Ledoit and Wolf (2008) argue that the JKM test is not valid under fat tails or when returns are serially correlated. In order to address this potential shortcoming, I also estimate robust standard errors using studentised time series bootstrap. I follow standard practice and apply the Ledoit and Wolf (2008) under a two-sided hypothesis by simulating 5,000 datasets using circular block bootstrap. The critical values are then estimated by the empirical quantiles of the simulated datasets. Under this test, I estimate bootstrapped standard errors making no assumptions about the distribution of popularity growth.

The results in Tables 4.5 and 4.6 reject the null hypothesis of equal Sharpe ratios for almost all cases under both test configurations. This means that despite the proximity of the benchmark portfolios to the efficient frontier in many sectors, the efficient portfolio at the same level of risk offer statistically significantly higher performance. A more acid test of performance comparison could be done on an out-of-sample basis. However, the lack of historical data for my study on the benchmark portfolio performance means that this is left for future research.

4.2.4 Managerial Implications

The proposed optimal keyword portfolio approach has the disadvantage against competing benchmark methods of being more complicated to implement. Specifically, it requires a number of parameters to be estimated and an optimisation problem to be solved. Moreover, when the number of keywords in the set exceeds the sample observations, standard optimisation methods, namely quadratic programming cannot provide an optimal solution. Although various techniques exist in the financial literature that can be employed (e.g., see Ledoit and Wolf, 2004), they, unfortunately, carry significant complexity and computational cost.

In order to ease practical implementation, I propose here a simplification of the portfolio

Table 4.5
Jobson-Korkie-Memmel Test of Equality in Keyword Portfolio Performance

This table presents the p-values of the parametric test of JKM test of Jobson and Korkie (1981) and Memmel (2003). The null hypothesis is that there is no difference in the Sharpe ratio of the benchmark portfolios and that of the corresponding portfolio on the efficient frontier for the same level of risk. ***, **, * denote the singificance at the 1%, 5% and 10% level, respectively.

Industries	BP1	BP2	BP3	BP4	BP5
Advertising Services	0.0000***	0.0469**	0.0072***	0.0204**	0.0279**
Beauty	0.0030***	0.0020***	0.0145**	0.0015***	0.0012***
Consumer Electronics	0.0072***	0.0231**	0.0112**	0.0175**	0.0157**
Fashion & Style	0.0016***	0.0002***	0.0123**	0.0002***	0.0000***
Finance	0.0110***	0.0171**	0.0148**	0.0093***	0.0126**
Health	0.0001***	0.0063***	0.0038***	0.0019***	0.0023***
Hobbies & Leisure	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Home Appliances	0.0002***	0.0001***	0.0001***	0.0000***	0.0000***
Internet	0.0041***	0.0005***	0.0017***	0.0002***	0.0004***
Internet & Telecom.	0.0342**	0.0820*	0.0724*	0.0415**	0.0476**
Management Cons.	0.0408**	0.0295**	0.0420**	0.0299**	0.0299**
Motor Vehicles	0.0000***	0.0001***	0.0006***	0.0001***	0.0000***
Real Estate	0.0012***	0.0013***	0.0041***	0.0013***	0.0013***
Social Network	0.0019***	0.0022***	0.0035***	0.0021***	0.0010***
Travel & Tourism	0.0000***	0.0005***	0.0011***	0.0003***	0.0003***

Table 4.6
Ledoit-Wolf Test of Equality in Keyword Portfolio Performance

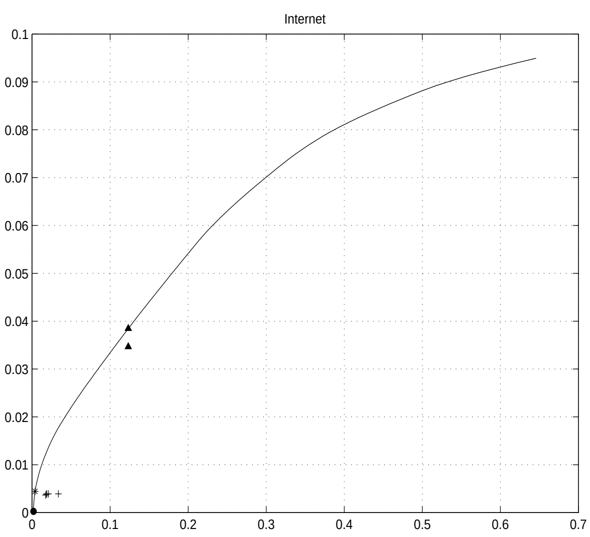
This table presents the p-values of the non-parametric test of Ledoit-Wolf (2008). The null hypothesis is that there is no difference in the Sharpe ratio of the benchmark portfolios and that of the portfolio on the efficient frontier for the same level of risk. The standard errors of the test are estimated via bootstrap. ***, **, * denote the 1%, 5% and 10% level of significance respectively.

Industries	BP1	BP2	BP3	BP4	BP5
Advertising Services	0.0068***	0.0918*	0.0564*	0.0668*	0.0564*
Beauty	0.0058***	0.1124	0.0144**	0.0872*	0.0938*
Consumer Electronics	0.1712	0.0542*	0.1494	0.1304	0.1814
Fashion & Style	0.0010***	0.0180**	0.0354**	0.0066***	0.0140**
Finance	0.0326**	0.0266**	0.0168**	0.0164**	0.0216**
Health	0.0002***	0.0192**	0.0174**	0.0216**	0.0146**
Hobbies & Leisure	0.0002***	0.0114**	0.0572*	0.0106**	0.0088***
Home Appliances	0.0004***	0.0008***	0.0004***	0.0006***	0.0012***
Internet	0.0028***	0.0004***	0.0010***	0.0002***	0.0006***
Internet & Telecom.	0.0768*	0.1048	0.1102	0.0478**	0.0794*
Management Cons.	0.2036	0.2240	0.1310	0.2160	0.2256
Motor Vehicles	0.0002***	0.0004***	0.0002***	0.0032***	0.0002***
Real Estate	0.0046***	0.0034***	0.0120**	0.0060***	0.0048***
Social Network	0.0002***	0.0006***	0.0002***	0.0004***	0.0016***
Travel & Tourism	0.0006***	0.0250**	0.0316**	0.0116**	0.0164**

Table 4.7
Sharpe Ratio Heuristic

This table presents the p-values of the JKM parametric test. The null hypothesis is that there is no difference in the Sharpe ratio of two portfolios built under the Sharpe Ratio heuristic and the portfolio on the efficient frontier at the same level of risk. EW10P invests equally on 10 keywords with the highest Sharpe Ratio. ***, **, * denote the 1%, 5% and 10% level of significance respectively.

Industries	EW10P
Advertising Services	0.2404
Beauty	0.1789
Consumer Electronics	0.2167
Fashion & Style	0.2702
Finance	0.1790
Health	0.3134
Hobbies & Leisure	0.1123
Home Appliances	0.0710*
Internet	0.2964
Internet & Telecom.	0.3266
Management Cons.	0.1734
Motor Vehicles	0.1598
Real Estate	0.2656
Social Network	0.2884
Travel & Tourism	0.0992*



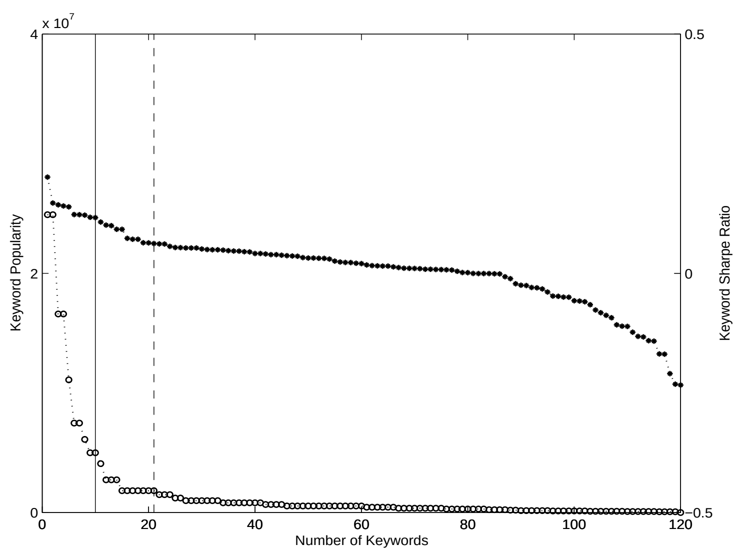


Figure 4.4 Sharpe Ratio Heuristic The left figure displays the risk (standard deviation in popularity growth) on the x axis and the expected return (average popularity growth) on the y axis for the *Internet* sector. The solid line is the efficient keyword frontier, the filled circle and the star are the minimum variance and the maximum sharpe ratio portfolios on the efficient frontiers, the crosses are the five benchmark portfolios and the triangles are the Sharpe ratio heuristic portfolio and the efficient portfolio for the respective level of risk. In the right figure, the circles rank the keywords by their popularity (left y axis) while the vertical dotted line separates head from long tail keywords. The filled circles rank the keywords by their Sharpe ratio (right y axis) while the vertical solid line demonstrates the 10 keywords with the highest Sharpe ratio.

theory method and evaluate its effectiveness in my sample. Rather than undertaking the optimisation process described, I propose the ranking of keywords on the basis of their risk-adjusted performance as measured by the Sharpe ratio (average growth rate in SVI over standard deviation of growth rates). I then suggest an equally weighted advertising investment in the keywords with the 10 largest Sharpe ratios. The use of reward-to-risk criteria for asset selection has been applied in the financial literature (see, for example, Rachev et al., 2007). The choice for the portfolio size is based on research findings in the financial literature which show that diversification benefits are marginal for portfolios that are larger than 10 assets (Evans and Archer, 1968). The shortcomings of this simplified approach are that it will not provide an optimal solution and does not fully account for the effect of correlation between investment returns. Moreover, it will not provide optimal portfolios over a frontier and will not accommodate varying risk preferences.

A simple graphical comparison, as shown in Figure 4.4, suggests small differences in performance against the frontier. However, in the presence of sampling variation, differences compared to the optimal solution may be statistically insignificant for a given level of risk. In order to formally test this, I compare the portfolio Sharpe ratios for the simplified method and the full method. The results in Table 4.7 indicate that the difference in performance is statistically insignificant at the 5 percent level. In my robustness checks I show that this result holds even if I increase the number of keywords in the simplified method from 10 to 20 or 30. This robustness check is inspired by the findings of researchers, such as Evans and Archer (1968), Elton and Gruber (1977), and Statman (1987), that find that the marginal returns to diversification become insignificant only for portfolio sizes after 30 assets.

4.2.5 Robustness Checks

I perform various robustness checks for my empirical results. First, there is strong criticism in the financial literature for the estimation errors in the covariance matrix when the sample size is smaller than the number of assets (see Ledoit and Wolf, 2004). To mitigate any concerns for such bias, I replicate the analysis using longer sample periods for the estimation of mean and variance-covariance portfolio statistics (R1 in Appendix C). My findings suggest that the portfolio solution offer statistically significantly higher risk-adjusted performance than alternative ad hoc solutions. Second, I replicate the analysis using a different threshold to clean the data from non illiquid keywords (R2 in Appendix C). Thus, I discard all the keywords with more than 10% constant SVIs between successive periods in the sample. The results remain robust. Finally, in addition to selecting 10 keywords with the highest Sharpe ratio in the proposed risk-adjusted alternative, I assess portfolios that include all the keywords with a Sharpe ratio above the average Sharpe ratio of all the keywords in the sample. The results indicate that this method does not differ significantly from the efficient.

4.3 Limitations and Future Research

My research carries a number of limitations. First, the empirical analysis is based on in-sample estimates. This is because there is lack of time series data for clicks, conversion rates, costs, and purchases. Google Ad Words provides only current estimations for this metrics. As a result, I cannot apply an out-of-sample comparison of the performance of various methodologies with the mean-variance framework. Such an analysis could be extended in the future either with the collection of daily estimates from Google Ad Words or using historical data from a specific advertiser. Second, the comparison between various strategies is performed in terms of performance and risk, as they are defined in my theoretical framework. Yet, this analysis could be extended to test the keyword selection based on my methodology in terms of other performance criteria such as CTRs and conversion rates with regression analysis.

4.4 Conclusion

This paper proposes a new framework for budget allocation under uncertainty in paid search advertising building on financial portfolio theory. My model relates directly the performance in sponsored advertising with changes in search traffic. This suggests that widely used criteria such as click-through-rates and conversion rates are not relevant. In addition to a performance criterion that complies with the financial principles, I introduce the importance of risk for individual keywords and keyword portfolios. These are measured in terms of variance and covariance in the search traffic. My empirical analysis provides guidance for the estimation of the efficient keyword frontier employing a novel proxy for web traffic based on the search activity of online users. An advantage related to this method is that it offers a set of efficient solutions accounting for the level of risk of each advertiser. Compared to popular alternatives used in the literature based on various criteria, I demonstrate that my solution leads to statistically better results. I also show that a simplification of the proposed method performs well with little computational complexity.

Chapter 5

Conclusions

5.1 Summary and Implications

This thesis deals with three issues related to covariance. The first chapter compares the predictive ability of several popular multivariate volatility models. The models under consideration employ daily, high-frequency and option-implied information and range from fully parametric to model-free. A rigorous empirical evaluation is performed across various equity markets, forecast horizons, loss functions and market regimes. In addition to the statistical examination of the differences across models, the economic gains are investigated in a global minimum-variance framework.

The analysis suggests that VHAR is the best performing model, both in statistical and economic terms. A novel hybrid estimator combining realised correlations with option-implied volatilities does not perform equally well. However, when the option-implied volatilities are adjusted for the volatility risk-premium bias reported in the literature, the performance of the model improves substantially. Multivariate GARCH models are inferior than less parametrised alternatives both in statistical and economic terms. The economic evaluation shows that forecasts from models employing high-frequency data lead to portfolios with lower risk relative to the $1/N$ benchmark. They also offer competing stability in the presence of transaction costs. Finally, the ranking of the models is maintained during the recent global financial crisis, although with increasing forecast errors.

These findings offer significant implications for a broad range of financial applications.

Inaccurate estimations of covariance are associated with higher overall portfolio risk and sub-optimal investing choices. This is more pronounced in large scale portfolios such as mutual funds or institutional investments. Financial institutions also deal with the market consequences of incorrect estimates of the true covariance matrix. Yet, the systemic dependence across markets imposes further regulatory implications in terms of the Basel III framework for the calculation of the Value-at-Risk and the minimum required capital. Higher reserved capital is related to underinvestment, while less reserved capital increases the default probability. Furthermore, accurate covariance forecasting is a key process for effective asset pricing and hedging. The former requires the covariance between the returns of the asset and the market and the latter the covariance between the returns of the underlying asset and the derivative.

The second essay studies the determinants of cross-market covariance and the excess comovement anomaly in particular. Correlated fundamentals fail to explain why markets move more together. Correlated sentiment and correlated news are examined as alternative explanations of return comovement. In this essay, I propose correlated investors' attention as a rational determinant of excess comovement. When investors concentrate on market-wide news, there are less cognitive constraints to absorb asset-specific news. As a result, correlated inferences put similar pressure on prices.

Employing the Search Volume Index, I estimate the correlation in information demand for equity market news across 33 international economies. My results reveal that there is significant co-attention in stock markets indicating that investors coordinate on similar information. Information processing constraints coerce investors into identifying simple ways to allocate their attention. Investigating a number of factors that may attract investors' interest such as market capitalisation, financial flows, location, cultural proximity, and news supply, I show that correlated news explain only a part of the variability in co-attention. This finding sheds some light on how investors process information and respond to news supply.

Exploring co-attention as a determinant of excess comovement, I reveal a strong and positive effect on excess comovement above other explanations such as correlated capital flows, distance, and correlated news. This effect is more pronounced across developed stock markets and volatile market conditions. My results suggest that the correlated demand for general market news imposes similar dynamics across markets. These are interpreted in terms of the way investors select to prioritise their attention. Correlated news fail to identify a similar impact on return comovement indicating that markets are driven by the consumption rather than the production of information. I also identify a distinct effect of local and international effects on comovement, indicating that co-attention is not only produced from investors who share their attention between various stock markets, but also from investors who present similar information demand patterns across markets. However, exploring co-attention as a channel of financial contagiousness and crisis propagation, I find that international investors appear to impose indirectly similar market reactions across unrelated market economies.

Explaining the excess comovement anomaly provides theoretical contributions that increase the understanding about financial markets. In addition to excess comovement, co-attention is connected theoretically and empirically to a number of stylised facts related to the higher international stock market correlation across developed countries and extreme market conditions. Direct implications also lie in international investing, portfolio diversification opportunities, and accurate covariance forecasting.

The third essay examines the role of risk in paid search advertising decisions under uncertainty measured by the variance and covariance of volatile returns. The budget allocation problem is examined under a mean-variance solution, drawing on financial portfolio theory. This solution departs from existing approaches that maximise sales or clicks and complies to the financial principles. Thus, the risk of individual keywords (variance) and from combination of keywords in advertising portfolios (covariance) is also taken into consideration. This approach also deviates from other researches which examine the mean-variance approach in marketing problems in that the objective function targets at maximising expected returns or profit growths instead of sales. This is in line with the overall firm objective and the portfolio theory.

As profits in sponsored advertising are a function of web traffic, under mild hypotheses, the profit growth is simplified to changes in the web traffic suggesting that the optimisation of clicking opportunities is more important than the click-through-rates or other performance criteria. This conclusion also allows a further contribution regarding the implementation of this framework. The empirical analysis provides managerial guidance proposing a novel proxy of keyword popularity. The Search Volume Index is a more accurate and consistent measure for the expected popularity. This is because historical data of search intensity across keywords are provided by Google, which also offers the advertising platform. Another advantage is that it can also be used in cases where historical data are not available for the performance of various keywords or in cases of new products and services.

The empirical application involves the estimation of the so called efficient frontiers maximising the expected growth in SVI at every level of risk. The outcome indicates the keywords that should be selected in each portfolio along with the budget that should be allocated. This approach does not offer a unique solution, but a series of efficient portfolios that change in accordance with the required level of risk each advertiser is willing to undertake. Higher levels of risk are compensated with higher returns. Compared to widely applied heuristics in paid search advertising, this framework offers statistically significantly higher risk-adjusted performance. Finally, a simple heuristic based on the risk-adjusted performance of keywords approximates the efficient solution for the respective level of risk quite well.

5.2 Directions for Future Research

These essays investigate covariance from three difference perspectives. The empirical findings and the limitations reported in each chapter identify areas for future research and extensions. The first essay is restricted between five markets within Europe to account for non-synchronous trading. An analysis in further geographic areas and stock markets is subject to the availability of high-frequency and option-implied data. Another issue of concern is that only developed countries are examined. Findings in the literature lend support to the idea that there are higher diversification opportunities in emerging markets since there are different dynamics that govern the comovement between developed and emerging economies. This study could also examine the economic gains of alternative models from investing to less stable markets. Another possible extension of this thesis involves the examination of realised GARCH models. This thesis deals with the most popular GARCH specifications. However, more recent advancements in GARCH models consider the inclusion of high-frequency information (Hansen et al., 2012, 2014). A main conclusion is that there is an advantage in models that employ realised data. It would be interesting to study whether the realised multivariate GARCH models outperform the simpler parametric or non-parametric versions. Motivated by Bauer and Vorkink (2011) who accommodate factors that predict volatilities such as treasury bill, dividend yield, credit spread, slope of term structure and the scorecard in addition to past volatilities, future research in covariance forecasting could be extended to incorporate the impact of alternative sources of excess covariance.

The second essay offers several areas for future research. For instance, the proxy used summarises the attention to market-wide information through information demand in search engines. However, the web traffic and the information in more sophisticated platforms and databases for financial information such as Reuters or EDGAR could also be examined. Another possible extension relies on the analysis of co-attention in higher frequencies such as daily and intraday data. This is very important to examine the short-term effect of information on stock markets. However, problems related to the non-availability of long enough history, and non-synchronicity should also be addressed, especially in microstructure research. The measurement of the economic gains from an international portfolio strategy that accounts for investors' co-attention on stock markets could be possible in the spirit of Israelsen (2016). This analysis, though, requires an extension of the sample to further stock markets.

The third essay can be extended in various ways. The most important is to test the out-of-sample performance of the mean-variance solution in relation to alternative methodologies.

This extension requires historical data for alternative strategies. The ideal scenario involves the comparison of past performance of an advertiser with theoretical solutions offered by the financial portfolio theory. Future research in this area may also investigate the effect of the suggested keyword selection method on alternative performance criteria used in marketing within a regression analysis framework.

Appendices

Appendix A - Chapter 2

Table A.1

Descriptive Statistics of Returns

This table reports the mean, standard deviation, minimum, maximum, skewness and kurtosis for each index for daily, weekly, and monthly returns estimated from close prices.

Index	Mean	St.Dev.	Min.	Max.	Skew.	Kurt.
			Panel A: Daily Returns			
AEX	-0.1750	0.1825	-0.0853	0.1086	-0.2499	11.8064
CAC	-0.1441	0.1824	-0.0600	0.0842	0.0325	7.3099
DAX	-0.1287	0.1924	-0.0836	0.0904	-0.0366	8.4217
FTSE	-0.1419	0.1497	-0.0595	0.0657	-0.1119	8.2933
SMI	-0.1217	0.1517	-0.0996	0.0878	-0.2018	13.6577
			Panel B: Weekly Returns			
AEX	-0.0330	0.0791	-0.0853	0.0709	-0.3176	11.7813
CAC	-0.0268	0.0789	-0.0517	0.0530	-0.0386	5.1862
DAX	-0.0333	0.0815	-0.0631	0.0495	0.0294	5.3508
FTSE	-0.0246	0.0640	-0.0434	0.0406	-0.2355	5.7494
SMI	-0.0391	0.0632	-0.0546	0.0545	0.1231	7.9316
			Panel C: Monthly Returns			
AEX	0.0064	0.0390	-0.0282	0.0615	1.4993	8.8793
CAC	0.0052	0.0372	-0.0307	0.0444	0.6549	5.4925
DAX	0.0052	0.0388	-0.0291	0.0541	0.7953	6.3152
FTSE	-0.0008	0.0321	-0.0237	0.0461	1.3899	7.4758
SMI	0.0066	0.0323	-0.0348	0.0419	0.4166	6.4441

Table A.2

Pairwise GW Test Results: LA

This table reports the average pairwise differences in losses derived from the absolute deviation loss function (LA) of the models in columns 2-16 from the models in column 1. ** and * report significant differences at 99% and 95% level of confidence respectively for the Giacomini-White test.

	A-ScBEKK	DiagBEKK	A-DiagBEKK	CCC	A-CCC	DCC	A-DCC	OGARCH	A-OGARCH	EWMA	LRCOV	HICOV	Adj-HICOV	adj-HAR-HICOV	VHAR
Panel A: Daily															
ScBEKK	−0.0076**	−0.0019**	−0.0121**	0.0375**	0.0339**	−0.0025	−0.0025	−0.0058**	−0.0060*	−0.0106**	−0.0225**	0.2060**	−0.0248**	0.0612**	−0.0460**
A-ScBEKK		0.0057**	−0.0045**	0.0451**	0.0415**	0.0051**	0.0051**	0.0018	0.0016	−0.0030*	−0.0149**	0.2136**	−0.0172**	0.0688**	−0.0384**
DiagBEKK			−0.0102**	0.0395**	0.0359**	−0.0006	−0.0006	−0.0039*	−0.0040	−0.0087**	−0.0205**	0.2080**	−0.0228**	0.0632**	−0.0440**
A-DiagBEKK				0.0497**	0.0461**	0.0096**	0.0096**	0.0063**	0.0061*	0.0015	−0.0103*	0.2181**	−0.0127**	0.0733**	−0.0338**
CCC					−0.0036**	−0.0401**	−0.0401**	−0.0434**	−0.0435**	−0.0482**	−0.0600**	0.1685**	−0.0623**	0.0237**	−0.0835**
A-CCC						−0.0365**	−0.0365**	−0.0398**	−0.0399**	−0.0446**	−0.0564**	0.1721**	−0.0587**	0.0273**	−0.0799**
DCC							0.0000	−0.0033**	−0.0034	−0.0081**	−0.0199**	0.2086**	−0.0223**	0.0638**	−0.0434**
A-DCC								−0.0033**	−0.0034	−0.0081**	−0.0199**	0.2086**	−0.0223**	0.0638**	−0.0434**
OGARCH									−0.0001	−0.0048**	−0.0166**	0.2119**	−0.0190**	0.0671**	−0.0401**
A-OGARCH										−0.0047	−0.0165**	0.2120**	−0.0188**	0.0672**	−0.0400**
EWMA											−0.0118*	0.2167**	−0.0142**	0.0719**	−0.0353**
LRCOV												0.2285**	−0.0023	0.0837**	−0.0235**
HICOV													−0.2308**	−0.1448**	−0.2520**
Adj-HICOV														0.0860**	−0.0212**
adj-HAR-HICOV															−0.1072**
Panel B: Weekly															
ScBEKK	−0.0085**	−0.0027**	−0.0109**	0.0453**	0.0441**	−0.0047	−0.0047	−0.0040	−0.0011	−0.0122**	−0.0285**	0.2188**	0.0711**	0.0795**	−0.0443**
A-ScBEKK		0.0058**	−0.0024	0.0539**	0.0526**	0.0038	0.0039	0.0045	0.0074*	−0.0037	−0.0200**	0.2274**	0.0796**	0.0880**	−0.0358**
DiagBEKK			−0.0082**	0.0481**	0.0468**	−0.0020	−0.0019	−0.0013	0.0016	−0.0095**	−0.0258**	0.2216**	0.0738**	0.0822**	−0.0416**
A-DiagBEKK				0.0563**	0.0550**	0.0063	0.0063	0.0069	0.0098*	−0.0013	−0.0175**	0.2298**	0.0821**	0.0904**	−0.0334**
CCC					−0.0013	−0.0500**	−0.0500**	−0.0494**	−0.0465**	−0.0575**	−0.0738**	0.1735**	0.0258**	0.0342**	−0.0897**
A-CCC						−0.0488**	−0.0487**	−0.0481**	−0.0452**	−0.0563**	−0.0726**	0.1748**	0.0270**	0.0354**	−0.0884**
DCC							0.0000	0.0006	0.0035	−0.0075**	−0.0238**	0.2235**	0.0758**	0.0842**	−0.0397**
A-DCC								0.0006	0.0035	−0.0075**	−0.0238**	0.2235**	0.0758**	0.0842**	−0.0397**
OGARCH									0.0029	−0.0082**	−0.0244**	0.2229**	0.0752**	0.0835**	−0.0403**
A-OGARCH										−0.0111**	−0.0274**	0.2200**	0.0722**	0.0806**	−0.0432**
EWMA											−0.0163**	0.2311**	0.0833**	0.0917**	−0.0321**
LRCOV												0.2473**	0.0996**	0.1080**	−0.0159**
HICOV													−0.1477**	−0.1394**	−0.2632**
Adj-HICOV														0.0084	−0.1155**
adj-HAR-HICOV															−0.1238**
Panel C: Monthly															
ScBEKK	−0.0068*	−0.0056*	−0.0104	0.0269*	0.0245	−0.0006	−0.0006	0.0013	0.0034	−0.0144*	−0.0208*	0.2196**	0.1179**	0.1177**	−0.0450**
A-ScBEKK		0.0012	−0.0036	0.0337*	0.0313*	0.0062	0.0061	0.0081	0.0102*	−0.0076	−0.0140	0.2264**	0.1246**	0.1244**	−0.0382**
DiagBEKK			−0.0048	0.0325*	0.0301*	0.0050	0.0050	0.0069	0.0090	−0.0088	−0.0152	0.2252**	0.1235**	0.1233**	−0.0394**
A-DiagBEKK				0.0373**	0.0349*	0.0098	0.0098	0.0117	0.0138	−0.0040	−0.0104	0.2300**	0.1283**	0.1281**	−0.0346**
CCC					−0.0024	−0.0275*	−0.0276*	−0.0256	−0.0235	−0.0413**	−0.0477**	0.1927**	0.0909**	0.0908**	−0.0719**
A-CCC						−0.0251	−0.0252	−0.0232	−0.0211	−0.0389*	−0.0453**	0.1951**	0.0933**	0.0931**	−0.0695**
DCC							0.0000	0.0019	0.0040	−0.0138**	−0.0202**	0.2202**	0.1185**	0.1183**	−0.0444**
A-DCC								0.0019	0.0041	−0.0137**	−0.0202**	0.2202**	0.1185**	0.1183**	−0.0444**
OGARCH									0.0021	−0.0157**	−0.0221**	0.2183**	0.1166**	0.1164**	−0.0463**
A-OGARCH										−0.0178**	−0.0242**	0.2162**	0.1144**	0.1143**	−0.0484**
EWMA											−0.0064	0.2340**	0.1322**	0.1320**	−0.0306**
LRCOV												0.2404**	0.1387**	0.1385**	−0.0242**
HICOV													−0.1017**	−0.1019**	−0.2646**
Adj-HICOV														−0.0002	−0.1629**
adj-HAR-HICOV															−0.1627**

Table A.3

Pairwise GW Test Results: LE

This table reports the average pairwise differences in losses derived from the Euclidean quadratic loss function (LE) of the models in columns 2-16 from the models in column 1. ** and * report significant differences at 99% and 95% level of confidence respectively for the Giacomini-White test.

	A-ScBEKK	**DiagBEKK**	**A-DiagBEKK**	**CCC**	**A-CCC**	**DCC**	**A-DCC**	**OGARCH**	**A-OGARCH**	**EWMA**	**LRCOV**	**HICOV**	**Adj-HICOV**	**adj-HAR-HICOV**	**VHAR**
Panel A: Daily															
ScBEKK	−0.0006*	0.0001	−0.0012**	0.0064**	0.0074**	−0.0006	−0.0006	−0.0017*	−0.0022*	−0.0011*	0.0015	0.0129**	−0.0016*	0.0014	−0.0034**
A-ScBEKK		0.0007*	−0.0006*	0.0070**	0.0080**	0.0000	0.0000	−0.0011	−0.0016*	−0.0005	0.0021	0.0135**	−0.0009	0.0020*	−0.0028**
DiagBEKK			−0.0012**	0.0064**	0.0073**	−0.0007	−0.0007	−0.0018*	−0.0023*	−0.0011*	0.0014	0.0128**	−0.0016*	0.0013	−0.0035**
A-DiagBEKK				0.0076**	0.0086**	0.0006	0.0006	−0.0005	−0.0010	0.0001	0.0027	0.0141**	−0.0004	0.0026**	−0.0022**
CCC					0.0009**	−0.0070**	−0.0070**	−0.0081**	−0.0087**	−0.0075**	−0.0050	0.0065*	−0.0080**	−0.0050*	−0.0099**
A-CCC						−0.0080**	−0.0080**	−0.0091**	−0.0096**	−0.0085**	−0.0059	0.0055	−0.0089**	−0.0060**	−0.0108**
DCC							0.0000	−0.0011**	−0.0016**	−0.0005	0.0021	0.0135**	−0.0010	0.0020**	−0.0028**
A-DCC								−0.0011**	−0.0016**	−0.0005	0.0021	0.0135**	−0.0010	0.0020**	−0.0028**
OGARCH									−0.0005	0.0006*	0.0032	0.0146**	0.0001	0.0031**	−0.0017*
A-OGARCH										0.0011*	0.0037	0.0151**	0.0007	0.0036**	−0.0012
EWMA											0.0026	0.0140**	−0.0005	0.0025**	−0.0023**
LRCOV												0.0114**	−0.0030	−0.0001	−0.0049
HICOV													−0.0145**	−0.0115**	−0.0163**
Adj-HICOV														0.0029**	−0.0019*
adj-HAR-HICOV															−0.0048**
Panel B: Weekly															
ScBEKK	−0.0004	0.0000	−0.0006	0.0058**	0.0068**	−0.0007	−0.0007	−0.0013	−0.0010	−0.0009	−0.0007	0.0152**	0.0062**	0.0031*	−0.0022**
A-ScBEKK		0.0004	−0.0002	0.0063**	0.0072**	−0.0003	−0.0003	−0.0009	−0.0006	−0.0005	−0.0003	0.0156**	0.0067**	0.0035**	−0.0018**
DiagBEKK			−0.0006*	0.0058**	0.0068**	−0.0007	−0.0007	−0.0013	−0.0010	−0.0009	−0.0007	0.0152**	0.0062**	0.0031*	−0.0022**
A-DiagBEKK				0.0064**	0.0074**	−0.0001	−0.0001	−0.0007	−0.0004	−0.0003	−0.0001	0.0158**	0.0068**	0.0037**	−0.0016*
CCC					0.0010**	−0.0065**	−0.0065**	−0.0071**	−0.0069**	−0.0068**	−0.0065**	0.0094**	0.0004	−0.0027	−0.0081**
A-CCC						−0.0075**	−0.0075**	−0.0081**	−0.0078**	−0.0077**	−0.0075**	0.0084*	−0.0006	−0.0037	−0.0090**
DCC							0.0000	−0.0006*	−0.0003	−0.0002	0.0000	0.0159**	0.0069**	0.0038**	−0.0015*
A-DCC								−0.0006*	−0.0003	−0.0002	0.0000	0.0159**	0.0069**	0.0038**	−0.0015*
OGARCH									0.0003	0.0004	0.0006	0.0165**	0.0075**	0.0044**	−0.0009
A-OGARCH										0.0001	0.0003	0.0162**	0.0073**	0.0041**	−0.0012*
EWMA											0.0002	0.0161**	0.0072**	0.0040**	−0.0013*
LRCOV												0.0159**	0.0069**	0.0038**	−0.0015
HICOV													−0.0090*	−0.0121**	−0.0174**
Adj-HICOV														−0.0031	−0.0085**
adj-HAR-HICOV															−0.0053**
Panel C: Monthly															
ScBEKK	0.0001	−0.0002	−0.0003	0.0033	0.0044	0.0001	0.0001	−0.0005	0.0003	−0.0004	0.0000	0.0183**	0.0091**	0.0067**	−0.0014*
A-ScBEKK		−0.0003	−0.0004	0.0032	0.0043*	0.0000	0.0000	−0.0006	0.0002	−0.0005	−0.0001	0.0182**	0.0090**	0.0066**	−0.0015*
DiagBEKK			−0.0001	0.0034	0.0046*	0.0003	0.0003	−0.0003	0.0004	−0.0002	0.0001	0.0184**	0.0092**	0.0069**	−0.0012*
A-DiagBEKK				0.0035*	0.0047*	0.0004	0.0004	−0.0002	0.0005	−0.0001	0.0002	0.0185**	0.0093**	0.0070**	−0.0011
CCC					0.0011**	−0.0032	−0.0032	−0.0038	−0.0030	−0.0037	−0.0033*	0.0150**	0.0058**	0.0034	−0.0047*
A-CCC						−0.0043	−0.0043	−0.0049	−0.0042	−0.0048	−0.0045*	0.0138*	0.0047**	0.0023	−0.0058*
DCC							0.0000	−0.0006	0.0001	−0.0005	−0.0002	0.0181**	0.0090**	0.0066**	−0.0015*
A-DCC								−0.0006	0.0001	−0.0005	−0.0002	0.0181**	0.0090**	0.0066**	−0.0015*
OGARCH									0.0008	0.0001	0.0004	0.0187**	0.0096*	0.0072**	−0.0009
A-OGARCH										−0.0006	−0.0003	0.0180**	0.0088*	0.0065**	−0.0016
EWMA											0.0003	0.0186**	0.0095**	0.0071**	−0.0010
LRCOV												0.0183**	0.0091**	0.0068**	−0.0013*
HICOV													−0.0092	−0.0115*	−0.0196**
Adj-HICOV														−0.0023	−0.0105**
adj-HAR-HICOV															−0.0081**

Table A.4

Pairwise GW Test Results: LF

This table reports the average pairwise differences in losses derived from the Frobenius quadratic loss function (LF) of the models in columns 2-16 from the models in column 1. ** and * report significant differences at 99% and 95% level of confidence respectively for the Giacomini-White test.

