The term structure of interest rates as predictor of stock market volatility

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Abstract

We examine the forecasting power of the volatility of the slope of the US Treasury yield curve on US stock market volatility. Consistent with theoretical asset pricing models, we find that the volatility of the slope of the term structure of interest rates has significant forecasting power on stock market volatility for forecasting horizon ranging from one up to twelve months. Moreover, the term structure volatility has significant forecasting power when used for volatility predictions of the intra-day returns of S&P500 constituents, with the predictive power being higher for stocks belonging to the telecommunications and financial sector. Our forecasting models show that the forecasting power of yield curve volatility is higher to and absorbs that of Economic Policy Uncertainty and Monetary Policy Uncertainty, showing that the main channel through which the yield curve volatility affects the stock market is not only related with uncertainty about monetary policy actions or policy rates, but also with uncertainty regarding the future cash flows and dividend payments of US equities. Lastly, we show that the forecasting power of term structure volatility significantly increases during the post-2007 Great recession period which coincides with the Fed adopting unconventional monetary policies to stimulate the economy.

Key words: Term structure, term spread, slope, monetary policy, interest rates, stock-market volatility

JEL classification: E43, G17

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1. Introduction

Stock market volatility fluctuates over time, with the economic explanation being still a debatable issue. The sources of time-variation in the volatility of equity prices are attributed to market-specific factors like the long-memory property of volatility (Andersen *et al*., 2007; Bollerslev and Mikkelsen, 1996; Christensen and Nielsen, 2007; among others), to changes in leverage (Black, 1976; Christie, 1982; Catania and Proietti, 2020; Gallo and Otranto, 2015), expected stock returns (Merton, 1980; French *et al*., 1987; among others) and to macroeconomic factors related with business cycles and monetary policy (Bansal and Yaron, 2004; Bekaert *et al*., 2013; Beltratti and Morana, 2006; Choudhry et al. 2016; Corradi *et al*., 2013; Engle *et al*., 2013; Hamilton and Lin, 1996; Paye, 2012; Schwert, 1989; among others). Schwert (1989) is the first to point out that "if macroeconomic data provide information about the volatility of either future expected cash flows, or future discount rates, they can explain why stock return volatility changes over time". Schwert (1989) is also the first to give a pure macroeconomic answer to the question "Why volatility changes over time", by showing that macroeconomic uncertainty measured as the volatility of US industrial production and interest rates, forecasts aggregate stock-market volatility. Cochrane (2011) provides more evidence in favor of the findings of Schwert (1989), by identifying the increasing importance of macroeconomic factors like the variability of interest rates in determining equity risk premia. Recently, Ma et al. (2022) and Segnon et al. (2024) show the significant predictive information content of economic policy uncertainty and geopolitical risk on stock market volatility. Moreover, a few relevant studies show that monetary policy uncertainty is a robust predictor of stock market volatility (Beltratti and Morana, 2006; Kaminska and Roberts-Sklar, 2018). For example Kaminska and Roberts-Sklar (2018) show that monetary policy uncertainty has significant predictive power on stock-return volatility for both short- and long-term forecasting horizons.

Independently, the literature on the term structure of interest rates has shown that the slope of the term structure reveals information about future economic activity (Doshi *et al*., 2018; Estrella and Hardouvelis, 1991; Cremers *et al*., 2021) and about the future price path of stock market prices[1] (Chen *et al*., 1986, 2013; Campbell, 1986; Resnick and Shoesmith, 2002; Faria and Verona, 2020; Maio, 2013; Patelis, 1997; Neuhierl and Weber, 2019). For example, Patelis (1997) finds that shifts in monetary policy are significant predictors of equity market returns since they affect both the time-variation in expected cash flows and in discount rates.

Even though the macro-finance literature has extensively shown the structural linkages between business cycles, interest rates and the stock market, there is no evidence showing the predictive information content of yield curve volatility on stock-market volatility. We attempt to fill this gap in the literature by examining the forecasting power of the volatility of the slope of the term structure of interest rates (SLOPERV henceforth) on stock-market volatility. We focus on SLOPERV because we strongly support the view that it affects stock-market volatility through two structurally different channels: the first one is the time variation of the volatility of the discount factors used for the discounting of future cash flows (the dividends plus capital gains) of stocks. The other, is the risk being present through the increased dispersion of the expectations about the future path of the economy, and consequently, the increased volatility risk in the stock-market which under the efficient market hypothesis, must reflect macroeconomic fundamentals. According to the findings in the literature, the term spread (the slope of the Treasury yield curve) reflects expectations about future cash flows and about the future level of interest rates. If the shape of the yield curve could remain constant through time, then there would be no (macroeconomic at least) uncertainty in the process of discounting the

[1]According to Chen, Roll and Ross (1986) the "systematic forces that influence returns are those that change discount factors and expected cash flows". Following this kind of empirical approach, Chen, Roll and Ross (1986) find that the slope of the term structure, the industrial production growth, the default spread and both the expected and unexpected component of inflation are the systematic macroeconomic factors priced in the stock-market.

future cash flows. According to these arguments, the SLOPERV is an important macroeconomic factor generating turbulence and large fluctuations in stock market prices. Concerning the benefits of our approach when compared with news-related Economic Policy Uncertainty (EPU henceforth) and Monetary Policy Uncertainty (MPU henceforth) measures, we believe that our market-data-based approach is more relevant for investors and forward looking, compared to the ex-post analysis of newspapers for terms related to monetary or economic policy uncertainty.

Our econometric analysis verifies our hypotheses and provides several contributions in the macro-finance literature. First, we find that the SLOPERV is a robust in-sample and out-of-sample predictor of stock market volatility, with the predictability being higher for medium and long-term forecasting horizon, when deploying both a bivariate along with a multivariate forecasting regression setting in which we control for the persistence and long-memory property of stock market volatility series (Bekaert and Hoerova, 2014; Christensen *et al*., 2010; Corsi, 2009; among others). In more detail, our empirical analysis reveals a positive robust statistical relationship between SLOPERV and US stock-market volatility. More specifically, we find that SLOPERV is a robust predictor of the volatility of stock market returns for various forecasting horizons ranging from 1 up to 12 months, outperforming variables related to monetary and economic policy uncertainty. Therefore, our analysis shows that the forecasting power of SLOPERV provides statistically and economically differentiated and incremental predictive power relative to that of Economic Policy Uncertainty (EPU henceforth) and Monetary Policy Uncertainty (MPU henceforth). In this way we show that the channel through which the SLOPERV affects stock market volatility, not only passes through the interest rate volatility (monetary policy uncertainty) channel, but also through the 'dispersion of expectations about future cash flows' channel. Interestingly, the SLOPERV factor, besides outperforming EPU and MPU, also outperforms the VIX and autoregressive stock market volatility models for medium and long-term stock market volatility predictions. These results are the first to show that, during the post-2008 global financial crisis period, the SLOPERV has the highest forecasting power on long-term stock market volatility when compared to that of standard stock market volatility forecasting models which include the VIX and the lagged stock market volatility as predictors (Corsi, 2009; Bekaert and Hoerova, 2014; Paye, 2012). Moreover, our analysis is the first to show that the volatility in the slope factor is a common forecasting factor of the return volatility of S&P 500 constituents, with the predictability being higher for stocks belonging to the financial and telecommunications sector. These findings contribute to the literature identifying the industry-level effects of US monetary policy, according to which the cyclical stock market sectors like tech-firms and telecommunications are more sensitive to monetary policy shocks (Bernanke and Kuttner, 2005; Ehrman and Fratzscher, 2004).