	A-ScBEKK	DiagBEKK	A-DiagBEKK	CCC	A-CCC	DCC	A-DCC	OGARCH	A-OGARCH	EWMA	LRCOV	HICOV	Adj-HICOV	adj-HAR-HICOV	VHAR
Panel A: Daily															
ScBEKK	−0.0011**	0.0000	−0.0019**	0.0100**	0.0114**	−0.0011	−0.0011	−0.0026*	−0.0034*	−0.0017*	0.0014	0.0203**	−0.0024*	0.0022	−0.0054**
A-ScBEKK		0.0011*	−0.0008**	0.0110**	0.0124**	0.0000	0.0000	−0.0016	−0.0023*	−0.0006	0.0025	0.0214**	−0.0014	0.0033*	−0.0043**
DiagBEKK			−0.0019**	0.0100**	0.0114**	−0.0011	−0.0011	−0.0026*	−0.0034*	−0.0017*	0.0014	0.0203**	−0.0024*	0.0022	−0.0054**
A-DiagBEKK				0.0119**	0.0133**	0.0008	0.0008	−0.0007	−0.0015	0.0002	0.0033	0.0222**	−0.0005	0.0041**	−0.0035**
CCC					0.0014**	−0.0110**	−0.0110**	−0.0126**	−0.0134**	−0.0116**	−0.0086	0.0103*	−0.0124**	−0.0078*	−0.0153**
A-CCC						−0.0124**	−0.0124**	−0.0140**	−0.0148**	−0.0130**	−0.0100	0.0089*	−0.0138**	−0.0092**	−0.0167**
DCC							0.0000	−0.0016**	−0.0023*	−0.0006	0.0025	0.0214**	−0.0014	0.0033**	−0.0043**
A-DCC								−0.0016**	−0.0023*	−0.0006	0.0025	0.0214**	−0.0014	0.0033**	−0.0043**
OGARCH									−0.0008	0.0010	0.0040	0.0229**	0.0002	0.0048**	−0.0028**
A-OGARCH										0.0017	0.0048	0.0237**	0.0010	0.0056**	−0.0020*
EWMA											0.0031	0.0220**	−0.0008	0.0039**	−0.0037**
LRCOV												0.0189**	−0.0038	0.0008	−0.0068
HICOV													−0.0227**	−0.0181**	−0.0257**
Adj-HICOV														0.0046**	−0.0029**
adj-HAR-HICOV															−0.0076**
Panel B: Weekly															
ScBEKK	−0.0008*	−0.0001	−0.0010*	0.0091**	0.0106**	−0.0013	−0.0013	−0.0019	−0.0014	−0.0014	−0.0012	0.0240**	0.0096**	0.0050**	−0.0034**
A-ScBEKK		0.0007	−0.0003	0.0098**	0.0114**	−0.0005	−0.0005	−0.0012	−0.0007	−0.0006	−0.0004	0.0248**	0.0104**	0.0057**	−0.0026**
DiagBEKK			−0.0010*	0.0091**	0.0107**	−0.0012	−0.0012	−0.0019	−0.0014	−0.0013	−0.0011	0.0241**	0.0097**	0.0050*	−0.0033*
A-DiagBEKK				0.0101**	0.0116**	−0.0002	−0.0002	−0.0009	−0.0004	−0.0003	−0.0001	0.0251**	0.0107**	0.0060**	−0.0023*
CCC					0.0015**	−0.0103**	−0.0103**	−0.0110**	−0.0105**	−0.0105**	−0.0103**	0.0149**	0.0005	−0.0041	−0.0125**
A-CCC						−0.0119**	−0.0119**	−0.0125**	−0.0120**	−0.0120**	−0.0118**	0.0134**	−0.0010	−0.0056	−0.0140**
DCC							0.0000	−0.0007	−0.0002	−0.0001	0.0001	0.0253**	0.0109**	0.0062**	−0.0021*
A-DCC								−0.0007	−0.0002	−0.0001	0.0001	0.0253**	0.0109**	0.0062**	−0.0021*
OGARCH									0.0005	0.0005	0.0007	0.0259**	0.0115**	0.0069**	−0.0014
A-OGARCH										0.0001	0.0003	0.0255**	0.0111**	0.0064**	−0.0019*
EWMA											0.0002	0.0254**	0.0110**	0.0064**	−0.0020*
LRCOV												0.0252**	0.0108**	0.0062**	−0.0022
HICOV													−0.0144*	−0.0190**	−0.0274**
Adj-HICOV														−0.0046	−0.0130**
adj-HAR-HICOV															−0.0084**
Panel C: Monthly															
ScBEKK	0.0000	−0.0003	−0.0005	0.0051	0.0069	−0.0001	−0.0001	−0.0006	0.0006	−0.0006	−0.0002	0.0283**	0.0141**	0.0105**	−0.0022*
A-ScBEKK		−0.0004	−0.0006	0.0051	0.0068	−0.0001	−0.0001	−0.0007	0.0005	−0.0006	−0.0002	0.0283**	0.0140**	0.0105**	−0.0022
DiagBEKK			−0.0002	0.0055	0.0072*	0.0002	0.0002	−0.0003	0.0009	−0.0003	0.0002	0.0287**	0.0144**	0.0109**	−0.0018*
A-DiagBEKK				0.0057*	0.0074*	0.0004	0.0004	−0.0001	0.0011	−0.0001	0.0003	0.0288**	0.0146**	0.0111**	−0.0016
CCC					0.0017**	−0.0052	−0.0052	−0.0058	−0.0046	−0.0057	−0.0053*	0.0232**	0.0090**	0.0054	−0.0073*
A-CCC						−0.0070	−0.0070	−0.0075	−0.0063	−0.0075	−0.0071*	0.0214**	0.0072**	0.0037	−0.0090*
DCC							0.0000	−0.0005	0.0007	−0.0005	−0.0001	0.0284**	0.0142**	0.0106**	−0.0021
A-DCC								−0.0005	0.0007	−0.0005	−0.0001	0.0284**	0.0142**	0.0106**	−0.0021
OGARCH									0.0012	0.0000	0.0005	0.0290**	0.0147*	0.0112**	−0.0015
A-OGARCH										−0.0012	−0.0008	0.0277**	0.0135*	0.0100**	−0.0027
EWMA											0.0004	0.0289**	0.0147**	0.0111**	−0.0016
LRCOV												0.0285**	0.0143**	0.0107**	−0.0020*
HICOV													−0.0142	−0.0178*	−0.0305**
Adj-HICOV														−0.0036	−0.0162**
adj-HAR-HICOV															−0.0127**

Table A.5

Pairwise GW Test Results: LS

This table reports the average pairwise differences in losses derived from the Stein loss function (LS) of the models in columns 2-16 from the models in column 1. ** and * report significant differences at 99% and 95% level of confidence respectively for the Giacomini-White test.

	A-ScBEKK	DiagBEKK	A-DiagBEKK	CCC	A-CCC	DCC	A-DCC	OGARCH	A-OGARCH	EWMA	LRCOV	HICOV	Adj-HICOV	adj-HAR-HICOV	VHAR
Panel A: Daily															
ScBEKK	0.0322**	0.0193*	−0.0003	1.1708**	2.8987**	−0.3235**	−0.3229**	0.0204	0.0303	0.9962**	−0.9596**	0.3242*	−0.7699**	−0.3869**	−1.2872**
A-ScBEKK		−0.0129	−0.0325	1.1385**	2.8664**	−0.3557**	−0.3551**	−0.0119	−0.0019	0.9640**	−0.9918**	0.2919*	−0.8021**	−0.4192**	−1.3195**
DiagBEKK			−0.0196	1.1514**	2.8794**	−0.3428**	−0.3422**	0.0011	0.0110	0.9769**	−0.9789**	0.3048*	−0.7892**	−0.4062**	−1.3065**
A-DiagBEKK				1.1711**	2.8990**	−0.3232**	−0.3226**	0.0207	0.0306	0.9965**	−0.9593**	0.3245**	−0.7696**	−0.3866**	−1.2869**
CCC					1.7279**	−1.4943**	−1.4936**	−1.1504**	−1.1405**	−0.1745	−2.1303**	−0.8466**	−1.9407**	−1.5577**	−2.4580**
A-CCC						−3.2222**	−3.2216**	−2.8783**	−2.8684**	−1.9024**	−3.8582**	−2.5745**	−3.6686**	−3.2856**	−4.1859**
DCC							0.0006	0.3439**	0.3538**	1.3197**	−0.6361**	0.6477**	−0.4464**	−0.0634	−0.9637**
A-DCC								0.3433**	0.3532**	1.3191**	−0.6367**	0.6470**	−0.4470**	−0.0640	−0.9643**
OGARCH									0.0099	0.9759**	−0.9799**	0.3038**	−0.7903**	−0.4073**	−1.3076**
A-OGARCH										0.9659**	−0.9899**	0.2939**	−0.8002**	−0.4172**	−1.3175**
EWMA											−1.9558**	−0.6721**	−1.7662**	−1.3832**	−2.2835**
LRCOV												1.2837**	0.1896*	0.5726**	−0.3277**
HICOV													−1.0941**	−0.7111**	−1.6114**
Adj-HICOV														0.3830**	−0.5173**
adj-HAR-HICOV															−0.9003**
Panel B: Weekly															
ScBEKK	0.0221	0.0058	−0.0133	1.1023**	2.8039**	−0.3054**	−0.3062**	0.0214	0.0379	1.0936**	−1.1752**	0.1265	7.3218**	−0.5104**	−1.1860**
A-ScBEKK		−0.0164	−0.0355	1.0802**	2.7818**	−0.3275**	−0.3283**	−0.0007	0.0158	1.0715**	−1.1973**	0.1044	7.2997**	−0.5325**	−1.2081**
DiagBEKK			−0.0191	1.0966**	2.7982**	−0.3111**	−0.3120**	0.0157	0.0322	1.0879**	−1.1809**	0.1207	7.3160**	−0.5162**	−1.1917**
A-DiagBEKK				1.1157**	2.8173**	−0.2920**	−0.2929**	0.0348	0.0513	1.1070**	−1.1618**	0.1399	7.3351**	−0.4971**	−1.1726**
CCC					1.7016**	−1.4077**	−1.4085**	−1.0809**	−1.0644**	−0.0087	−2.2775**	−0.9758*	6.2195**	−1.6127**	−2.2883**
A-CCC						−3.1093**	−3.1101**	−2.7825**	−2.7660**	−1.7103**	−3.9791**	−2.6774**	4.5179**	−3.3143**	−3.9899**
DCC							−0.0008	0.3268**	0.3433**	1.3990**	−0.8698**	0.4319**	7.6271**	−0.2050	−0.8806**
A-DCC								0.3276**	0.3441**	1.3998**	−0.8690**	0.4327**	7.6280**	−0.2042	−0.8798**
OGARCH									0.0165	1.0722**	−1.1966**	0.1051	7.3004**	−0.5318**	−1.2074**
A-OGARCH										1.0557**	−1.2131**	0.0886	7.2839**	−0.5483**	−1.2239**
EWMA											−2.2688**	−0.9671**	6.2282**	−1.6040**	−2.2796**
LRCOV												1.3017**	8.4969**	0.6648**	−0.0108
HICOV													7.1953**	−0.6369**	−1.3125**
Adj-HICOV														−7.8322**	−8.5078**
adj-HAR-HICOV															−0.6756**
Panel C: Monthly															
ScBEKK	0.0501	0.0350**	0.0665	0.7415*	2.3117**	−0.1875	−0.1897	0.0487	0.0901	1.4250**	−1.0065**	−0.1053	69.1174**	−0.3582	−0.9958**
A-ScBEKK		−0.0151	0.0165	0.6915*	2.2616**	−0.2375	−0.2398	−0.0014	0.0400	1.3749**	−1.0565**	−0.1553	69.0673**	−0.4083	−1.0459**
DiagBEKK			0.0316	0.7066*	2.2767**	−0.2224	−0.2247	0.0137	0.0551	1.3900**	−1.0414**	−0.1402	69.0824**	−0.3932	−1.0308**
A-DiagBEKK				0.6750*	2.2451**	−0.2540	−0.2563	−0.0178	0.0235	1.3584**	−1.0730**	−0.1718	69.0509**	−0.4248	−1.0624**
CCC					1.5702**	−0.9290*	−0.9313*	−0.6928*	−0.6515	0.6834*	−1.7480**	−0.8468	68.3759**	−1.0998	−1.7374**
A-CCC						−2.4991**	−2.5014**	−2.2630**	−2.2216**	−0.8867	−3.3182**	−2.4170*	66.8057**	−2.6699**	−3.3075**
DCC							−0.0023*	0.2362*	0.2775**	1.6124**	−0.8190**	0.0822	69.3049**	−0.1708	−0.8084**
A-DCC								0.2384*	0.2798**	1.6147**	−0.8167**	0.0845	69.3071**	−0.1685	−0.8061**
OGARCH									0.0414**	1.3763**	−1.0552**	−0.1540	69.0687**	−0.4069	−1.0445**
A-OGARCH										1.3349**	−1.0965**	−0.1953	69.0273**	−0.4483	−1.0859**
EWMA											−2.4314**	−1.5303**	67.6924**	−1.7832**	−2.4208**
LRCOV												0.9012**	70.1239**	0.6482**	0.0106
HICOV													69.2227**	−0.2530**	−0.8906**
Adj-HICOV														−69.4756**	−70.1132**
adj-HAR-HICOV															−0.6376**

Table A.6

Pairwise GW Test Results: LQ

This table reports the average pairwise differences in losses of the models in columns 2-16 from the models in column 1. ** and * report significant differences at 99% and 95% level of confidence respectively for the Giacomini-White test.

	A-ScBEKK	DiagBEKK	A-DiagBEKK	CCC	A-CCC	DCC	A-DCC	OGARCH	A-OGARCH	EWMA	LRCOV	HICOV	Adj-HICOV	adj-HAR-HICOV	VHAR
Panel A: Daily															
ScBEKK	0.0322**	0.0193*	−0.0003	1.1708**	2.8987**	−0.3235**	−0.3229**	0.0204	0.0303	0.9962**	−0.9596**	0.3242*	−0.7699**	−0.3869**	−1.2872**
A-ScBEKK		−0.0129	−0.0325	1.1385**	2.8664**	−0.3557**	−0.3551**	−0.0119	−0.0019	0.9640**	−0.9918**	0.2919*	−0.8021**	−0.4192**	−1.3195**
DiagBEKK			−0.0196	1.1514**	2.8794**	−0.3428**	−0.3422**	0.0011	0.0110	0.9769**	−0.9789**	0.3048*	−0.7892**	−0.4062**	−1.3065**
A-DiagBEKK				1.1711**	2.8990**	−0.3232**	−0.3226**	0.0207	0.0306	0.9965**	−0.9593**	0.3245**	−0.7696**	−0.3866**	−1.2869**
CCC					1.7279**	−1.4943**	−1.4936**	−1.1504**	−1.1405**	−0.1745	−2.1303**	−0.8466**	−1.9407**	−1.5577**	−2.4580**
A-CCC						−3.2222**	−3.2216**	−2.8783**	−2.8684**	−1.9024**	−3.8582**	−2.5745**	−3.6686**	−3.2856**	−4.1859**
DCC							0.0006	0.3439**	0.3538**	1.3197**	−0.6361**	0.6477**	−0.4464**	−0.0634	−0.9637**
A-DCC								0.3433**	0.3532**	1.3191**	−0.6367**	0.6470**	−0.4470**	−0.0640	−0.9643**
OGARCH									0.0099	0.9759**	−0.9799**	0.3038**	−0.7903**	−0.4073**	−1.3076**
A-OGARCH										0.9659**	−0.9899**	0.2939**	−0.8002**	−0.4172**	−1.3175**
EWMA											−1.9558**	−0.6721**	−1.7662**	−1.3832**	−2.2835**
LRCOV												1.2837**	0.1896*	0.5726**	−0.3277**
HICOV													−1.0941**	−0.7111**	−1.6114**
Adj-HICOV														0.3830**	−0.5173**
adj-HAR-HICOV															−0.9003**
Panel B: Weekly															
ScBEKK	0.0221	0.0058	−0.0133	1.1023**	2.8039**	−0.3054**	−0.3062**	0.0214	0.0379	1.0936**	−1.1752**	0.1265	7.3218**	−0.5104**	−1.1860**
A-ScBEKK		−0.0164	−0.0355	1.0802**	2.7818**	−0.3275**	−0.3283**	−0.0007	0.0158	1.0715**	−1.1973**	0.1044	7.2997**	−0.5325**	−1.2081**
DiagBEKK			−0.0191	1.0966**	2.7982**	−0.3111**	−0.3120**	0.0157	0.0322	1.0879**	−1.1809**	0.1207	7.3160**	−0.5162**	−1.1917**
A-DiagBEKK				1.1157**	2.8173**	−0.2920**	−0.2929**	0.0348	0.0513	1.1070**	−1.1618**	0.1399	7.3351**	−0.4971**	−1.1726**
CCC					1.7016**	−1.4077**	−1.4085**	−1.0809**	−1.0644**	−0.0087	−2.2775**	−0.9758*	6.2195**	−1.6127**	−2.2883**
A-CCC						−3.1093**	−3.1101**	−2.7825**	−2.7660**	−1.7103**	−3.9791**	−2.6774**	4.5179**	−3.3143**	−3.9899**
DCC							−0.0008	0.3268**	0.3433**	1.3990**	−0.8698**	0.4319**	7.6271**	−0.2050	−0.8806**
A-DCC								0.3276**	0.3441**	1.3998**	−0.8690**	0.4327**	7.6280**	−0.2042	−0.8798**
OGARCH									0.0165	1.0722**	−1.1966**	0.1051	7.3004**	−0.5318**	−1.2074**
A-OGARCH										1.0557**	−1.2131**	0.0886	7.2839**	−0.5483**	−1.2239**
EWMA											−2.2688**	−0.9671**	6.2282**	−1.6040**	−2.2796**
LRCOV												1.3017**	8.4969**	0.6648**	−0.0108
HICOV													7.1953**	−0.6369**	−1.3125**
Adj-HICOV														−7.8322**	−8.5078**
adj-HAR-HICOV															−0.6756**
Panel C: Monthly															
ScBEKK	0.0501	0.0350**	0.0665	0.7415*	2.3117**	−0.1875	−0.1897	0.0487	0.0901	1.4250**	−1.0065**	−0.1053	69.1174**	−0.3582	−0.9958**
A-ScBEKK		−0.0151	0.0165	0.6915*	2.2616**	−0.2375	−0.2398	−0.0014	0.0400	1.3749**	−1.0565**	−0.1553	69.0673**	−0.4083	−1.0459**
DiagBEKK			0.0316	0.7066*	2.2767**	−0.2224	−0.2247	0.0137	0.0551	1.3900**	−1.0414**	−0.1402	69.0824**	−0.3932	−1.0308**
A-DiagBEKK				0.6750*	2.2451**	−0.2540	−0.2563	−0.0178	0.0235	1.3584**	−1.0730**	−0.1718	69.0509**	−0.4248	−1.0624**
CCC					1.5702**	−0.9290*	−0.9313*	−0.6928*	−0.6515	0.6834*	−1.7480**	−0.8468	68.3759**	−1.0998	−1.7374**
A-CCC						−2.4991**	−2.5014**	−2.2630**	−2.2216**	−0.8867	−3.3182**	−2.4170*	66.8057**	−2.6699**	−3.3075**
DCC							−0.0023*	0.2362*	0.2775**	1.6124**	−0.8190**	0.0822	69.3049**	−0.1708	−0.8084**
A-DCC								0.2384*	0.2798**	1.6147**	−0.8167**	0.0845	69.3071**	−0.1685	−0.8061**
OGARCH									0.0414**	1.3763**	−1.0552**	−0.1540	69.0687**	−0.4069	−1.0445**
A-OGARCH										1.3349**	−1.0965**	−0.1953	69.0273**	−0.4483	−1.0859**
EWMA											−2.4314**	−1.5303**	67.6924**	−1.7832**	−2.4208**
LRCOV												0.9012**	70.1239**	0.6482**	0.0106
HICOV													69.2227**	−0.2530**	−0.8906**
Adj-HICOV														−69.4756**	−70.1132**
adj-HAR-HICOV															−0.6376**

Table A.7

Giacomini-White test of Out-of-Sample Forecasting Performance: Using 1,250 In-sample Observations

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step, model parameters are estimated using in-sample a rolling overlapping window of 1,250 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the GW test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.1729	0.0156	0.0232	1.9596	−19.4799
A-ScBEKK	0.1682	0.0149	0.0221	1.9362	−19.5034
DiagBEKK	0.1722	0.0156	0.0233	1.9505	−19.4891
A-DiagBEKK	0.1631	0.0148	0.0220	1.8748	−19.5648
CCC	0.1580	0.0144	0.0213	1.5653	−19.8743
A-CCC	0.1511	0.0138	0.0202	1.5328	−19.9067
DCC	0.1624	0.0144	0.0214	1.6622	−19.7773
A-DCC	0.1624	0.0144	0.0214	1.6622	−19.7773
OGARCH	0.1662	0.0145	0.0215	1.9326	−19.5070
A-OGARCH	0.1562	0.0132	0.0196	1.9138	−19.5258
EWMA	0.1641	0.0154	0.0229	3.1971	−18.2425
LRCOV	0.1521	0.0179	0.0259	1.2379	−20.2017
HICOV	0.3802	0.0292	0.0447	2.5279	−18.9117
Adj-HICOV	0.1392	0.0127	0.0188	1.2761	−20.1634
adj-HAR-HICOV	0.2361	0.0178	0.0268	1.8129	−19.6267
VHAR	0.0826*	0.0066*	0.0098*	0.2451*	−21.1944*
	Panel B: Weekly Forecasts				
ScBEKK	0.1376	0.0070	0.0105	1.3601	−19.6289
A-ScBEKK	0.1306	0.0065	0.0096	1.3468	−19.6422
DiagBEKK	0.1370	0.0070	0.0106	1.3557	−19.6333
A-DiagBEKK	0.1254	0.0064	0.0095	1.2960	−19.6929
CCC	0.1147	0.0055	0.0081	0.9735	−20.0155
A-CCC	0.1085	0.0052	0.0076	0.9496	−20.0394
DCC	0.1196	0.0055	0.0082	1.0541	−19.9349
A-DCC	0.1196	0.0055	0.0082	1.0541	−19.9349
OGARCH	0.1259	0.0057	0.0085	1.3613	−19.6276
A-OGARCH	0.1157	0.0049	0.0074	1.3520	−19.6369
EWMA	0.1274	0.0067	0.0101	2.4352	−18.5537
LRCOV	0.1268	0.0086	0.0128	0.7246	−20.2644
HICOV	0.3576	0.0195	0.0302	2.0219	−18.9671
Adj-HICOV	0.1038	0.0055	0.0082	0.5149	−20.4740
adj-HAR-HICOV	0.2022	0.0088	0.0134	1.1707	−19.8182
VHAR	0.0531*	0.0022*	0.0032*	0.0981*	−20.8908*
	Panel C: Monthly Forecasts				
ScBEKK	0.1078	0.0031	0.0047	0.9770	−19.7245
A-ScBEKK	0.1021	0.0028	0.0042	0.9894	−19.7121
DiagBEKK	0.1077	0.0031	0.0047	0.9769	−19.7245
A-DiagBEKK	0.0974	0.0028	0.0041	0.9589	−19.7425
CCC	0.0786	0.0019	0.0028	0.6722	−20.0293
A-CCC	0.0777	0.0019	0.0028	0.6690	−20.0325
DCC	0.0826	0.0019	0.0028	0.7247	−19.9768
A-DCC	0.0826	0.0019	0.0028	0.7247	−19.9768
OGARCH	0.0906	0.0020	0.0031	1.0536	−19.6479
A-OGARCH	0.0856	0.0018	0.0027	1.0556	−19.6459
EWMA	0.0953	0.0029	0.0043	1.8322	−18.8693
LRCOV	0.1448	0.0074	0.0112	0.9108	−19.7907
HICOV	0.3402	0.0161	0.0251	1.8276	−18.8739
Adj-HICOV	0.0871	0.0027	0.0040	0.3337	−20.3678
adj-HAR-HICOV	0.1849	0.0057	0.0087	0.9726	−19.7289
VHAR	0.0360*	0.0008*	0.0011*	0.0559*	−20.6456*

Table A.8

Giacomini-White test of Out-of-Sample Forecasting Performance with Sample Starting from 2002

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations starting from 2002. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	Losses				
	L_A	L_E	L_F	L_S	L_Q
	Panel A: Daily Forecasts				
ScBEKK	0.1929	0.0199	0.0297	2.3692	−18.7928
A-ScBEKK	0.1833	0.0191	0.0283	2.4222	−18.7398
DiagBEKK	0.1895	0.0198	0.0296	2.3783	−18.7837
A-DiagBEKK	0.1772	0.0182	0.0271	2.3782	−18.7838
CCC	0.2383	0.0283	0.0428	3.8580	−17.3040
A-CCC	0.2366	0.0294	0.0445	5.9266	−15.2354
DCC	0.1881	0.0187	0.0279	1.9477	−19.2143
A-DCC	0.1881	0.0187	0.0279	1.9477	−19.2143
OGARCH	0.1850	0.0175	0.0262	2.4129	−18.7491
A-OGARCH	0.1832	0.0169†	0.0252†	2.4218	−18.7402
EWMA	0.1793	0.0184	0.0275	3.4463	−17.7157
LRCOV	0.1640	0.0208†	0.0301†	1.1416	−20.0203
HICOV	0.4207	0.0358	0.0548	2.5311	−18.6309
Adj-HICOV	0.1658	0.0181	0.0269	1.3492	−19.8128
adj-HAR-HICOV	0.2645	0.0218	0.0328	1.8085	−19.3535
VHAR	0.1396*	0.0155*	0.0229*	0.8318*	−20.3302*
	Panel B: Weekly Forecasts				
ScBEKK	0.1729	0.0116	0.0174	2.1076	−18.6171
A-ScBEKK	0.1618	0.0110	0.0164	2.1476	−18.5771
DiagBEKK	0.1684	0.0114	0.0171	2.1076	−18.6171
A-DiagBEKK	0.1580	0.0107†	0.0159†	2.0872	−18.6374
CCC	0.2279	0.0192	0.0293	3.5321	−17.1926
A-CCC	0.2282	0.0204	0.0312	5.5682	−15.1564
DCC	0.1640	0.0103†	0.0153†	1.6869	−19.0378
A-DCC	0.1640	0.0103†	0.0153†	1.6869	−19.0378
OGARCH	0.1658	0.0097†	0.0146†	2.1495	−18.5752
A-OGARCH	0.1664	0.0100†	0.0152†	2.1697	−18.5550
EWMA	0.1568	0.0103	0.0155	3.2875	−17.4372
LRCOV	0.1356	0.0104†	0.0155†	0.6639†	−20.0608†
HICOV	0.4145	0.0303	0.0469	2.0707	−18.6540
Adj-HICOV	0.2483	0.0192	0.0292	8.9542	−11.7704
adj-HAR-HICOV	0.2664	0.0156	0.0238	1.4514	−19.2733
VHAR	0.1203*	0.0087*	0.0131*	0.6625*	−20.0621*
	Panel C: Monthly Forecasts				
ScBEKK	0.1937	0.0101	0.0154	2.2457	−18.2066
A-ScBEKK	0.1845	0.0102	0.0154†	2.3208	−18.1315
DiagBEKK	0.1845	0.0098	0.0148†	2.2776	−18.1747
A-DiagBEKK	0.1777	0.0097†	0.0146†	2.3377	−18.1146
CCC	0.2249	0.0145	0.0222	3.2629	−17.1895
A-CCC	0.2243	0.0159	0.0244	5.1752	−15.2771
DCC	0.1878	0.0098†	0.0147†	1.9731	−18.4792
A-DCC	0.1878	0.0098†	0.0147†	1.9731	−18.4792
OGARCH	0.1909	0.0092†	0.0142†	2.2996	−18.1527
A-OGARCH	0.1925	0.0102†	0.0158†	2.3548	−18.0976
EWMA	0.1738	0.0095†	0.0144†	3.7161	−16.7362
LRCOV	0.1629	0.0100	0.0150	0.9639*	−19.4884*
HICOV	0.4377	0.0327	0.0503	1.9645	−18.4878
Adj-HICOV	0.3168	0.0213	0.0326	70.7516	50.2993
adj-HAR-HICOV	0.3331	0.0188	0.0289	1.7889	−18.6634
VHAR	0.1358*	0.0083*	0.0125*	0.9747†	−19.4776†

Table A.9

Giacomini-White test of Out-of-Sample Forecasting Performance Using Sample Starting from 2003

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations starting from 2003. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.2010	0.0232	0.0346	2.6078	−18.4099
A-ScBEKK	0.1920	0.0222	0.0330	2.6727	−18.3449
DiagBEKK	0.1971	0.0230	0.0344	2.6100	−18.4077
A-DiagBEKK	0.1842	0.0213	0.0316	2.5868	−18.4308
CCC	0.2582	0.0331	0.0500	4.2450	−16.7727
A-CCC	0.2568	0.0344	0.0519	6.5585	−14.4591
DCC	0.1972	0.0218	0.0324	2.0845	−18.9331
A-DCC	0.1972	0.0218	0.0324	2.0845	−18.9331
OGARCH	0.1922	0.0203	0.0303	2.5847	−18.4330
A-OGARCH	0.1913	0.0196†	0.0291†	2.5946	−18.4230
EWMA	0.1902	0.0215	0.0320	3.7613	−17.2563
LRCOV	0.1762	0.0242†	0.0351†	1.1696	−19.8480
HICOV	0.4409	0.0408	0.0625	2.5430	−18.4747
Adj-HICOV	0.1789	0.0212	0.0316	1.3969	−19.6208
adj-HAR-HICOV	0.2774	0.0251	0.0377	1.8503	−19.1674
VHAR	0.1506*	0.0182*	0.0268*	0.8682*	−20.1495*
	Panel B: Weekly Forecasts				
ScBEKK	0.1804	0.0134	0.0201	2.3695	−18.2028
A-ScBEKK	0.1694	0.0128	0.0191	2.4185	−18.1537
DiagBEKK	0.1751	0.0133	0.0199	2.3621	−18.2102
A-DiagBEKK	0.1641	0.0124†	0.0185†	2.3192	−18.2531
CCC	0.2476	0.0225	0.0343	3.9240	−16.6483
A-CCC	0.2483	0.0238	0.0364	6.1979	−14.3743
DCC	0.1717	0.0119†	0.0177†	1.8440	−18.7283
A-DCC	0.1717	0.0119†	0.0177†	1.8440	−18.7283
OGARCH	0.1725	0.0112†	0.0168†	2.3436	−18.2287
A-OGARCH	0.1746	0.0116†	0.0176†	2.3676	−18.2047
EWMA	0.1670	0.0120†	0.0180†	3.6400	−16.9323
LRCOV	0.1491	0.0123†	0.0183†	0.7217*	−19.8506*
HICOV	0.4328	0.0343	0.0531	2.0721	−18.5002
Adj-HICOV	0.2643	0.0222	0.0338	9.3162	−11.2561
adj-HAR-HICOV	0.2765	0.0176	0.0269	1.4896	−19.0826
VHAR	0.1322*	0.0103*	0.0155*	0.7287†	−19.8436†
	Panel C: Monthly Forecasts				
ScBEKK	0.2001	0.0116†	0.0175†	2.5666	−17.7324
A-ScBEKK	0.1917	0.0118†	0.0178†	2.6579	−17.6411
DiagBEKK	0.1903	0.0113†	0.0170†	2.5987	−17.7004
A-DiagBEKK	0.1833	0.0112†	0.0168†	2.6615	−17.6376
CCC	0.2430	0.0169	0.0258	3.6219	−16.6771
A-CCC	0.2435	0.0185	0.0283	5.7628	−14.5362
DCC	0.1962	0.0113†	0.0168†	2.2225	−18.0766
A-DCC	0.1962	0.0113†	0.0168†	2.2225	−18.0766
OGARCH	0.1985	0.0106†	0.0162†	2.5588	−17.7403
A-OGARCH	0.2026	0.0118†	0.0182†	2.6263	−17.6728
EWMA	0.1854	0.0110†	0.0166†	4.1733	−16.1258
LRCOV	0.1774	0.0117	0.0175	1.0901*	−19.2090*
HICOV	0.4489	0.0360	0.0553	1.9567	−18.3423
Adj-HICOV	0.3350	0.0243	0.0372	73.8893	53.5902
adj-HAR-HICOV	0.3327	0.0191	0.0292	1.8487	−18.4504
VHAR	0.1490*	0.0098*	0.0147*	1.1081†	−19.1910†

Table A.10

Giacomini-White Test of Out-of-Sample Forecasting Performance: Using Non-Overlapping Forecasts

This table reports the average non-overlapping forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling of 1,000 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.1757	0.0167	0.0249	2.1970	−19.2481
A-ScBEKK	0.1681	0.0161	0.0238	2.2292	−19.2159
DiagBEKK	0.1737	0.0167	0.0249	2.2163	−19.2288
A-DiagBEKK	0.1636	0.0155	0.0230	2.1967	−19.2484
CCC	0.2132	0.0231	0.0349	3.3677	−18.0774
A-CCC	0.2096	0.0241	0.0363	5.0957	−16.3495
DCC	0.1732	0.0161	0.0238	1.8735	−19.5716
A-DCC	0.1732	0.0161	0.0238	1.8741	−19.5710
OGARCH	0.1699	0.0150	0.0223	2.2173	−19.2278
A-OGARCH	0.1697	0.0145†	0.0215	2.2273	−19.2178
EWMA	0.1651	0.0156	0.0232	3.1932	−18.2519
LRCOV	0.1532	0.0181†	0.0263†	1.2374	−20.2077
HICOV	0.3817	0.0296	0.0452	2.5211	−18.9240
Adj-HICOV	0.1509	0.0151	0.0225	1.4271	−20.0181
adj-HAR-HICOV	0.2369	0.0181	0.0271	1.8101	−19.6351
VHAR	0.1297*	0.0133*	0.0195*	0.9097*	−20.5354*
	Panel B: Weekly Forecasts				
ScBEKK	0.1531	0.0103	0.0154	2.0021	−18.9741
A-ScBEKK	0.1471	0.0102	0.0151	2.0229	−18.9532
DiagBEKK	0.1525	0.0106	0.0157†	2.0023	−18.9739
A-DiagBEKK	0.1456	0.0102†	0.0151†	1.9948	−18.9813
CCC	0.2057	0.0168	0.0256	3.1563	−17.8198
A-CCC	0.2032	0.0179	0.0273	5.2325	−15.7437
DCC	0.1511	0.0101†	0.0147†	1.6903	−19.2858
A-DCC	0.1511	0.0101†	0.0147†	1.6907	−19.2855
OGARCH	0.1510	0.0092†	0.0137†	1.9936	−18.9826
A-OGARCH	0.1552	0.0095†	0.0143†	1.9976	−18.9785
EWMA	0.1424	0.0096†	0.0143†	3.1442	−17.8319
LRCOV	0.1317	0.0107†	0.0157†	0.7641†	−20.2121†
HICOV	0.3747	0.0284	0.0441	1.9793	−18.9968
Adj-HICOV	0.2310	0.0167	0.0252	9.7691	−11.2070
adj-HAR-HICOV	0.2330	0.0144	0.0219	1.3678	−19.6084
VHAR	0.1144*	0.0087*	0.0128*	0.7592*	−20.217*
	Panel C: Monthly Forecasts				
ScBEKK	0.1712	0.0088†	0.0133†	1.9106†	−18.8166†
A-ScBEKK	0.1703	0.0092†	0.0139†	2.0161†	−18.7112†
DiagBEKK	0.1647	0.0083†	0.0125†	1.9677	−18.7595
A-DiagBEKK	0.1610	0.0087†	0.0133†	2.0625†	−18.6648†
CCC	0.1929	0.0123†	0.0188†	2.9604†	−17.7668†
A-CCC	0.1971	0.0140†	0.0214†	4.7206†	−16.0067†
DCC	0.1632	0.0065†	0.0099†	1.6761	−19.0512
A-DCC	0.1632	0.0065*	0.0099*	1.6731	−19.0542
OGARCH	0.1700	0.0076†	0.0117†	1.9288	−18.7984
A-OGARCH	0.1758	0.0109†	0.0170†	1.9814	−18.7458
EWMA	0.1579	0.0081†	0.0123†	3.2918	−17.4354
LRCOV	0.1546	0.0097†	0.0145†	0.9227*	−19.8045*
HICOV	0.3853	0.0281†	0.0429†	1.8611	−18.8661
Adj-HICOV	0.2865	0.0176†	0.0270†	71.9458	51.2186
adj-HAR-HICOV	0.2747	0.0140	0.0213	1.5838	−19.1434
VHAR	0.1278*	0.0083†	0.0124†	0.9346†	−19.7927†

Table A.11

Giacomini-White Test of Out-of-Sample Forecasting Performance: Using Martens' Overnight Returns

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling overlapping window of 1,000 overnight returns estimating following Martens (2002). The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.2974	0.0439	0.0660	2.8921	−16.2788
A-ScBEKK	0.2835	0.0418	0.0630	2.8578	−16.3132
DiagBEKK	0.2932	0.0430	0.0645	2.9005	−16.2705
A-DiagBEKK	0.2636	0.0394†	0.0586†	2.8259	−16.3450
CCC	0.3747	0.0599	0.0903	3.0813	−16.0897
A-CCC	0.3443	0.0604	0.0911	4.4921	−14.6789
DCC	0.3062	0.0454	0.0690	2.3108	−16.8602
A-DCC	0.3062	0.0454	0.0690	2.3166	−16.8543
OGARCH	0.3015	0.0435	0.0659	2.7360	−16.4349
A-OGARCH	0.3227	0.0483	0.0752	2.7087	−16.4622
EWMA	0.3014	0.0451	0.0682	4.1032	−15.0678
LRCOV	0.2527	0.0490†	0.0713†	1.3446	−17.8263
HICOV	0.3019	0.0400	0.0597	1.7751	−17.3958
Adj-HICOV	0.2355	0.0448	0.0669	2.6265	−16.5445
adj-HAR-HICOV	0.2289	0.0400†	0.0594†	1.7536	−17.4174
VHAR	0.2138*	0.0358*	0.0530*	0.9718*	−18.1992*
	Panel B: Weekly Forecasts				
ScBEKK	0.2576	0.0248	0.0377	2.5757	−16.1232
A-ScBEKK	0.2452	0.0239	0.0368	2.5349	−16.1639
DiagBEKK	0.2536	0.0240	0.0364	2.5795	−16.1194
A-DiagBEKK	0.2266	0.0208†	0.0311†	2.5245	−16.1744
CCC	0.3530	0.0379	0.0577	2.5789	−16.1200
A-CCC	0.3264	0.0393	0.0598	3.9117	−14.7872
DCC	0.2709	0.0271	0.0418	2.0188	−16.6801
A-DCC	0.2709	0.0271	0.0418	2.0211	−16.6778
OGARCH	0.2695	0.0257†	0.0399†	2.4226	−16.2763
A-OGARCH	0.2933	0.0322†	0.0515	2.3918	−16.3070
EWMA	0.2620	0.0265	0.0410	3.8946	−14.8043
LRCOV	0.2107	0.0236†	0.0352†	0.7505†	−17.9484†
HICOV	0.2729	0.0231	0.0349	1.0960	−17.6028
Adj-HICOV	0.4264	0.0497	0.0759	20.0301	1.3312
adj-HAR-HICOV	0.2059	0.0218†	0.0326†	0.9957	−17.7032
VHAR	0.1845*	0.0195*	0.0292*	0.7424*	−17.9565*
	Panel C: Monthly Forecasts				
ScBEKK	0.2867	0.0228†	0.0352†	2.7472	−15.6642
A-ScBEKK	0.2806	0.0236†	0.0369†	2.6580	−15.7534
DiagBEKK	0.2809	0.0218†	0.0336†	2.7858	−15.6257
A-DiagBEKK	0.2500	0.0191†	0.0288†	2.6905	−15.7209
CCC	0.3460	0.0283	0.0433	2.3355	−16.0759
A-CCC	0.3215	0.0301	0.0461	3.2976	−15.1139
DCC	0.3041	0.0260†	0.0406†	2.2450	−16.1664
A-DCC	0.3041	0.0261†	0.0406†	2.2399	−16.1716
OGARCH	0.3063	0.0256†	0.0405†	2.6444	−15.7670
A-OGARCH	0.3221	0.0302†	0.0484†	2.6414	−15.7700
EWMA	0.2931	0.0266†	0.0419†	4.5285	−13.8829
LRCOV	0.2473	0.0216	0.0325	0.9916*	−17.4198*
HICOV	0.3012	0.0221†	0.0336†	1.0305†	−17.3809†
Adj-HICOV	0.4886	0.0484	0.0745	126.0610	107.6496
adj-HAR-HICOV	0.2570	0.0201†	0.0307†	1.2526	−17.1589
VHAR	0.2073*	0.0179*	0.0271*	1.0092†	−17.4022†

Table A.12

Giacomini-White Test of Out-of-Sample Forecasting Performance: Using Hansen's Overnight Returns

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling overlapping window of 1,000 overnight returns estimating following (Hansen and Lunde, 2005). The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.3267	0.0635†	0.1036†	−4.5513	−25.4435
A-ScBEKK	0.3110	0.0595†	0.0972†	−4.6837	−25.5758
DiagBEKK	0.3255	0.0630†	0.1030†	−4.4428	−25.3349
A-DiagBEKK	0.3082	0.0611†	0.1005†	−4.5360	−25.4281
CCC	0.4473	0.0942	0.1567	−2.2305*	−23.1226*
A-CCC	0.4341	0.0960	0.1600	−3.4843	−24.3764
DCC	0.3324	0.0616†	0.1002†	−3.8070	−24.6991
A-DCC	0.3324	0.0616†	0.1002†	−3.8301	−24.7222
OGARCH	0.3242	0.0587†	0.0951†	−4.2062	−25.0983
A-OGARCH	0.3324	0.0578*	0.0931*	−4.2183	−25.1105
EWMA	0.3239	0.0618†	0.1003†	−5.7145	−26.6066
LRCOV	0.3129	0.0716†	0.1142†	−2.8959†	−23.7880†
HICOV	0.3573	0.0583†	0.0949†	−2.5902†	−23.4823†
Adj-HICOV	0.2955	0.0669†	0.1091†	−7.6787†	−28.5709†
adj-HAR-HICOV	0.2796*	0.0594†	0.0965†	−4.0784†	−24.9705†
VHAR	0.6239	0.1286	0.2136	−1164.1885	−1185.0806
	Panel B: Weekly Forecasts				
ScBEKK	0.2798	0.0343†	0.0562†	−4.3890	−25.2413
A-ScBEKK	0.2650	0.0320†	0.0524†	−4.4929	−25.3451
DiagBEKK	0.2800	0.0341†	0.0561†	−4.2517	−25.1039
A-DiagBEKK	0.2693	0.0330†	0.0550†	−4.3168	−25.1690
CCC	0.4225	0.0613	0.1031	−2.3118	−23.1641
A-CCC	0.4137	0.0642	0.1083	−3.6259	−24.4781
DCC	0.2847	0.0336	0.0545	−3.6904	−24.5427
A-DCC	0.2847	0.0336	0.0545	−3.7069	−24.5591
OGARCH	0.2793	0.0314*	0.0509*	−4.0860	−24.9382
A-OGARCH	0.2938	0.0337†	0.0543†	−4.0984	−24.9506
EWMA	0.2752	0.0331†	0.0537†	−5.7033	−26.5556
LRCOV	0.2609†	0.0348†	0.0568†	1.1998*	−19.6525
HICOV	0.3207	0.0331†	0.0547†	1.3469†	−19.5054
Adj-HICOV	0.5301	0.0748	0.1246	25.3841	4.5318*
adj-HAR-HICOV	0.2503*	0.0324†	0.0530†	1.8377†	−19.0146
VHAR	0.6244	0.0945	0.1581	−945.2836	−966.1359
	Panel C: Monthly Forecasts				
ScBEKK	0.2998†	0.0296†	0.0486†	−3.9011	−24.5946
A-ScBEKK	0.2934*	0.0296*	0.0486†	−3.9066	−24.6001
DiagBEKK	0.3000†	0.0297†	0.0490†	−3.6598	−24.3533
A-DiagBEKK	0.2945†	0.0303†	0.0507†	−3.7025	−24.3960
CCC	0.4103	0.0462	0.0782	−2.2154*	−22.909*
A-CCC	0.4033	0.0497	0.0843	−3.4081	−24.1016
DCC	0.3152	0.0305†	0.0494†	−3.3194	−24.0130
A-DCC	0.3152	0.0305†	0.0494†	−3.3236	−24.0171
OGARCH	0.3147	0.0297†	0.0484*	−3.8432	−24.5367
A-OGARCH	0.3314	0.0334†	0.0545†	−3.8175	−24.5110
EWMA	0.3019†	0.0301†	0.0486†	−5.6563	−26.3498
LRCOV	0.3069†	0.0322†	0.0530†	−4.8437†	−25.5372†
HICOV	0.3561	0.0317†	0.0527†	−3.2431†	−23.9366†
Adj-HICOV	0.6047	0.0728	0.1222	−3.3287†	−24.0222†
adj-HAR-HICOV	0.3098†	0.0300†	0.0499†	−6.8144†	−27.5079†
VHAR	0.6261	0.0772	0.1296	−888.8826	−909.5761

Table A.13

Giacomini-White Test of Out-of-Sample Forecasting Performance Using Squared Overnight Returns

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling overlapping window of 1,000 overnight squared returns. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.3703	0.0770†	0.1217†	2.7228	−17.6982
A-ScBEKK	0.3551	0.0733†	0.1162†	2.6489	−17.7720
DiagBEKK	0.3648	0.0763†	0.1205†	2.7334	−17.6876
A-DiagBEKK	0.3323	0.0724†	0.1144†	2.6030	−17.8180
CCC	0.4300	0.1029	0.1631	3.4520	−16.9689
A-CCC	0.3947	0.1037	0.1645	4.5980	−15.8229
DCC	0.3711	0.0738†	0.1168†	2.3074	−18.1136
A-DCC	0.3711	0.0738†	0.1168†	2.3104	−18.1106
OGARCH	0.3678	0.0693†	0.1096†	2.6320	−17.7890
A-OGARCH	0.3790	0.0669*	0.1066*	2.5980	−17.8229
EWMA	0.3697	0.0752†	0.1190†	3.5082	−16.9128
LRCOV	0.3952	0.1186	0.1884	2.4830	−17.9379
HICOV	0.3877	0.0740†	0.1177†	2.5331	−17.8879
Adj-HICOV	0.2932*	0.0837†	0.1328†	3.9272	−16.4938
adj-HAR-HICOV	0.3077	0.0776†	0.1232†	2.7280	−17.6930
VHAR	0.3011†	0.0747†	0.1187†	1.6913*	−18.7297*
	Panel B: Weekly Forecasts				
ScBEKK	0.2832	0.0347†	0.0543†	2.0999	−17.5093
A-ScBEKK	0.2683	0.0324†	0.0509†	2.0312	−17.5780
DiagBEKK	0.2798	0.0343†	0.0536†	2.1001	−17.5092
A-DiagBEKK	0.2544	0.0316†	0.0493†	2.0022	−17.6070
CCC	0.3877	0.0568	0.0895	2.6409	−16.9684
A-CCC	0.3599	0.0583	0.0920	3.7103	−15.8990
DCC	0.2866	0.0325†	0.0509†	1.6934	−17.9159
A-DCC	0.2866	0.0325†	0.0509†	1.6936	−17.9156
OGARCH	0.2803	0.0291*	0.0454*	2.0027	−17.6065
A-OGARCH	0.2943	0.0296†	0.0471†	1.9683	−17.6409
EWMA	0.2786	0.0335†	0.0525†	2.9758	−16.6334
LRCOV	0.2625	0.0360†	0.0569†	1.1785†	−18.4307†
HICOV	0.3135	0.0349†	0.0553†	1.4250	−18.1842
Adj-HICOV	0.4568	0.0707	0.1115	22.4377	2.8284
adj-HAR-HICOV	0.2470	0.0367†	0.0580†	1.4679	−18.1413
VHAR	0.2270*	0.0320†	0.0504†	1.1678*	−18.4415*
	Panel C: Monthly Forecasts				
ScBEKK	0.3028	0.0303†	0.0475†	2.1633	−17.0294
A-ScBEKK	0.2951	0.0307†	0.0483†	2.0856	−17.1070
DiagBEKK	0.2977	0.0300†	0.0469†	2.2021	−16.9906
A-DiagBEKK	0.2676	0.0286†	0.0446*	2.1097	−17.0829
CCC	0.3754	0.0413	0.0649	2.2906	−16.9021
A-CCC	0.3498	0.0434	0.0684	3.0494	−16.1433
DCC	0.3168	0.0307†	0.0482†	1.8266	−17.3661
A-DCC	0.3168	0.0308†	0.0483†	1.8213	−17.3714
OGARCH	0.3177	0.0294†	0.0464†	2.1365	−17.0562
A-OGARCH	0.3287	0.0330†	0.0525†	2.1337	−17.0590
EWMA	0.3076	0.0315†	0.0496†	3.3832	−15.8095
LRCOV	0.2930	0.0353†	0.0553†	1.2463†	−17.9464†
HICOV	0.3278	0.0303†	0.0476†	1.2024*	−17.9903*
Adj-HICOV	0.5202	0.0642	0.1011	132.3440	113.1513
adj-HAR-HICOV	0.2842	0.0309†	0.0486†	1.5521†	−17.6405†
VHAR	0.2374*	0.0284*	0.0446†	1.4097†	−17.7830†

Table A.14

Giacomini-White Test of Out-of-Sample Forecasting Performance: Without Interpolation in High-Frequency Data

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.3443	0.0297	0.0477	1.8590	−19.6062
A-ScBEKK	0.3381	0.0309	0.0502	1.8003	−19.6650
DiagBEKK	0.3336	0.0279	0.0447	1.8727	−19.5926
A-DiagBEKK	0.2864	0.0206	0.0329	1.8052	−19.6601
CCC	0.3483	0.0346	0.0550	1.5078	−19.9575
A-CCC	0.3270	0.0327	0.0514	1.5387	−19.9266
DCC	0.3530	0.0362	0.0581	1.4826	−19.9827
A-DCC	0.3531	0.0362	0.0581	1.4837	−19.9815
OGARCH	0.3589	0.0365	0.0592	1.8091	−19.6562
A-OGARCH	0.3942	0.0516	0.0848	1.8026	−19.6626
EWMA	0.3564	0.0357	0.0576	2.2610	−19.2043
LRCOV	0.1521	0.0152†	0.0236†	1.1871	−20.2782
HICOV	0.2163	0.0144	0.0223	1.6791	−19.7861
Adj-HICOV	0.1501	0.0132	0.0206	1.3186	−20.1467
adj-HAR-HICOV	0.2425	0.0165	0.0256	1.7994	−19.6659
VHAR	0.1290*	0.0114*	0.0178*	0.8610*	−20.6043*
	Panel B: Weekly Forecasts				
ScBEKK	0.3324	0.0241	0.0390	1.5281	−19.5026
A-ScBEKK	0.3279	0.0261	0.0427	1.4718	−19.5588
DiagBEKK	0.3200	0.0221	0.0357	1.5371	−19.4935
A-DiagBEKK	0.2684	0.0144	0.0232	1.4906	−19.5400
CCC	0.3399	0.0295	0.0470	1.2199	−19.8107
A-CCC	0.3185	0.0281	0.0444	1.2536	−19.7770
DCC	0.3445	0.0310	0.0501	1.1915	−19.8392
A-DCC	0.3446	0.0310	0.0501	1.1916	−19.8390
OGARCH	0.3496	0.0314	0.0515	1.4796	−19.5511
A-OGARCH	0.3836	0.0454	0.0750	1.4699	−19.5608
EWMA	0.3449	0.0309	0.0503	1.9731	−19.0575
LRCOV	0.1254	0.0076†	0.0118†	0.6492†	−20.3814†
HICOV	0.3554	0.0220	0.0345	1.8930	−19.1376
Adj-HICOV	0.2269	0.0146	0.0227	8.8781	−12.1525
adj-HAR-HICOV	0.2384	0.0116	0.0182	1.3930	−19.6377
VHAR	0.1108*	0.0064*	0.0100*	0.6283*	−20.4024*
	Panel C: Monthly Forecasts				
ScBEKK	0.3487	0.0245	0.0397	1.5693	−19.1929
A-ScBEKK	0.3464	0.0274	0.0447	1.5104	−19.2518
DiagBEKK	0.3331	0.0215	0.0347	1.5768	−19.1854
A-DiagBEKK	0.2720	0.0123	0.0196	1.5515	−19.2106
CCC	0.3643	0.0302	0.0481	1.3798	−19.3823
A-CCC	0.3342	0.0263	0.0414	1.3971	−19.3651
DCC	0.3677	0.0314	0.0505	1.3659	−19.3962
A-DCC	0.3677	0.0314	0.0506	1.3649	−19.3973
OGARCH	0.3740	0.0324	0.0530	1.5467	−19.2155
A-OGARCH	0.3870	0.0386	0.0635	1.5428	−19.2194
EWMA	0.3591	0.0342	0.0556	2.1893	−18.5729
LRCOV	0.1484	0.0073	0.0114	0.8438†	−19.9184†
HICOV	0.3586	0.0227	0.0355	1.6688	−19.0933
Adj-HICOV	0.2889	0.0166	0.0259	69.1362	48.3740
adj-HAR-HICOV	0.2928	0.0144	0.0225	1.5855	−19.1767
VHAR	0.1244*	0.0061*	0.0095*	0.8345*	−19.9277*

Table A.15

Diebold-Mariano Test of Out-of-Sample Forecasting Performance

This table reports the average forecast errors for each statistical loss function for 1-day, 5-day and 22-day forecasts. In each step, model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Diebold-Mariano test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: Daily Forecasts				
ScBEKK	0.1757	0.0167	0.0249	2.1970	−19.2481
A-ScBEKK	0.1681	0.0161	0.0238	2.2292	−19.2159
DiagBEKK	0.1737	0.0167	0.0249	2.2163	−19.2288
A-DiagBEKK	0.1636	0.0155	0.0230	2.1967	−19.2484
CCC	0.2132	0.0231	0.0349	3.3677	−18.0774
A-CCC	0.2096	0.0241	0.0363	5.0957	−16.3495
DCC	0.1732	0.0161	0.0238	1.8735	−19.5716
A-DCC	0.1732	0.0161	0.0238	1.8741	−19.5710
OGARCH	0.1699	0.0150	0.0223	2.2173	−19.2278
A-OGARCH	0.1697	0.0145	0.0215	2.2273	−19.2178
EWMA	0.1651	0.0156	0.0232	3.1932	−18.2519
LRCOV	0.1532	0.0181	0.0263	1.2374	−20.2077
HICOV	0.3817	0.0296	0.0452	2.5211	−18.9240
Adj-HICOV	0.1509	0.0151	0.0225	1.4271	−20.0181
adj-HAR-HICOV	0.2369	0.0181	0.0271	1.8101	−19.6351
VHAR	0.1297*	0.0133*	0.0195*	0.9097*	−20.5354*
	Panel B: Weekly Forecasts				
ScBEKK	0.1563	0.0094	0.0141	1.9004	−19.0945
A-ScBEKK	0.1478	0.0090	0.0134	1.9226	−19.0724
DiagBEKK	0.1536	0.0094	0.0141	1.9062	−19.0888
A-DiagBEKK	0.1453	0.0088	0.0131	1.8871	−19.1079
CCC	0.2016	0.0152	0.0232	3.0028	−17.9922
A-CCC	0.2004	0.0162	0.0247	4.7044	−16.2906
DCC	0.1516	0.0087	0.0129	1.5951	−19.3999
A-DCC	0.1516	0.0087	0.0129	1.5942	−19.4007
OGARCH	0.1522	0.0081†	0.0122†	1.9219	−19.0731
A-OGARCH	0.1552	0.0084	0.0127	1.9384	−19.0566
EWMA	0.1441	0.0085	0.0128	2.9941	−18.0009
LRCOV	0.1278	0.0087	0.0129	0.7253†	−20.2697†
HICOV	0.3751	0.0246	0.0381	2.0270	−18.9680
Adj-HICOV	0.2274	0.0156	0.0237	9.2222	−11.7727
adj-HAR-HICOV	0.2358	0.0125	0.0191	1.3901	−19.6049
VHAR	0.1120*	0.0072*	0.0108*	0.7145*	−20.2805*
	Panel C: Monthly Forecasts				
ScBEKK	0.1708	0.0080	0.0121	1.9851	−18.7264
A-ScBEKK	0.1640	0.0081	0.0122	2.0352	−18.6763
DiagBEKK	0.1652	0.0078	0.0118	2.0201	−18.6914
A-DiagBEKK	0.1604	0.0077	0.0116	2.0516	−18.6599
CCC	0.1977	0.0113	0.0173	2.7266	−17.9849
A-CCC	0.1953	0.0124	0.0190	4.2968	−16.4147
DCC	0.1702	0.0081	0.0120	1.7976	−18.9139
A-DCC	0.1702	0.0081	0.0120	1.7954	−18.9161
OGARCH	0.1721	0.0075†	0.0115†	2.0338	−18.6777
A-OGARCH	0.1742	0.0083†	0.0127†	2.0752	−18.6364
EWMA	0.1564	0.0076†	0.0115†	3.4101	−17.3014
LRCOV	0.1500	0.0080	0.0119	0.9786*	−19.7329*
HICOV	0.3904	0.0263	0.0404	1.8798	−18.8317
Adj-HICOV	0.2887	0.0171	0.0262	71.1025	50.3910
adj-HAR-HICOV	0.2885	0.0147	0.0227	1.6269	−19.0846
VHAR	0.1258*	0.0066*	0.0100*	0.9893†	−19.7222†

Table A.16

Giacomini-White Test for Tranquil and Turmoil Periods: 1-day Forecasts

This table reports the average forecast errors for each statistical loss function for 1-day forecasts across calm and turbulent economic conditions. In each step, model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: 1/1/2000 - 31/7/2007				
ScBEKK	0.0745	0.0009	0.0014	1.7331	−21.6925
A-ScBEKK	0.0690	0.0008	0.0013	1.7070	−21.7186
DiagBEKK	0.0758	0.0009	0.0014	1.7515	−21.6741
A-DiagBEKK	0.0784	0.0009	0.0015	1.6833	−21.7423
CCC	0.1141	0.0013	0.0020	1.2304	−22.1952
A-CCC	0.0763	0.0008	0.0013	1.3551	−22.0706
DCC	0.0669	0.0008	0.0013	1.6051	−21.8205
A-DCC	0.0669	0.0008	0.0013	1.6051	−21.8205
OGARCH	0.0657	0.0008	0.0013	1.7369	−21.6887
A-OGARCH	0.066	0.0008	0.0013	1.7625	−21.6632
EWMA	0.0570	0.0007	0.0011	3.2564	−20.1693
LRCOV	0.0548	0.0008†	0.0013†	1.0705	−22.3551
HICOV	0.1824	0.0032	0.0048	2.7072	−20.7184
Adj-HICOV	0.0514	0.0006	0.0010†	1.0501	−22.3756
AdjHAR-HICOV	0.1114	0.0014	0.0021	1.8364	−21.5892
VHAR	0.0454*	0.0006*	0.0009*	0.7249*	−22.7007*
	Panel B: 1/8/2007 - 31/12/2009				
ScBEKK	0.3683	0.0631	0.0935	4.1382	−13.4727
A-ScBEKK	0.3501	0.0609	0.0897	4.3605	−13.2504
DiagBEKK	0.3570	0.0628	0.0930	4.0767	−13.5343
A-DiagBEKK	0.3187	0.0579	0.0854	4.1460	−13.4649
CCC	0.4792	0.0893	0.1341	9.4046	−8.2064
A-CCC	0.5189	0.0934	0.1404	15.3871	−2.2239
DCC	0.3692	0.0580	0.0856	2.7378	−14.8731
A-DCC	0.3692	0.0580	0.0856	2.7378	−14.8731
OGARCH	0.3572	0.0545†	0.0805†	3.9572	−13.6537
A-OGARCH	0.3457	0.0525†	0.0774†	3.9502	−13.6607
EWMA	0.3716	0.0580	0.0858	4.4890	−13.1219
LRCOV	0.3486	0.0684†	0.0983†	1.2723	−16.3387
HICOV	0.7993	0.1073	0.1638	2.3975	−15.2134
Adj-HICOV	0.3676	0.0581	0.0859	1.8733	−15.7376
AdjHAR-HICOV	0.4828	0.0667	0.0997	1.8694	−15.7416
VHAR	0.2931*	0.0501*	0.0732*	1.0465*	−16.5644*
	Panel C: 1/1/2010 - 19/04/2016				
ScBEKK	0.1546	0.0071	0.0108	1.6932	−20.1899
A-ScBEKK	0.1500	0.0068	0.0103	1.6829	−20.2003
DiagBEKK	0.1545	0.0073	0.0110	1.7441	−20.139
A-DiagBEKK	0.1485	0.0068	0.0102	1.7157	−20.1674
CCC	0.1628	0.0091	0.0139	2.1647	−19.7184
A-CCC	0.1604	0.0095	0.0146	3.0956	−18.7876
DCC	0.1534	0.0080	0.0119	1.6815	−20.2016
A-DCC	0.1534	0.0080	0.0119	1.6827	−20.2004
OGARCH	0.1523	0.0072	0.0109	1.7997	−20.0835
A-OGARCH	0.1563	0.0070	0.0106	1.8080	−20.0752
EWMA	0.1422	0.0071	0.0107	2.6618	−19.2213
LRCOV	0.1296	0.0079†	0.0117†	1.3114	−20.5718
HICOV	0.3254	0.0135	0.0208	2.4713	−19.4118
Adj-HICOV	0.1196	0.0062†	0.0093†	1.4527	−20.4304
AdjHAR-HICOV	0.2080	0.0081	0.0123	1.7735	−20.1097
VHAR	0.1110*	0.0057*	0.0086*	0.9539*	−20.9292*

Table A.17

Giacomini-White Test for Tranquil and Turmoil Periods: 5-day Forecasts

This table reports the average forecast errors for each statistical loss function for 5-day forecasts across calm and turbulent economic conditions. In each step, model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: 1/1/2000 - 31/7/2007				
ScBEKK	0.0668	0.0005	0.0009	1.3308	−21.7143
A-ScBEKK	0.0613	0.0005	0.0008	1.3000	−21.7451
DiagBEKK	0.0683	0.0006	0.0009	1.3455	−21.6996
A-DiagBEKK	0.0712	0.0006	0.0010	1.2548	−21.7903
CCC	0.1096	0.0010	0.0016	0.8718	−22.1733
A-CCC	0.0687	0.0005	0.0008	0.9750	−22.0701
DCC	0.0603	0.0005	0.0008	1.2120	−21.8331
A-DCC	0.0603	0.0005	0.0008	1.2120	−21.8331
OGARCH	0.0603	0.0005	0.0008	1.3535	−21.6916
A-OGARCH	0.0621	0.0006	0.0010	1.3775	−21.6677
EWMA	0.0478	0.0004	0.0006	2.9217	−20.1235
LRCOV	0.0415	0.0004	0.0006	0.5038	−22.5413
HICOV	0.1816	0.0030	0.0045	2.2740	−20.7712
Adj-HICOV	0.0770	0.0008	0.0012	7.6531	−15.3921
AdjHAR-HICOV	0.1256	0.0016	0.0023	1.6098	−21.4354
VHAR	0.0364*	0.0003*	0.0005*	0.4562*	−22.589*
	Panel B: 1/8/2007 - 31/12/2009				
ScBEKK	0.3373	0.0356	0.0529	4.2396	−12.8528
A-ScBEKK	0.3104	0.0338	0.0497	4.4188	−12.6736
DiagBEKK	0.3217	0.0351	0.0522	4.1604	−12.9321
A-DiagBEKK	0.2861†	0.0327†	0.0482†	4.1855	−12.9070
CCC	0.4655	0.0597	0.0904	9.1290	−7.9634
A-CCC	0.5124	0.0636	0.0965	14.9797	−2.1127
DCC	0.3235	0.0303†	0.0446†	2.7156	−14.3768
A-DCC	0.3235	0.0303†	0.0446†	2.7156	−14.3768
OGARCH	0.3254	0.0285†	0.0425†	4.0085	−13.0839
A-OGARCH	0.3113	0.0289†	0.0432†	4.0323	−13.0602
EWMA	0.3363	0.0313†	0.0465†	4.6970	−12.3954
LRCOV	0.2891	0.0319†	0.0468†	0.9753*	−16.1171*
HICOV	0.7800	0.0871	0.1346	1.8611	−15.2314
Adj-HICOV	0.5032	0.0562	0.0848	10.3915	−6.7009
AdjHAR-HICOV	0.4349	0.0415	0.0629	1.2680	−15.8245
VHAR	0.2575*	0.0269*	0.0398*	1.0881†	−16.0044†
	Panel C: 1/1/2010 - 19/04/2016				
ScBEKK	0.1333	0.0039	0.0061	1.2975	−20.1306
A-ScBEKK	0.1302	0.0039	0.0060	1.2868	−20.1413
DiagBEKK	0.1333	0.0041	0.0063	1.3313	−20.0968
A-DiagBEKK	0.1298	0.0039	0.0059	1.3325	−20.0956
CCC	0.1481	0.0056	0.0086	1.7565	−19.6716
A-CCC	0.1489	0.0062	0.0096	2.6949	−18.7332
DCC	0.1331	0.0047	0.0070	1.3636	−20.0644
A-DCC	0.1331	0.0047	0.0070	1.3620	−20.0660
OGARCH	0.1336	0.0042	0.0065	1.4154	−20.0127
A-OGARCH	0.1436	0.0045	0.0070	1.4252	−20.0028
EWMA	0.1203	0.0039	0.0061	2.3769	−19.0512
LRCOV	0.1108	0.0041	0.0063	0.7445	−20.6836
HICOV	0.3202	0.0118	0.0186	1.9621	−19.4660
Adj-HICOV	0.1996	0.0078	0.0120	9.5897	−11.8384
AdjHAR-HICOV	0.2166	0.0071	0.0110	1.3226	−20.1055
VHAR	0.0953*	0.0032*	0.0049*	0.7053*	−20.7228*

Table A.18

Giacomini-White Test for Tranquil and Turmoil Periods: 22-day Forecasts

This table reports the average forecast errors for each statistical loss function for 22-day forecasts across calm and turbulent economic conditions. In each step, model parameters are estimated using in-sample a rolling overlapping window of 1,000 observations. The best model, that is, the model with the minimum average losses, is indicated in * for each panel. † shows the models that yield as accurate forecasts as the best model at the 5% significance level based on the pairwise Giacomini-White test.

Models	**Losses**				
	$\mathbf{L_A}$	$\mathbf{L_E}$	$\mathbf{L_F}$	$\mathbf{L_S}$	$\mathbf{L_Q}$
	Panel A: 1/1/2000 - 31/7/2007				
ScBEKK	0.0710	0.0005	0.0009	1.0765	−21.8174
A-ScBEKK	0.0666	0.0005	0.0008	1.0300	−21.8638
DiagBEKK	0.0727	0.0006	0.0009	1.0922	−21.8016
A-DiagBEKK	0.0777	0.0006	0.0010	0.9922	−21.9017
CCC	0.1189	0.0011	0.0018	0.7740	−22.1199
A-CCC	0.0697	0.0004	0.0007	0.7263	−22.1676
DCC	0.0722	0.0006	0.0009	1.0081	−21.8857
A-DCC	0.0722	0.0006	0.0009	1.0081	−21.8857
OGARCH	0.0739	0.0006	0.0010	1.1393	−21.7546
A-OGARCH	0.0764	0.0007	0.0012	1.1593	−21.7346
EWMA	0.0485	0.0003†	0.0005†	2.7813	−20.1125
LRCOV	0.0423†	0.0003†	0.0005†	0.3852*	−22.5087*
HICOV	0.1802	0.0031	0.0047	2.0764	−20.8174
Adj-HICOV	0.0967	0.0009	0.0013	60.5831	37.6892
AdjHAR-HICOV	0.1647	0.0028	0.0042	1.9437	−20.9501
VHAR	0.0386*	0.0003*	0.0004*	0.4376†	−22.4562†
	Panel B: 1/8/2007 - 31/12/2009				
ScBEKK	0.3676	0.0305†	0.0457†	5.2878	−11.4154
A-ScBEKK	0.3442†	0.0311†	0.0461†	5.6368	−11.0665
DiagBEKK	0.343	0.0299†	0.0444†	5.3177	−11.3855
A-DiagBEKK	0.3201†	0.0296†	0.044†	5.6617	−11.0416
CCC	0.4501	0.0443	0.0675	8.5202	−8.1831
A-CCC	0.5048	0.0491	0.0750	14.2234	−2.4798
DCC	0.3574	0.0290†	0.0427†	4.1206	−12.5827
A-DCC	0.3574	0.0290†	0.0427†	4.1206	−12.5827
OGARCH	0.3619	0.0269†	0.0409†	4.9461	−11.7571
A-OGARCH	0.3549†	0.0295†	0.0449†	5.0847	−11.6185
EWMA	0.3710	0.0286†	0.0429†	6.0144	−10.6888
LRCOV	0.3516	0.0303†	0.0449†	1.8753†	−14.8279†
HICOV	0.8210	0.0924	0.1413	1.8913†	−14.8119†
Adj-HICOV	0.6494	0.0618	0.0945	81.0291	64.3259
AdjHAR-HICOV	0.4511	0.0356†	0.0538†	1.6827*	−15.0206*
VHAR	0.2927*	0.0254*	0.0378*	1.9104†	−14.7928†
	Panel C: 1/1/2010 - 19/04/2016				
ScBEKK	0.1460	0.0032†	0.0050†	1.1781	−19.9624
A-ScBEKK	0.1444	0.0032†	0.0049†	1.1625	−19.9781
DiagBEKK	0.1440	0.0031†	0.0048†	1.2248	−19.9157
A-DiagBEKK	0.1412	0.0030†	0.0046†	1.2034	−19.9371
CCC	0.1408	0.0038	0.0058†	1.4939	−19.6466
A-CCC	0.1403	0.0044	0.0068	2.2993	−18.8412
DCC	0.1481	0.0040	0.0059	1.3068	−19.8338
A-DCC	0.1481	0.0040	0.0059	1.3024	−19.8381
OGARCH	0.1492	0.0036	0.0055	1.3698	−19.7708
A-OGARCH	0.1546	0.0039	0.0062	1.3846	−19.7559
EWMA	0.1289	0.0033	0.0051	2.729	−18.4115
LRCOV	0.1274	0.0033	0.0051	0.9363†	−20.2043†
HICOV	0.3319	0.0126	0.0199	1.7752	−19.3654
Adj-HICOV	0.2478	0.0081	0.0126	72.6471	51.5065
AdjHAR-HICOV	0.2890	0.0128	0.0201	1.4439	−19.6967
VHAR	0.1061*	0.0026*	0.0041*	0.9162*	−20.2244*

Table A.19

Model Confidence Set: Range Statistic

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the range statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.052	12	0.043	8	0.000	8	0.000
A-ScBEKK	8	0.000	10*	0.052	10	0.043	9	0.000	9	0.000
DiagBEKK	10	0.000	11*	0.052	11	0.043	10	0.000	10	0.000
A-DiagBEKK	5	0.000	4*	0.074	4*	0.067	12	0.000	12	0.000
CCC	14	0.000	14	0.043	14	0.041	7	0.000	7	0.000
A-CCC	13	0.000	15	0.043	15	0.041	15	0.000	15	0.000
DCC	11	0.000	8*	0.052	9	0.043	4	0.000	4	0.000
A-DCC	9	0.000	7*	0.052	8	0.043	5	0.000	6	0.000
OGARCH	7	0.000	3*	0.095	3*	0.077	13	0.000	13	0.000
A-OGARCH	6	0.000	2*	0.154	2*	0.119	14	0.000	14	0.000
EWMA	4	0.000	6*	0.052	6	0.043	16	0.000	16	0.000
LRCOV	3	0.000	9*	0.052	7	0.043	2	0.000	2	0.000
HICOV	16	0.000	16	0.027	16	0.024	11	0.000	11	0.000
Adj-HICOV	2	0.000	5*	0.074	5*	0.067	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13	0.043	13	0.041	6	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	11	0.000	11*	0.181	11*	0.214	5	0.000	4	0.000
A-ScBEKK	5	0.000	9*	0.181	9*	0.214	4	0.000	5	0.000
DiagBEKK	8	0.000	10*	0.181	10*	0.214	8	0.000	8	0.000
A-DiagBEKK	4	0.000	4*	0.195	4*	0.239	11	0.000	11	0.000
CCC	13	0.000	12*	0.181	12*	0.214	10	0.000	10	0.000
A-CCC	12	0.000	14	0.020	13	0.021	14	0.000	14	0.000
DCC	9	0.000	7*	0.181	7*	0.214	7	0.000	7	0.000
A-DCC	10	0.000	8*	0.181	8*	0.214	6	0.000	6	0.000
OGARCH	7	0.000	2*	0.195	2*	0.239	12	0.000	12	0.000
A-OGARCH	6	0.000	3*	0.195	3*	0.239	13	0.000	13	0.000
EWMA	3	0.000	5*	0.181	6*	0.214	15	0.000	15	0.000
LRCOV	2	0.000	6*	0.181	5*	0.230	2*	0.603	2*	0.609
HICOV	16	0.000	16	0.020	16	0.021	9	0.000	9	0.000
Adj-HICOV	14	0.000	15	0.020	15	0.021	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	13	0.028	14	0.021	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	8	0.000	8*	0.257	10*	0.189	7	0.001	7	0.001
A-ScBEKK	5	0.000	10*	0.257	9*	0.189	4	0.001	4	0.001
DiagBEKK	6	0.000	6*	0.257	6*	0.189	9	0.001	9	0.001
A-DiagBEKK	4	0.000	3*	0.257	3*	0.189	10	0.001	10	0.001
CCC	13	0.000	12*	0.157	12*	0.189	11	0.001	11	0.001
A-CCC	12	0.000	13	0.035	13*	0.054	14	0.001	14	0.001
DCC	11	0.000	11*	0.257	8*	0.189	8	0.001	8	0.001
A-DCC	10	0.000	9*	0.257	7*	0.189	6	0.001	6	0.001
OGARCH	9	0.000	2*	0.327	2*	0.317	12	0.001	12	0.001
A-OGARCH	7	0.000	7*	0.257	11*	0.189	13	0.001	13	0.001
EWMA	3	0.000	4*	0.257	4*	0.189	15	0.000	15	0.000
LRCOV	2	0.000	5*	0.257	5*	0.189	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.000	16	0.002	5	0.001	5	0.001
Adj-HICOV	15	0.000	14	0.000	15	0.002	16	0.000	16	0.000
adj-HAR-HICOV	14	0.000	15	0.000	14	0.019	3	0.001	3	0.001
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.739	2*	0.739

Table A.20

Model Confidence Set with 90% Level of Confidence

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the quadratic statistic. * indicates the models that are not eliminated from the set at 90% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.076	12*	0.071	8	0.000	8	0.000
A-ScBEKK	8	0.000	10*	0.081	10*	0.079	9	0.000	9	0.000
DiagBEKK	10	0.000	11*	0.076	11*	0.074	10	0.000	10	0.000
A-DiagBEKK	5	0.000	4*	0.094	4*	0.100	13	0.000	13	0.000
CCC	14	0.000	14*	0.059	14	0.050	7	0.000	7	0.000
A-CCC	13	0.000	15	0.047	15	0.040	15	0.000	15	0.000
DCC	9	0.000	8*	0.081	9*	0.079	4	0.000	4	0.000
A-DCC	11	0.000	7*	0.081	8*	0.079	5	0.000	5	0.000
OGARCH	7	0.000	3*	0.094	3*	0.100	12	0.000	12	0.000
A-OGARCH	6	0.000	2*	0.119	2*	0.111	14	0.000	14	0.000
EWMA	4	0.000	6*	0.081	6*	0.100	16	0.000	16	0.000
LRCOV	3	0.000	9*	0.081	7*	0.100	2	0.000	2	0.000
HICOV	16	0.000	16	0.029	16	0.023	11	0.000	11	0.000
Adj-HICOV	2	0.000	5*	0.094	5*	0.100	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13*	0.065	13*	0.059	6	0.000	6	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	10	0.000	11*	0.194	11*	0.225	4	0.001	5	0.000
A-ScBEKK	5	0.000	9*	0.225	9*	0.269	5	0.001	4	0.000
DiagBEKK	7	0.000	10*	0.204	10*	0.244	8	0.001	8	0.000
A-DiagBEKK	4	0.000	4*	0.225	4*	0.269	11	0.001	11	0.000
CCC	13	0.000	12*	0.105	12*	0.118	10	0.001	10	0.000
A-CCC	12	0.000	14	0.047	13*	0.065	14	0.001	14	0.000
DCC	9	0.000	7*	0.225	7*	0.269	7	0.001	7	0.000
A-DCC	11	0.000	8*	0.225	8*	0.269	6	0.001	6	0.000
OGARCH	6	0.000	2*	0.225	2*	0.269	12	0.001	12	0.000
A-OGARCH	8	0.000	3*	0.225	3*	0.269	13	0.001	13	0.000
EWMA	3	0.000	5*	0.225	6*	0.269	15	0.000	15	0.000
LRCOV	2	0.001	6*	0.225	5*	0.269	2*	0.590	2*	0.631
HICOV	16	0.000	16	0.022	16	0.026	9	0.001	9	0.000
Adj-HICOV	14	0.000	15	0.041	15	0.039	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	13*	0.063	14	0.043	3	0.001	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	8	0.000	8*	0.338	10*	0.414	6	0.004	6	0.007
A-ScBEKK	5	0.000	9*	0.338	9*	0.414	4	0.004	4	0.007
DiagBEKK	6	0.000	5*	0.338	6*	0.414	9	0.004	9	0.007
A-DiagBEKK	4	0.000	3*	0.338	3*	0.414	10	0.004	10	0.007
CCC	13	0.000	12*	0.202	12*	0.223	11	0.004	11	0.007
A-CCC	12	0.000	13*	0.110	13*	0.127	14	0.004	14	0.006
DCC	11	0.000	11*	0.338	8*	0.414	8	0.004	8	0.007
A-DCC	10	0.000	10*	0.338	7*	0.414	7	0.004	7	0.007
OGARCH	9	0.000	2*	0.338	2*	0.414	12	0.004	12	0.007
A-OGARCH	7	0.000	7*	0.338	11*	0.386	13	0.004	13	0.007
EWMA	3	0.000	4*	0.338	4*	0.414	15	0.000	15	0.001
LRCOV	2	0.000	6*	0.338	5*	0.414	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.014	16	0.008	5	0.004	5	0.007
Adj-HICOV	15	0.000	15	0.021	15	0.017	16	0.000	16	0.000
adj-HAR-HICOV	14	0.000	14	0.033	14	0.046	3	0.004	3	0.007
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.741	2*	0.744