Our findings provide further insights to those of Neuhierl and Weber (2019), Resnick and Shoesmith (2002) and Faria and Verona (2020) who show that the term spread is a robust in sample and out of sample predictor of equity market returns and risk premia. Our contribution in the field is that we show for the first time in the literature that the SLOPERV factor includes information which is related to economic forces which are incremental to those included in the variation of short-term interest rates and monetary policy uncertainty. Moreover, our subsample forecasting analysis shows that the in-sample and out-of-sample forecasting power of the SLOPERV has exponentially increased in the post-2007 Great Recession period. More specifically, our out-of-sample recursive forecasting exercise shows that the real-time out-of-sample forecasting power of the SLOPERV increases during the Great Recession and remains high afterwards, with the SLOPERV being the most significant macroeconomic predictor of stock market volatility in the post-2007 period.

Our findings add further insights and contribution to the strand of the macro-finance literature identifying tighter linkages between financial markets and the macroeconomy after the Great Recession (Abbate *et al.*, 2016; Caldara *et al.*, 2016; Prieto et al., 2016). Additionally, our findings provide new insights to those of the monetary policy literature identifying the effectiveness of the communication channel of monetary policy via unconventional policies like forward guidance which also initiated during the Great Recession (see Swanson, 2021).[2] By showing an increased forecasting power of SLOPERV in the post-2008 Great Recession era, we implicitly show that stock market participants have been paying more attention and they are more trustful and re-active to macroeconomic expectations revealed by the slope of the US Treasury curve. Consequently, the rising dispersion of yield-curve based expectations (proxied by SLOPERV) has a more pronounced effect on the volatility of stock market prices. With the Fed being more transparent and committed towards her decisions about the future level of interest rates, the slope of the yield curve has become a more 'reliable' (by stock market participants) indicator of the future level of interest rates and economic activity. Hence, the increasing volatility of the slope of the yield curve, results to higher perceptions about interest rate risk and cash-flow risk by market participants, which ultimately leads to higher stock market volatility.

[2] At the end of 2008, following several rate cuts, the FFR reached the zero-lower bound (ZLB). Thereafter, the Fed employed various non-conventional policy tools to overcome the ZLB constraint for providing monetary stimulus. These include more explicit forward guidance, aiming to influence the path of future short-term rates, as well as Large Scale Asset Purchases (LSAPs) and liquidity facilities, which changed the size and composition of the Fed's balance sheet. At the beginning of forward guidance during the ZLB, the Fed adopted a qualitative tone in its communication with post-FOMC meeting statements including phrases such as the FFR will remain near zero for "an extended period" (FOMC statement of March 18, 2009). This then evolved to date-based guidance, specifying future dates such as "at least through mid-2015" (September 13, 2012). Finally, a threshold-based approach was adopted linking the first-rate increase to developments in inflation and unemployment.

Our analysis sheds light on the literature and the policy implications which are related with the risk-taking channel of monetary policy. The policy recommendation stemming from our results, is that monetary policies aiming at reducing risk and uncertainty in the equity market should turn their attention on SLOPERV. Even though the slope of the US Treasury curve cannot be entirely controlled or targeted by the Fed, any monetary policy aiming at reducing volatility in the slope of the term structure results in more financial stability (lower stock market volatility).

The remainder of the paper is structured as follows. In Section 2, we describe the data and the methodology for estimating stock market volatility and our bivariate and multivariate OLS forecasting models. In Section 3 we present some descriptive statistics, and we analyze the in-sample and out-of-sample results of the OLS forecasting regression models. In Section 4 we report our robustness checks. Finally, Section 5 concludes and presents some policy implications.

2. Data-Methodology

2.1 Macroeconomic and stock market data

We obtain daily data for the 3-monnth US-Treasury Bill rate, the 10-year US-government bond yield and the Moody's Baa corporate bond yield from the FRED database. The Baa default spread (BAA) is the difference between the Baa corporate bond yield and the 10-year US government bond yield. The daily data for WTI crude oil prices and the monthly data for the US Industrial Production Index have been downloaded from Datastream. The monthly time series for EPU and MPU which are based on the Baker *et al.* (2016) methodology are downloaded from the EPU website available at: http://www.policyuncertainty.com.

2.2 Stock market volatility and yield curve volatility

In order to capture stock market volatility, we construct the Realized Variance time series by using intraday (5-minute) observations following Andersen *et al*. (2007) methodology. We calculate the sum of squared 5-minute logarithmic returns filtered through an MA(1) process:

$$SP500RV_t = \sum_{i=1}^{n} r_i^2 \tag{1}$$

Where the returns $r_i = \log(v_i/v_{i-1})$, with v_i denoting the price series of S&P 500 index and i the number of intraday observations in each period. We similarly estimate the S&P 500 companies realized variance for our sectoral analysis. Finally, we estimate in a similar way the crude oil volatility (OILRV) as the realized variance of the daily WTI crude oil prices. Following Estrella and Hardouvelis (1991), we estimate the daily slope (term spread) of the term structure of interest rates as the difference between the daily 10-year US-government bond yield (USGOV10) and the 3-month US-Treasury Bill rate (USTBIL3). The volatility of the slope of the term structure (SLOPERV) is then estimated as the monthly realized variance of the daily term spread for each monthly period as shown in Equation (2) below:

$$SLOPERV_t = \sum_{i=1}^{n}(USGOV10_i - USTBIL3_i)^2 \tag{2}$$

In equation (3) above, the $USGOV10_i$ and the $USTBIL3_i$ are the daily yields of the US government bond yield and the 3-month US Treasury Bill respectively, with n defining the number of trading days for each monthly period. Hence, for a given monthly period t, the $SLOPERV_t$ is estimated as the monthly variance of the daily term spread observed during the month. Consequently, our SLOPERV factor captures the monthly variation of the daily term spread (daily slope of the yield curve). Following Schwert (1989), our arguments on the positive impact of SLOPERV on stock market volatility, are based in the following stock-price valuation formula:

$$E_t(P_{t+1}) = E_t\left[\sum_{k=1}^{\infty}\frac{D_k}{(1+r_{t+k})^k}\right] \tag{3}$$