Table A.21

Model Confidence Set: 75% Level of Confidence

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the quadratic statistic. * indicates the models that are not eliminated from the set at 75% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.069	12*	0.082	8	0.000	8	0.000
A-ScBEKK	8	0.000	10*	0.071	10*	0.086	9	0.000	9	0.000
DiagBEKK	10	0.000	11*	0.071	11*	0.086	10	0.000	10	0.000
A-DiagBEKK	5	0.000	5*	0.084	4*	0.110	12	0.000	12	0.000
CCC	14	0.000	14	0.048	14	0.047	7	0.000	7	0.000
A-CCC	13	0.000	15	0.046	15	0.035	15	0.000	15	0.000
DCC	11	0.000	8*	0.071	9*	0.086	4	0.000	4	0.000
A-DCC	9	0.000	7*	0.071	8*	0.093	5	0.000	5	0.000
OGARCH	7	0.000	4*	0.084	3*	0.110	13	0.000	13	0.000
A-OGARCH	6	0.000	2*	0.122	2*	0.110	14	0.000	14	0.000
EWMA	4	0.000	6*	0.071	6*	0.110	16	0.000	16	0.000
LRCOV	3	0.000	9*	0.071	7*	0.110	2	0.000	2	0.000
HICOV	16	0.000	16	0.020	16	0.019	11	0.000	11	0.000
Adj-HICOV	2	0.001	3*	0.084	5*	0.110	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13*	0.051	13*	0.059	6	0.000	6	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	9	0.000	11*	0.212	11*	0.226	5	0.000	4	0.000
A-ScBEKK	5	0.000	9*	0.237	9*	0.278	4	0.000	5	0.000
DiagBEKK	7	0.000	10*	0.223	10*	0.251	8	0.000	8	0.000
A-DiagBEKK	4	0.000	4*	0.237	4*	0.278	11	0.000	11	0.000
CCC	13	0.000	12*	0.117	12*	0.116	10	0.000	10	0.000
A-CCC	12	0.000	13*	0.067	13*	0.065	14	0.000	14	0.000
DCC	10	0.000	7*	0.237	8*	0.278	7	0.000	7	0.000
A-DCC	11	0.000	8*	0.237	7*	0.278	6	0.000	6	0.000
OGARCH	8	0.000	2*	0.237	2*	0.278	12	0.000	12	0.000
A-OGARCH	6	0.000	3*	0.237	3*	0.278	13	0.000	13	0.000
EWMA	3	0.000	5*	0.237	6*	0.278	15	0.000	15	0.000
LRCOV	2	0.000	6*	0.237	5*	0.278	2*	0.568	2*	0.579
HICOV	16	0.000	16	0.025	16	0.022	9	0.000	9	0.000
Adj-HICOV	14	0.000	15	0.033	15	0.038	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	14	0.038	14	0.045	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	8	0.000	8*	0.317	10*	0.372	7	0.004	7	0.015
A-ScBEKK	5	0.000	10*	0.317	9*	0.372	4	0.004	4	0.015
DiagBEKK	6	0.000	5*	0.317	5*	0.372	9	0.004	9	0.015
A-DiagBEKK	4	0.000	3*	0.317	3*	0.372	10	0.004	10	0.015
CCC	13	0.000	12*	0.162	12*	0.208	11	0.004	11	0.015
A-CCC	12	0.000	13*	0.086	13*	0.111	14	0.003	14	0.014
DCC	11	0.000	11*	0.317	8*	0.372	8	0.004	8	0.015
A-DCC	10	0.000	9*	0.317	7*	0.372	6	0.004	6	0.015
OGARCH	9	0.000	2*	0.329	2*	0.372	12	0.004	12	0.015
A-OGARCH	7	0.000	7*	0.317	11*	0.350	13	0.004	13	0.015
EWMA	3	0.000	4*	0.317	4*	0.372	15	0.000	15	0.000
LRCOV	2	0.000	6*	0.317	6*	0.372	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.016	16	0.008	5	0.004	5	0.015
Adj-HICOV	15	0.000	15	0.020	15	0.015	16	0.000	16	0.000
adj-HAR-HICOV	14	0.000	14	0.033	14	0.032	3	0.004	3	0.015
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.724	2*	0.739

Table A.22

Model Confidence Set of Relative Forecasting Performance: Using 1,250 In-Sample Observations

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	Loss Functions									
	L_A		L_E		L_F		L_S		L_Q	
	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value
Panel A: Daily Forecasts										
ScBEKK	11	0.000	12*	0.071	12*	0.080	8	0.000	8	0.000
A-ScBEKK	7	0.000	6*	0.072	9*	0.083	11	0.000	11	0.000
DiagBEKK	9	0.000	11*	0.072	11*	0.083	9	0.000	9	0.000
A-DiagBEKK	4	0.000	5*	0.072	5*	0.083	12	0.000	12	0.000
CCC	14	0.000	14	0.044	14*	0.054	7	0.000	7	0.000
A-CCC	13	0.000	15	0.031	15	0.042	15	0.000	15	0.000
DCC	12	0.000	9*	0.072	10*	0.083	6	0.000	6	0.000
A-DCC	10	0.000	8*	0.072	8*	0.083	4	0.000	4	0.000
OGARCH	8	0.000	4*	0.072	4*	0.083	13	0.000	13	0.000
A-OGARCH	6	0.000	2*	0.094	2*	0.093	14	0.000	14	0.000
EWMA	5	0.000	7*	0.072	6*	0.083	16	0.000	16	0.000
LRCOV	3	0.000	10*	0.072	7*	0.083	2	0.000	2	0.000
HICOV	16	0.000	16	0.023	16	0.024	10	0.000	10	0.000
Adj-HICOV	2	0.000	3*	0.072	3*	0.083	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13*	0.055	13*	0.065	5	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	8	0.000	11*	0.194	11*	0.232	4	0.001	4	0.001
A-ScBEKK	5	0.000	7*	0.246	7*	0.286	5	0.001	5	0.001
DiagBEKK	6	0.000	10*	0.216	10*	0.275	9	0.001	9	0.001
A-DiagBEKK	3	0.000	4*	0.246	4*	0.286	10	0.001	10	0.001
CCC	13	0.000	12*	0.114	12*	0.117	11	0.001	11	0.001
A-CCC	12	0.000	14	0.042	14	0.047	14	0.001	14	0.001
DCC	11	0.000	8*	0.216	8*	0.276	7	0.001	7	0.001
A-DCC	10	0.000	9*	0.216	9*	0.276	6	0.001	6	0.001
OGARCH	9	0.000	2*	0.246	2*	0.286	12	0.001	12	0.001
A-OGARCH	7	0.000	3*	0.246	3*	0.286	13	0.001	13	0.001
EWMA	4	0.000	5*	0.246	6*	0.286	15	0.000	15	0.000
LRCOV	2	0.000	6*	0.246	5*	0.286	2*	0.641	2*	0.624
HICOV	16	0.000	16	0.025	16	0.025	8	0.001	8	0.001
Adj-HICOV	15	0.000	15	0.037	15	0.042	16	0.000	16	0.000
adj-HAR-HICOV	14	0.000	13*	0.058	13*	0.063	3	0.001	3	0.001
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	7	0.001	9*	0.344	11*	0.344	9	0.015	9	0.016
A-ScBEKK	6	0.001	6*	0.383	6*	0.361	8	0.015	8	0.016
DiagBEKK	5	0.001	5*	0.383	4*	0.361	10	0.015	10	0.016
A-DiagBEKK	3	0.001	3*	0.383	2*	0.361	5	0.015	5	0.016
CCC	13	0.001	12*	0.180	12*	0.193	11	0.015	11	0.016
A-CCC	12	0.001	13*	0.097	13*	0.091	14	0.011	14	0.011
DCC	11	0.001	11*	0.326	10*	0.353	7	0.015	7	0.016
A-DCC	10	0.001	10*	0.340	9*	0.353	6	0.015	6	0.016
OGARCH	9	0.001	2*	0.383	3*	0.361	12	0.015	12	0.016
A-OGARCH	8	0.001	7*	0.383	8*	0.353	13	0.014	13	0.016
EWMA	4	0.001	4*	0.383	5*	0.361	15	0.000	15	0.000
LRCOV	2	0.001	8*	0.383	7*	0.353	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.010	16	0.009	4	0.015	4	0.016
Adj-HICOV	15	0.000	15	0.013	15	0.015	16	0.000	16	0.000
adj-HAR-HICOV	14	0.000	14	0.035	14	0.033	3	0.015	3	0.016
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.914	2*	0.899

Table A.23

Model Confidence Set of Relative Forecasting Performance with Sample Starting from 2002

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.089	12*	0.099	8	0.000	8	0.000
A-ScBEKK	8	0.000	10*	0.108	10*	0.120	11	0.000	11	0.000
DiagBEKK	10	0.000	11*	0.097	11*	0.110	10	0.000	10	0.000
A-DiagBEKK	5	0.000	4*	0.108	4*	0.158	12	0.000	13	0.000
CCC	14	0.000	14*	0.053	14*	0.066	7	0.000	7	0.000
A-CCC	13	0.000	15	0.040	15*	0.056	15	0.000	15	0.000
DCC	9	0.000	8*	0.108	8*	0.120	6	0.000	6	0.000
A-DCC	11	0.000	6*	0.108	7*	0.123	4	0.000	4	0.000
OGARCH	7	0.000	3*	0.109	3*	0.158	13	0.000	12	0.000
A-OGARCH	6	0.000	2*	0.173	2*	0.176	14	0.000	14	0.000
EWMA	4	0.000	7*	0.108	9*	0.120	16	0.000	16	0.000
LRCOV	2	0.001	9*	0.108	6*	0.158	2	0.000	2	0.000
HICOV	16	0.000	16	0.027	16	0.034	9	0.000	9	0.000
Adj-HICOV	3	0.001	5*	0.108	5*	0.158	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13*	0.072	13*	0.080	5	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	11	0.000	11*	0.228	11*	0.263	4	0.001	4	0.001
A-ScBEKK	5	0.000	9*	0.313	9*	0.358	5	0.001	5	0.001
DiagBEKK	8	0.000	10*	0.283	10*	0.324	9	0.001	9	0.001
A-DiagBEKK	4	0.000	4*	0.329	5*	0.387	11	0.001	11	0.001
CCC	13	0.000	12*	0.121	12*	0.129	10	0.001	10	0.001
A-CCC	12	0.000	14	0.040	13*	0.070	14	0.001	14	0.001
DCC	9	0.000	6*	0.329	6*	0.387	6	0.001	6	0.001
A-DCC	10	0.000	7*	0.329	7*	0.387	7	0.001	7	0.001
OGARCH	7	0.000	2*	0.329	2*	0.387	12	0.001	12	0.001
A-OGARCH	6	0.000	3*	0.329	3*	0.387	13	0.001	13	0.001
EWMA	3	0.000	8*	0.329	8*	0.387	15	0.000	15	0.000
LRCOV	2	0.001	5*	0.329	4*	0.387	2*	0.963	2*	0.957
HICOV	16	0.000	16	0.026	16	0.030	8	0.001	8	0.001
Adj-HICOV	14	0.000	15	0.035	15	0.050	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	13*	0.057	14*	0.053	3	0.001	3	0.001
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	9	0.000	10*	0.363	11*	0.364	7	0.007	5	0.006
A-ScBEKK	5	0.000	11*	0.363	10*	0.371	8	0.007	8	0.006
DiagBEKK	6	0.000	6*	0.363	7*	0.395	9	0.007	9	0.006
A-DiagBEKK	4	0.000	3*	0.363	3*	0.395	10	0.007	10	0.006
CCC	13	0.000	12*	0.196	12*	0.197	11	0.007	11	0.006
A-CCC	12	0.000	13*	0.102	13*	0.113	14	0.007	14	0.006
DCC	10	0.000	7*	0.363	6*	0.395	6	0.007	7	0.006
A-DCC	11	0.000	8*	0.363	8*	0.395	4	0.007	6	0.006
OGARCH	8	0.000	2*	0.417	2*	0.395	12	0.007	12	0.006
A-OGARCH	7	0.000	9*	0.363	9*	0.371	13	0.007	13	0.006
EWMA	3	0.000	4*	0.363	4*	0.395	15	0.001	15	0.000
LRCOV	2	0.000	5*	0.363	5*	0.395	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.015	16	0.018	5	0.007	3	0.006
Adj-HICOV	14	0.000	14	0.043	14*	0.051	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	15	0.023	15	0.025	3	0.007	4	0.006
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.802	2*	0.793

Table A.24

Model Confidence Set of Relative Forecasting Performance with Sample Starting from 2003

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.104	12*	0.095	9	0.000	9	0.000
A-ScBEKK	8	0.000	10*	0.122	10*	0.114	11	0.000	11	0.000
DiagBEKK	10	0.000	11*	0.112	11*	0.104	10	0.000	10	0.000
A-DiagBEKK	4	0.000	4*	0.129	4*	0.134	14	0.000	13	0.000
CCC	14	0.000	14*	0.068	14*	0.070	8	0.000	8	0.000
A-CCC	13	0.000	15*	0.056	15*	0.061	15	0.000	15	0.000
DCC	9	0.000	7*	0.123	8*	0.114	4	0.000	4	0.000
A-DCC	11	0.000	6*	0.123	7*	0.117	6	0.000	6	0.000
OGARCH	7	0.000	3*	0.146	3*	0.134	12	0.000	12	0.000
A-OGARCH	5	0.000	2*	0.256	2*	0.201	13	0.000	14	0.000
EWMA	6	0.000	8*	0.123	9*	0.114	16	0.000	16	0.000
LRCOV	2	0.003	9*	0.123	6*	0.134	2	0.000	2	0.000
HICOV	16	0.000	16	0.039	16	0.048	7	0.000	7	0.000
Adj-HICOV	3	0.003	5*	0.123	5*	0.134	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13*	0.086	13*	0.079	5	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	11	0.002	11*	0.331	11*	0.362	4	0.001	7	0.000
A-ScBEKK	5	0.002	9*	0.410	9*	0.487	8	0.001	8	0.000
DiagBEKK	8	0.002	10*	0.367	10*	0.424	10	0.001	9	0.000
A-DiagBEKK	3	0.002	4*	0.414	4*	0.501	11	0.001	11	0.000
CCC	13	0.001	12*	0.151	12*	0.177	9	0.001	10	0.000
A-CCC	12	0.002	14*	0.057	14*	0.068	14	0.001	14	0.000
DCC	9	0.002	5*	0.414	5*	0.501	5	0.001	5	0.000
A-DCC	10	0.002	6*	0.414	6*	0.501	6	0.001	4	0.000
OGARCH	7	0.002	2*	0.414	2*	0.501	12	0.001	12	0.000
A-OGARCH	6	0.002	3*	0.414	3*	0.501	13	0.001	13	0.000
EWMA	4	0.002	8*	0.414	8*	0.501	15	0.000	15	0.000
LRCOV	2	0.003	7*	0.414	7*	0.501	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.042	16	0.044	7	0.001	6	0.000
Adj-HICOV	14	0.000	15	0.050	15*	0.057	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	13*	0.076	13*	0.103	3	0.001	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.839	2*	0.831
Panel C: Monthly Forecasts										
ScBEKK	9	0.000	10*	0.498	10*	0.469	8	0.012	8	0.016
A-ScBEKK	6	0.001	11*	0.498	11*	0.469	5	0.012	5	0.016
DiagBEKK	5	0.001	5*	0.506	5*	0.563	9	0.012	9	0.016
A-DiagBEKK	3	0.001	3*	0.506	3*	0.563	10	0.012	10	0.016
CCC	13	0.000	12*	0.241	12*	0.233	11	0.012	11	0.016
A-CCC	12	0.000	13*	0.125	13*	0.121	14	0.010	14	0.011
DCC	10	0.000	6*	0.506	6*	0.563	7	0.012	7	0.016
A-DCC	11	0.000	7*	0.506	7*	0.563	6	0.012	6	0.016
OGARCH	7	0.001	2*	0.581	2*	0.563	12	0.012	12	0.016
A-OGARCH	8	0.001	9*	0.498	9*	0.469	13	0.012	13	0.016
EWMA	4	0.001	4*	0.506	4*	0.563	15	0.001	15	0.002
LRCOV	2	0.003	8*	0.506	8*	0.517	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.013	16	0.012	3	0.012	3	0.016
Adj-HICOV	14	0.000	15	0.026	15	0.019	16	0.000	16	0.000
adj-HAR-HICOV	15	0.000	14	0.043	14	0.034	4	0.012	4	0.016
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.710	2*	0.716

Table A.25

Model Confidence Set of Relative Forecasting Performance: Using Non-Overlapping Forecasts

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	12	0.000	12*	0.063	12*	0.077	8	0.000	8	0.000
A-ScBEKK	8	0.000	10*	0.063	10*	0.090	9	0.000	9	0.000
DiagBEKK	10	0.000	11*	0.063	11*	0.085	10	0.000	10	0.000
A-DiagBEKK	5	0.000	4*	0.076	4*	0.101	13	0.000	13	0.000
CCC	14	0.000	14	0.043	14*	0.053	7	0.000	7	0.000
A-CCC	13	0.000	15	0.032	15	0.041	15	0.000	15	0.000
DCC	9	0.000	8*	0.063	9*	0.090	4	0.000	4	0.000
A-DCC	11	0.000	7*	0.063	8*	0.090	5	0.000	5	0.000
OGARCH	7	0.000	3*	0.076	3*	0.101	12	0.000	12	0.000
A-OGARCH	6	0.000	2*	0.123	2*	0.126	14	0.000	14	0.000
EWMA	4	0.000	6*	0.063	6*	0.101	16	0.000	16	0.000
LRCOV	3	0.000	9*	0.063	7*	0.101	2	0.000	2	0.000
HICOV	16	0.000	16	0.017	16	0.031	11	0.000	11	0.000
Adj-HICOV	2	0.000	5*	0.076	5*	0.101	3	0.000	3	0.000
adj-HAR-HICOV	15	0.000	13	0.049	13*	0.060	6	0.000	6	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	8	0.002	9*	0.346	9*	0.394	8	0.003	9	0.002
A-ScBEKK	5	0.002	7*	0.346	8*	0.394	9	0.003	8	0.002
DiagBEKK	7	0.002	10*	0.346	10*	0.394	10	0.003	10	0.002
A-DiagBEKK	4	0.002	5*	0.346	5*	0.394	11	0.003	11	0.002
CCC	13	0.002	12*	0.266	12*	0.262	7	0.003	7	0.002
A-CCC	12	0.002	13*	0.212	13*	0.176	14	0.003	14	0.002
DCC	11	0.002	8*	0.346	7*	0.394	5	0.003	4	0.002
A-DCC	10	0.002	6*	0.346	6*	0.394	4	0.003	5	0.002
OGARCH	6	0.002	2*	0.511	2*	0.407	12	0.003	12	0.002
A-OGARCH	9	0.002	3*	0.430	3*	0.394	13	0.003	13	0.002
EWMA	3	0.002	4*	0.347	4*	0.394	15	0.000	15	0.000
LRCOV	2	0.003	11*	0.346	11*	0.394	2*	0.893	2*	0.903
HICOV	16	0.000	15*	0.127	15*	0.108	6	0.003	6	0.002
Adj-HICOV	15	0.000	16*	0.112	16*	0.086	16	0.000	16	0.000
adj-HAR-HICOV	14	0.000	14*	0.167	14*	0.139	3	0.003	3	0.002
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	9	0.039	9*	0.558	9*	0.580	4*	0.063	4*	0.051
A-ScBEKK	8	0.039	10*	0.513	10*	0.546	8*	0.063	8*	0.051
DiagBEKK	7	0.039	6*	0.632	6*	0.666	9*	0.063	9*	0.051
A-DiagBEKK	4	0.039	5*	0.632	5*	0.666	10*	0.063	10*	0.051
CCC	13	0.028	12*	0.285	12*	0.315	11*	0.063	11*	0.051
A-CCC	11	0.039	13*	0.223	13*	0.230	14*	0.063	14*	0.051
DCC	6	0.039	2*	0.632	2*	0.679	6*	0.063	6*	0.051
A-DCC	5	0.039	1*	1.000	1*	1.000	5*	0.063	5*	0.051
OGARCH	10	0.039	4*	0.632	4*	0.679	12*	0.063	12*	0.051
A-OGARCH	12	0.034	11*	0.418	11*	0.435	13*	0.063	13*	0.051
EWMA	3	0.039	7*	0.632	7*	0.666	15	0.004	15	0.011
LRCOV	2	0.039	8*	0.558	8*	0.580	1*	1.000	1*	1.000
HICOV	16	0.001	14*	0.109	14*	0.131	7*	0.063	7*	0.051
Adj-HICOV	14	0.002	16*	0.076	16*	0.094	16	0.000	16	0.000
adj-HAR-HICOV	15	0.001	15*	0.091	15*	0.109	3*	0.063	3*	0.051
VHAR	1*	1.000	3*	0.632	3*	0.679	2*	0.818	2*	0.800

Table A.26

Model Confidence Set of Relative Forecasting Performance: Overnight Returns

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	Loss Functions									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	9	0.000	11*	0.126	10*	0.145	12	0.000	12	0.000
A-ScBEKK	5	0.000	5*	0.126	5*	0.145	14	0.000	14	0.000
DiagBEKK	10	0.000	9*	0.126	7*	0.145	13	0.000	13	0.000
A-DiagBEKK	6	0.000	2*	0.126	3*	0.145	15	0.000	15	0.000
CCC	16	0.000	15*	0.084	16*	0.075	5	0.000	5	0.000
A-CCC	13	0.000	16*	0.066	15*	0.102	9	0.000	9	0.000
DCC	15	0.000	12*	0.126	13*	0.145	6	0.000	6	0.000
A-DCC	14	0.000	13*	0.126	12*	0.145	8	0.000	7	0.000
OGARCH	12	0.000	6*	0.126	8*	0.145	11	0.000	11	0.000
A-OGARCH	8	0.000	14*	0.126	14*	0.145	10	0.000	10	0.000
EWMA	7	0.000	8*	0.126	11*	0.145	16	0.000	16	0.000
LRCOV	4	0.000	10*	0.126	6*	0.145	2	0.000	2	0.000
HICOV	11	0.000	4*	0.126	4*	0.145	4	0.000	4	0.000
Adj-HICOV	3	0.000	7*	0.126	9*	0.145	7	0.000	8	0.000
adj-HAR-HICOV	2	0.000	3*	0.126	2*	0.145	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	7	0.000	10*	0.142	9*	0.186	9	0.000	9	0.000
A-ScBEKK	5	0.000	4*	0.183	5*	0.203	12	0.000	12	0.000
DiagBEKK	8	0.000	7*	0.152	7*	0.188	10	0.000	10	0.000
A-DiagBEKK	4	0.000	2*	0.183	2*	0.203	14	0.000	14	0.000
CCC	15	0.000	14*	0.093	14*	0.094	5	0.000	5	0.000
A-CCC	14	0.000	15*	0.065	15*	0.066	8	0.000	8	0.000
DCC	10	0.000	12*	0.136	11*	0.165	7	0.000	7	0.000
A-DCC	9	0.000	13*	0.129	12*	0.154	6	0.000	6	0.000
OGARCH	13	0.000	8*	0.152	8*	0.186	13	0.000	13	0.000
A-OGARCH	12	0.000	11*	0.141	13*	0.141	11	0.000	11	0.000
EWMA	6	0.000	9*	0.145	10*	0.172	15	0.000	15	0.000
LRCOV	3	0.000	5*	0.181	4*	0.203	2*	0.700	2*	0.724
HICOV	11	0.000	6*	0.152	6*	0.188	4	0.000	4	0.000
Adj-HICOV	16	0.000	16	0.030	16	0.043	16	0.000	16	0.000
adj-HAR-HICOV	2	0.003	3*	0.183	3*	0.203	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	7	0.001	6*	0.260	6*	0.223	9	0.000	9	0.004
A-ScBEKK	6	0.001	9*	0.260	9*	0.223	10	0.000	11	0.004
DiagBEKK	8	0.001	7*	0.260	7*	0.223	11	0.000	10	0.004
A-DiagBEKK	3	0.001	2*	0.264	2*	0.238	12	0.000	12	0.004
CCC	15	0.000	14*	0.202	14*	0.172	5	0.010	5	0.012
A-CCC	10	0.000	15*	0.152	15*	0.143	6	0.006	6	0.008
DCC	12	0.000	10*	0.260	10*	0.223	8	0.000	8	0.004
A-DCC	11	0.000	11*	0.260	11*	0.223	7	0.000	7	0.004
OGARCH	13	0.000	8*	0.260	8*	0.223	14	0.000	14	0.004
A-OGARCH	14	0.000	13*	0.239	13*	0.201	13	0.000	13	0.004
EWMA	5	0.001	12*	0.259	12*	0.223	15	0.000	15	0.000
LRCOV	2	0.001	5*	0.260	5*	0.223	1*	1.000	1*	1.000
HICOV	9	0.000	4*	0.260	4*	0.223	3*	0.848	3*	0.851
Adj-HICOV	16	0.000	16*	0.056	16	0.047	16	0.000	16	0.000
adj-HAR-HICOV	4	0.001	3*	0.260	3*	0.223	4*	0.061	4*	0.063
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.848	2*	0.851

Table A.27

Model Confidence Set of Relative Forecasting Performance: Using Hansen Overnight Returns

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	Loss Functions									
	L_A		L_E		L_F		L_S		L_Q	
	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value
Panel A: Daily Forecasts										
ScBEKK	9	0.000	12*	0.267	13*	0.207	6	0.000	6	0.001
A-ScBEKK	5	0.002	5*	0.948	5*	0.897	5	0.000	5	0.001
DiagBEKK	10	0.000	11*	0.332	11*	0.310	8	0.000	8	0.001
A-DiagBEKK	3	0.002	6*	0.803	7*	0.530	7	0.000	7	0.001
CCC	15	0.000	14*	0.123	14*	0.104	16	0.000	16	0.000
A-CCC	14	0.000	15*	0.076	15*	0.069	14	0.000	14	0.001
DCC	12	0.000	8*	0.496	8*	0.389	12	0.000	12	0.001
A-DCC	11	0.000	7*	0.630	6*	0.606	11	0.000	11	0.001
OGARCH	8	0.000	3*	0.979	3*	0.973	10	0.000	10	0.001
A-OGARCH	7	0.000	1*	1.000	1*	1.000	9	0.000	9	0.001
EWMA	6	0.002	9*	0.444	9*	0.377	3	0.001	3	0.002
LRCOV	4	0.002	10*	0.405	10*	0.373	13	0.000	13	0.001
HICOV	13	0.000	2*	0.979	2*	0.973	15	0.000	15	0.001
Adj-HICOV	2	0.016	13*	0.211	12*	0.242	2	0.001	2	0.002
adj-HAR-HICOV	1*	1.000	4*	0.979	4*	0.973	4	0.001	4	0.002
VHAR	16	0.000	16	0.031	16	0.041	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	7	0.011	12*	0.715	12*	0.761	4	0.000	4	0.000
A-ScBEKK	3*	0.324	2*	0.929	2*	0.876	3	0.000	3	0.000
DiagBEKK	8	0.009	10*	0.758	11*	0.788	6	0.000	6	0.000
A-DiagBEKK	4*	0.227	5*	0.883	6*	0.866	5	0.000	5	0.000
CCC	14	0.000	13*	0.250	13*	0.262	12	0.000	12	0.000
A-CCC	13	0.000	14*	0.104	14*	0.114	11	0.000	11	0.000
DCC	11	0.005	8*	0.803	8*	0.824	10	0.000	10	0.000
A-DCC	10	0.006	9*	0.758	9*	0.824	9	0.000	9	0.000
OGARCH	6*	0.051	1*	1.000	1*	1.000	8	0.000	8	0.000
A-OGARCH	9	0.006	6*	0.883	5*	0.876	7	0.000	7	0.000
EWMA	5*	0.170	4*	0.883	4*	0.876	2	0.002	2	0.002
LRCOV	2*	0.361	11*	0.758	10*	0.824	13	0.000	13	0.000
HICOV	12	0.000	7*	0.883	7*	0.866	14	0.000	14	0.000
Adj-HICOV	15	0.000	15	0.048	15*	0.052	16	0.000	16	0.000
adj-HAR-HICOV	1*	1.000	3*	0.929	3*	0.876	15	0.000	15	0.000
VHAR	16	0.000	16	0.028	16	0.035	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	5*	0.625	2*	1.000	3*	1.000	6*	0.114	6*	0.149
A-ScBEKK	1*	1.000	1*	1.000	2*	1.000	7*	0.114	7*	0.149
DiagBEKK	4*	0.625	4*	1.000	5*	0.996	1*	1.000	1*	1.000
A-DiagBEKK	2*	0.925	7*	0.999	9*	0.939	3*	0.852	3*	0.845
CCC	14	0.001	13*	0.311	13*	0.268	16	0.000	11	0.000
A-CCC	13	0.001	14*	0.136	14*	0.098	8*	0.090	8*	0.124
DCC	9*	0.195	8*	0.988	6*	0.972	10	0.022	10	0.011
A-DCC	10*	0.144	9*	0.942	7*	0.946	9	0.022	9	0.034
OGARCH	8*	0.319	3*	1.000	1*	1.000	5*	0.165	5*	0.204
A-OGARCH	11*	0.051	12*	0.784	11*	0.752	4*	0.347	4*	0.383
EWMA	3*	0.664	6*	1.000	4*	1.000	12	0.005	12	0.000
LRCOV	6*	0.625	11*	0.867	12*	0.705	13	0.005	14	0.000
HICOV	12	0.004	10*	0.921	10*	0.858	11	0.022	13	0.000
Adj-HICOV	16	0.000	15	0.040	15	0.027	2*	1.000	2*	1.000
adj-HAR-HICOV	7*	0.625	5*	1.000	8*	0.946	14	0.005	15	0.000
VHAR	15	0.000	16	0.020	16	0.018	15	0.002	16	0.000

Table A.28

Model Confidence Set of Relative Forecasting Performance: Using Squared Overnight Returns

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	Loss Functions									
	L_A		L_E		L_F		L_S		L_Q	
	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value
Panel A: Daily Forecasts										
ScBEKK	11	0.000	13*	0.268	13*	0.298	5	0.002	5	0.001
A-ScBEKK	6	0.000	6*	0.535	6*	0.543	7	0.002	7	0.001
DiagBEKK	9	0.000	12*	0.306	12*	0.334	8	0.002	13	0.001
A-DiagBEKK	4	0.000	3*	0.535	3*	0.601	9	0.002	8	0.001
CCC	16	0.000	15*	0.123	15*	0.147	13	0.002	12	0.001
A-CCC	10	0.000	14*	0.162	14*	0.197	14	0.002	14	0.001
DCC	14	0.000	8*	0.471	8*	0.515	2	0.002	2	0.001
A-DCC	13	0.000	7*	0.484	7*	0.520	3	0.002	3	0.001
OGARCH	8	0.000	2*	0.535	2*	0.601	12	0.002	11	0.001
A-OGARCH	12	0.000	1*	1.000	1*	1.000	11	0.002	10	0.001
EWMA	5	0.000	10*	0.449	10*	0.506	16	0.000	16	0.000
LRCOV	7	0.000	16*	0.095	16*	0.110	4	0.002	4	0.001
HICOV	15	0.000	5*	0.535	5*	0.543	6	0.002	6	0.001
Adj-HICOV	1*	1.000	11*	0.330	11*	0.352	15	0.002	15	0.000
adj-HAR-HICOV	3	0.028	9*	0.471	9*	0.509	10	0.002	9	0.001
VHAR	2*	0.206	4*	0.535	4*	0.543	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	10	0.001	13*	0.483	11*	0.549	8	0.003	8	0.001
A-ScBEKK	5	0.003	5*	0.851	5*	0.828	9	0.003	9	0.001
DiagBEKK	9	0.001	10*	0.571	10*	0.613	10	0.003	10	0.001
A-DiagBEKK	3	0.003	3*	0.891	3*	0.841	11	0.003	12	0.001
CCC	15	0.000	14*	0.259	14*	0.272	7	0.003	7	0.001
A-CCC	13	0.000	15*	0.161	15*	0.166	14	0.003	14	0.001
DCC	12	0.001	6*	0.749	6*	0.754	5	0.003	5	0.001
A-DCC	11	0.001	7*	0.726	7*	0.754	6	0.003	6	0.001
OGARCH	7	0.003	1*	1.000	1*	1.000	13	0.003	13	0.001
A-OGARCH	8	0.001	2*	0.891	2*	0.841	12	0.003	11	0.001
EWMA	6	0.003	9*	0.646	9*	0.666	15	0.001	15	0.000
LRCOV	4	0.003	11*	0.543	12*	0.511	2*	0.753	2*	0.781
HICOV	14	0.000	12*	0.517	13*	0.491	3	0.004	3	0.009
Adj-HICOV	16	0.000	16*	0.087	16*	0.093	16	0.000	16	0.000
adj-HAR-HICOV	2	0.017	8*	0.648	8*	0.666	4	0.003	4	0.005
VHAR	1*	1.000	4*	0.891	4*	0.828	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	8	0.005	9*	0.758	7*	0.835	9	0.017	9	0.013
A-ScBEKK	5	0.009	10*	0.758	11*	0.770	7	0.017	8	0.013
DiagBEKK	7	0.006	4*	0.768	4*	0.835	10	0.017	10	0.013
A-DiagBEKK	2	0.009	2*	0.963	1*	1.000	12	0.017	12	0.013
CCC	15	0.000	14*	0.374	14*	0.365	5	0.017	5	0.016
A-CCC	12	0.001	15*	0.227	15*	0.225	11	0.017	11	0.013
DCC	11	0.001	5*	0.768	5*	0.835	8	0.017	7	0.013
A-DCC	13	0.001	8*	0.758	9*	0.770	6	0.017	6	0.013
OGARCH	10	0.001	3*	0.963	3*	0.952	14	0.015	14	0.011
A-OGARCH	14	0.001	12*	0.668	12*	0.649	13	0.015	13	0.013
EWMA	6	0.009	11*	0.758	10*	0.770	15	0.001	15	0.002
LRCOV	4	0.009	13*	0.616	13*	0.595	2*	0.674	2*	0.667
HICOV	9	0.001	6*	0.768	6*	0.835	1*	1.000	1*	1.000
Adj-HICOV	16	0.000	16*	0.084	16*	0.084	16	0.000	16	0.000
adj-HAR-HICOV	3	0.009	7*	0.758	8*	0.770	4	0.033	4	0.021
VHAR	1*	1.000	1*	1.000	2*	0.985	3	0.033	3	0.025

Table A.29

Model Confidence Set of Relative Forecasting Performance: Without Interpolation in High-Frequency Data

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day, 5-day and 22-day forecasts. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: Daily Forecasts										
ScBEKK	14	0.000	10	0.035	10	0.030	11	0.000	11	0.000
A-ScBEKK	10	0.000	8	0.035	8	0.030	8	0.000	8	0.000
DiagBEKK	12	0.000	9	0.035	9	0.030	13	0.000	13	0.000
A-DiagBEKK	9	0.000	6	0.035	7	0.030	9	0.000	9	0.000
CCC	16	0.000	15	0.035	14	0.030	4	0.000	4	0.000
A-CCC	7	0.000	7	0.035	6	0.030	7	0.000	7	0.000
DCC	11	0.000	12	0.035	12	0.030	6	0.000	6	0.000
A-DCC	13	0.000	13	0.035	13	0.030	5	0.000	5	0.000
OGARCH	15	0.000	16	0.035	16	0.029	14	0.000	14	0.000
A-OGARCH	8	0.000	11	0.035	11	0.030	15	0.000	15	0.000
EWMA	5	0.000	14	0.035	15	0.029	16	0.000	16	0.000
LRCOV	3	0.000	4	0.035	3*	0.063	2	0.000	2	0.000
HICOV	4	0.000	3	0.035	4	0.031	10	0.000	10	0.000
Adj-HICOV	2	0.001	2	0.036	2*	0.063	3	0.000	3	0.000
adj-HAR-HICOV	6	0.000	5	0.035	5	0.030	12	0.000	12	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: Weekly Forecasts										
ScBEKK	10	0.000	9	0.038	9	0.039	10	0.000	10	0.000
A-ScBEKK	7	0.000	8	0.038	8	0.039	9	0.000	9	0.000
DiagBEKK	9	0.000	7	0.038	7	0.039	11	0.000	11	0.000
A-DiagBEKK	6	0.000	5	0.038	5	0.039	4	0.000	4	0.000
CCC	15	0.000	15	0.038	12	0.039	3	0.000	3	0.000
A-CCC	8	0.000	6	0.038	6	0.039	5	0.000	5	0.000
DCC	12	0.000	13	0.038	14	0.039	6	0.000	7	0.000
A-DCC	13	0.000	12	0.038	15	0.039	7	0.000	6	0.000
OGARCH	16	0.000	16	0.038	16	0.039	12	0.000	12	0.000
A-OGARCH	11	0.000	11	0.038	11	0.039	13	0.000	13	0.000
EWMA	5	0.000	14	0.038	13	0.039	15	0.000	15	0.000
LRCOV	2	0.000	2*	0.052	2	0.048	2*	0.121	2*	0.121
HICOV	14	0.000	10	0.038	10	0.039	14	0.000	14	0.000
Adj-HICOV	3	0.000	4	0.038	4	0.039	16	0.000	16	0.000
adj-HAR-HICOV	4	0.000	3	0.038	3	0.039	8	0.000	8	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: Monthly Forecasts										
ScBEKK	10	0.000	8	0.036	8	0.037	11	0.000	11	0.000
A-ScBEKK	7	0.000	10	0.036	9	0.037	6	0.000	6	0.000
DiagBEKK	9	0.000	7	0.036	6	0.037	10	0.000	10	0.000
A-DiagBEKK	5	0.000	3	0.036	3	0.037	3	0.000	3	0.000
CCC	16	0.000	13	0.036	13	0.037	5	0.000	5	0.000
A-CCC	8	0.000	6	0.036	7	0.037	7	0.000	7	0.000
DCC	14	0.000	12	0.036	12	0.037	9	0.000	9	0.000
A-DCC	13	0.000	9	0.036	11	0.037	8	0.000	8	0.000
OGARCH	15	0.000	15	0.036	15	0.037	14	0.000	14	0.000
A-OGARCH	11	0.000	14	0.036	14	0.037	13	0.000	13	0.000
EWMA	6	0.000	16	0.036	16	0.037	15	0.000	15	0.000
LCOV	2	0.000	2	0.036	2	0.037	2*	0.675	2*	0.722
HICOV	12	0.000	11	0.036	10	0.037	12	0.000	12	0.000
Adj-HICOV	4	0.000	5	0.036	5	0.037	16	0.000	16	0.000
adj-HAR-HICOV	3	0.000	4	0.036	4	0.037	4	0.000	4	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

Table A.30

Model Confidence Set for Tranquil and Turmoil Periods: 1-day Forecasts (Different Definition of the Global Financial Crisis)

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day ahead forecasts across calm and turbulent economic conditions. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: 1/1/2000 - 31/7/2007										
ScBEKK	10	0.000	6*	0.131	6*	0.117	9	0.000	9	0.000
A-ScBEKK	5	0.000	5*	0.197	5*	0.185	10	0.000	10	0.000
DiagBEKK	12	0.000	7*	0.119	7*	0.117	11	0.000	11	0.000
A-DiagBEKK	11	0.000	11*	0.118	11*	0.117	14	0.000	14	0.000
CCC	15	0.000	16*	0.076	16*	0.074	4	0.001	4	0.000
A-CCC	13	0.000	14*	0.103	14*	0.109	8	0.000	8	0.000
DCC	7	0.000	13*	0.118	13*	0.117	6	0.000	6	0.000
A-DCC	8	0.000	12*	0.118	12*	0.117	7	0.000	7	0.000
OGARCH	9	0.000	10*	0.119	9*	0.117	13	0.000	13	0.000
A-OGARCH	6	0.000	4*	0.417	4*	0.418	15	0.000	15	0.000
EWMA	4	0.004	9*	0.119	10*	0.117	16	0.000	16	0.000
LRCOV	3	0.004	2*	0.526	2*	0.561	2	0.001	2	0.000
HICOV	16	0.000	15*	0.080	15*	0.076	12	0.000	12	0.000
Adj-HICOV	2	0.032	3*	0.526	3*	0.561	3	0.001	3	0.000
AdjHAR-HICOV	14	0.000	8*	0.119	8*	0.117	5	0.000	5	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: 1/8/2007-31/12/2009										
ScBEKK	12	0.007	12*	0.130	12*	0.136	9	0.004	9	0.007
A-ScBEKK	8	0.012	11*	0.151	11*	0.157	10	0.004	10	0.007
DiagBEKK	9	0.011	10*	0.165	10*	0.164	5	0.004	5	0.007
A-DiagBEKK	2	0.012	4*	0.513	4*	0.519	11	0.004	11	0.007
CCC	13	0.006	14*	0.082	14*	0.078	14	0.004	14	0.007
A-CCC	14	0.004	15*	0.064	15*	0.069	16	0.004	16	0.007
DCC	10	0.009	6*	0.314	6*	0.282	6	0.004	6	0.007
A-DCC	11	0.007	5*	0.382	5*	0.351	7	0.004	7	0.007
OGARCH	5	0.012	3*	0.785	3*	0.770	13	0.004	13	0.007
A-OGARCH	4	0.012	2*	0.785	2*	0.770	12	0.004	12	0.007
EWMA	7	0.012	7*	0.260	7*	0.252	15	0.004	15	0.007
LRCOV	3	0.012	9*	0.218	9*	0.212	2	0.004	2	0.007
HICOV	16	0.000	16*	0.051	16	0.050	8	0.004	8	0.007
Adj-HICOV	6	0.012	8*	0.218	8*	0.212	3	0.004	3	0.007
AdjHAR-HICOV	15	0.002	13*	0.098	13*	0.097	4	0.004	4	0.007
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: 1/1/2010-19/04/2016										
ScBEKK	8	0.000	7*	0.068	8*	0.056	7	0.000	7	0.000
A-ScBEKK	7	0.000	6*	0.068	6*	0.056	4	0.000	4	0.000
DiagBEKK	11	0.000	11*	0.068	10*	0.056	9	0.000	9	0.000
A-DiagBEKK	6	0.000	5*	0.068	5*	0.056	11	0.000	11	0.000
CCC	13	0.000	14*	0.056	14	0.035	13	0.000	13	0.000
A-CCC	5	0.000	15	0.046	15	0.031	15	0.000	14	0.000
DCC	14	0.000	13*	0.066	13	0.042	5	0.000	5	0.000
A-DCC	12	0.000	12*	0.066	12	0.045	6	0.000	6	0.000
OGARCH	9	0.000	9*	0.068	9*	0.056	10	0.000	10	0.000
A-OGARCH	10	0.000	3*	0.068	3*	0.056	12	0.000	12	0.000
EWMA	4	0.000	4*	0.068	4*	0.056	16	0.000	16	0.000
LRCOV	3	0.000	8*	0.068	7*	0.056	2	0.000	2	0.000
HICOV	16	0.000	16	0.021	16	0.008	14	0.000	15	0.000
Adj-HICOV	2	0.005	2*	0.492	2*	0.491	3	0.000	3	0.000
AdjHAR-HICOV	15	0.000	10*	0.068	11*	0.056	8	0.000	8	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

Table A.31

Model Confidence Set for Tranquil and Turmoil Periods: 5-day Forecasts (Different Definition of the Global Financial Crisis)

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 5-day ahead forecasts across calm and turbulent economic conditions. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	Loss Functions									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: 1/1/2000 - 31/7/2007										
ScBEKK	5	0.003	4*	0.115	3*	0.139	9	0.000	9	0.000
A-ScBEKK	3	0.012	2*	0.115	2*	0.139	10	0.000	10	0.000
DiagBEKK	6	0.003	5*	0.115	5*	0.139	11	0.000	11	0.000
A-DiagBEKK	8	0.003	7*	0.115	7*	0.139	12	0.000	12	0.000
CCC	15	0.000	13*	0.080	13*	0.090	4	0.000	4	0.000
A-CCC	12	0.002	14*	0.074	14*	0.089	8	0.000	8	0.000
DCC	9	0.003	11*	0.115	11*	0.139	5	0.000	5	0.000
A-DCC	10	0.003	10*	0.115	10*	0.139	6	0.000	6	0.000
OGARCH	11	0.003	12*	0.115	12*	0.139	13	0.000	13	0.000
A-OGARCH	7	0.003	3*	0.115	6*	0.139	14	0.000	14	0.000
EWMA	4	0.012	8*	0.115	8*	0.139	15	0.000	15	0.000
LRCOV	2	0.050	9*	0.115	9*	0.139	2*	0.680	2*	0.702
HICOV	16	0.000	15*	0.052	15*	0.065	7	0.000	7	0.000
Adj-HICOV	14	0.000	16	0.038	16*	0.052	16	0.000	16	0.000
AdjHAR-HICOV	13	0.000	6*	0.115	4*	0.139	3	0.000	3	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel B: 1/8/2007-31/12/2009										
ScBEKK	12	0.002	11*	0.248	11*	0.257	8	0.015	8	0.022
A-ScBEKK	8	0.006	10*	0.335	10*	0.342	9	0.015	9	0.022
DiagBEKK	6	0.006	9*	0.401	9*	0.409	7	0.015	7	0.022
A-DiagBEKK	3	0.026	7*	0.636	7*	0.675	10	0.015	10	0.022
CCC	11	0.004	14*	0.080	14*	0.072	13	0.015	13	0.021
A-CCC	13	0.002	15*	0.070	15*	0.060	15	0.008	15	0.014
DCC	9	0.006	5*	0.636	5*	0.700	4	0.015	4	0.022
A-DCC	10	0.005	6*	0.636	6*	0.700	5	0.015	5	0.022
OGARCH	5	0.006	2*	0.842	2*	0.838	12	0.015	12	0.022
A-OGARCH	4	0.014	4*	0.636	4*	0.700	11	0.015	11	0.022
EWMA	7	0.006	8*	0.548	8*	0.552	14	0.009	14	0.014
LRCOV	2	0.026	3*	0.715	3*	0.779	1*	1.000	1*	1.000
HICOV	16	0.000	16*	0.052	16	0.050	6	0.015	6	0.022
Adj-HICOV	14	0.002	12*	0.148	12*	0.140	16	0.001	16	0.004
AdjHAR-HICOV	15	0.000	13*	0.090	13*	0.085	3	0.015	3	0.022
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.419	2*	0.379
Panel C: 1/1/2010-19/04/2016										
ScBEKK	5	0.000	5	0.040	5	0.024	5	0.001	5	0.000
A-ScBEKK	4	0.000	2	0.040	2	0.024	4	0.001	3	0.000
DiagBEKK	7	0.000	7	0.040	7	0.024	6	0.001	6	0.000
A-DiagBEKK	6	0.000	4	0.040	3	0.024	9	0.001	9	0.000
CCC	12	0.000	12	0.036	12	0.021	10	0.001	10	0.000
A-CCC	8	0.000	14	0.034	14	0.017	14	0.000	14	0.000
DCC	9	0.000	9	0.040	10	0.023	8	0.001	8	0.000
A-DCC	10	0.000	11	0.040	11	0.023	7	0.001	7	0.000
OGARCH	11	0.000	10	0.040	9	0.023	12	0.001	11	0.000
A-OGARCH	13	0.000	8	0.040	8	0.023	11	0.001	12	0.000
EWMA	3	0.000	3	0.040	4	0.024	15	0.000	15	0.000
LRCOV	2	0.000	6	0.040	6	0.024	2	0.008	2	0.016
HICOV	16	0.000	16	0.005	16	0.003	13	0.000	13	0.000
Adj-HICOV	15	0.000	15	0.024	15	0.013	16	0.000	16	0.000
AdjHAR-HICOV	14	0.000	13	0.036	13	0.017	3	0.001	4	0.000
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000

Table A.32

Model Confidence Set for Tranquil and Turmoil Periods: 22 day Forecasts (Different Definition of the Global Financial Crisis)

This table reports the ranking along with the p-values of the models for the Model Confidence Set test for each statistical loss function for 1-day ahead forecasts across calm and turbulent economic conditions. The hypothesis testing for the relative performance between models is estimated using the semi-quadratic statistic. * indicates the models that are not eliminated from the set at 95% level of confidence.

Models	**Loss Functions**									
	$\mathbf{L_A}$		$\mathbf{L_E}$		$\mathbf{L_F}$		$\mathbf{L_S}$		$\mathbf{L_Q}$	
	Rank	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**	**Rank**	**p-value**
Panel A: 1/1/2000 - 31/7/2007										
ScBEKK	5	0.040	3*	0.145	3*	0.145	10	0.001	10	0.001
A-ScBEKK	3*	0.076	1*	1.000	1*	1.000	9	0.001	9	0.001
DiagBEKK	6	0.040	4*	0.138	4*	0.145	12	0.001	12	0.001
A-DiagBEKK	7	0.019	5*	0.138	5*	0.145	11	0.001	11	0.001
CCC	13	0.001	13*	0.106	13*	0.099	3	0.001	3	0.001
A-CCC	9	0.018	9*	0.138	9*	0.145	5	0.001	5	0.001
DCC	10	0.018	10*	0.138	10*	0.145	7	0.001	7	0.001
A-DCC	11	0.018	11*	0.138	11*	0.145	8	0.001	8	0.001
OGARCH	12	0.013	12*	0.135	12*	0.131	13	0.001	13	0.001
A-OGARCH	8	0.018	7*	0.138	8*	0.145	14	0.001	14	0.000
EWMA	4*	0.063	8*	0.138	7*	0.145	15	0.000	15	0.000
LRCOV	2*	0.076	6*	0.138	6*	0.145	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.014	16	0.020	6	0.001	6	0.001
Adj-HICOV	15	0.000	15	0.035	15	0.040	16	0.000	16	0.000
AdjHAR-HICOV	14	0.000	14*	0.070	14*	0.070	4	0.001	4	0.001
VHAR	1*	1.000	2*	0.782	2*	0.770	2*	0.161	2*	0.165
Panel B: 1/8/2007-31/12/2009										
ScBEKK	12	0.006	10*	0.382	10*	0.395	8*	0.101	8*	0.102
A-ScBEKK	8	0.020	11*	0.345	11*	0.367	9*	0.091	9*	0.093
DiagBEKK	6	0.020	9*	0.409	9*	0.451	7*	0.101	7*	0.107
A-DiagBEKK	2	0.020	4*	0.431	4*	0.501	10*	0.086	10*	0.083
CCC	11	0.011	12*	0.228	12*	0.223	13	0.050	13	0.047
A-CCC	13	0.002	13*	0.125	13*	0.135	15	0.027	15	0.018
DCC	9	0.020	5*	0.431	5*	0.501	5*	0.171	5*	0.163
A-DCC	10	0.013	7*	0.431	6*	0.501	6*	0.121	6*	0.120
OGARCH	5	0.020	2*	0.704	2*	0.625	11*	0.086	11*	0.083
A-OGARCH	7	0.020	8*	0.409	8*	0.451	12*	0.086	12*	0.083
EWMA	4	0.020	3*	0.561	3*	0.625	14	0.037	14	0.025
LRCOV	3	0.020	6*	0.431	7*	0.501	2*	0.357	2*	0.347
HICOV	16	0.000	16	0.023	16	0.029	3*	0.357	3*	0.347
Adj-HICOV	14	0.000	15	0.030	15	0.035	16	0.007	16	0.006
AdjHAR-HICOV	15	0.000	14	0.049	14*	0.053	4*	0.357	4*	0.347
VHAR	1*	1.000	1*	1.000	1*	1.000	1*	1.000	1*	1.000
Panel C: 1/1/2010-19/04/2016										
ScBEKK	7	0.011	3*	0.648	5*	0.610	4	0.002	4	0.002
A-ScBEKK	5	0.011	4*	0.648	3*	0.610	3	0.002	3	0.002
DiagBEKK	6	0.011	5*	0.648	4*	0.610	6	0.002	6	0.002
A-DiagBEKK	8	0.011	2*	0.648	2*	0.610	7	0.001	7	0.002
CCC	9	0.011	8*	0.261	8*	0.246	10	0.001	10	0.000
A-CCC	4	0.011	13*	0.113	13*	0.098	14	0.001	14	0.000
DCC	11	0.003	9*	0.202	10*	0.134	9	0.001	9	0.000
A-DCC	10	0.004	10*	0.163	11*	0.115	8	0.001	8	0.002
OGARCH	12	0.003	11*	0.126	9*	0.158	11	0.001	11	0.000
A-OGARCH	13	0.003	12*	0.123	12*	0.107	12	0.001	12	0.000
EWMA	2	0.011	7*	0.364	7*	0.355	15	0.000	15	0.000
LRCOV	3	0.011	6*	0.439	6*	0.409	1*	1.000	1*	1.000
HICOV	16	0.000	16	0.011	16	0.008	13	0.001	13	0.000
Adj-HICOV	15	0.000	15	0.023	15	0.023	16	0.000	16	0.000
AdjHAR-HICOV	14	0.002	14*	0.078	14*	0.063	5	0.002	5	0.002
VHAR	1*	1.000	1*	1.000	1*	1.000	2*	0.644	2*	0.656

Appendix B - Chapter 3

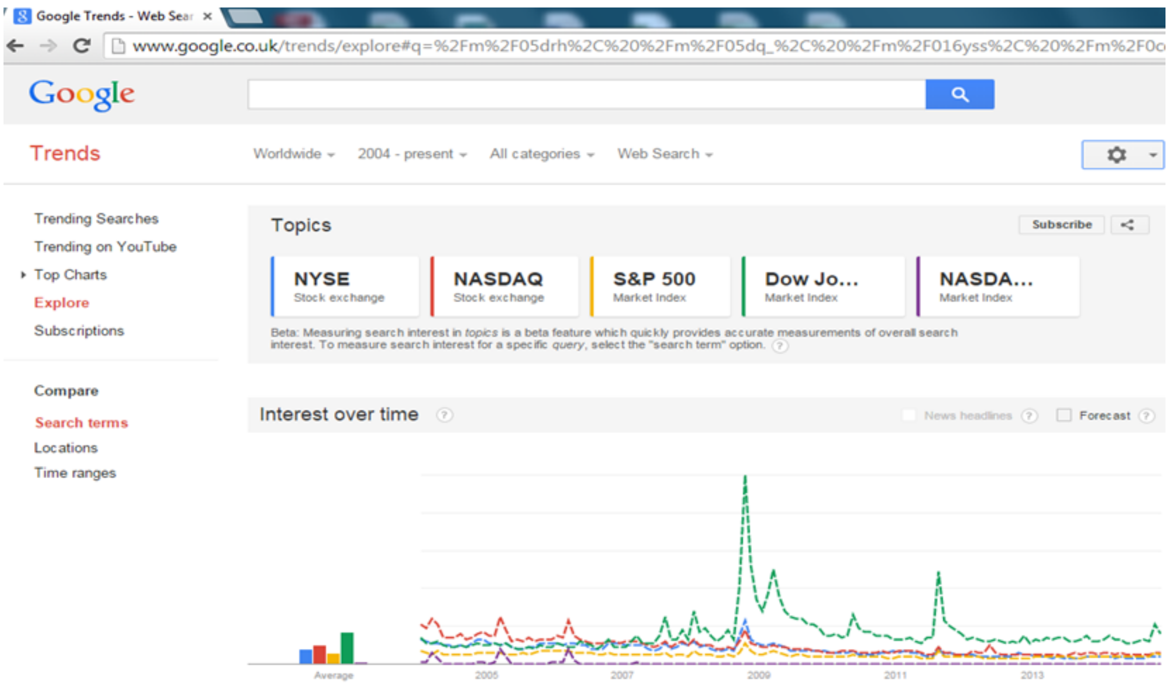


Figure B.1 Topic Selection in Google Trends The figure displays the methodology followed for the selection of Google Trends Query for U.S. market. The keyword with the highest interest over time is selected among a pool of queries for stock exchanges and stock market indexes.

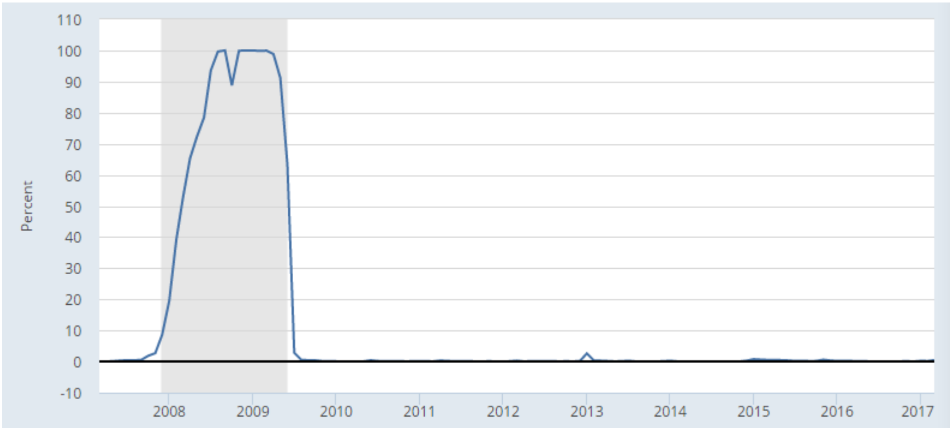


Figure B.2 Monthly Recessionary Probabilities

Source: FRED

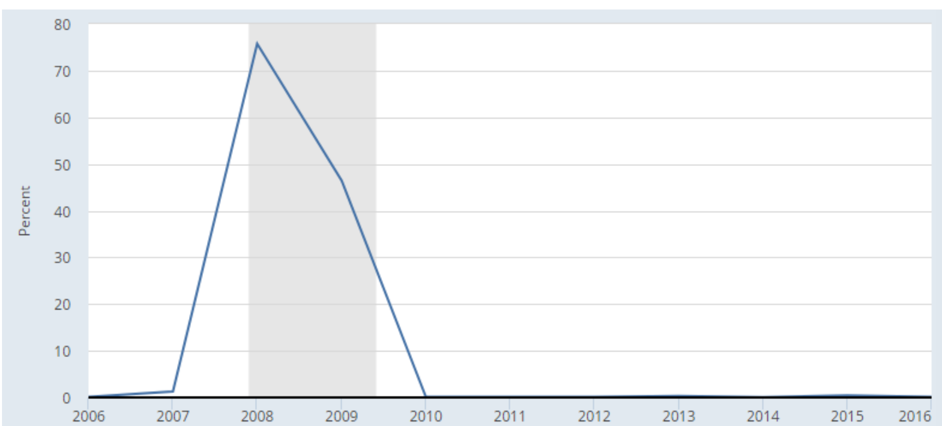


Figure B.3 Annual Recessionary Probabilities

Source: FRED

Table B.1

Reuters News Queries

This table presents the codes used to identify news for stock markets. They identify news related to a stock market index or a country.

#	Country	Reuters News Query
1	Austria	AUT—.ATX
2	Finland	.OMXHPI—FIN
3	France	.FCHI—FRA
4	Germany	DEU—.GDAXI
5	Ireland	.ISEQ—IRL
6	Italy	.FTMIB—ITA
7	Netherlands	.AEX—NLD
8	Norway	.OSEAX—NOR
9	Spain	.SMSI—.IBEX—ESP
10	Sweden	.OMXSPI—SWE
11	Switzerland	CHE—.SSMI
12	UK	.FTSE—GBR—.FTMX
13	Australia	.AXJO—AUS
14	Hong Kong	HKG—.HSI
15	Japan	JPN—.N225
16	New Zealand	.NZ50—NZL
17	Singapore	.STI—SGP
18	Canada	.GSPTSE—CAN
19	USA	.DJI—.SPX—USA—.NDX
20	India	.BSESN—IND
21	Indonesia	.JKSE—IDN
22	Malaysia	MYS—.KLSE
23	Philippines	.PSI—PHL
24	Thailand	.SETI—THA
25	Brazil	.BVSP—BRA
26	Chile	.IPSA—CHL
27	Colombia	.IGBC—COL
28	Mexico	.MXX—MEX
29	Peru	.SPBLPGPT—PER
30	Poland	.WIG20—POL
31	Rusia	.MCX—RUS
32	Turkey	.XU100—TUR
33	South Africa	.JALSH—ZAF

Table B.2

Summary Statistics: Returns and SVIs

This table presents the mean, minimum, maximum, standard deviation, skewness and kurtosis of weekly returns and Search Volume Indices. The logarithmic returns (in %) are calculated using the respective country MSCI indices. The summary statistics are estimated for raw SVIs (in %) excluding the maximum that is always bounded to 100 for the week with the highest volume in searches. The last row presents the summary statistics for the returns of MSCI World Index.

	Returns						SVI				
Country	**Mean**	**Min**	**Max**	**StDev**	**Skew**	**Kurt**	**Mean**	**Min**	**StDev**	**Skew**	**Kurt**
Developed											
AT	−0.0293	−29.79	21.93	4.47	−0.83	5.22	17.7548	3	12.20	1.43	4.34
FI	−0.0065	−16.27	19.06	4.08	−0.37	2.39	20.2437	2	15.35	1.79	3.62
FR	0.0268	−18.50	16.40	3.46	−0.55	3.30	11.0798	2	7.13	6.54	64.94
DE	0.0673	−18.02	16.75	3.54	−0.67	3.45	24.8567	13	7.71	4.59	33.79
IE	−0.0778	−23.26	22.46	4.31	−0.88	5.04	14.9985	3	10.21	2.44	11.20
IT	−0.0837	−20.95	14.97	3.92	−0.49	3.03	36.6248	4	16.35	0.38	0.27
NL	0.0603	−17.04	12.90	3.24	−0.64	3.00	14.8301	4	8.10	4.83	37.87
NO	0.0604	−23.70	23.71	4.52	−0.65	4.60	24.8981	3	12.32	1.97	6.70
ES	−0.0041	−29.73	17.14	4.02	−0.78	5.82	40.3988	9	12.71	0.73	2.08
SE	0.0975	−22.29	19.90	4.08	−0.12	4.25	21.9010	6	12.12	1.61	3.82
CH	0.0870	−12.96	11.88	2.57	−0.61	3.69	27.6071	4	14.60	1.64	4.03
GB	0.0039	−20.70	16.69	3.11	−0.68	5.85	15.8626	6	8.35	5.54	45.47
AU	0.0725	−21.63	21.28	3.74	−0.53	5.55	24.7903	3	13.26	1.51	3.66
HK	0.0998	−25.98	22.53	3.16	−0.36	11.21	23.6972	8	9.61	2.39	9.36
JP	0.0382	−17.31	9.22	2.76	−0.76	3.79	22.0857	7	10.18	2.79	15.06
NZ	0.0324	−19.47	12.30	3.11	−0.81	4.06	24.7326	6	10.01	2.33	10.71
SG	0.0765	−23.86	18.87	3.12	−0.56	8.34	42.4106	4	15.13	0.34	0.36
CA	0.0863	−26.98	21.42	3.50	−0.89	9.34	20.9365	3	12.48	1.61	4.06
US	0.1053	−15.13	13.10	2.52	−0.46	6.09	13.4239	5	7.71	4.85	35.91
Emerging											
IN	0.1348	−22.82	23.82	4.30	−0.36	5.04	33.4284	18	8.76	1.33	4.81
ID	0.2048	−31.97	23.03	4.68	−0.61	5.55	22.5805	6	12.43	1.40	2.81
MY	0.0684	−15.00	9.46	2.56	−0.53	3.76	43.9882	13	13.59	0.45	0.54
PH	0.2027	−21.33	20.77	3.75	−0.38	4.18	45.9424	8	14.67	0.07	0.59
TH	0.0982	−26.45	19.60	3.79	−0.39	4.88	52.3176	20	12.87	0.57	0.72
BR	0.0935	−37.11	29.55	5.40	−0.54	5.18	21.3309	3	12.75	1.65	4.72
CL	0.0778	−19.80	13.41	3.41	−0.74	4.38	32.1861	6	16.52	0.54	−0.07
CO	0.2413	−32.54	16.79	4.56	−1.01	6.91	29.0709	5	14.15	0.91	1.19
MX	0.1261	−27.74	23.82	4.11	−0.36	6.46	19.2230	3	11.21	1.93	6.55
PE	0.1792	−25.58	27.39	4.62	−0.42	4.40	17.9705	3	11.19	2.30	9.23
PL	0.0021	−25.35	24.83	4.68	−0.36	3.67	29.4018	3	17.35	0.79	0.02
RU	0.1036	−34.17	45.11	5.15	−0.55	16.10	8.6928	1	6.60	5.04	56.20
TR	0.0322	−23.24	21.23	5.62	−0.50	1.61	36.5894	6	17.60	0.70	0.21
ZA	0.0923	−19.39	27.28	4.38	−0.10	3.56	49.1802	16	14.88	0.75	0.25
WRL	0.0759	−17.10	14.22	2.56	−0.68	6.39	-	-	-	-	-

Table B.3

Summary Statistics: LSVIs

This table shows summary statistics and the results for the Augmented Dickey-Fuller (ADF) unit root test, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test and the Ljung-Box autocorrelation test for the abnormal SVIs estimated by the methodology of Vlastakis and Markellos (2012). *, †, and ‡ denote significance at 1%, 5% and 10% level of significance respectively.

Country	Mean	Min	Max	StDev	Skew	Kurt	DF-NC	DF-C	DF-CT	KPSS-mu	KPSS-tau	LB(8)	LB(20)
Developed													
AT	−0.3361	−164.22	129.93	33.32	0.07	2.45	$-29.24^\dagger$	$-29.22^\dagger$	$-29.21^\dagger$	0.08	0.01	136.2*	189.9*
FI	−0.4298	−196.61	230.26	62.68	0.02	0.87	$-31.34^\dagger$	$-31.32^\dagger$	$-31.30^\dagger$	0.17	0.03	149.2*	165.6*
FR	0.0141	−120.40	120.40	26.05	0.29	3.60	$-26.95^\dagger$	$-26.93^\dagger$	$-26.91^\dagger$	0.07	0.03	80.7*	119.4*
DE	−0.0409	−82.20	98.45	16.35	0.65	5.32	$-24.29^\dagger$	$-24.27^\dagger$	$-24.25^\dagger$	0.04	0.02	55.5*	69.4*
IE	−0.3081	−239.79	173.46	48.62	−0.27	2.60	$-28.89^\dagger$	$-28.87^\dagger$	$-28.85^\dagger$	0.17	0.02	150.6*	156.5*
IT	0.1087	−123.21	114.51	25.50	−0.07	4.30	$-25.95^\dagger$	$-25.93^\dagger$	$-25.92^\dagger$	0.04	0.04	139.3*	169.8*
NL	−0.1733	−165.82	129.93	27.28	−0.07	5.17	$-25.77^\dagger$	$-25.76^\dagger$	$-25.74^\dagger$	0.06	0.03	111.2*	135.4*
NO	0.0331	−194.59	203.69	44.71	0.06	2.87	$-30.83^\dagger$	$-30.81^\dagger$	$-30.79^\dagger$	0.19	0.01	160.5*	174.9*
ES	0.0703	−82.32	83.29	21.37	0.15	2.16	$-26.28^\dagger$	$-26.26^\dagger$	$-26.24^\dagger$	0.03	0.01	77.7*	120.0*
SE	−0.0719	−157.55	157.55	33.99	0.06	3.32	$-29.20^\dagger$	$-29.18^\dagger$	$-29.18^\dagger$	0.04	0.03	114.1*	163.6*
CH	−0.3255	−207.94	231.68	53.58	−0.02	1.99	$-27.43^\dagger$	$-27.41^\dagger$	$-27.39^\dagger$	0.03	0.04	138.1*	164.5*
GB	−0.0735	−82.67	160.94	22.95	0.80	5.20	$-23.74^\dagger$	$-23.72^\dagger$	$-23.7^\dagger$	0.07	0.05	46.1*	58.8*
AU	0.1550	−189.71	226.87	50.23	0.23	2.58	$-28.76^\dagger$	$-28.74^\dagger$	$-28.72^\dagger$	0.10	0.04	151.3*	177.7*
HK	−0.0291	−125.28	117.87	24.61	0.06	3.37	$-26.22^\dagger$	$-26.20^\dagger$	$-26.19^\dagger$	0.15	0.05	188.0*	196.5*
JP	0.0072	−107.88	156.06	21.47	0.87	6.81	$-25.06^\dagger$	$-25.04^\dagger$	$-25.03^\dagger$	0.05	0.02	62.4*	70.2*
NZ	−0.1384	−198.10	163.14	41.00	0.04	2.97	$-30.91^\dagger$	$-30.89^\dagger$	$-30.87^\dagger$	0.03	0.01	163.2*	208.1*
SG	0.1555	−179.18	212.03	23.88	0.65	16.87	$-27.03^\dagger$	$-27.01^\dagger$	$-27.00^\dagger$	0.10	0.09	131.3*	177.6*
CA	0.1424	−188.71	212.82	51.02	−0.01	1.81	$-29.35^\dagger$	$-29.32^\dagger$	$-29.3^\dagger$	0.11	0.02	124.9*	152.5*
US	0.0498	−126.57	158.41	21.03	1.37	15.53	$-22.67^\dagger$	$-22.65^\dagger$	$-22.63^\dagger$	0.04	0.03	54.4*	67.1*
Emerging													
IN	−0.1134	−74.92	82.93	14.28	0.19	4.35	$-27.07^\dagger$	$-27.06^\dagger$	$-27.04^\dagger$	0.07	0.03	126.1*	133.2*
ID	−0.2126	−160.94	189.71	40.44	0.29	2.32	$-29.29^\dagger$	$-29.27^\dagger$	$-29.25^\dagger$	0.01	0.01	134.4*	144.9*
MY	0.0528	−71.78	114.51	23.75	0.18	1.89	$-29.33^\dagger$	$-29.31^\dagger$	$-29.30^\dagger$	0.10	0.02	105.9*	137.6*
PH	−0.0978	−181.24	196.94	44.25	0.14	3.93	$-31.21^\dagger$	$-31.18^\dagger$	$-31.16^\dagger$	0.06	0.03	190.3*	219.0*
TH	−0.0136	−96.94	84.73	19.16	−0.11	4.05	$-30.31^\dagger$	$-30.28^\dagger$	$-30.26^\dagger$	0.03	0.03	209.1*	232.9*
BR	0.1944	−189.71	204.77	43.82	0.10	3.70	$-30.12^\dagger$	$-30.10^\dagger$	$-30.08^\dagger$	0.10	0.10	191.2*	240.7*
CL	−0.2433	−126.22	136.22	28.93	0.00	1.77	$-27.43^\dagger$	$-27.41^\dagger$	$-27.39^\dagger$	0.02	0.01	117.6*	133.5*
CO	−0.2094	−202.44	202.44	46.75	−0.08	2.62	$-27.73^\dagger$	$-27.71^\dagger$	$-27.69^\dagger$	0.05	0.03	134.5*	154.00*
MX	−0.3005	−188.27	237.16	40.50	0.12	3.91	$-26.05^\dagger$	$-26.04^\dagger$	$-26.02^\dagger$	0.04	0.02	108.5*	122.7*
PE	−0.1978	−182.45	215.95	33.22	−0.06	6.60	$-30.35^\dagger$	$-30.33^\dagger$	$-30.32^\dagger$	0.04	0.03	146.8*	190.1*
PL	−0.2054	−152.61	142.14	28.51	−0.26	5.19	$-28.64^\dagger$	$-28.62^\dagger$	$-28.61^\dagger$	0.08	0.03	158.9*	171.3*
RU	0.1201	−219.72	219.72	45.35	0.37	4.71	$-28.36^\dagger$	$-28.33^\dagger$	$-28.31^\dagger$	0.04	0.02	144.9*	175.6*
TR	−0.2023	−154.04	179.18	29.95	0.31	6.57	$-29.64^\dagger$	$-29.61^\dagger$	$-29.61^\dagger$	0.02	0.01	113.8*	132.6*
ZA	0.0185	−127.45	119.63	27.74	0.10	2.33	$-28.26^\dagger$	$-28.23^\dagger$	$-28.21^\dagger$	0.08	0.01	156.0*	169.7*

Table B.4

Summary Statistics: Returns from Stock Market Indices

This table presents the mean, minimum, maximum, standard deviation, skewness and kurtosis of weekly logarithmic returns (in %) estimated from the most popular stock market indices.

Country	Mean	Min	Max	StDev	Skew	Kurt
Developed						
AT	−0.0809	−12.54	12.61	2.01	−0.33	8.92
FI	−0.0356	−10.19	9.50	1.73	−0.30	6.82
FR	−0.0582	−11.74	12.14	1.83	0.45	11.28
DE	0.0171	−9.60	12.37	1.77	0.33	9.75
IE	−0.1190	−15.15	9.05	1.80	−1.65	15.35
IT	−0.1718	−10.86	12.17	2.00	0.11	6.98
NL	−0.0122	−11.86	12.32	1.79	0.17	12.49
NO	−0.0271	−14.52	15.28	2.29	−0.15	9.41
ES	−0.1257	−8.84	14.97	1.84	0.87	11.54
SE	0.0220	−10.31	13.70	1.99	0.30	10.15
CH	−0.0217	−7.51	10.02	1.31	0.31	10.78
GB	−0.0451	−10.49	11.36	1.59	0.15	13.33
AU	0.0297	−12.19	8.51	1.68	−0.14	7.40
HK	−0.0007	−13.59	9.73	1.68	−0.53	9.16
JP	0.0216	−6.71	6.03	1.39	−0.33	2.74
NZ	−0.0044	−8.94	4.12	1.18	−1.06	6.55
SG	−0.0668	−7.19	7.15	1.41	−0.12	4.46
CA	−0.0887	−10.18	8.71	1.53	−1.06	11.03
US	0.0035	−8.01	10.51	1.14	0.28	20.06
Emerging						
IN	−0.0441	−11.71	19.05	1.99	0.59	15.47
ID	−0.1883	−13.82	8.34	1.94	−1.20	9.32
MY	−0.0789	−11.01	5.22	1.12	−1.33	15.59
PH	−0.0477	−13.91	6.14	1.53	−1.54	11.73
TH	−0.1378	−11.60	7.85	1.61	−0.66	6.15
BR	−0.0777	−13.99	16.86	2.56	0.19	8.09
CL	−0.14	−11.67	14.55	1.51	0.16	21.47
CO	−0.169	−12.03	5.68	1.63	−1.67	8.93
MX	0.0333	−10.68	15.21	1.85	0.56	12.59
PE	−0.0198	−14.46	13.55	1.90	−0.25	14.75
PL	0.0698	−9.65	9.70	1.92	−0.29	4.30
RU	0.0093	−21.87	16.21	2.57	−1.00	12.62
TR	−0.0736	−15.49	16.69	2.58	−0.50	6.79
ZA	0.0161	−12.85	10.69	1.90	−0.41	6.61

Table B.5

Summary Statistics of Co-attention and Return Correlations based on Alternative Specifications

This table presents the summary statistics (mean, median, minimum, maximum, standard deviation, skewness and kurtosis) of alternative variables used in the analysis for robustness checks. ASVI is the abnormal SVI of Da et al. (2011) and LSVI follows the methodology used in Vlastakis and Markellos (2012). Specification indexed with "L" and "SE" deal with search volume indices of local users in each country and on search term queries based totally on stock exchange topics. Subscripts "I" indicate that return correlations are estimated between major stock market indices instead of country MSCI.