According to the fundamental stock-market valuation formula shown in Equation (3), the conditional expected stock price $E_{t-1}p_t$ is the sum of the discounted dividends plus capital gains D_k discounted with the discount rates $(1+r_{t+k})$. Thus, it is quite reasonable to assume that the volatility of stock-market prices will depend on the dispersion of expectations about future cash-flows and about future interest rates both proxied by an increasing SLOPERV. Since the slope of the term structure reflects expectations about equity prices and macroeconomic outcomes (Estrella and Hardouvelis, 1991; Neuhierl and Weber, 2019; among others), an increase in SLOPERV is translated to increasing dispersion of expectations of market participants regarding future discount rates and cash-flows, ultimately resulting in increased stock market volatility.

2.3 Forecasting regression models

In this section we describe the forecasting regression models used in our analysis. We follow the OLS forecasting approach of Paye (2012) and Bekaert and Hoerova (2014) by using the logarithms of Realized Variances in the predictive regressions[3]. First, we estimate a bivariate regression model using only SLOPERV as predictor of stock-market volatility (SP500RV), as shown below:

$$ln(SP500RV_{t+h}) = b_0 + b_1 ln(SLOPERV_t) + \varepsilon_{t+h} \tag{4}$$

[3] Bekaert and Hoerova (2014) mention that the realized variance series typically have right-skewed distributions while logarithmic variance series tend to have near Gaussian distributions, hence the forecast accuracy of linear forecasting models is higher when using logarithmic variances.

We estimate the forecasting regression model shown in (3) for forecast horizon h=1, 2, 3, 6, 9 and 12 months. Following Paye (2012), we additionally estimate a multivariate forecasting OLS regression model in which we include some well-established (in the relevant literature) stock market volatility predictors in the right-hand side of the regression equation. More specifically, motivated by the standard models shown in the volatility forecasting literature indicating the persistence and the long-memory property of stock market volatility (Andersen *et al*., 2007; Bekaert and Hoerova, 2014; Christensen *et al*., 2010; Corsi, 2009; among others), we include the lagged SP500RV as predictor. Following the literature which identifies the effect of EPU on stock market returns and volatility (see, e.g., Amengual and Xiu, 2014; Antonakakis et al., 2013, Kang and Ratti, 2013, Liu and Zhang, 2015; among others), we include EPU in the right-hand side of the predictive regression equation. In addition, following the strand of the literature which shows that monetary policy shocks and uncertainty have a significant effect on stock-market volatility (Bekaert *et al*., 2013; Kaminska and Roberts-Sklar, 2018), we include the MPU index in our information variable set. Lastly, following the results of the relevant macro-finance literature which show the effect of business cycles on stock-price returns and volatility (Schwert, 1989; Engle *et al.*, 2013; Paye, 2012) we control for some business cycle variables which are linked with stock-market volatility like growth rate of US Industrial Production, the Baa Moody's corporate yield spread (BAA)[4] and the SLOPE (the difference between the 10-year government bond rate and 3-month US Treasury yield). Finally, following the findings in the literature which identifies significant volatility spillover effects from crude oil market to US stock market (Arouri *et al*., 2011, Xu *et al*., 2019), we include OILRV as an additional predictor of SP500RV. The baseline multivariate forecasting regression model on SP500RV is given in Equation (5) below:

[4] The Baa spread is treated in the literature as a measure of global financial risk (Epstein et al., 2019; Akinci, 2013).

$$ln(SP500RV_{t+h}) = b_0 + b_1 ln(SP500RV_t) + b_2 SLOPE_t + b_3 ln(SLOPERV_t) + b_4 ln(EPU_t) + b_5 ln(MPU_t) + b_6 BAA_t + b_7 dln(IPI)_t + b_8 ln(OILRV)_t + \varepsilon_{t+h} \quad (5)$$

In order to examine the real-time forecasting power of our bivariate and multivariate forecasting models, we estimate the same set of models using a recursive out-of-sample scheme and an initial window of 5 years and estimate the recursive coefficients and R^2s along with the Root Mean Squared Forecast Errors (RMSFEs) and the Mean Absolute Forecast Errors (MAFEs) of the recursive bivariate and multivariate forecasting models[5].

3. Econometric analysis

3.1 Descriptive statistics

In this section we present the descriptive statistics for our times series variables. **Tables 1** and **2** below report the descriptive statistics and the correlation matrix of our explanatory variables.

[Insert Tables 1 and 2 Here]

From **Tables 1 and 2** we observe low correlation for all the pairs of explanatory variables used in the predictive regressions. **Table 2** reports a high correlation between the VIX and SP500RV, hence, we do not include the VIX on our time series regressions to avoid potential multicollinearity issues in our multivariate forecasting analysis[6]. Moreover, **Figure 1** shows the time series for SP500RV along with the SLOPERV.

[5] The relevant literature on volatility modelling has emphasized the noteworthy performance of the HAR-RV model introduced by Corsi (2009). While acknowledging that the HAR-RV model would be very pertinent to our analysis, we are unable to include it in our empirical design due to data availability restrictions.
[6] The results of our multivariate regression models remain qualitatively the same when using the VIX index instead of the lagged SP500RV in our list of stock market volatility predictors. These results are available upon request.

[Insert Figure 1 Here]

From **Figure 1** we can observe that many of the positive jumps in SLOPERV precede those of SP500RV. This is preliminary evidence showing that SLOPERV could act as early warning signal of increasing stock market volatility. We also show that the co-jumps in these two series are more common during the post-2007 period. Moreover, **Figure 1** shows significantly higher values of the SP500RV and SLOPERV, during 2007 and 2008. This period also coincides with the period of the recent financial crisis of 2007-2008 in which FED intervention attempted to control the financial turbulence (see Cecchetti; 2008, inter alia)

3.2 Forecasting regression models

3.2.1 In sample evidence

In this section we present the results of our in-sample predictive regression analysis. First, we present the results of our bivariate forecasting regression models using SLOPERV as predictor of SP500RV. **Table 3** below presents the regression results of the bivariate forecasting regression model in which we use SLOPERV as predictor of stock-market volatility.

[Insert Table 3 Here]

From **Table 3** we observe that the SLOPERV is a statistically significant predictor of stock-market volatility for forecasting horizon ranging from 1 up to 12 months when utilizing our full sample (1990-2017). Moreover, when performing a subsample analysis splitting the sample to pre-2007 and post-2007 period, we find that the predictive power of SLOPERV significantly increases in the post-2007 period[7]. For example, the R^2 value increases from

[7] We also estimate the regression model using a different subsample that excludes the financial crisis period, starting after 2009, to ensure that the higher predictability of SLOPERV on stock market volatilitypost-2007 is not

12.6% to 31.8% when running the bivariate regression model using SLOPERV as predictor for the post-2007 sample. On the contrary, our analysis for the pre-2007 period shows that there was no significant predictive information content of SLOPERV on SP500RV, implicitly indicating the immunity of US stock market volatility to changes in the shape of the US Treasury yield curve during this period. The increase in the forecasting power of SLOPERV coincides with the increased transparency in the communication channel of the US monetary authority (e.g. the forward guidance which started in 2008 in an effort to ameliorate the macroeconomic impact of the 2007-2008 financial turmoil). In this way, our results provide further insights to the literature focusing on the effectiveness of forward guidance on the US stock market (Swanson, 2021). While this literature shows the increased impact of forward guidance and unconventional monetary policy on US equity prices, what we additionally show, is that the impact of SLOPERV on stock market volatility significantly increases during the period in which the more transparent monetary policy (like forward guidance) has been adopted by the Fed.

Tables 4 and **5** below report the OLS regression results of our multivariate predictive regression model shown in Equation (4). In more detail, in **Table 4** we report the regression results for our full sample, spanning the period from 1990 to 2017, while in **Table 5** we report the results of the multivariate model when using the pre- and post-2007 sample respectively.

[Insert Tables 4 and 5 Here]

driven by the financial crisis. We choose 2009 as a cut-off point for this analysis since the relevant studies (e.g. Cecchetti, 2008) assume that the financial crisis ended in the fall of 2008. We provide these further results in the online appendix.

From **Table 4** we observe that, when estimating the multivariate model using the full (1990-2017) sample, the SLOPERV remains a statistically significant predictor of SP500RV for 12-month forecasting horizon, with the lagged SP500RV absorbing the predictive information content of SLOPERV for shorter-term horizon, due to the long-memory property and high persistence of the SP500RV series (Corsi, 2009; Bekaert and Hoerova, 2014; Catania and Proietti, 2020). However, the results shown in **Table 5** clearly show that for the post-2007 period the SLOPERV factor is a statistically significant predictor of stock market volatility for medium and long run forecast horizon absorbing the predictive information content of popular macroeconomic and monetary policy uncertainty proxies like EPU and MPU. Most importantly, our multivariate forecasting results show that the SLOPERV factor adds incremental forecasting power when added into a multivariate forecasting regression model which contains the well-established stock market volatility predictors like the VIX and autoregressive SP500RV terms in the information variable set[8].

3.2.2 Out-of-sample evidence

In this section we move from the in-sample volatility forecasting estimations to a real-time out-of-sample regression setting so that the data used for stock market volatility predictions to be available to the forecaster the time the forecast is being made. More specifically, we use a dynamic recursive estimation scheme with an initial 5-year window of monthly observations spanning from January 1990 to December 1994, hence the first volatility forecast is being made for January 1995. The estimation window is then extended by one month to obtain a new out-of-sample forecast, with the recursive dynamic out-of-sample forecasting exercise covering the period from January 1995 to December 2017. **Figure 4** below reports the beta coefficients (the

[8] We additionally estimate a multivariate regression model in which we use the VIX instead of the lagged SP500RV and our results remain qualitatively the same. These additional OLS regression results can be available upon request.

b_1 coefficient of the SLOPERV used for making the out-of-sample stock market volatility forecasts, see equation (3)) and the respective recursive R^2s when using the recursive OLS estimation approach.

[Insert Figure 4 Here]

The recursive coefficients and R^2s shown in **Figure 4** clearly show that the forecasting power of SLOPERV on stock market volatility is very low during the early 1990s and 2000s, while it jumps during the Great Recession and remains high and significant for the recent post-2008 recession period. For example, the beta (b_1) coefficient of SLOPERV becomes statistically significant after 2008. In addition, the recursive R^2 rises from approximately 5% to almost 10% when moving to the post-2008 period. The significance of the SLOPERV forecasts during the post-2008 period remains high for both short- and long-term forecast horizon, ranging from 1 up to 12 months. These results are in line with those of Abbate *et al.* (2016) and Prieto et al. (2016) who find that the dynamic correlations between financial shocks and the macroeconomy have increased during the post-2008 Great recession period. In addition, the increased forecasting power of SLOPERV coincides with the increased transparency of US monetary policy during the post-2008 period, which resulted to the effectiveness of forward guidance on US equity market (Swanson, 2021). Our findings provide further support and insights to those of Diebold and Yilmaz (2012) who show that volatility spillovers across US stock and bond markets have intensified after the 2007 global financial crisis. Finally, **Table 6** reports the RMSFEs for our bivariate and multivariate regression models shown in Equations (3) and (4).

[Insert Table 6 Here]

The RMSFEs shown in **Table 6** show that the out-of-sample forecasting results are completely in line with their in-sample counterparts. More specifically, when utilizing our full sample, we find that the best performing model for horizons ranging from 1 up to 9 months is the autoregressive volatility model, while the bivariate model which includes SLOPERV as predictor is the best performing model for long-term (12-month) forecast horizon. Interestingly, when performing the forecasting exercise for the post-2007 sample, we find that for medium (6 and 9 month) and long-term (12-month) forecast horizons, the best performing model is the bivariate model including only SLOPERV as stock market volatility predictor[9]. The statistical significance of the forecasting performance is further evaluated using a superior predictive ability (SPA) test (Hansen, 2001) that tests whether the best performing model is indeed superior to the benchmark. The results represented using 1, 2 or three stars for 10%, 5% and 1% levels of statistical significance, respectively, confirm that the performance of the models is indeed statistically significant, at least at the 5% level. These results are new to the volatility forecasting literature, since they show for the first time that the SLOPERV factor outperforms the VIX and the lagged SP500RV when used for medium and long-term stock market volatility forecasting. Our results remain the same if we use Mean Absolute Forecast Errors (MAEs) instead of RMSFEs as our criterion for forecast accuracy[10].