Variable	Mean	Median	Min	Max	Stdev	Skew	Kurt
			Co-Attention				
$\mathbf{CoAtt}^{LSVI}$	0.1247	0.1160	-0.5098	0.8904	0.2018	0.2709	0.1248
$\mathbf{CoAtt}^{ASVI_{SE}}$	0.1260	0.1175	-0.5170	0.7873	0.2021	0.2153	-0.0311
$\mathbf{CoAtt}^{LSVI_{SE}}$	0.0780	0.0757	-0.5751	0.7052	0.1854	0.1072	-0.1001
$\mathbf{CoAtt}^{LSVI_{L}}$	0.0834	0.0834	-0.9216	0.9787	0.2271	-0.1723	1.2128
			Return Correlation				
$\mathbf{CoRet}^{AR1_{I}}$	0.4956	0.5029	-0.2596	0.9901	0.2355	-0.1999	-0.4851
$\mathbf{CoRet}^{ARW_{I}}$	0.4979	0.4998	-0.2463	0.9880	0.2329	-0.1498	-0.5466
$\mathbf{CoRet}^{ERW_{I}}$	0.5164	0.5198	-0.2349	0.9880	0.2224	-0.1443	-0.5329

Table B.6

Average Pairwise Co-Attention and Return Correlation based on Alternative Specifications

This table presents in panel A the number of pairs and the average pairwise attention and return correlations estimated using total sample weekly data along with standard errors in parenthesis for alternative specifications used in robustness checks. More specifically, ASVI is the abnormal SVI of Da et al. (2011), LSVI follows the methodology used in Vlastakis and Markellos (2012). Specifications indexed with "L" and "SE" deal with search volume indices of local users in each country and on search term queries based totally on stock exchange topics. Subscripts "I" indicate that return correlations are estimated between major stock market indices instead of country MSCI. The last four columns presents the number and averages for the significant pairs splitting them to positive and negative. Panel B replicates the analysis for annual correlations computed with 52-week data. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

Variable			**Significant**					
	Total	**Mean**	**Total**	**Mean**	**Positive**	**Mean**	**Negative**	**Mean**
			Panel A: Total-sample-period Correlations					
CoAtt^{LSVI}	528	0.2470*** (0.0041)	451	0.2866	390	0.3548	61	-0.1890
CoAtt$^{ASVI_{SE}}$	528	0.1295*** (0.0042)	358	0.1747	357	0.1755	1	-0.1147
CoAtt$^{LSVI_{SE}}$	528	0.1742*** (0.0033)	426	0.2135	338	0.3221	88	-0.2292
CoAtt$^{ASVI_{L}}$	528	0.1614*** (0.0046)	417	0.1912	417	0.1912	0	—
CoAtt$^{LSVI_{L}}$	528	0.1989*** (0.0036)	412	0.2481	377	0.2830	35	-0.1496
CoRet$^{AR1_{I}}$	528	0.5870*** (0.0139)	527	0.5878	527	0.5878	0	—
CoRet$^{ARW_{I}}$	528	0.5899*** (0.0140)	527	0.5907	527	0.5907	0	—
CoRet$^{ERW_{I}}$	528	0.7840*** (0.0122)	528	0.7840	528	0.7840	0	—
			Panel B: Annual Correlations					
CoAtt^{LSVI}	6,864	0.1702*** (0.0027)	2,156	0.4036	2,007	0.4512	149	-0.3435
CoAtt$^{ASVI_{SE}}$	6,864	0.1329*** (0.0026)	1628	0.3676	1,516	0.4142	112	-0.3437
CoAtt$^{LSVI_{SE}}$	6,864	0.1264*** (0.0023)	1,666	0.3605	1529	0.4159	137	-0.3373
CoAtt$^{ASVI_{L}}$	6,768	0.1610*** (0.0034)	1,751	0.4294	1,671	0.4658	80	-0.4547
CoAtt$^{LSVI_{L}}$	6,864	0.1605*** (0.0031)	1,937	0.4166	1767	0.4848	170	-0.4186
CoRet$^{AR1_{I}}$	6,864	0.5446*** (0.0046)	5,598	0.6144	5,598	0.6144	0	—
CoRet$^{ARW_{I}}$	6,864	0.5470*** (0.0046)	5,619	0.6145	5,619	0.6145	0	—
CoRet$^{ERW_{I}}$	6,864	0.5638*** (0.0045)	5,815	0.6188	5,815	0.6188	0	—

Table B.7

Correlation Matrix between Co-Attention based on Alternative Specifications and Co-News

This table presents the correlation matrix of various alternative specifications for the estimation of co-attention. ASVI is the abnormal SVI of Da et al. (2011) and LSVI follows the methodology used in Vlastakis and Markellos (2012). Specifications indexed with "L" and "SE" deal with search volume indices of local users in each country and on search term queries based totally on stock exchange topics. The last row includes the correlation of all co-attention specifications with a proxy for correlated news. Co-attention reflects the correlation between information demand while co-news reflects the correlation between information supply.

	ASVI	**LSVI**	**ASVI**$_L$	**LSVI**$_L$	**ASVI**$_{SE}$	**LSVI**$_{SE}$
LSVI	0.7331*					
ASVI$_L$	0.6225*	0.4955*				
LSVI$_L$	0.3724*	0.4029*	0.5888*			
ASVI$_{SE}$	0.6109*	0.4166*	0.3948*	0.2221*		
LSVI$_{SE}$	0.3440*	0.4945*	0.2286*	0.1854*	0.6285*	
CoNews	0.1079*	0.1460*	0.0986*	0.0971*	0.0456*	0.0640*

Table B.8

Stock Market Comovement and Co-Attention: Without Lagged Dependent Variable

This table reports the slope coefficients and cluster robust standard errors from panel regressions of return correlation on co-attention controlling for correlation explained by fundamentals (*LogFL*), geographical distance (*LogDist*), and correlated news (*CoNews*) including year and fixed effects (not reported) for heterogeneity in each pair and over time. Co-attention and return correlations are derived using yearly non overlapping data. Co-attention is estimated based on ASVI of (Da et al., 2011). Columns 2-4 report the results using return correlations estimated from the residuals of a first order autoregressive model (AR1), the residuals from a first order autoregressive model including the MSCI World Index as a global factor (AR1W), and the residuals from a regression of excess returns (subtracting the riskless rate) on excess MSCI World Index returns (ERW). The US 3-month T-bill is used to approximate the risk free rate. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	AR1	**ARW1**	**ERW**
CoAtt$_{t-1}$	0.1091***	0.1169***	0.1094***
	(0.0152)	(0.0147)	(0.0151)
LogFL$_{t-1}$	0.0044**	0.0042**	0.0044**
	(0.0015)	(0.0015)	(0.0015)
LogDist	−0.0506**	−0.0504**	−0.0525***
	(0.0157)	(0.0155)	(0.0155)
CoNews$_{t-1}$	0.0227	0.0211	0.0061
	(0.0874)	(0.0879)	(0.0885)
Obs	5,828	5,828	5,828
Adj-R^2	0.3999	0.4050	0.4029
FE	Y	Y	Y
TE	Y	Y	Y

Table B.9

Stock Market Comovement and Co-attention estimated using LSVI

This table reports the beta coefficients and cluster robust standard errors from panel regressions of return correlation on co-attention controlling for persistent correlation (*CoRet*) and for correlation explained by fundamentals (*LogFL*), geographical distance (*LogDist*), and correlated news (*CoNews*) including year and fixed effects for heterogeneity in each pair and over time. Co-attention and return correlations are derived using yearly non overlapping data. Co-attention is estimated using SVI following the alternative methodology of Vlastakis and Markellos (2012). Model 2-4 explore for differences in the effect of co-attention for developed economies, for pairs including the US, and for different market regimes. Panel A, B and C report the results using return correlations estimated from the residuals of a first order autoregressive model (AR1), the residuals from an AR(1) including the MSCI World Index as a global factor (AR1W), and the residuals from a regression of excess returns (subtracting the riskless rate) on excess MSCI World Index returns (ERW). The US 3-month T-bill is used to approximate the risk free rate. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	AR1				**AR1W**				**ERW**			
	ALL	**MC**	**US**	**MR**	**ALL**	**MC**	**US**	**MR**	**ALL**	**MC**	**US**	**MR**
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
CoAtt$_{t-1}$	0.0812***	0.1159***	0.0679***	0.0727***	0.0862***	0.1292***	0.0740***	0.0738***	0.0838***	0.1151***	0.0695***	0.0712***
	(0.0151)	(0.0227)	(0.0158)	(0.0166)	(0.0150)	(0.0220)	(0.0157)	(0.0167)	(0.0153)	(0.0230)	(0.0160)	(0.0169)
CoRet$_{t-1}$	0.2011***	0.1945***	0.1985***	0.2008***	0.1990***	0.1925***	0.1962***	0.1987***	0.1915***	0.1847***	0.1885***	0.1911***
	(0.0176)	(0.0169)	(0.0177)	(0.0176)	(0.0176)	(0.0168)	(0.0177)	(0.0175)	(0.0173)	(0.0166)	(0.0174)	(0.0172)
LogFL$_{t-1}$	0.0037**	0.0028*	0.0032*	0.0037**	0.0035**	0.0026*	0.0031*	0.0036**	0.0037**	0.0029*	0.0032*	0.0038**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0013)	(0.0013)
LogDist	−0.0408**	−0.0312*	−0.0404**	−0.0406**	−0.0408**	−0.0315**	−0.0404**	−0.0406**	−0.0431***	−0.0336**	−0.0426***	−0.0428***
	(0.0127)	(0.0122)	(0.0127)	(0.0127)	(0.0126)	(0.0120)	(0.0125)	(0.0126)	(0.0127)	(0.0121)	(0.0127)	(0.0127)
CoNews$_{t-1}$	0.0265	0.0336	0.0328	0.0297	0.0254	0.0307	0.0313	0.0300	0.0130	0.0205	0.0198	0.0177
	(0.0732)	(0.0712)	(0.0738)	(0.0734)	(0.0740)	(0.0721)	(0.0746)	(0.0742)	(0.0747)	(0.0729)	(0.0753)	(0.0748)
EMG		−0.2248***				−0.2085***				−0.2535***		
		(0.0412)				(0.0415)				(0.0421)		
MIX		−0.1074**				−0.1018**				−0.1081**		
		(0.0381)				(0.0385)				(0.0386)		
CoAt$_{t-1}$:EMG		−0.0290				−0.0393				−0.0220		
		(0.0411)				(0.0408)				(0.0417)		
CoAtt$_{t-1}$:MIX		−0.0796**				−0.0948***				−0.0745**		
		(0.0272)				(0.0264)				(0.0280)		
USIndex			0.0223				0.0266				0.0265	
			(0.0290)				(0.0288)				(0.0291)	
CoAtt$_{t-1}$:USIndex			0.1516***				0.1374**				0.1632***	
			(0.0425)				(0.0429)				(0.0447)	
Recession				0.3380***				0.3302***				0.3057***
				(0.0125)				(0.0123)				(0.0123)
CoAtt$_{t-1}$:Recession				0.0416				0.0605·				0.0619·
				(0.0322)				(0.0318)				(0.0333)
Adj-R^2	0.4224	0.4262	0.4241	0.4224	0.4261	0.4303	0.4277	0.4264	0.423	0.4267	0.4251	0.4233
Obs	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828	5,828
FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table B.10

Stock Market Comovement and Co-attention Using Alternative Stock Market Indices and Search Queries

This table reports the beta coefficients and robust standard errors from panel regressions of return correlation on co-attention controlling for persistent correlation ($CoRet_{t-1}$) and for correlation explained by fundamentals (*LogFL*), geographical distance (*LogDist*), and correlated news (*CoNews*) including year and fixed effects for heterogeneity in each pair and over time. Co-attention and return correlations are derived using yearly non overlapping data. In Panel A, return correlations are estimated using the most important stock market index of each country instead of the MSCI indices. In Panel B, co-attention is estimated based on ASVI of Da et al. (2011) using stock exchanges as search topics for all countries instead of the most popular query between stock market index and stock exchange. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	Panel A: *CoRet* between Major Stock Market Indices			**Panel B: *CoAtt* between ASVIs for Stock Exchanges**		
	AR1	**AR1W**	**ERW**	**AR1**	**AR1W**	**ERW**
CoAtt$_{t-1}$	0.0812***	0.0862***	0.0838***	0.0572***	0.0594***	0.0549***
	(0.0151)	(0.0150)	(0.0153)	(0.0148)	(0.0148)	(0.0150)
CoRet$_{t-1}$	0.2011***	0.1990***	0.1915***	0.1989***	0.1966***	0.1892***
	(0.0176)	(0.0176)	(0.0173)	(0.0180)	(0.0179)	(0.0177)
LogFL$_{t-1}$	0.0037**	0.0035**	0.0037**	0.0041**	0.0040**	0.0042***
	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
LogDist	−0.0408**	−0.0408**	−0.0431***	−0.0425**	−0.0427***	−0.0448***
	(0.0127)	(0.0126)	(0.0127)	(0.0129)	(0.0128)	(0.0129)
CoNews$_{t-1}$	0.0265	0.0254	0.0130	0.0431	0.0432	0.0306
	(0.0732)	(0.074)	(0.0747)	(0.0742)	(0.0751)	(0.0758)
Adj-R^2	0.3834	0.3851	0.3540	0.4204	0.4239	0.4207
Obs	5,828	5,828	5,828	5,828	5,828	5,828
FE	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y

Table B.11

Robustness Checks for Co-Attention and Return Correlation from mGARCH model

This table reports the beta coefficients and robust standard errors from panel regressions of weekly return correlation on co-attention controlling for persistent correlation (*CoRet*), for attention of each country ($ASVI_i$ and $ASVI_j$) and for correlation explained by fundamentals (*LogFL*), geographical distance (*LogDist*), and correlated news (*CoNews*) including year and fixed effects for heterogeneity in each pair and over time. Co-attention and return correlations are derived using weekly data via a multivariate GARCH model (diagonal BEKK). Co-attention is estimated based on *LSVI* of Vlastakis and Markellos (2012). The analysis is replicated for returns based on stock market indices instead of country MSCI Indices and for SVIs for stock exchange queries. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	Alternative CoAtt: LSVI			**Stock Market Indices**			**SE Queries**		
	AR1	**AR1W**	**ERW**	**AR1**	**AR1W**	**ERW**	**AR1**	**AR1W**	**ERW**
CoAtt$_{t-1}$	0.0056***	0.0064***	0.0065***	0.0051***	0.0065***	0.0200***	0.0117***	0.0117***	0.0114***
	(0.0004)	(0.0002)	(0.0002)	(0.0007)	(0.0007)	(0.0022)	(0.0007)	(0.0007)	(0.0006)
ASVI$_{i,t-1}$	0.0012***	0.0011***	0.0012***	0.0013***	0.0016***	0.0010***	0.0013***	0.0013***	0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ASVI$_{j,t-1}$	0.0010***	0.0010***	0.0010***	0.0007***	0.0010***	0.0003**	0.0014***	0.0014***	0.0016***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CoRet$_{t-1}$	0.9756***	0.9762***	0.9752***	0.9782***	0.9785***	0.9087***	0.9766***	0.9771***	0.9763***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0066)	(0.0005)	(0.0005)	(0.0005)
LogFL$_{t-1}$	0.0001**	0.0001*	0.0001.	0.0001**	0.0000	0.0003*	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
LogDist	−0.0008***	−0.0009***	−0.0010***	−0.0008***	−0.0009***	−0.0078***	−0.0010***	−0.0009***	−0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0015)	(0.0002)	(0.0002)	(0.0002)
CoNews$_{t-1}$	0.0015	0.0015	0.0003	0.0010	0.0016	−0.0039	0.0021	0.0018	0.0007
	(0.0017)	(0.0017)	(0.0018)	(0.0017)	(0.0018)	(0.0099)	(0.0016)	(0.0015)	(0.0017)
Adj-R^2	0.9783	0.9791	0.9813	0.9755	0.972	0.9129	0.9796	0.9801	0.9822
Obs	355,344	355,344	355,344	352,703	352,703	352,703	344,784	344,784	344,784
FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table B.12

Return Comovement on Positive and Negative Co-Attention

Panel A reports the beta coefficients along with robust standard errors of return correlation on all positive co-attention and on significant positive co-attention controlling for persistent correlation, capital flows, distance and correlated news. Panel B displays the same regressions analysis when co-attention is negative. Co-attention and return correlations are derived using annual non overlapping data. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ denote the level of significance.

	All			**Significant**		
	AR1	**AR1W**	**ERW**	**AR1**	**AR1W**	**ERW**
	Panel A: Positive Co-Attention					
CoAtt$_{t-1}$	0.1130***	0.1250***	0.1185***	0.1369***	0.1571***	0.1398***
	(0.0191)	(0.0188)	(0.0194)	(0.0327)	(0.0317)	(0.0322)
CoRet$_{t-1}$	0.2413***	0.2367***	0.2233***	0.3774***	0.3737***	0.3593***
	(0.0192)	(0.0192)	(0.0193)	(0.0265)	(0.0266)	(0.0264)
LogFL$_{t-1}$	0.0067***	0.0065***	0.0068***	0.0094***	0.0095***	0.0096***
	(0.0014)	(0.0014)	(0.0014)	(0.0022)	(0.0022)	(0.0022)
LogDist	−0.0329**	−0.0327**	−0.0354**	−0.0479***	−0.0473***	−0.0461***
	(0.0108)	(0.0106)	(0.0109)	(0.0099)	(0.0099)	(0.0103)
CoNews$_{t-1}$	0.1063	0.0995	0.0918	0.1429	0.1386	0.1474
	(0.0943)	(0.0935)	(0.0981)	(0.0979)	(0.0978)	(0.0998)
Adj-R^2	0.2999	0.3021	0.2953	0.3094	0.3128	0.2953
Obs	4,373	4,373	4,373	1,794	1,794	1,794
FE	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y
	Panel B: Negative Co-Attention					
CoAtt$_{t-1}$	−0.0346	−0.0407	−0.0383	−0.4066	−0.3835	−0.7299*
	(0.0797)	(0.0789)	(0.0801)	(0.3834)	(0.4109)	(0.3349)
CoRet$_{t-1}$	0.2090***	0.2181***	0.2043***	0.2361***	0.2281**	0.3803***
	(0.0455)	(0.0456)	(0.0477)	(0.0449)	(0.0701)	(0.0610)
LogFL$_{t-1}$	0.0025	0.0020	0.0034	−0.0376*	−0.0381·	−0.0428·
	(0.0033)	(0.0033)	(0.0033)	(0.0173)	(0.0178)	(0.0206)
LogDist	−0.0615***	−0.0611***	−0.0576***	−0.2288***	−0.2278***	−0.1967***
	(0.0151)	(0.0148)	(0.0148)	(0.0196)	(0.0171)	(0.0158)
CoNews$_{t-1}$	−0.0558	−0.0419	−0.0563	−0.0171	−0.0423	0.0305
	(0.1407)	(0.1462)	(0.1300)	(0.1470)	(0.1685)	(0.0828)
Adj-R^2	0.1459	0.1509	0.1237	0.5533	0.5284	0.3092
Obs	1,020	1,020	1,020	28	28	28
FE	Y	Y	Y	Y	Y	Y
TE	Y	Y	Y	Y	Y	Y

Table B.13

Estimation Results from the BEKK Model for Return Correlation

This tables presents the coefficients for the mean and variance-covariance equations derived from the BEKK model using the residuals of returns from *AR1*, *AR1W*, and *ERW*. Coefficients at level of significance higher than 5 percent are not reported. The last column examines whether the stationarity condition is satisfied.

Country	AR1					AR1W					ERW				
	Mean	Var-Covar			Stationarity	Mean	Var-Covar			Stationarity	Mean	Var-Covar			Stationarity
	c	G	V	W		c	G	V	W		c	G	V	W	
AT		0.0586	0.1297	0.9864	0.9897		0.0590	0.1306	0.9862	0.9897		0.0566	0.1281	0.9867	0.9900
FI		0.0743	0.1322	0.9854	0.9884		0.0717	0.1318	0.9854	0.9885		0.0763	0.1339	0.9849	0.9879
FR		0.0036	0.1134	0.9900	0.9929		0.0036	0.1140	0.9899	0.9929		0.0041	0.1179	0.9888	0.9917
DE		0.0089	0.1136	0.9898	0.9925		0.0085	0.1114	0.9902	0.9929		0.0107	0.1183	0.9885	0.9911
IE		0.0851	0.1392	0.9854	0.9903		0.0850	0.1388	0.9854	0.9902		0.0980	0.1536	0.9821	0.9882
IT		0.0154	0.1141	0.9910	0.9952		0.0164	0.1183	0.9904	0.9948		0.0144	0.1095	0.9914	0.9948
NL		0.0101	0.1175	0.9891	0.9921		0.0101	0.1171	0.9892	0.9922		0.0111	0.1220	0.9879	0.9907
NO		0.0695	0.1265	0.9850	0.9861		0.0696	0.1245	0.9853	0.9864		0.0738	0.1315	0.9842	0.9859
ES		0.0280	0.1142	0.9903	0.9937		0.0294	0.1190	0.9895	0.9932		0.0253	0.1082	0.9909	0.9935
SE		0.0372	0.1254	0.9864	0.9886		0.0361	0.1265	0.9863	0.9888		0.0412	0.1329	0.9850	0.9879
CH		0.0197	0.1223	0.9872	0.9895		0.0194	0.1228	0.9872	0.9897		0.0245	0.1353	0.9845	0.9875
GB		0.0188	0.1379	0.9843	0.9879		0.0190	0.1385	0.9842	0.9878		0.0202	0.1427	0.9831	0.9869
AU		0.0670	0.1483	0.9802	0.9828		0.0634	0.1462	0.9809	0.9835		0.0673	0.1523	0.9798	0.9831
HK	-0.2231	0.1261	0.2092	0.9651	0.9753		0.1237	0.2069	0.9659	0.9758		0.1082	0.1855	0.9716	0.9783
JP	-0.1838	0.1466	0.1513	0.9755	0.9745		0.1365	0.1403	0.9774	0.9750		0.1538	0.1739	0.9714	0.9739
NZ		0.0899	0.1325	0.9833	0.9845		0.0858	0.1288	0.9842	0.9852		0.1002	0.1384	0.9820	0.9834
SG	-0.1732	0.0609	0.1846	0.9716	0.9780	-0.1542	0.0582	0.1789	0.9730	0.9786		0.0549	0.1714	0.9754	0.9808
CA		0.0520	0.1664	0.9779	0.9840		0.0517	0.1665	0.9778	0.9838		0.0547	0.1681	0.9771	0.9830
US		0.0263	0.1580	0.9804	0.9862		0.0250	0.1546	0.9813	0.9868		0.0360	0.1598	0.9786	0.9832
IN	-0.2574		0.1640	0.9725	0.9726	-0.2464		0.1613	0.9734	0.9735		0.2850	0.1599	0.9754	0.9769
ID	-0.2547	0.3472	0.1829	0.9689	0.9721		0.3519	0.1788	0.9695	0.9720		0.3185	0.1726	0.9722	0.9750
MY	-0.1630	0.0985	0.1494	0.9759	0.9747	-0.1593	0.0972	0.1489	0.9761	0.9750		0.0998	0.1507	0.9771	0.9774
PH		0.2674	0.1571	0.9727	0.9709		0.2732	0.1565	0.9727	0.9707		0.2498	0.1661	0.9732	0.9748
TH		0.2228	0.1697	0.9733	0.9761		0.2248	0.1686	0.9734	0.9760		0.2099	0.1651	0.9752	0.9782
BR	-0.3281	0.1970	0.1636	0.9747	0.9769	-0.3108	0.1918	0.1613	0.9754	0.9774		0.1776	0.1526	0.9781	0.9800
CL	-0.2096	0.1498	0.1687	0.9741	0.9773	-0.2132	0.1467	0.1652	0.9750	0.9779		0.1361	0.1629	0.9763	0.9798
CO	-0.2969	0.3018	0.1593	0.9760	0.9780	-0.3115	0.2970	0.1593	0.9760	0.9780		0.3468	0.1695	0.9731	0.9755
MX		0.1003	0.1582	0.9782	0.9819		0.0967	0.1515	0.9798	0.9830		0.0947	0.1492	0.9804	0.9834
PE		0.2859	0.1614	0.9742	0.9752		0.2792	0.1602	0.9746	0.9755		0.2619	0.1551	0.9767	0.9781
PL		0.1038	0.1197	0.9871	0.9886		0.1054	0.1169	0.9874	0.9887		0.0990	0.1180	0.9876	0.9894
RU	-0.2589	0.2973	0.1577	0.9760	0.9775	-0.2521	0.2954	0.1582	0.9760	0.9776		0.2983	0.1636	0.9756	0.9785
TR		0.3001	0.1083	0.9853	0.9826		0.2909	0.1078	0.9856	0.9831		0.3022	0.1101	0.9854	0.9832
ZA		0.1042	0.1298	0.9838	0.9848		0.1007	0.1290	0.9842	0.9852		0.1029	0.1331	0.9838	0.9857

Table B.14

Estimation Results from the BEKK Model for Alternative Co-Attention

This tables presents the coefficients for the mean and variance-covariance equations derived from the BEKK model for co-attention estimated with *LSVI*. Coefficients at level of significance higher than 5 percent are not reported. The last column examines whether the stationarity condition is satisfied.

Country	LSVI				
	Mean	Variance-Covariance			Stationarity
	c	G	V	W	
AT		0.2954	0.4059	0.7312	0.6993
FI		0.5312	0.4342	0.5285	0.4679
FR		0.0156	0.2361	0.9646	0.9862
DE		0.0118	0.2582	0.9617	0.9915
IE		0.4494	0.4342	0.6015	0.5503
IT		0.0304	0.2163	0.9593	0.9671
NL		0.0122	0.2450	0.9645	0.9903
NO		0.4587	0.4595	0.5601	0.5248
ES		0.0679	0.2618	0.9295	0.9326
SE		0.4577	0.3837	0.6269	0.5402
CH		0.6295	0.3696	0.4578	0.3462
GB		0.0126	0.2115	0.9703	0.9862
AU		0.4567	0.4241	0.5922	0.5305
HK		0.3423	0.4098	0.6923	0.6472
JP		0.1922	0.3122	0.8409	0.8046
NZ		0.5750	0.4017	0.5004	0.4118
SG		0.3918	0.4645	0.6305	0.6133
CA		0.4057	0.4128	0.6466	0.5885
US		0.0437	0.2400	0.9469	0.9542
IN		0.4821	0.3906	0.6019	0.5148
ID	-0.0325	0.6029	0.4184	0.4522	0.3795
MY		0.4460	0.4195	0.6089	0.5468
PH		0.4905	0.4535	0.5423	0.4997
TH		0.5415	0.4226	0.5201	0.4491
BR		0.4755	0.4335	0.5778	0.5218
CL		0.5302	0.4268	0.5286	0.4616
CO		0.5667	0.4258	0.4797	0.4115
MX		0.4515	0.3913	0.6242	0.5428
PE		0.6356	0.4109	0.4086	0.3358
PL		0.4370	0.4103	0.6224	0.5557
RU		0.6027	0.3338	0.5097	0.3712
TR		0.6132	0.3664	0.4781	0.3628
ZA		0.4957	0.3862	0.5882	0.4951

Appendix C - Chapter 4

Using 5-year Historical Data

Table C.1
Keyword Description

This table presents the number of keywords for each industry (No), the average monthly searches (AMS), the expected number of clicks, click-through-rates (CTR) and the cost-per-click (CPC) for sets of relevant keywords in 15 industries provided by Google Ad Words. CPR estimates the cost per reservation, that is, the CPC divided by the CTR.

Industry	Code	No	AMS	Clicks	CTR	CPC	CPR
Advertising Services	ADS	142	187,010	115	0.0219	2.1642	19.59
Beauty	BTY	158	173,654	84	0.0290	1.6892	2.55
Consumer Electronics	CEL	196	181,691	78	0.0238	1.8999	2.30
Fashion & Style	FNS	144	96,465	26	0.0301	1.6593	1.43
Finance	FNC	68	188,525	193	0.0159	2.0121	2.44
Health	HLT	205	227,660	162	0.0199	1.9346	2.65
Hobbies & Leisure	HNL	197	165,721	110	0.0259	1.8620	9.64
Home Appliances	HAP	277	49,871	120	0.0274	2.1334	2.75
Internet	INR	127	6,653,835	198	0.0274	1.5120	1.86
Internet & Telecom.	TEL	40	467,750	149	0.0244	1.8105	2.99
Management Cons.	MCS	75	14,529	9	0.0202	2.1949	3.31
Motor Vehicles	MVH	222	190,884	168	0.0389	1.7921	11.04
Real Estate	RES	191	171,173	227	0.0269	2.2459	2.58
Social Network	SNT	157	72,319	8	0.0593	0.5840	0.32
Travel & Tourism	TNT	277	138,886	87	0.0408	1.9181	13.55
Average	-	165	598,665	116	0.0288	1.8275	5.27

(R1)

Table C.2

Descriptive Statistics of Changes in SVIs (R1)

This table presents the average mean (μ) and standard deviation (σ) for weekly percentage changes in SVIs. The last column estimates the average correlation (ρ) between all keywords for each sector.

Industry	μ	σ	ρ
Advertising Services	0.0069	0.1209	0.2100
Beauty	0.0067	0.0977	0.0395
Consumer Electronics	0.0078	0.1207	0.1179
Fashion & Style	0.0143	0.1757	0.0182
Finance	0.0093	0.1351	0.1788
Health	0.0074	0.1151	0.2389
Hobbies & Leisure	0.0089	0.1232	0.0277
Home Appliances	0.0097	0.1344	0.1119
Internet	0.0042	0.0819	0.0208
Internet & Telecom.	0.0049	0.0960	0.0173
Management Cons.	0.0099	0.1461	0.2174
Motor Vehicles	0.0052	0.0950	0.0660
Real Estate	0.0062	0.1105	0.2379
Social Network	0.0054	0.1104	0.0355
Travel & Tourism	0.0100	0.1389	0.0763
Average	0.0078	0.1201	0.1085

Table C.3

Regression of Average SVI Changes against Standard Deviation (R1)

This table shows the slope of average weekly percent changes in SVIs regressed on the standard deviation along with the relevant t-statistics estimated using robust standard errors. The last column reports the adjusted R-squared of the regression.

Industry	Slope	t-statistic	R^2-adj
Advertising Services	0.1049	25.6979	0.8968
Beauty	0.1207	13.4338	0.8744
Consumer Electronics	0.1464	6.9099	0.8968
Fashion & Style	0.1460	20.1697	0.9305
Finance	0.1275	20.8303	0.9485
Health	0.1113	19.7567	0.9049
Hobbies & Leisure	0.1939	4.1942	0.7818
Home Appliances	0.1158	31.7455	0.9231
Internet	0.1303	11.0928	0.8558
Internet & Telecom.	0.0977	7.1414	0.8274
Management Cons.	0.1243	23.2855	0.9254
Motor Vehicles	0.1047	13.6787	0.8433
Real Estate	0.1066	24.3303	0.8608
Social Network	0.0994	22.8164	0.6796
Travel & Tourism	0.1434	8.9876	0.8610
Average	0.1249	16.9381	0.8673

Table C.4

Keyword Portfolio Sizes (R1)

This table exhibits the number of keywords for each strategy invests the budget. EP averages the number of keywords across 100 portfolios on the efficient frontier. MVP is the minimum variance portfolio, SRP is the portfolio with the maximum Sharpe Ratio, BP1 and BP2 are the benchmark portfolios 1 and 2 that invest equally in the most and the least popular keywords respectively (short head vs. long tail), BP3 and BP4 are the benchmark portfolios 3 and 4 that invest equally in the keywords with the highest CTRs and the lowest CPRs respectively, and B5 is the portfolio that invests equally in all keywords in the dataset.

Industries	EP	MVP	SRP	BP1	BP2	BP3	BP4	BP5
Advertising Services	22	40	42	21	121	44	133	142
Beauty	21	61	67	39	119	36	133	158
Consumer Electronics	13	58	63	25	171	67	152	196
Fashion & Style	34	73	79	33	111	30	104	144
Finance	20	24	25	17	51	32	58	68
Health	23	53	54	68	137	58	161	205
Hobbies & Leisure	16	79	80	35	162	65	181	197
Home Appliances	40	66	76	65	212	77	218	277
Internet	18	68	59	10	117	29	96	127
Internet & Telecom.	15	30	31	10	30	16	31	40
Management Cons.	21	27	34	23	52	21	57	75
Motor Vehicles	30	79	69	40	182	42	213	222
Real Estate	25	37	42	20	171	52	146	191
Social Network	35	76	70	53	104	42	129	157
Travel & Tourism	25	81	74	60	217	47	265	277
Average	24	57	58	35	130	44	138	165

Table C.5

JKM Test of Equality in Keyword Portfolio Performance (R1)

This table presents the p-values of the parametric test of JKM test of Jobson and Korkie (1981) and Memmel (2003). The null hypothesis is that there is no difference in the Sharpe ratio of the benchmark portfolios and that of the corresponding portfolio on the efficient frontier for the same level of risk. ***, **, * denote the 1%, 5% and 10% level of significance respectively.

Industries	BPrtf1	BPrtf2	BPrtf3	BPrtf4	BPrtf5
Advertising Services	0.0000***	0.0007***	0.0016***	0.0004***	0.0003***
Beauty	0.0000***	0.0000***	0.0001***	0.0000***	0.0000***
Consumer Electronics	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Fashion & Style	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Finance	0.0003***	0.0009***	0.0004***	0.0003***	0.0004***
Health	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Hobbies & Leisure	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Home Appliances	0.0000***	0.0001***	0.0000***	0.0000***	0.0000***
Internet	0.0005***	0.0000***	0.0000***	0.0000***	0.0000***
Internet & Telecom.	0.0243**	0.0226**	0.0670*	0.0337**	0.0434**
Management Cons.	0.0172**	0.0111**	0.0316**	0.0120**	0.0113**
Motor Vehicles	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Real Estate	0.0000***	0.0000***	0.0002***	0.0000***	0.0000***
Social Network	0.0000***	0.0001***	0.0002***	0.0000***	0.0000***
Travel & Tourism	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

Table C.6

LW Test of Equality in Keyword Portfolio Performance (R1)

This table presents the p-values of the non-parametric test of Ledoit-Wolf (2008). The null hypothesis is that there is no difference in the Sharpe ratio of the benchmark portfolios and that of the portfolio on the efficient frontier for the same level of risk. The standard errors of the test are estimated via bootstrap. ***, **, * denote the 1%, 5% and 10% level of significance respectively.

Industries	BPrtf1	BPrtf2	BPrtf3	BPrtf4	BPrtf5
Advertising Services	0.0002***	0.0006***	0.0002***	0.0002***	0.0002***
Beauty	0.0002***	0.0002***	0.0004***	0.0002***	0.0002***
Consumer Electronics	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Fashion & Style	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Finance	0.0006***	0.0002***	0.0002***	0.0002***	0.0002***
Health	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Hobbies & Leisure	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Home Appliances	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Internet	0.0004***	0.0002***	0.0002***	0.0002***	0.0002***
Internet & Telecom.	0.0148**	0.0048***	0.0248**	0.0362**	0.0176**
Management Cons.	0.0020***	0.0008***	0.0026***	0.0010***	0.0004***
Motor Vehicles	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Real Estate	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
Social Network	0.0002***	0.0002***	0.0002***	0.0002***	0.0004***
Travel & Tourism	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***

Table C.7

Sharpe Ratio Heuristic (R1)

This table presents the p-values of the JKM parametric test. The null hypothesis is that there is no difference in the Sharpe ratio of two portfolios built under the Sharpe Ratio heuristic and the portfolio on the efficient frontier at the same level of risk. EWSR selects the keywords with Sharpe Ratio higher than the average Sharpe Ratio of all keywords in the portfolio. EW10P selects 10 keywords with the highest Sharpe Ratio.