3.2.3 Forecasting volatility of the S&P500 constituents

In this section we report the results of the predictive regression models on the volatility of the intra-day returns of the 504 constituents of the S&P500 index[11]. We estimate the Realized Variance of S&P500 constituents in the same way we have estimated the SP500RV, as shown

[9] We also perform the same out-of-sample analysis using a subsample that starts after 2009, to ensure that the results are not driven by the period of the financial crisis. We provide the tables with the RMSFEs in the online appendix.
[10] The table reporting MAEs can be found in our online Appendix.
[11] The full list of our 504 S&P 500 constituents can be provided upon request.

in Equation (2). In this way, we examine for which sectors of the stock market, our SLOPERV factor has highest forecasting power when used for forecasting the volatility of individual stocks belonging to each of the stock market sectors. In more detail, we group the S&P500 constituents with respect to the sector to which they belong, which, according to the ICB industry classification is composed by the following ten industries-categories: Utilities, Telecommunications, Technology, Oil and Gas, Industrials, Health Care, Financials, Consumer Services, Consumer Goods and Basic Materials. We then report the average R^2s of the bivariate regressions of SLOPERV on the realized variance for stocks belonging to each stock market sector. **Figure 2** below shows the average R^2s and the Newey-West (1987) t-statistics of the firm-level bivariate regressions on stocks belonging market sector when using SLOPERV, EPU and MPU as predictors of the realized variance of S&P500 constituents.

[Insert Figure 2 Here]

From **Figure 2** it is evident that the forecasting power of the SLOPERV is factor is higher when compared to that of EPU or MPU, a fact which shows that SLOPERV is a better macroeconomic signal of rising volatility risk of individual stocks[12]. Interestingly, from **Figure 2** we observe that the SLOPERV has the highest forecasting power for stocks belonging to the telecommunications and financial sector. These findings provide further insights on the literature showing the heterogeneous effects of US monetary policy shocks on the stock prices of US listed firms, according to which the cyclical and more capital-intensive industries like the technology and communications are more sensitive to monetary policy shocks (Bernanke and Kuttner, 2005; Ehrman and Fratzscher, 2004). The higher forecasting power of SLOPERV

[12] The results shown in Figure 2 refer to short-term (1-month horizon forecasts). Our claims on the superiority of SLOPERV forecasts when compared to EPU and MPU-based volatility forecasts remain the same for medium- and long-term forecasting horizon. These additional results can be found in our Appendix.

on the return volatility of stocks belonging to the financial sector is broadly in line with the findings of Hippler and Hassan (2015) who show that US financial firms are more sensitive to macroeconomic stress conditions. Finally, **Figure 3** reports the respective out-of-sample results when using a recursive estimation scheme with an initial 5-year time series sample spanning from January 1990 to December 1994.

[Insert Figure 3 Here]

The out-of-sample forecasting regression results shown in **Table 3** clearly show that the SLOPERV outperforms EPU and MPU in terms of volatility forecasting power in a real-time out-of-sample forecasting regression setting.

3.3 VAR estimates

In order to control for possible endogeneity issues between yield curve and stock market volatility, we estimate a multivariate VAR model in which we include among other variables, the SLOPE, the SLOPERV and the SP500RV as endogenous variables[13]. In more detail, we estimate a 6-factor VAR model inspired by VAR ordering and variable selection with Bloom (2009). The multivariate VAR model includes 5 lags of the endogenous variables and has the following VAR ordering[14]:

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[13] The endogeneity might be the outcome of high autocorrelation (persistence) in stock market volatility and yield curve volatility series. For instance, the high persistence and the long-memory property of stock market volatility is already well-established finding in the literature (Corsi, 2009; Christensen et al., 2010; among others). We come up to similar conclusions for SP500RV, since the correlograms reported at our online Appendix show a significant persistence for our SP500RV series. On the other hand, the persistence for our SLOPERV factor is still present but much less according to the respective correlogram. In addition, the most of AR lag-length selection criteria select optimal autoregressive models ranging from 3 to 5 lags for SP500RV and SLOPERV. In conclusion, even though both SP500RV and SLOPERV are stationary series (see Table 1), we report a significant autocorrelation for both series.

14 The lag-length of the multivariate VAR model was chosen using the Akaike information criterion. Moreover, the choice of 5 lags controls for autocorrelation structure of SP500RV and SLOPERV. Moreover, our VAR results are insensitive to the choice of lags included. Additional IRF estimates for our VAR model with fewer or less lags included are available upon request.

$$Y=[SLOPE\ \ SLOPERV\ \ SP500RV\ \ FFR\ \ IPI\ \ EMPL] \qquad (6)$$

In Equation (6) below, FFR is the montly Fed Funds rate, IPI is the growth rate of Industrial Production Index and EMPL is the growth rate of US employment. The economic assumptions of our VAR ordering is that shocks first affect the interest rate and equity markets, then the policy rate and finally quantities (IPI and EMPL). We estimate the Orthogonalized Impulse Response Functions (IRFs) based on the Cholesky decomposition of the innovations matrix. **Figure 5** below shows the estimated IRFs of SP500RV and SLOPERV to a one standard deviation shock in the SLOPERV and SP500RV respectively[15].

[Insert Figure 5 Here]

From **Figure 5** we observe that the SLOPERV does not have a statistically significant response to SP500RV shocks. This result indicates that there is no causal effect of stock market volatility on yield curve volatility. On the other hand, our VAR analysis shows that a shock in SLOPERV results in a persistent rise of SP500RV, with the effect remaining positive and significant for 7 months after the initial yield curve volatility shock. Our VAR results provide further robustness to our OLS results and conclusions based on the regression analysis, since we find that the causal effect is unidirectional, stemming from SLOPERV to SP500RV and not vice-versa[16]. Finally, the responses of SLOPERV and SP500RV to their own structural innovations are another indicator of the persistence of these volatility series.

[15] For brevity we do not report the response of SP500RV and SLOPERV to IPI, FFR and EMPL shocks.

[16] Our estimated IRFs are insensitive to the VAR ordering, with the estimated responses of SP500RV and SLOPERV remaining unaffected when estimating the VAR with alternative VAR orderings. These additional VAR results are available upon request.

4. Robustness

In this section we describe the additional forecasting models and tests we have conducted which provide robustness on our baseline forecasting regression analysis analytically presented in the paper. First, to examine whether our findings for the post-crisis period are driven by the 2007-2008 crisis, we conduct an additional subsample analysis by excluding the crisis period for our sample. The results when utilizing our alternative post-crisis sample spanning the period from January 2009 to December 2017, remain qualitatively the same. With this robustness test we show that the forecasting power of SLOPERV is not driven by the inclusion of the Great Recession period in our time series sample. In addition, we control for the zero-lower bound period by including instead of the Fed funds rate, the shadow policy rate introduced by Wu and Zhang (2019) and our results remain unaltered. Moreover, in order to control for the persistence of stock market volatility (Corsi 2009), we run our regression models including more lags of the stock market volatility variable and our results remain unchanged. We also estimate a three-factor model that captures the time-variation in the US Treasury yield curve by the estimation of three unobservable (latent) factors (the first three principal components), which represent the time variation in the level, slope, and curvature of the yield curve. Hence, instead of the observable slope of the term structure of interest rates, we estimate the SLOPERV as the realized variance of the second principal component of a three-factor model capturing the changes in the US -Treasury yield curve. The econometric results remain unaltered when using the unobservable yield curve factors in the econometric analysis. Moreover, we conduct robustness checks on the sectoral analysis outlined in section 3.2.3, which are presented in the online appendix. Specifically, we augment the appendix with additional figures illustrating the detailed t-statistic and R^2 values for predicting firm-level volatility among S&P 500 constituents belonging in the financial services and telecommunications sectors. Our purpose is to ensure that the average t-statistic and R^2 values reported in Subsection 3.2.3 are not influenced by outliers. Our additional firm-level results confirm that SLOPERV remains a robust predictor of volatility for firms within the financial services and telecommunications sectors.

5. Conclusions

We empirically examine the predictive power of SLOPERV on stock-market volatility and find that rising volatility of the slope of the US Treasury yield curve is associated with rising stock-market volatility. More specifically, we find that the volatility in the slope of the term structure of interest rates has significant in-sample and out-of-sample forecasting power on stock-market volatility. Interestingly, when forecasting the volatility of S&P500 constituents, we find that the SLOPERV has higher predictive power when forecasting the return volatility of stocks belonging to the telecommunications and financial sector. These results contribute to those of the relevant literature showing that cyclical stock market industries like telecommunications are more sensitive to monetary policy shocks (Bernanke and Kuttner, 2005; Ehrman and Fratzscher, 2004).

Moreover, our time varying out-of-sample forecasting exercise shows that the forecasting power of SLOPERV spikes during the 2008 Great Recession and remains high for the rest of the post-2008 crisis period. These results provide further empirical insights on the literature showing the effectiveness of US unconventional monetary policies like the forward guidance on the US equity market, who also originated at the beginning of 2008 when the Fed policy became more transparent by adopting macro-prudential unconventional policies like forward guidance to prevent the financial meltdown (Hattori *et al*., 2016; Swanson, 2021). Our findings implicitly show that the increased transparency of unconventional Fed policies during the post-2008 period has resulted to a higher response of the stock market to changes in the slope of the

US Treasury curve. Moreover, our results are broadly in line with the findings on the macro-finance literature showing the tighter linkages between financial markets and the macroeconomy in the post-2008 period (Abbate et al., 2016, Caldara *et al*., 2016; Prieto *et al*., 2016). The policy implication of our findings is that the rising volatility of the slope of the yield curve can be used by policymakers and market professionals as an early warning signal of rising stock market turbulence. Moreover, another policy implication stemming from our forecasting analysis, is that the effective targeting (by the Fed) of the variability of the slope of the US Treasury curve could work towards promoting greater financial stability.

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Table 1. Descriptive statistics

This table shows the descriptive statistics along with the ADF unit root tests for the explanatory variables which we include in the right-hand side of the forecasting regressions. With *, **, and *** we reject the hypothesis of a unit root for 10%, 5% and 1% confidence level respectively. All the time series have monthly frequency and cover the period from January 1990 till December 2017. All variables are in log-levels, except BAA and SLOPE which are used as levels and IPI which is the log-difference of the US Industrial Production Index.

	VIX	SLOPE	SLOPE RV	SP500RV	MPU	EPU	IPI	BAA	OILRV
Mean	0.194	0.018	-8.461	-6.699	4.318	4.627	0.002	0.024	-6.409
Median	0.175	0.019	-8.544	-6.819	4.297	4.592	0.002	0.022	-6.571
Maximum	0.626	0.037	-4.978	-3.019	6.011	5.502	0.021	0.060	-3.111
Minimum	0.101	-0.007	-11.078	-8.693	2.808	4.047	-0.043	0.013	-8.846
Std. Dev.	0.076	0.011	0.979	0.922	0.583	0.291	0.006	0.008	1.175
Skewness	1.971	-0.216	0.477	0.671	0.090	0.408	-1.589	1.609	0.321
Kurtosis	9.420	2.080	3.518	3.428	2.666	2.539	11.797	7.536	2.388
ADF Test	-3.99***	-3.80**	-9.15***	-4.14***	-9.42***	-5.66***	-4.98***	-3.75**	-4.52***

Table 2. Correlation Table

	VIX	SLOPE	SLOPE RV	SP500RV	MPU	EPU	IPI	BAA	OILRV
VIX	1.00								
SLOPE	0.06	1.00							
SLOPERV	0.45	0.08	1.00						
SP500RV	0.89	-0.01	0.47	1.00					
MPU	0.41	0.11	0.34	0.38	1.00				
EPU	0.42	0.44	0.20	0.32	0.51	1.00			
IPI	-0.25	0.01	-0.14	-0.22	-0.21	-0.23	1.00		
BAA	0.65	0.34	0.25	0.57	0.24	0.62	-0.42	1.00	
OILRV	0.24	0.05	0.07	0.26	-0.03	0.45	-0.31	0.57	1.00

Table 3. Forecasting stock market volatility using the volatility in the level of the yield curve as predictor
This table shows the results of the bivariate forecasting regressions of the volatility in the slope of the US Treasury yield curve (SLOPERV) on the US stock-market volatility (SP500RV). The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The full monthly dataset covers the period from January 1990 till December 2017. Panel A reports the regression results for the full dataset (1990-2017), Panel B reports the regression results for the subsample covering the pre-crisis period (Jan 1990 – Dec 2006) and Panel C reports the regression results for the subsample covering the post US Great Recession period (Jan 2007 – Dec 2017). The estimated bivariate predictive regression model is given below:

$$ln(SP500RV_{t+h}) = b_0 + b_1 ln(SLOPERV_t) + \varepsilon_{t+h}$$

Panel A: Full sample (Jan 1990-Dec 2017)