Industries	Sharpe Ratio	
	EWSR	EW10P
Advertising Services	0.1109	0.3688
Beauty	0.1287	0.4533
Consumer Electronics	0.3953	0.0716
Fashion & Style	0.0741	0.0076
Finance	0.4088	0.4315
Health	0.1873	0.4033
Hobbies & Leisure	0.1013	0.0095
Home Appliances	0.4387	0.0965
Internet	0.1582	0.1079
Internet & Telecom.	0.1366	0.2460
Management Cons.	0.3319	0.3202
Motor Vehicles	0.3995	0.2996
Real Estate	0.2731	0.4750
Social Network	0.3832	0.4704
Travel & Tourism	0.0064	0.0111

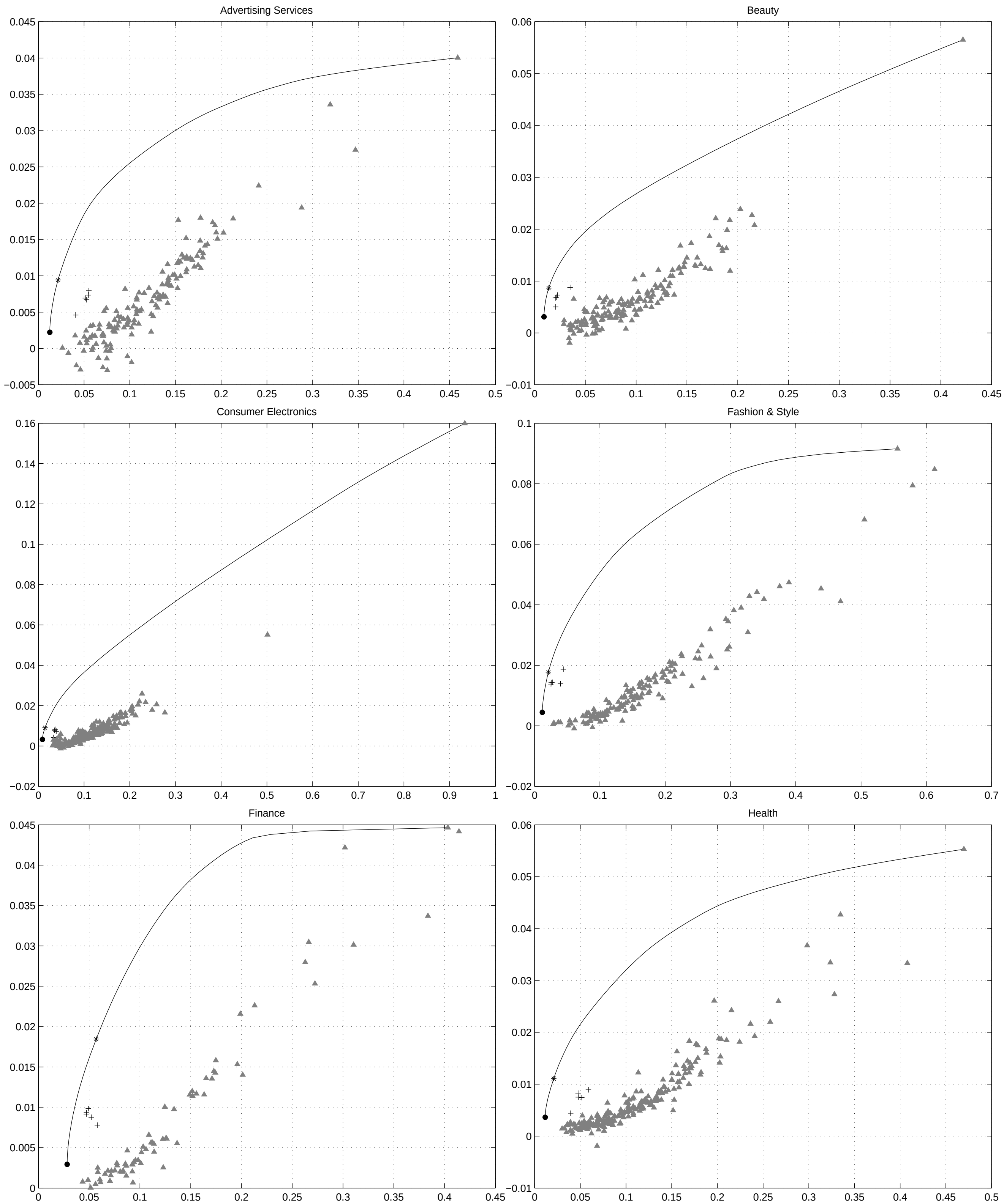


Figure C.1 Efficient Keyword Frontiers in Industries 1-6 (R1) The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles corrrespond to individual keywords.

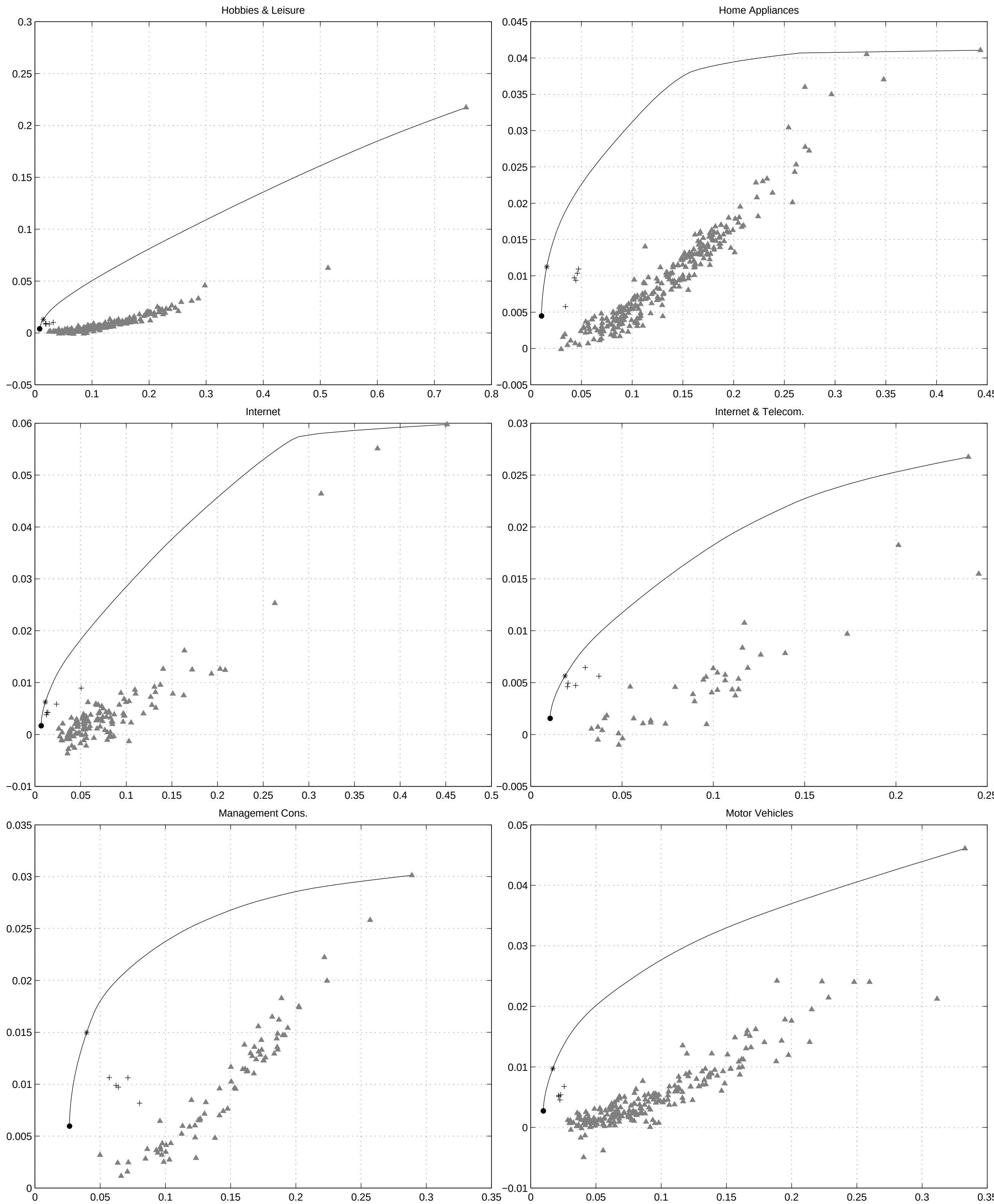


Figure C.2 Efficient Keyword Frontiers in Industries 7-12 (R1) The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

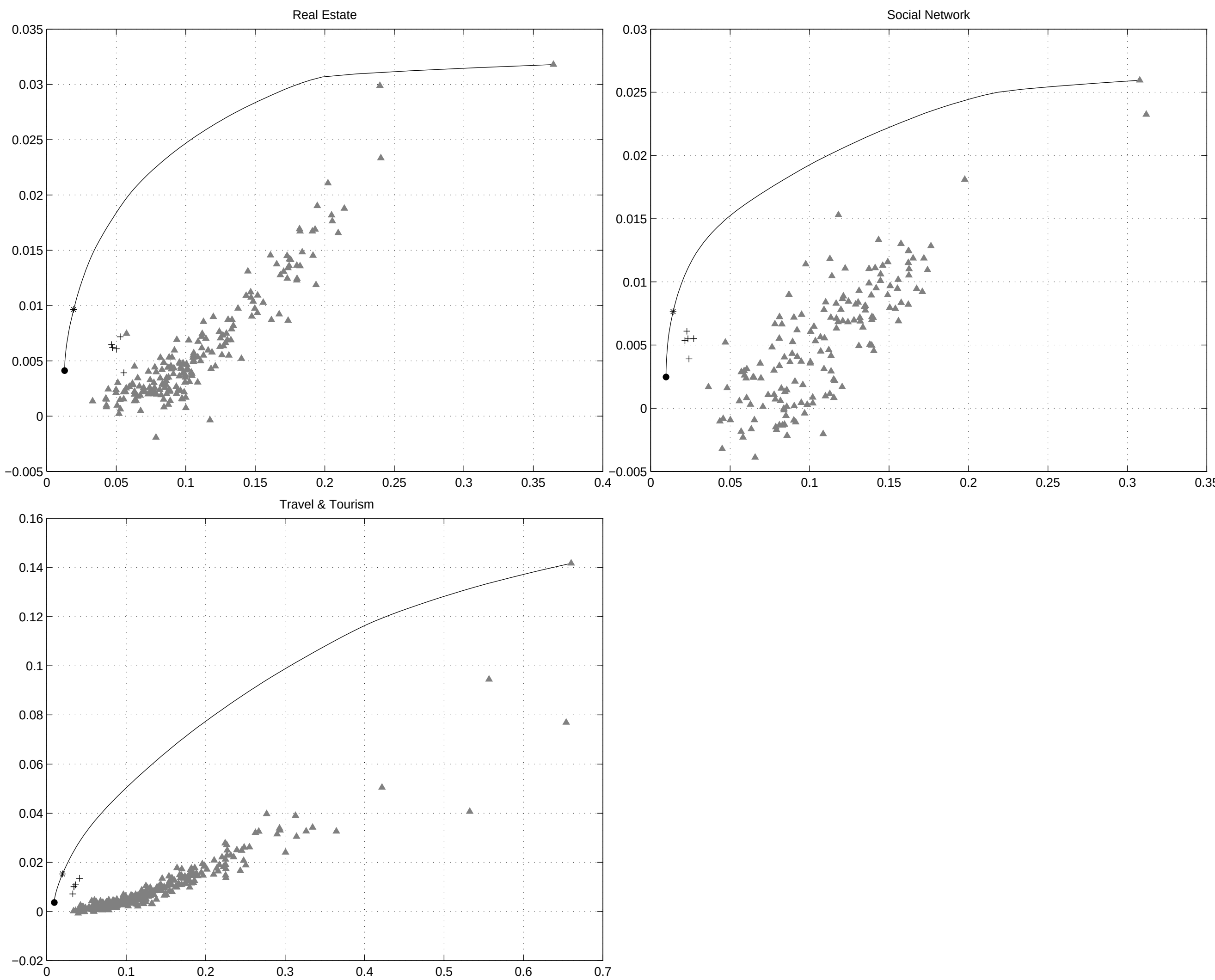


Figure C.3 Efficient Keyword Frontiers in Industries 13-15 (R1) The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

R2 - Discarding Keywords with more than 10% Missing Values

Table C.8
Keyword Description (R2)

This table presents the number of keywords for each industry (No), the average monthly searches (AMS), the expected number of clicks, click-through-rates (CTR) and the cost-per-click (CPC) for sets of relevant keywords in 15 industries provided by Google Ad Words. CPR estimates the cost per reservation, that is, the CPC divided by the CTR.

Industry	Code	No	AMS	Clicks	CTR	CPC	CPR
Advertising Services	ADS	63	242,610	58	0.0279	1.96	4.96
Beauty	BTY	53	74,287	44	0.0426	1.78	2.81
Consumer Electronics	CEL	35	93,400	109	0.0290	1.87	2.76
Fashion & Style	FNS	63	120,556	24	0.0268	1.47	1.13
Finance	FNC	36	228,497	107	0.0174	1.85	1.87
Health	HLT	91	155,854	112	0.0239	1.78	1.92
Hobbies & Leisure	HNL	50	132,936	65	0.0377	1.95	3.27
Home Appliances	HAP	170	27,315	66	0.0295	2.22	5.51
Internet	INR	31	1,059,000	60	0.0268	1.38	2.13
Internet & Telecom.	TEL	11	478,382	68	0.0335	1.39	1.34
Management Cons.	MCS	44	10,421	5	0.0198	2.12	3.26
Motor Vehicles	MVH	66	77,629	93	0.0624	1.58	4.40
Real Estate	RES	80	68,206	128	0.0304	2.21	7.17
Social Network	SNT	105	63,735	3	0.0532	0.47	0.26
Travel & Tourism	TNT	88	154,269	62	0.0254	1.89	3.42
Average	-	66	199,140	67	0.0324	1.73	3.08

Table C.9

Descriptive Statistics of Changes in SVIs (R2)

This table presents the average mean (μ) and standard deviation (σ) for weekly percentage changes in SVIs. The last column estimates the average correlation (ρ) between all keywords for each sector.

Industry	μ	σ	ρ
Advertising Services	0.0084	0.1318	0.1079
Beauty	0.0094	0.1136	0.0228
Consumer Electronics	0.0091	0.1421	0.1249
Fashion & Style	0.0137	0.1649	0.0146
Finance	0.0138	0.1485	0.2541
Health	0.0111	0.1375	0.1723
Hobbies & Leisure	0.0155	0.1638	0.0316
Home Appliances	0.0134	0.1529	0.0939
Internet	0.0052	0.1075	0.0146
Internet & Telecom.	0.0066	0.1190	0.0859
Management Cons.	0.0135	0.1648	0.0753
Motor Vehicles	0.0083	0.1107	0.0486
Real Estate	0.0097	0.1341	0.1158
Social Network	0.0016	0.1167	0.0353
Travel & Tourism	0.0101	0.1398	0.0758
Average	0.0099	0.1365	0.0853

Table C.10

Regression of Average SVI Changes against Standard Deviation (R2)

This table shows the slope of average weekly percent changes in SVIs regressed on the standard deviation along with the relevant t-statistics estimated using robust standard errors. The last column reports the adjusted R-squared of the regression.

Industry	Slope	t-statistic	R^2-adj
Advertising Services	0.1193	10.6891	0.5710
Beauty	0.1385	12.9784	0.8546
Consumer Electronics	0.1137	15.2134	0.7947
Fashion & Style	0.1826	11.3983	0.9149
Finance	0.1802	10.8411	0.9221
Health	0.1263	11.1701	0.8082
Hobbies & Leisure	0.2181	7.4109	0.8455
Home Appliances	0.1307	32.3556	0.8506
Internet	0.1384	16.6859	0.8756
Internet & Telecom.	0.0979	10.4545	0.6721
Management Cons.	0.1657	15.2147	0.8656
Motor Vehicles	0.1451	6.9574	0.8096
Real Estate	0.1195	20.1768	0.7114
Social Network	0.1178	5.6042	0.5877
Travel & Tourism	0.1683	8.6738	0.8140
Average	0.1441	13.0550	0.7932

Table C.11
Keyword Portfolio Sizes (R2)

This table exhibits the number of keywords for each strategy invests the budget. EP averages the number of keywords across 100 portfolios on the efficient frontier. MVP is the minimum variance portfolio, SRP is the portfolio with the maximum Sharpe Ratio, BP1 and BP2 are the benchmark portfolios 1 and 2 that invest equally in the most and the least popular keywords respectively (short head vs. long tail), BP3 and BP4 are the benchmark portfolios 3 and 4 that invest equally in the keywords with the highest CTRs and the lowest CPRs respectively, and B5 is the portfolio that invests equally in all keywords in the dataset.

Industries	EP	MVP	SRP	BP1	BP2	BP3	BP4	BP5
Advertising Services	15	28	23	3	60	17	50	63
Beauty	9	30	30	14	39	7	45	53
Consumer Electronics	5	19	16	7	28	13	29	35
Fashion & Style	13	33	32	12	51	23	48	63
Finance	7	17	10	8	28	17	30	36
Health	11	33	36	24	67	26	66	91
Hobbies & Leisure	8	28	26	9	41	14	38	50
Home Appliances	18	41	39	27	143	50	149	170
Internet	8	23	14	3	28	7	24	31
Internet & Telecom.	7	7	7	3	8	4	7	11
Management Cons.	15	25	25	12	32	12	32	44
Motor Vehicles	13	30	27	15	51	10	62	66
Real Estate	15	29	25	18	62	25	74	80
Social Network	19	41	37	30	75	38	83	105
Travel & Tourism	15	30	29	15	73	31	63	88
Average	12	28	25	13	52	20	53	66

Table C.12
JKM Test of Equality in Keyword Portfolio Performance (R2)

This table presents the p-values of the parametric test of JKM test of Jobson and Korkie (1981) and Memmel (2003). The null hypothesis is that there is no difference in the Sharpe ratio of the benchmark portfolios and that of the corresponding portfolio on the efficient frontier for the same level of risk. ***, **, * denote the 1%, 5% and 10% level of significance respectively.

Industries	BPrtf1	BPrtf2	BPrtf3	BPrtf4	BPrtf5
Advertising Services	0.0017***	0.0393**	0.0291**	0.0236**	0.0345**
Beauty	0.0147**	0.0336**	0.0739**	0.0212**	0.0173**
Consumer Electronics	0.1086	0.1074	0.0825*	0.1087	0.1089
Fashion & Style	0.0165**	0.0238**	0.0750*	0.0176**	0.0162**
Finance	0.0129**	0.0338**	0.0311**	0.0235**	0.0246**
Health	0.0024***	0.0146**	0.0284**	0.0072***	0.0083***
Hobbies & Leisure	0.0039***	0.0169**	0.0763*	0.0099***	0.0076***
Home Appliances	0.0001***	0.0043***	0.0039***	0.0019***	0.0021***
Internet	0.0425**	0.0458**	0.1534	0.0449**	0.0447**
Internet & Telecom.	0.1509	0.2283	0.2677	0.2919	0.2143
Management Cons.	0.1451	0.0835*	0.1281	0.1060	0.0887*
Motor Vehicles	0.0088***	0.0079***	0.0544*	0.0039***	0.0027***
Real Estate	0.0052***	0.0122**	0.0158**	0.0094***	0.0089***
Social Network	0.0047***	0.0052***	0.0045***	0.0024***	0.0027***
Travel & Tourism	0.0228**	0.0177**	0.0231**	0.0126**	0.0162**

Table C.13

LW Test of Equality in Keyword Portfolio Performance (R2)

This table presents the p-values of the non-parametric test of Ledoit-Wolf (2008). The null hypothesis is that there is no difference in the Sharpe ratio of the benchmark portfolios and that of the portfolio on the efficient frontier for the same level of risk. The standard errors of the test are estimated via bootstrap. ***, **, * denote the 1%, 5% and 10% level of significance respectively.

Industries	BPrtf1	BPrtf2	BPrtf3	BPrtf4	BPrtf5
Advertising Services	0.0034***	0.0838*	0.0454**	0.0836*	0.1136
Beauty	0.0332**	0.1958	0.0420**	0.1608	0.1642
Consumer Electronics	0.1644	0.1514	0.1846	0.1900	0.2208
Fashion & Style	0.2114	0.0308**	0.1124	0.0506*	0.0634*
Finance	0.0090***	0.0068***	0.0372**	0.0026***	0.0052***
Health	0.0004***	0.0428**	0.0088***	0.0392**	0.0292**
Hobbies & Leisure	0.0064***	0.2290	0.0058***	0.1276	0.0830*
Home Appliances	0.0004***	0.0060***	0.0022***	0.0016***	0.0044***
Internet	0.0808*	0.1318	0.3053	0.1276	0.1430
Internet & Telecom.	0.1688	0.3063	0.5241	0.4073	0.2300
Management Cons.	0.3321	0.1978	0.2743	0.3111	0.2997
Motor Vehicles	0.0070***	0.0006***	0.0272**	0.0008***	0.0006***
Real Estate	0.0128**	0.0294**	0.0196**	0.0330**	0.0256**
Social Network	0.0084***	0.0044***	0.0020***	0.0060***	0.0058***
Travel & Tourism	0.0888*	0.0766*	0.1082	0.0566*	0.0694*

Table C.14

Sharpe Ratio Heuristic (R2)

This table presents the p-values of the JKM parametric test. The null hypothesis is that there is no difference in the Sharpe ratio of two portfolios built under the Sharpe Ratio heuristic and the portfolio on the efficient frontier at the same level of risk. EWSR selects the keywords with Sharpe Ratio higher than the average Sharpe Ratio of all keywords in the portfolio. EW10P selects 10 keywords with the highest Sharpe Ratio.

Industries	Sharpe Ratio	
	EWSR	**EW10P**
Advertising Services	0.0890	0.0832
Beauty	0.2537	0.0558
Consumer Electronics	0.1087	0.1213
Fashion & Style	0.1013	0.0493
Finance	0.1624	0.1624
Health	0.0156	0.0708
Hobbies & Leisure	0.0376	0.0330
Home Appliances	0.0251	0.0168
Internet	0.0875	0.1297
Internet & Telecom.	0.2549	0.2010
Management Cons.	0.1317	0.0911
Motor Vehicles	0.0911	0.0804
Real Estate	0.0175	0.1125
Social Network	0.1401	0.2010
Travel & Tourism	0.1055	0.0967

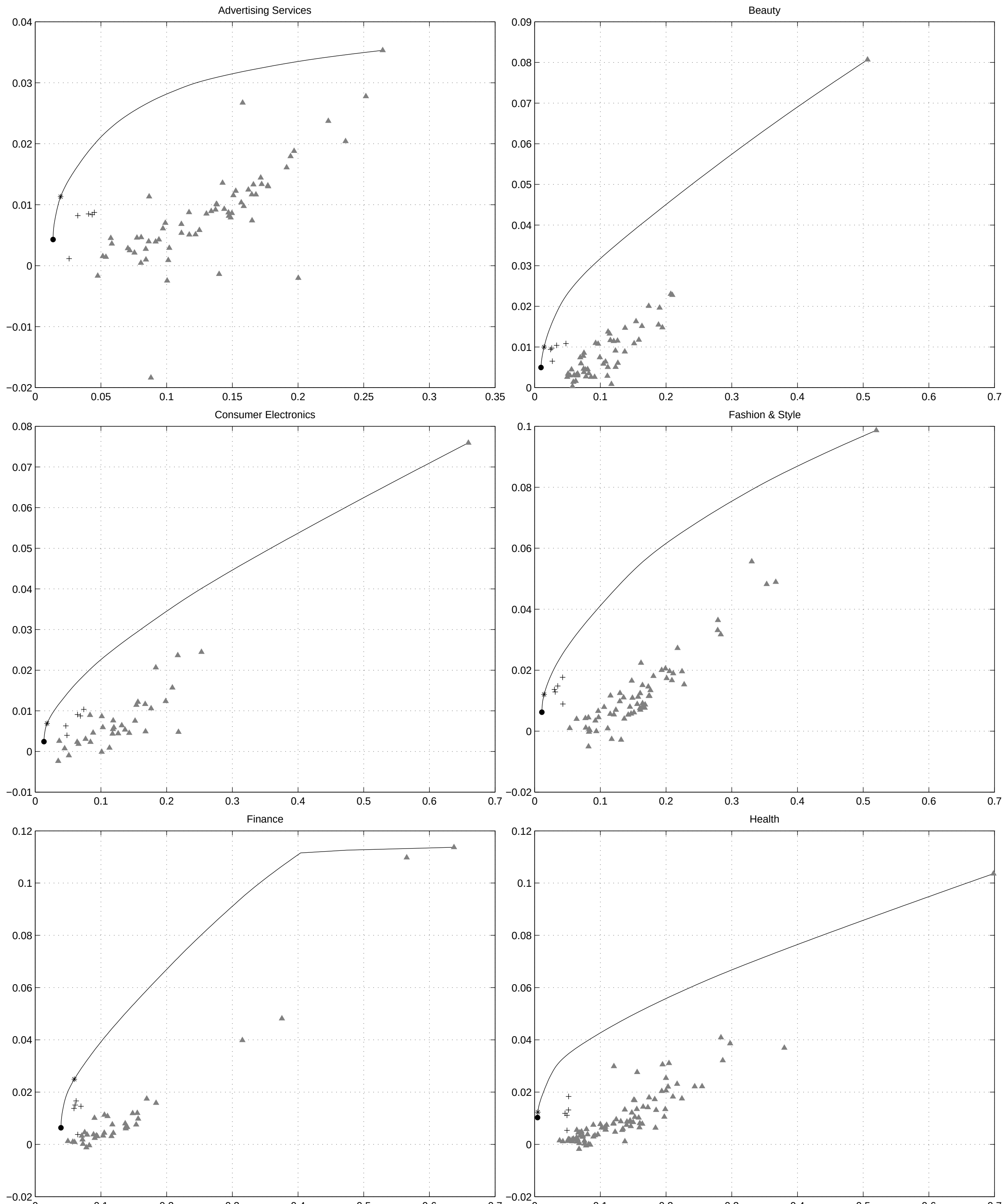


Figure A1 Efficient Keyword Frontiers for Industries 1-6 (R2) The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

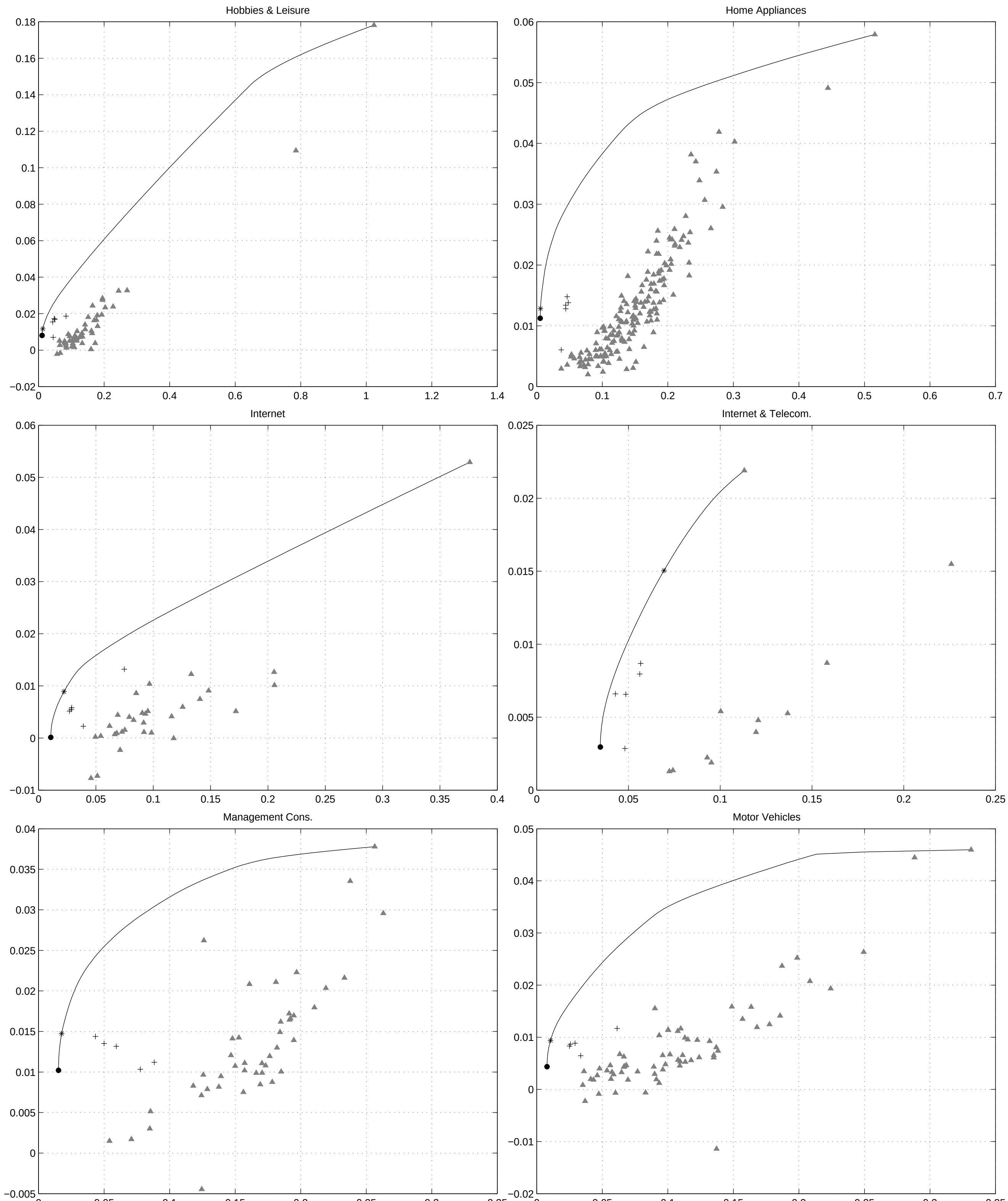


Figure A2 Efficient Keyword Frontiers for Industries 7-12 (R2) The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

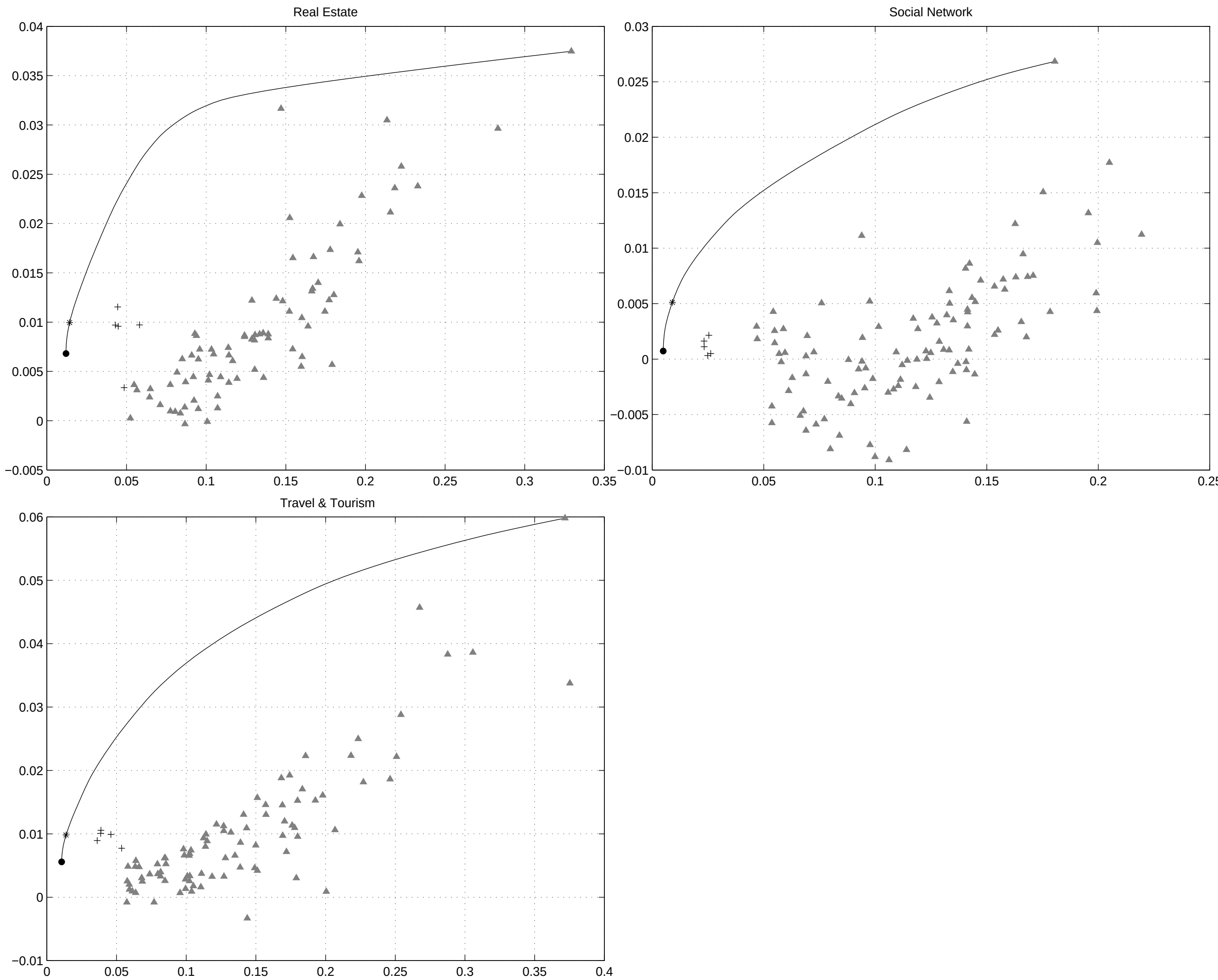


Figure A3 Efficient Keyword Frontiers 13-15 (R2) The figures display the risk (standard deviation in popularity growth) on the horizontal axis and the expected return (average popularity growth) on the vertical axis. Solid lines represent efficient keyword frontiers, filled circles and stars correspond to the minimum variance and the maximum Sharpe ratio portfolios, respectively. Crosses represent the five benchmark portfolios while triangles correspond to individual keywords.

Bibliography

Abou Nabout, N., Lilienthal, M. and Skiera, B. (2014), 'Empirical Generalizations in Search Engine Advertising', *Journal of Retailing* **90**(2), 206–216.

Agarwal, A., Leung, A. C. M., Konana, P. and Kumar, A. (2017), 'Cosearch Attention and Stock Return Predictability in Supply Chains', *Information Systems Research* **28**(2), 265–288.

Alexander, C. (2001), 'Orthogonal GARCH', *in* 'Mastering risk (vol:2)', Prentice-Hall, NY, pp. 21–38.

Alexander, C. (2008), *'Market risk analysis (Vol. II): Practical financial econometrics'*, John Wiley & Sons, UK.

Alexander, C. and Chibumba, A. (1997), 'Multivariate Orthogonal Factor GARCH'. Unpublished Working Paper. University of Sussex, Mimeo.

Allen, F. and Gale, D. (2000), 'Financial Contagion', *Journal of Political Economy* **108**(1), 1–33.

Aloui, R., Aïssa, M. S. B. and Nguyen, D. K. (2011), 'Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?', *Journal of Banking & Finance* **35**(1), 130–141.

Andersen, T. G. and Bollerslev, T. (1997), 'Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long-Run in High Frequency Returns', *Journal of Finance* **52**(3), 975–1005.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Ebens, H. (2001), 'The distribution of realized stock return volatility', *Journal of Financial Economics* **61**(1), 43–76.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2001), 'The Distribution of Realized Exchange Rate Volatility', *Journal of the American Statistical Association* **96**(453), 42–55.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2003), 'Modeling And Forecasting Realized Volatility', *Econometrica* **71**(2), 579–625.

Andrei, D. and Hasler, M. (2014), 'Investor Attention and Stock Market Volatility', *Review of Financial Studies* **28**(1), 33–72.

Andrews, D. W. K. (1991), 'Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation', *Econometrica* **59**(3), 817–858.

Ang, A. and Bekaert, G. (2002), 'International Asset Allocation with Regime Shifts', *Review of Financial Studies* **15**(4), 1137–1187.

Anton, M. and Polk, C. (2014), 'Connected Stocks', *Journal of Finance* **69**(3), 1099–1127.

Bae, K.-H., Karolyi, G. A. and Stulz, R. M. (2003), 'A New Approach to Measuring Financial Contagion', *Review of Financial Studies* **16**(3), 717–763.

Banerjee, A. V. (1992), 'A Simple Model of Herd Behavior', *Quarterly Journal of Economics* **107**(3), 797–817.

Barber, B. M. and Odean, T. (2008), 'All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors', *Review of Financial Studies* **21**(2), 785–818.

Barberis, N., Shleifer, A. and Wurgler, J. (2005), 'Comovement', *Journal of Financial Economics* **75**(2), 283–317.

Barndorff-Nielsen, O. E. and Shephard, N. (2004), 'Econometric Analysis of Realized Covariation: High Frequency Based Covariance, Regression, and Correlation in Financial Economics', *Econometrica* **72**(3), 885–925.

Bartram, S. M., Griffin, J. M., Lim, T.-H. and Ng, D. T. (2015), 'How Important Are Foreign Ownership Linkages for International Stock Returns?', *Review of Financial Studies* **28**(11), 3036–3072.

Bauer, G. H. and Vorkink, K. (2011), 'Forecasting multivariate realized stock market volatility', *Journal of Econometrics* **160**(1), 93–101.

Bauwens, L., Laurent, S. and Rombouts, J. V. (2006), 'Multivariate GARCH models: a survey', *Journal of Applied Econometrics* **21**(1), 79–109.

Bekaert, G., Ehrmann, M., Fratzscher, M. and Mehl, A. (2014), 'The Global Crisis and Equity Market Contagion', *Journal of Finance* **69**(6), 2597–2649.

Bekaert, G. and Harvey, C. R. (1995), 'Time-Varying World Market Integration', *Journal of Finance* **50**(2), 403–444.

Bekaert, G. and Harvey, C. R. (1997), 'Emerging equity market volatility', *Journal of Financial Economics* **43**(1), 29–77.

Bekaert, G., Harvey, C. R. and Lumsdaine, R. L. (2002), 'The dynamics of emerging market equity flows', *Journal of International Money and Finance* **21**(3), 295–350.

Bekaert, G., Hodrick, R. J. and Zhang, X. (2009), 'International Stock Return Comovements', *Journal of Finance* **64**(6), 2591–2626.

Berman, R. (2016), 'Beyond the Last Touch: Attribution in Online Advertising'. Unpublished Working Paper. University of Pennsylvania - The Wharton School.

Beugelsdijk, S. and Frijns, B. (2010), 'A cultural explanation of the foreign bias in international asset allocation', *Journal of Banking & Finance* **34**(9), 2121–2131.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992), 'A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades', *Journal of Political Economy* **100**(5), 992–1026.

Bollerslev, T. (1986), 'Generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics* **31**(3), 307–327.

Bollerslev, T. (1990), 'Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model', *Review of Economics and Statistics* **32**(3), 498–505.

Bollerslev, T., Engle, R. F. and Wooldridge, J. M. (1988), 'A Capital Asset Pricing Model with Time-Varying Covariances', *Journal of Political Economy* **96**(1), 116–131.

Bollerslev, T., Marrone, J., Xu, L. and Zhou, H. (2014), 'Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence', *Journal of Financial and Quantitative Analysis* **49**(3), 633–661.

Bollerslev, T., Patton, A. J. and Quaedvlieg, R. (2016), 'Modeling and Forecasting (Un)Reliable Realized Covariances for More Reliable Financial Decisions'. Unpublished Working Paper. Duke University and Erasmus University Rotterdam.

Bollerslev, T. and Zhang, B. Y. (2003), 'Measuring and modeling systematic risk in factor pricing models using high-frequency data', *Journal of Empirical Finance* **10**(5), 533–558.

Borgs, C., Chayes, J., Immorlica, N., Jain, K., Etesami, O. and Mahdian, M. (2007), 'Dynamics of Bid Optimization in Online Advertisement Auctions', *in* 'Proceedings of the 16th International Conference on World Wide Web', ACM, Banff, Alberta, Canada, pp. 531–540.

Boyer, B. H. (2011), 'Style-Related Comovement: Fundamentals or Labels?', *Journal of Finance* **66**(1), 307–332.

Boyer, B. H., Kumagai, T. and Yuan, K. (2006), 'How Do Crises Spread? Evidence from Accessible and Inaccessible Stock Indices', *Journal of Finance* **61**(2), 957–1003.

Boyer, B. and Zheng, L. (2009), 'Investor flows and stock market returns', *Journal of Empirical Finance* **16**(1), 87–100.

Brealey, R. A., Cooper, I. A. and Kaplanis, E. (2010), 'Excess Comovement in International Equity Markets: Evidence from Cross-border Mergers', *Review of Financial Studies* **23**(4), 1718–1740.

Brennan, M. J. and Cao, H. H. (1997), 'International Portfolio Investment Flows', *Journal of Finance* **52**(5), 1851–1880.

Britten-Jones, M. and Neuberger, A. (2000), 'Option Prices, Implied Price Processes, and Stochastic Volatility', *Journal of Finance* **55**(2), 839–866.

Brockman, P., Liebenberg, I. and Schutte, M. (2010), 'Comovement, information production, and the business cycle', *Journal of Financial Economics* **97**(1), 107–129.

Brooks, C., Clare, A. and Persand, G. (2002), 'A note on estimating market–based minimum capital risk requirements: A multivariate garch approach', *The Manchester School* **70**(5), 666–681.

Brooks, R. and Del Negro, M. (2004), 'The rise in comovement across national stock markets: market integration or IT bubble?', *Journal of Empirical Finance* **11**(5), 659–680.

Brownlees, C., Engle, R. and Kelly, B. (2011), 'A practical guide to volatility forecasting through calm and storm', *Journal of Risk* **14**(2), 3–22.

Busch, T., Christensen, B. J. and Nielsen, M. Ø. (2011), 'The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets', *Journal of Econometrics* **160**(1), 48–57.

Buss, A. and Vilkov, G. (2012), 'Measuring Equity Risk with Option-Implied Correlations', *Review of Financial Studies* **25**(10), 3113–3140.

Calvo, G. A. (2004), 'Contagion in Emerging Markets: When Wall Street is a Carrier', *in* E. Bour, D. Heymann and F. Navajas, eds, 'Latin American Economic Crises: Trade and Labour', Palgrave Macmillan, UK, pp. 81–91.

Calvo, G. A. and Mendoza, E. G. (2000), 'Capital-Markets Crises and Economic Collapse in Emerging Markets: An Informational-Frictions Approach', *American Economic Review* **90**(2), 59–64.

Cao, M. and Wei, J. (2005), 'Stock market returns: A note on temperature anomaly', *Journal of Banking & Finance* **29**(6), 1559–1573.

Cappiello, L., Engle, R. F. and Sheppard, K. (2006), 'Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns', *Journal of Financial Econometrics* **4**(4), 537–572.

Cardozo, R. N. and Smith Jr, D. K. (1983), 'Applying Financial Portfolio Theory to Product Portfolio Decisions: An Empirical Study', *Journal of Marketing* **47**(2), 110–119.

Cardozo, R. N. and Smith Jr, D. K. (1985), 'On the Use of Financial Portfolio Theory in Marketing Decisions: a Reply to Devinney, Stewart, and Shocker', *Journal of Marketing* **49**(4), 113–115.

Carr, P. and Wu, L. (2009), 'Variance Risk Premiums', *Review of Financial Studies* **22**(3), 1311–1341.

Chan, K., Covrig, V. and Ng, L. (2005), 'What Determines the Domestic Bias and Foreign Bias? Evidence from Mutual Fund Equity Allocations Worldwide', *Journal of Finance* **60**(3), 1495–1534.

Chan, L. K., Karceski, J. and Lakonishok, J. (1999), 'On Portfolio Optimization: Forecasting Covariances and Choosing the Risk Model', *Review of Financial Studies* **12**(5), 937–974.

Chang, B.-Y., Christoffersen, P., Jacobs, K. and Vainberg, G. (2012), 'Option-Implied Measures of Equity Risk', *Review of Finance* **16**(2), 385–428.

Chauvet, M. (1998), 'An Econometric Characterization of Business Cycle Dynamics with Factor Structure and Regime Switching', *International Economic Review* **39**(4), 969–996.

Chemmanur, T. J. and Yan, A. (2010), 'Advertising, Investor Recognition, and Stock Returns'. Unpublished Working Paper. Boston College and Fordham University.

Chernov, M. (2007), 'On the Role of Risk Premia in Volatility Forecasting', *Journal of Business & Economic Statistics* **25**(4), 411–426.

Chiang, T. C., Jeon, B. N. and Li, H. (2007), 'Dynamic correlation analysis of financial contagion: Evidence from Asian markets', *Journal of International Money and Finance* **26**(7), 1206–1228.

Chiriac, R. and Voev, V. (2011), 'Modelling and forecasting multivariate realized volatility', *Journal of Applied Econometrics* **26**(6), 922–947.

Choi, H. and Varian, H. (2012), 'Predicting the Present with Google Trends', *Economic Record* **88**(1), 2–9.

Christodoulakis, G. A. and Satchell, S. E. (2002), 'Correlated ARCH (CorrARCH): Modelling the time-varying conditional correlation between financial asset returns', *European Journal of Operational Research* **139**(2), 351–370.

Clements, A., Doolan, M., Hurn, S., Becker, R. et al. (2009), 'Evaluating multivariate volatility forecasts', Technical report, National Centre for Econometric Research.

Cohen, L. and Frazzini, A. (2008), 'Economic Links and Predictable Returns', *Journal of Finance* **63**(4), 1977–2011.

Colacito, R., Engle, R. F. and Ghysels, E. (2011), 'A component model for dynamic correlations', *Journal of Econometrics* **164**(1), 45–59.

Copeland, P., Romano, R., Zhang, T., Hecht, G., Zigmond, D. and Stefansen, C. (2013), 'Google disease trends: an update', *Nature* **457**, 1012–1014.

Corsi, F. (2009), 'A Simple Approximate Long-Memory Model of Realized Volatility', *Journal of Financial Econometrics* **7**(2), 174–196.

Corsi, F. and Audrino, F. (2007), 'Realized Correlation Tick-by-Tick', *University of St. Gallen, Department of Economics, Discussion Paper* .

Corwin, S. A. and Coughenour, J. F. (2008), 'Limited Attention and the Allocation of Effort in Securities Trading', *Journal of Finance* **63**(6), 3031–3067.

Coval, J. D. and Moskowitz, T. J. (1999), 'Home Bias at Home: Local Equity Preference in Domestic Portfolios', *Journal of Finance* **54**(6), 2045–2073.

Coval, J. D. and Moskowitz, T. J. (2001), 'The Geography of Investment: Informed Trading and Asset Prices', *Journal of Political Economy* **109**(4), 811–841.

Coval, J. D. and Shumway, T. (2005), 'Do Behavioral Biases Affect Prices?', *Journal of Finance* **60**(1), 1–34.

Coval, J. and Stafford, E. (2007), 'Asset fire sales (and purchases) in equity markets', *Journal of Financial Economics* **86**(2), 479–512.

Da, Z., Engelberg, J. and Gao, P. (2011), 'In Search of Attention', *Journal of Finance* **66**(5), 1461–1499.

Da, Z., Engelberg, J. and Gao, P. (2015), 'The Sum of All FEARS Investor Sentiment and Asset Prices', *Review of Financial Studies* **28**(1), 1–32.

Dang, T. L., Moshirian, F. and Zhang, B. (2015), 'Commonality in news around the world', *Journal of Financial Economics* **116**(1), 82–110.

Danielsson, J. (2008), 'Blame the models', *Journal of Financial Stability* **4**(4), 321–328.

De Santis, G. (1993), 'Asset pricing and portfolio diversification: Evidence from emerging financial markets', Technical report, World Bank Discussion Papers.

DellaVigna, S. and Pollet, J. M. (2009), 'Investor Inattention and Friday Earnings Announcements', *Journal of Finance* **64**(2), 709–749.

DeMiguel, V., Garlappi, L. and Uppal, R. (2009), 'Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?', *Review of Financial Studies* **22**(5), 1915–1953.

DeMiguel, V., Plyakha, Y., Uppal, R. and Vilkov, G. (2013), 'Improving Portfolio Selection Using Option-Implied Volatility and Skewness', *Journal of Financial and Quantitative Analysis* **48**(6), 1813–1845.

Detemple, J. B. (1986), 'Asset Pricing in a Production Economy with Incomplete Information', *Journal of Finance* **41**(2), 383–391.

Detemple, J. and Murthy, S. (1994), 'Intertemporal asset pricing with heterogeneous beliefs', *Journal of Economic Theory* **62**(2), 294–320.

Devinney, T. M., Stewart, D. W. and Shocker, A. D. (1985), 'A Note on the Application of Portfolio Theory: a Comment on Cardozo and Smith', *Journal of Marketing* **49**(4), 107–112.

Dhar, V. and Ghose, A. (2010), 'Research Commentary-Sponsored Search and Market Efficiency', *Information Systems Research* **21**(4), 760–772.

Diamond, D. W. and Dybvig, P. H. (1983), 'Bank Runs, Deposit Insurance, and Liquidity', *Journal of Political Economy* **91**(3), 401–419.

Diebold, F. X. and Mariano, R. S. (1995), 'Comparing Predictive Accuracy', *Journal of Business & Economic Statistics* **13**(3).

Ding, Z. and Engle, R. F. (2001), 'Large Scale Conditional Covariance Matrix Modeling, Estimation and Testing', *Academia Economic Papers* **29**(2), 157–184.

Divecha, A. B., Drach, J. and Stefek, D. (1992), 'Emerging Markets: A Quantitative Perspective', *Journal of Portfolio Management* **19**(1), 41–50.

Drake, M. S., Jennings, J., Roulstone, D. T. and Thornock, J. R. (2016), 'The Comovement of Investor Attention'. Management Science. Forthcoming.

Driessen, J., Maenhout, P. J. and Vilkov, G. (2009), 'The Price of Correlation Risk: Evidence from Equity Options', *Journal of Finance* **64**(3), 1377–1406.

Duffie, D. (2008), 'Innovations in credit risk transfer: Implications for financial stability', Technical report, National Bureau of Economic Research, BIS.

Dugas, A. F., Jalalpour, M., Gel, Y., Levin, S., Torcaso, F., Igusa, T. and Rothman, R. E. (2013), 'Influenza Forecasting with Google Flu Trends', *PloS One* **8**(2), e56176.

Edelman, B. G., Ostrovsky, M. and Schwarz, M. (2005), 'Internet Advertising and the Generalized Second Price Auction: Selling Billions of Dollars Worth of Keywords', *American Economic Review* **97**(1), 242–259.

Edmans, A., Garcia, D. and Norli, Ø. (2007), 'Sports Sentiment and Stock Returns', *Journal of Finance* **62**(4), 1967–1998.

Elton, E. J. and Gruber, M. J. (1977), 'Risk Reduction and Portfolio Size: An Analytical Solution', *Journal of Business* **50**(4), 415–437.

Engle, R. (2002), 'Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models', *Journal of Business and Economic Statistics* **20**(3), 339–350.

Engle, R. and Colacito, R. (2006), 'Testing and Valuing Dynamic Correlations for Asset Allocation', *Journal of Business & Economic Statistics* **24**(2), 238–253.

Engle, R. F. and Kroner, K. F. (1995), 'Multivariate Simultaneous Generalized ARCH', *Econometric Theory* **11**(1), 122–150.

Erb, C. B., Harvey, C. R. and Viskanta, T. E. (1994), 'Forecasting International Equity Correlations', *Financial Analysts Journal* **50**(6), 32–45.

Errunza, V. R. (1977), 'Gains from Portfolio Diversification into Less Developed Countries' Securities', *Journal of International Business Studies* **8**(2), 83–99.

Evans, J. L. and Archer, S. H. (1968), 'Diversification and the Reduction of Dispersion: An Empirical Analysis', *Journal of Finance* **23**(5), 761–767.

Fama, E. F. (1965), 'The Behavior of Stock-Market Prices', *Journal of Business* **38**(1), 34–105.

Feng, L. and Seasholes, M. S. (2004), 'Correlated Trading and Location', *Journal of Finance* **59**(5), 2117–2144.

Field, A. P. (2001), 'Meta-analysis of correlation coefficients: a Monte Carlo comparison of fixed-and random-effects methods', *Psychological Methods* **6**(2), 161–180.

Fleming, J., Kirby, C. and Ostdiek, B. (2003), 'The economic value of volatility timing using "realized" volatility', *Journal of Financial Economics* **67**(3), 473–509.

Forbes, K. J. (2002), 'Are trade linkages important determinants of country vulnerability to crises?', *in* S. Edwards and J. A. Frankel, eds, 'Preventing currency crises in emerging markets', University of Chicago Press, pp. 77–130.

Forbes, K. J. and Rigobon, R. (2002), 'No Contagion, Only Interdependence: Measuring Stock Market Comovements', *Journal of Finance* **57**(5), 2223–2261.

French, K. R. and Roll, R. (1986), 'Stock return variances: The arrival of information and the reaction of traders', *Journal of Financial Economics* **17**(1), 5–26.

Frenkel, M., Funke, K. and Stadtmann, G. (2004), 'A panel analysis of bilateral FDI flows to emerging economies', *Economic Systems* **28**(3), 281–300.

Garcia, R. and Tsafack, G. (2011), 'Dependence structure and extreme comovements in international equity and bond markets', *Journal of Banking & Finance* **35**(8), 1954–1970.

Gennotte, G. (1986), 'Optimal Portfolio Choice Under Incomplete Information', *Journal of Finance* **41**(3), 733–746.

Gervais, S., Kaniel, R. and Mingelgrin, D. H. (2001), 'The High-Volume Return Premium', *Journal of Finance* **56**(3), 877–919.

Ghose, A. and Yang, S. (2009), 'An Empirical Analysis of Search Engine Advertising: Sponsored Search in Electronic Markets', *Management Science* **55**(10), 1605–1622.

Giacomini, R. and White, H. (2006), 'Tests of Conditional Predictive Ability', *Econometrica* **74**(6), 1545–1578.

Gibson, E. and Rader, N. (1979), 'Attention', *in* G. Hale and M. Lewis, eds, 'Attention and Cognitive Development', Springer, US, chapter 1, pp. 1–21.

Glosten, L. R., Jagannathan, R. and Runkle, D. E. (1993), 'On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks', *Journal of Finance* **48**(5), 1779–1801.

Glosten, L. R. and Milgrom, P. R. (1985), 'Bid, ask and transaction prices in a specialist market with heterogeneously informed traders', *Journal of Financial Economics* **14**(1), 71–100.

Goel, S., Hofman, J. M., Lahaie, S., Pennock, D. M. and Watts, D. J. (2010), 'Predicting consumer behavior with Web search', *Proceedings of the National Academy of Sciences of the United States of America* **107**(41), 17486–17490.

Gouriéroux, C., Jasiak, J. and Sufana, R. (2009), 'The Wishart autoregressive process of multivariate stochastic volatility', *Journal of Econometrics* **150**(2), 167–181.

Green, T. C. and Hwang, B.-H. (2009), 'Price-based return comovement', *Journal of Financial Economics* **93**(1), 37–50.

Grinblatt, M. and Keloharju, M. (2001), 'How Distance, Language, and Culture Influence Stockholdings and Trades', *Journal of Finance* **56**(3), 1053–1073.

Grossman, S. J. and Stiglitz, J. E. (1980), 'On the Impossibility of Informationally Efficient Markets', *American Economic Review* **70**(3), 393–408.

Grubel, H. G. (1968), 'Internationally Diversified Portfolios: Welfare Gains and Capital Flows', *American Economic Review* **58**(5), 1299–1314.

Grullon, G., Kanatas, G. and Weston, J. P. (2004), 'Advertising, breadth of ownership, and liquidity', *Review of Financial Studies* **17**(2), 439–461.

Halbleib, R. and Voev, V. (2016), 'Forecasting covariance matrices: A mixed approach', *Journal of Financial Econometrics* **14**(2), 383–417.

Hamao, Y., Masulis, R. W. and Ng, V. (1990), 'Correlations in Price Changes and Volatility Across International Stock Markets', *Review of Financial studies* **3**(2), 281–307.

Hameed, A., Kang, W. and Viswanathan, S. (2010), 'Stock Market Declines and Liquidity', *Journal of Finance* **65**(1), 257–293.

Hansen, P. R., Huang, Z. and Shek, H. H. (2012), 'Realized GARCH: a joint model for returns and realized measures of volatility', *Journal of Applied Econometrics* **27**(6), 877–906.

Hansen, P. R. and Lunde, A. (2005), 'A realized variance for the whole day based on intermittent high-frequency data', *Journal of Financial Econometrics* **3**(4), 525–554.

Hansen, P. R., Lunde, A. and Nason, J. M. (2011), 'The Model Confidence Set', *Econometrica* **79**(2), 453–497.

Hansen, P. R., Lunde, A. and Voev, V. (2014), 'Realized beta GARCH: a multivariate GARCH model with realized measures of volatility', *Journal of Applied Econometrics* **29**(5), 774–799.

Hasler, M. and Ornthanalai, C. (2015), 'Fluctuating Attention and Contagion: Theory and Evidence from the US Equity Market'. Working Paper. Rotman School of Management.

Hautsch, N., Kyj, L. M. and Malec, P. (2015), 'Do high-frequency data improve high-dimensional portfolio allocations?', *Journal of Applied Econometrics* **30**(2), 263–290.

Hedges, L. V. and Vevea, J. L. (1998), 'Fixed-and random-effects models in meta-analysis', *Psychological Methods* **3**(4), 486–504.

Hirshleifer, D., Lim, S. S. and Teoh, S. H. (2009), 'Driven to Distraction: Extraneous Events and Underreaction to Earnings News', *Journal of Finance* **64**(5), 2289–2325.

Hirshleifer, D. and Shumway, T. (2003), 'Good Day Sunshine: Stock Returns and the Weather', *Journal of Finance* **58**(3), 1009–1032.

Hirshleifer, D. and Teoh, S. H. (2003), 'Limited attention, information disclosure, and financial reporting', *Journal of Accounting and Economics* **36**(1), 337–386.

Höchstötter, M., Meyer, S., Riordan, R. and Storkenmaier, A. (2014), 'International stock market comovement and news', *Journal of Financial Research* **37**(4), 519–542.

Hofstede, G., Hofstede, G. J. and Minkov, M. (2010), *Cultures and organizations: Software of the mind. Revised and Expanded 3rd Edition*, McGraw-Hill, New York.

Hollstein, F. and Prokopczuk, M. (2016), 'Estimating Beta', *Journal of Financial and Quantitative Analysis* **51**(4), 1437–1466.

Holthausen Jr, D. M. and Assmus, G. (1982), 'Advertising Budget Allocation under Uncertainty', *Management Science* **28**(5), 487–499.

Hong, H., Kubik, J. D. and Stein, J. C. (2004), 'Social Interaction and Stock-Market Participation', *Journal of Finance* **59**(1), 137–163.

Hou, K., Xiong, W. and Peng, L. (2009), 'A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum'. Working paper. Ohio State University and Princeton.

Hsu, C.-C., Tseng, C.-P. and Wang, Y.-H. (2008), 'Dynamic hedging with futures: A copula-based GARCH model', *Journal of Futures Markets* **28**(11), 1095–1116.

International Monetary Fund (2007), 'Global Financial Stability Report: Financial Market Turbulence Causes, Consequences, and Policies', Technical report.

Israelsen, R. D. (2016), 'Does Common Analyst Coverage Explain Excess Comovement?', *Journal of Financial and Quantitative Analysis* **51**(4), 1193–1229.

Jacobs, H. (2015), 'The role of attention constraints for investor behavior and economic aggregates: what have we learnt so far?', *Management Review Quarterly* **65**(4), 217–237.

Jerath, K., Ma, L. and Park, Y.-H. (2014), 'Consumer Click Behavior at a Search Engine: The Role of Keyword Popularity', *Journal of Marketing Research* **51**(4), 480–486.

Jin, X. and Maheu, J. M. (2012), 'Modeling realized covariances and returns', *Journal of Financial Econometrics* **11**(2), 335–369.

Jobson, J. D. and Korkie, B. M. (1981), 'Performance Hypothesis Testing with the Sharpe and Treynor Measures', *Journal of Finance* **36**(4), 889–908.

Joo, M., Wilbur, K. C., Cowgill, B. and Zhu, Y. (2013), 'Television Advertising and Online Search', *Management Science* **60**(1), 56–73.

Kahneman, D. (1973), *Attention and Effort*, Prentice-Hall Englewood Cliffs, NJ.

Kallberg, J. and Pasquariello, P. (2008), 'Time-series and cross-sectional excess comovement in stock indexes', *Journal of Empirical Finance* **15**(3), 481–502.

Karolyi, G. A. and Stulz, R. M. (1996), 'Why Do Markets Move Together? An Investigation of US-Japan Stock Return Comovements', *Journal of Finance* **51**(3), 951–986.

Karolyi, G. A. and Stulz, R. M. (2003), 'Are financial assets priced locally or globally?', *in* G. M. Constantinides, M. Harris and R. M. Stulz, eds, 'Handbook of the Economics of Finance', North-Holland Publishers, New York, NY, pp. 975–1020.

Kim, C., Park, S., Kwon, K. and Chang, W. (2012*a*), 'An empirical study of the structure of relevant keywords in a search engine using the minimum spanning tree', *Expert Systems with Applications* **39**(4), 4432–4443.

Kim, C., Park, S., Kwon, K. and Chang, W. (2012*b*), 'How to select search keywords for online advertising depending on consumer involvement: An empirical investigation', *Expert Systems with Applications* **39**(1), 594–610.

King, M. A. and Wadhwani, S. (1990), 'Transmission of Volatility between Stock Markets', *Review of Financial Studies* **3**(1), 5–33.

King, M., Sentana, E. and Wadhwani, S. (1994), 'Volatiltiy and Links Between National Stock Markets', *Econometrica* **62**(4), 901–933.

Kodres, L. E. and Pritsker, M. (2002), 'A Rational Expectations Model of Financial Contagion', *Journal of Finance* **57**(2), 769–799.

Kogut, B. and Singh, H. (1988), 'The Effect of National Culture on the Choice of Entry Mode', *Journal of International Business Studies* **19**(3), 411–432.

Kourtis, A., Dotsis, G. and Markellos, R. N. (2012), 'Parameter uncertainty in portfolio selection: Shrinking the inverse covariance matrix', *Journal of Banking and Finance* **36**(9), 2522–2531.

Kourtis, A., Markellos, R. N. and Symeonidis, L. (2016), 'An International Comparison of Implied, Realized, and GARCH Volatility Forecasts', *Journal of Futures Markets* **36**(12), 1164–1193.

Kristoufek, L. (2013), 'Can Google Trends search queries contribute to risk diversification?', *Scientific Reports* **3**(2713), 1–5.

Kroner, K. F. and Ng, V. K. (1998), 'Modeling Asymmetric Comovements of Asset Returns', *Review of Financial Studies* **11**(4), 817–844.

Kyle, A. S. and Xiong, W. (2001), 'Contagion as a Wealth Effect', *Journal of Finance* **56**(4), 1401–1440.

Laurent, S., Rombouts, J. V. and Violante, F. (2012), 'On the forecasting accuracy of multivariate GARCH models', *Journal of Applied Econometrics* **27**(6), 934–955.

Laurent, S., Rombouts, J. V. and Violante, F. (2013), 'On loss functions and ranking forecasting performances of multivariate volatility models', *Journal of Econometrics* **173**(1), 1–10.

Ledoit, O., Santa-Clara, P. and Wolf, M. (2003), 'Flexible Multivariate GARCH Modeling with an Application to International Stock Markets', *Review of Economics and Statistics* **85**(3), 735–747.

Ledoit, O. and Wolf, M. (2004), 'Honey, I Shrunk the Sample Covariance Matrix', *The Journal of Portfolio Management* **30**(4), 110–119.

Ledoit, O. and Wolf, M. (2008), 'Robust performance hypothesis testing with the Sharpe ratio', *Journal of Empirical Finance* **15**(5), 850–859.

Ledoit, O. and Wolf, M. (2011), 'Robust Performances Hypothesis Testing With the Variance', *Wilmott* **2011**(55), 86–89.

Lee, C., Ma, P. and Wang, C. C. (2015), 'Search based peer firms: Aggregating investor perceptions through internet co-searches', *Journal of Financial Economics* **116**(2), 410–431.

Lessard, D. R. (1974), 'World, National, and Industry Factors in Equity Returns', *Journal of Finance* **29**(2), 379–391.

Leung, A. C. M., Agarwal, A., Konana, P. and Kumar, A. (2016), Network analysis of search dynamics: The case of stock habitats. Management Science. Forthcoming.

Levy, H. and Sarnat, M. (1970), 'International Diversification of Investment Portfolios', *American Economic Review* **60**(4), 668–675.

Lipsey, R. E., Feenstra, R. C., Hahn, C. H. and Hatsopoulos, G. N. (1999), 'The Role of Foreign Direct Investment in International Capital Flows', *in* M. Feldstein, ed., 'International Capital Flows', University of Chicago Press, Chicago, pp. 307–362.

Liu, Q. (2009), 'On portfolio optimization: How and when do we benefit from high-frequency data?', *Journal of Applied Econometrics* **24**(4), 560–582.

Long, J. B. D., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990), 'Noise Trader Risk in Financial Markets', *Journal of Political Economy* **98**(4), 703–738.

Longin, F. and Solnik, B. (1995), 'Is the correlation in international equity returns constant: 1960-1990?', *Journal of International Money and Finance* **14**(1), 3–26.

Longin, F. and Solnik, B. (2001), 'Extreme Correlation of International Equity Markets', *Journal of Finance* **56**(2), 649–676.

Lou, D. (2014), 'Attracting Investor Attention through Advertising', *Review of Financial Studies* **27**(6), 1797–1829.

Maheu, J. M. and McCurdy, T. H. (2011), 'Do high-frequency measures of volatility improve forecasts of return distributions?', *Journal of Econometrics* **160**(1), 69–76.

Malkiel, B. G. and Fama, E. F. (1970), 'Efficient Capital Markets: A Review Of Theory And Empirical Work', *Journal of Finance* **25**(2), 383–417.

Markowitz, H. (1952), 'Portfolio Selection', *Journal of Finance* **7**(1), 77–91.

Markowitz, H. M. (1968), *'Portfolio Selection: Efficient Diversification of Investments'*, Yale University Press, New Haven, Connecticut.

Markowitz, H. M. (2010), 'Portfolio Theory: As I Still See It', *Annual Review of Financial Economics* **2**(1), 1–23.

Martens, M. (2002), 'Measuring and forecasting S&P 500 index-futures volatility using high-frequency data', *Journal of Futures Markets* **22**(6), 497–518.

Melitz, J. and Toubal, F. (2014), 'Native language, spoken language, translation and trade', *Journal of International Economics* **93**(2), 351–363.

Memmel, C. (2003), 'Performance Hypothesis Testing with the Sharpe Ratio', *Finance Letters* **1**(1), 21–23.

Mondria, J. (2010), 'Portfolio choice, attention allocation, and price comovement', *Journal of Economic Theory* **145**(5), 1837–1864.

Mondria, J. and Quintana-Domeque, C. (2013), 'Financial Contagion and Attention Allocation', *Economic Journal* **123**(568), 429–454.

Morck, R., Yeung, B. and Yu, W. (2000), 'The information content of stock markets: why do emerging markets have synchronous stock price movements?', *Journal of Financial Economics* **58**(1), 215–260.

Mundy, P. and Newell, L. (2007), 'Attention, Joint Attention, and Social Cognition', *Current Directions in Psychological Science* **16**(5), 269–274.

Naik, P. A. and Raman, K. (2003), 'Understanding the Impact of Synergy in Multimedia Communications', *Journal of Marketing Research* **40**(4), 375–388.

Newey, W. K. and West, K. D. (1987), 'A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix', *Econometrica* **55**(3), 703–708.

O'brien, R. M. (2007), 'A Caution Regarding Rules of Thumb for Variance Inflation Factors', *Quality & Quantity* **41**(5), 673–690.

Oestreicher-Singer, G. and Sundararajan, A. (2012), 'The Visible Hand? Demand Effects of Recommendation Networks in Electronic Markets', *Management Science* **58**(11), 1963–1981.

Okimoto, T. (2008), 'New Evidence of Asymmetric Dependence Structures in International Equity Markets', *Journal of Financial and Quantitative Analysis* **43**(3), 787–815.

Patton, A. J. (2011), 'Volatility forecast comparison using imperfect volatility proxies', *Journal of Econometrics* **160**(1), 246–256.

Patton, A. J. and Sheppard, K. (2009), 'Evaluating Volatility and Correlation Forecasts', *in* T. G. Andersen, R. A. Davis, J.-P. Kreiss and T. V. Mikosch, eds, 'Handbook of Financial Time Series', Springer, Verlag Berlin Heidelburg, pp. 801–838.

Peng, L. and Xiong, W. (2002), 'Time to digest and volatility dynamics', *Duke University* .

Peng, L. and Xiong, W. (2006), 'Investor attention, overconfidence and category learning', *Journal of Financial Economics* **80**(3), 563–602.

Pindyck, R. S. and Rotemberg, J. J. (1993), 'The Comovement of Stock Prices', *The Quarterly Journal of Economics* **108**(4), 1073–1104.

Portes, R. and Rey, H. (2005), 'The determinants of cross-border equity flows', *Journal of International Economics* **65**(2), 269–296.

Portes, R., Rey, H. and Oh, Y. (2001), 'Information and capital flows: The determinants of transactions in financial assets', *European Economic Review* **45**(4), 783–796.

Prokopczuk, M. and Simen, C. W. (2014), 'The importance of the volatility risk premium for volatility forecasting', *Journal of Banking & Finance* **40**, 303–320.

Rachev, S., Jašić, T., Stoyanov, S. and Fabozzi, F. J. (2007), 'Momentum strategies based on reward–risk stock selection criteria', *Journal of Banking & Finance* **31**(8), 2325–2346.

Roberts, M. R., Whited, T. M. et al. (2013), 'Endogeneity in Empirical Corporate Finance', Vol. 2, Elsevier, North-Holland, pp. 493–572.

Rosenthal, R. and Rubin, D. B. (1982), 'Comparing effect sizes of independent studies.', *Psychological Bulletin* **92**(2), 500.

Ross, S. A. (1989), 'Information and Volatility: The No Arbitrage Martingale Approach to Timing and Resolution Irrelevancy', *Journal of Finance* **44**(1), 1–17.

Rusmevichientong, P. and Williamson, D. P. (2006), 'An Adaptive Algorithm for Selecting Profitable Keywords for Search-Based Advertising Services', *in* 'Proceedings 7th ACM Conference on Electronic Commerce', ACM, pp. 260–269.

Rutz, O. J. and Bucklin, R. E. (2007), A Model of Individual Keyword Performance in Paid Search Advertising. Working Paper. Yale University, New Haven, CT.

Rutz, O. J. and Bucklin, R. E. (2011), 'From Generic to Branded: A Model of Spillover in Paid Search Advertising', *Journal of Marketing Research* **48**(1), 87–102.

Rutz, O. J., Trusov, M. and Bucklin, R. E. (2011), 'Modeling Indirect Effects of Paid Search Advertising: Which Keywords Lead to More Future Visits?', *Marketing Science* **30**(4), 646–665.

Ryals, L., Dias, S. and Berger, M. (2007), 'Optimising marketing spend: return maximisation and risk minimisation in the marketing portfolio', *Journal of Marketing Management* **23**(9–10), 991–1011.

Sahni, N. S. (2016), 'Advertising Spillovers: Evidence from Online Field Experiments and Implications for Returns on Advertising', *Journal of Marketing Research* **53**(4), 459–478.

Santis, G. and Gerard, B. (1997), 'International Asset Pricing and Portfolio Diversification with Time-Varying Risk', *Journal of Finance* **52**(5), 1881–1912.

Scharfstein, D. S. and Stein, J. C. (1990), 'Herd Behavior and Investment', *American Economic Review* **80**(3), 465–479.

Schmidt, D. (2013), Investors' Attention and Stock Covariation. Working paper. INSEAD.

Schmidt, F. L. and Hunter, J. E. (2014), *Methods of meta-analysis: Correcting error and bias in research findings*, Sage Publications, Inc.

Seemann, A. (2011), *Joint Attention: New Developments in Psychology, Philosophy of Mind, and Social Neuroscience*, MIT Press, Massachusetts.

Sharpe, W. F. (1964), 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance* **19**(3), 425–442.

Shiller, R. J. (1981), 'The Use of Volatility Measures in Assessing Market Efficiency', *Journal of Finance* **36**(2), 291–304.

Shiller, R. J. (1989), 'Comovements in Stock Prices and Comovements in Dividends', *Journal of Finance* **44**(3), 719–729.

Shiller, R. J. (2003), 'From Efficient Markets Theory to Behavioral Finance', *Journal of Economic Perspectives* **17**(1), 83–104.

Silvennoinen, A. and Teräsvirta, T. (2009), Multivariate GARCH Models, *in* T. G. Andersen, R. A. Davis, J.-P. Kreiss and T. V. Mikosch, eds, 'Handbook of Financial Time Series', Springer, pp. 201–229.

Sims, C. A. (2003), 'Implications of rational inattention', *Journal of Monetary Economics* **50**(3), 665–690.

Skiera, B., Eckert, J. and Hinz, O. (2010), 'An analysis of the importance of the long tail in search engine marketing', *Electronic Commerce Research and Applications* **9**(6), 488–494.

Skintzi, V. D. and Xanthopoulos-Sisinis, S. (2007), 'Evaluation of correlation forecasting models for risk management', *Journal of Forecasting* **26**(7), 497–526.

Sparkman Jr, R. M. and Locander, W. B. (1980), 'Attribution Theory and Advertising Effectiveness', *Journal of Consumer Research* **7**(3), 219–224.

Statman, M. (1987), 'How Many Stocks Make a Diversified Portfolio?', *Journal of Financial and Quantitative Analysis* **22**(3), 353–363.

Swinyard, W. R. and Ray, M. L. (1977), 'Advertising-Selling Interactions: An Attribution Theory Experiment', *Journal of Marketing Research* **14**(4), 509–516.

Tse, Y. K. and Tsui, A. K. C. (2002), 'A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model With Time-Varying Correlations', *Journal of Business & Economic Statistics* **20**(3), 351–362.

Vayanos, D. (2004), Flight to quality, flight to liquidity, and the pricing of risk. Working Paper. NBER.

Veldkamp, L. L. (2006*a*), 'Information Markets and the Comovement of Asset Prices', *Review of Economic Studies* **73**(3), 823–845.

Veldkamp, L. L. (2006*b*), 'Media Frenzies in Markets for Financial Information', *American Economic Review* **96**(3), 577–601.

Vlastakis, N. and Markellos, R. N. (2012), 'Information demand and stock market volatility', *Journal of Banking & Finance* **36**(6), 1808–1821.

Vosen, S. and Schmidt, T. (2011), 'Forecasting private consumption: survey-based indicators vs. Google trends', *Journal of Forecasting* **30**(6), 565–578.

West, K. D. (1996), 'Asymptotic Inference About Predictive Ability', *Econometrica: Journal of the Econometric Society* **64**(5), 1067–1084.

Wintoki, M. B., Linck, J. S. and Netter, J. M. (2012), 'Endogeneity and the dynamics of internal corporate governance', *Journal of Financial Economics* **105**(3), 581–606.

Wu, L. and Brynjolfsson, E. (2015), 'The Future of Prediction: How Google Searches Foreshadow Housing Prices and Sales', *in* A. Goldfarb, S. M. Greenstein and C. E. Tucker, eds, 'Economic Analysis of the Digital Economy', University of Chicago Press, Chicago, pp. 89–118.

Yang, S. and Ghose, A. (2010), 'Analyzing the Relationship Between Organic and Sponsored Search Advertising: Positive, Negative, or Zero Interdependence?', *Marketing Science* **29**(4), 602–623.

Yeyati, E. L., Panizza, U. and Stein, E. (2007), 'The cyclical nature of North–South FDI flows', *Journal of International Money and Finance* **26**(1), 104–130.

Yuan, K. (2005), 'Asymmetric Price Movements and Borrowing Constraints: A Rational Expectations Equilibrium Model of Crises, Contagion, and Confusion', *Journal of Finance* **60**(1), 379–411.

Yuan, K., Zheng, L. and Zhu, Q. (2006), 'Are investors moonstruck? Lunar phases and stock returns', *Journal of Empirical Finance* **13**(1), 1–23.

Yuan, Y. (2015), 'Market-wide attention, trading, and stock returns', *Journal of Financial Economics* **116**(3), 548–564.

Zhang, D. and Lu, J. (2009), 'Batch-Mode Computational Advertising Based on Modern Portfolio Theory', *in* 'Proceedings of the 2nd International Conference on the Theory of Information Retrieval: Advances in Information Retrieval Theory', ICTIR, Cambridge, UK, pp. 380–383.

Zigmond, D. and Stipp, H. (2010), 'Assessing a New Advertising Effect', *Journal of Advertising Research* **50**(2), 162–168.