Horizon (h)	***b_0***	***t-stat (b_0)***	***b_1***	***t-stat (b_1)***	***% R^2***
1m	-3.83***	-4.04	0.34***	3.25	12.7
2m	-4.36***	-4.53	0.28***	2.69	8.3
3m	-4.54***	-4.57	0.26**	2.32	6.9
6m	-4.53***	-4.44	0.26**	2.22	6.9
9m	-4.81***	-5.92	0.23**	2.58	5.2
12m	-4.60***	-6.31	0.25***	3.35	6.5

Panel B: Pre-crisis sample (Jan 1990-Dec 2006)

Horizon (h)	***b_0***	***t-stat (b_0)***	***b_1***	***t-stat (b_1)***	***% R^2***
1m	-5.24***	-9.42	0.18***	2.78	2.9
2m	-5.87***	-9.95	0.10	1.59	0.7
3m	-5.98***	-10.98	0.10	1.59	0.4
6m	-6.02***	-10.09	0.09	1.21	0.3
9m	-6.3***	-8.90	0.05	0.72	-0.2
12m	-5.61***	-10.22	0.13***	2.65	1.4

Panel C: Post-crisis sample (Jan 2007-Dec 2017)

Horizon (h)	***b_0***	***t-stat (b_0)***	***b_1***	***t-stat (b_1)***	***% R^2***
1m	-2.21	-1.57	0.52***	3.33	31.8
2m	-2.63**	-2.36	0.47***	3.86	25.8
3m	-2.90	-1.59	0.44***	2.03	22.0
6m	-2.79***	-3.29	0.45***	5.08	23.1
9m	-3.04**	-2.36	0.43***	3.01	20.0
12m	-3.39***	-3.36	0.39***	3.59	16.2

Table 4. Forecasting stock market volatility (Jan 1990- Dec 2017 full sample) period
The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. *, ** and *** denote statistical significance at the 10%, 5% and 1% respectively based on the Newey-West standard errors for the coefficients. The baseline multivariate model is given below:

$$ln(SP500RV_{t+h}) = b_0 + b_1 ln(SP500RV_t) + b_2(SLOPE_t) + b_3 ln(SLOPERV_t) + b_4 ln(EPU_t) + b_5 ln(MPU_t) + b_6 BAA_t + b_7 dln(IPI)_t + b_8 ln(OILRV)_t + \varepsilon_{t+h}$$

Horizon(h)		***1m***	***2m***	***3m***	***6m***	***9m***	***12m***
CONST	Coef.	-1.216	-1.260	-0.420	-0.0563	-1.534	-0.0475
	t-stat	(-1.38)	(-0.99)	(-0.27)	(-0.03)	(-0.87)	(-0.03)
RV	Coef.	0.742***	0.634***	0.592***	0.550***	0.527***	0.443***
	t-stat	(15.33)	(10.30)	(8.55)	(8.39)	(7.32)	(6.26)
SLOPE	Coef.	-2.839	-3.005	-1.764	-6.424	-16.58***	-21.07***
	t-stat	(-0.83)	(-0.60)	(-0.27)	(-0.85)	(-2.66)	(-3.59)
SLOPERV	Coef.	-0.0006	-0.010	-0.002	0.060	0.059	0.117*
	t-stat	(-0.02)	(-0.21)	(-0.05)	(1.02)	(0.90)	(1.91)
EPU	Coef.	-0.185	-0.341	-0.547	-0.462	-0.0694	-0.553
	t-stat	(-0.89)	(-1.17)	(-1.61)	(-1.06)	(-0.16)	(-1.44)
MPU	Coef.	-0.0791	-0.108	-0.0773	-0.199	-0.278*	-0.0717
	t-stat	(-0.92)	(-1.06)	(-0.73)	(-1.42)	(-1.83)	(-0.53)
BAA	Coef.	18.01**	21.44**	19.69	13.36	3.931	8.297
	t-stat	(2.10)	(1.99)	(1.62)	(0.91)	(0.28)	(0.61)
IPI	Coef.	-8.166	-14.99	-13.54	-10.10	-12.63*	-1.438
	t-stat	(-0.84)	(-1.56)	(-1.51)	(-1.05)	(-1.68)	(-0.20)
OILRV	Coef.	-0.0487	-0.0519	-0.0165	-0.0553	-0.0928	-0.0531
	t-stat	(-1.45)	(-1.03)	(-0.25)	(-0.74)	(-1.18)	(-0.60)
% adj. R^2		62.3	47.5	40.6	32.8	30	31.2

Table 5. Forecasting stock market volatility (pre-crisis and post-crisis period) – multivariate model
The standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. *, ** and *** denote statistical significance at the 10%, 5% and 1% respectively based on the Newey-West standard errors for the coefficients.

Panel A: Pre-crisis period

Horizon		*1m*	*2m*	*3m*	*6m*	*9m*	*12m*
Const	Coef.	-2.868**	-2.406	-1.978	-2.330	-1.789	1.518
	t-stat	(-2.28)	(-1.41)	(-0.99)	(-1.32)	(-1.08)	(0.91)
RV	Coef.	0.710***	0.586***	0.497***	0.503***	0.537***	0.475***
	t-stat	(11.25)	(6.90)	(5.11)	(6.72)	(7.03)	(5.71)
SLOPE	Coef.	-8.668**	-9.101	-10.80	-16.26**	-19.14***	-21.95***
	t-stat	(-2.20)	(-1.62)	(-1.60)	(-2.26)	(-3.15)	(-3.87)
SLOPERV	Coef.	-0.0684	-0.103*	-0.086*	-0.070	-0.068	0.042
	t-stat	(-1.28)	(-1.86)	(-1.77)	(-1.20)	(-1.37)	(0.82)
EPU	Coef.	0.0278	-0.283	-0.373	-0.562	-0.474	-1.293***
	t-stat	(0.09)	(-0.66)	(-0.76)	(-1.31)	(-1.19)	(-3.72)
MPU	Coef.	-0.101	-0.135	-0.200	-0.082	-0.195	0.052
	t-stat	(-0.89)	(-1.01)	(-1.31)	(-0.63)	(-1.45)	(0.49)
BAA	Coef.	32.44***	45.27***	52.67***	49.39***	31.66	31.04
	t-stat	(3.25)	(3.18)	(3.12)	(2.68)	(1.65)	(1.42)
IPI	Coef.	2.588	-0.541	-0.323	8.361	-16.18**	-4.996
	t-stat	(0.28)	(-0.06)	(-0.03)	(0.89)	(-2.04)	(-0.52)
OILRV	Coef.	-0.017	0.024	0.068	-0.072	-0.110	-0.089
	t-stat	(-0.33)	(0.35)	(0.89)	(-0.90)	(-1.27)	(-1.23)
% adj. R^2		65.3	52.7	47.6	46.1	45.8	49.5

Panel B: Post-crisis period

Horizon		*1m*	*2m*	*3m*	*6m*	*9m*	*12m*
CONST	Coef.	-0.317	-1.456	-0.458	1.821	-0.763	-1.560
	t-stat	(-0.29)	(-1.02)	(-0.23)	(0.72)	(-0.29)	(-0.63)
RV	Coef.	0.648***	0.530***	0.540***	0.467***	0.475***	0.512***
	t-stat	(6.34)	(4.57)	(4.17)	(3.13)	(2.63)	(2.92)
SLOPE	Coef.	12.72*	17.18*	26.37**	22.26	-0.364	-3.068
	t-stat	(1.91)	(1.86)	(2.11)	(1.34)	(-0.04)	(-0.29)
SLOPERV	Coef.	0.108*	0.114	0.084	0.259**	0.251**	0.160**
	t-stat	(1.73)	(1.51)	(1.04)	(2.48)	(2.19)	(2.31)
EPU	Coef.	-0.373	-0.435	-0.820*	-0.743	-0.303	-0.799
	t-stat	(-1.42)	(-1.29)	(-1.97)	(-1.10)	(-0.49)	(-1.59)
MPU	Coef.	-0.002	0.051	0.259	-0.059	-0.090	0.335
	t-stat	(-0.01)	(0.29)	(1.46)	(-0.21)	(-0.32)	(1.27)
BAA	Coef.	6.685	2.725	-8.049	-26.39*	-23.35*	-25.73
	t-stat	(0.48)	(0.20)	(-0.55)	(-1.67)	(-1.66)	(-1.46)
IPI	Coef.	-16.01	-29.59***	-30.60***	-31.89***	-18.42	-18.42
	t-stat	(-1.18)	(-3.04)	(-4.23)	(-3.29)	(-1.48)	(-1.22)
OILRV	Coef.	-0.044	-0.140	-0.121	-0.177	-0.357**	-0.539***
	t-stat	(-0.50)	(-1.37)	(-0.86)	(-1.11)	(-2.21)	(-2.96)
% adj. R^2		60.3	46.6	42.0	33.6	26.6	35.9

Table 6. Out of sample root mean squared errors (RMSFEs)

The post-crisis sample starts from Jan 2002, hence the first forecast takes place for January 2007 since we are using an initial 5-year window.

Panel A: Full sample

Horizon (k)	*SLOPERV*	*EPU*	*MPU*	*VIX*	*SP500RV*	*MULT*
1m	0.907	0.957	0.948	0.643	**0.588*** **	0.604
2m	0.938	0.982	0.969	0.753	**0.713*** **	0.740
3m	0.951	0.992	0.981	0.805	**0.760*** **	0.807
6m	0.969	1.016	1.004	0.899	**0.835*** **	0.936
9m	1.006	1.048	1.037	0.960	**0.891** **	0.981
12m	1.017	1.072	1.064	1.011	0.946	**0.944*** **

Panel B: Pre-crisis Sample (starting from Jan 1990)

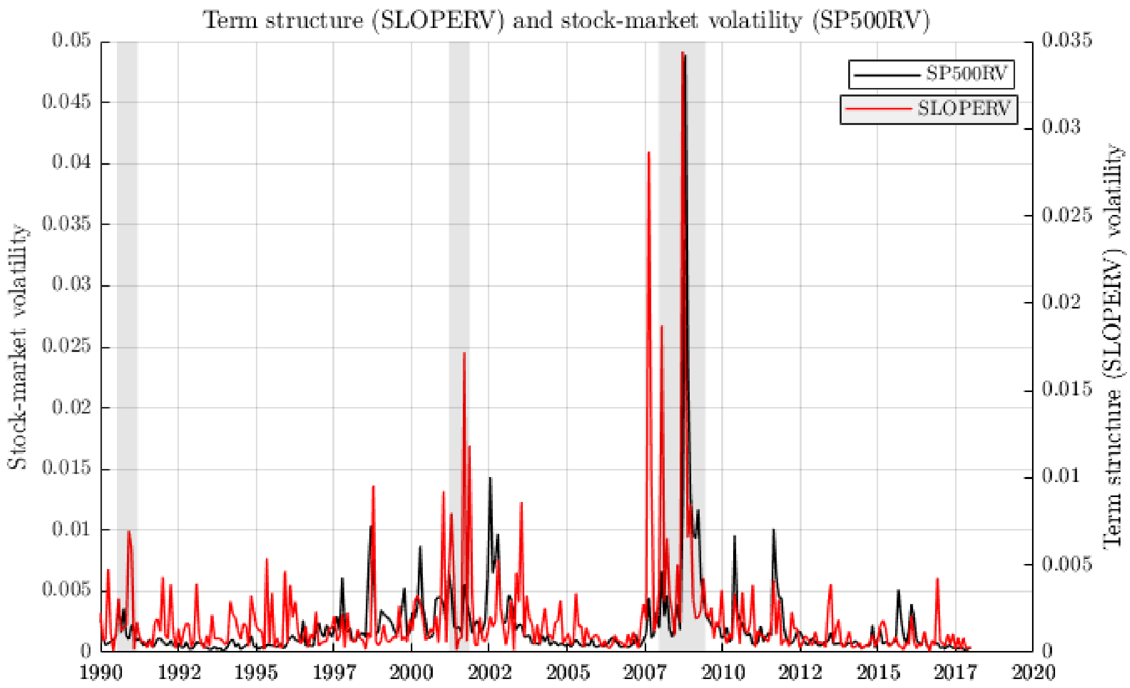
Horizon (k)	*SLOPERV*	*EPU*	*MPU*	*VIX*	*SP500RV*	*MULT*
1m	0.943	0.958	0.950	0.581	**0.540*** **	0.555
2m	0.963	0.980	0.968	0.702	**0.669*** **	0.683
3m	0.971	0.984	0.980	0.755	**0.720*** **	0.735
6m	1.000	1.010	1.005	0.779	**0.754*** **	0.818
9m	1.045	1.065	1.061	0.838	**0.805*** **	0.870
12m	1.076	1.098	1.111	0.940	0.881	**0.834** **

Panel C: Post-crisis Sample (starting from Jan 2002)

Horizon (k)	*SLOPERV*	*EPU*	*MPU*	*VIX*	*SP500RV*	*MULT*
1m	0.839	0.990	0.934	0.700	**0.642*** **	0.669
2m	0.886	1.010	0.965	0.822	**0.770** **	0.862
3m	0.917	1.033	0.978	0.880	**0.821** **	1.023
6m	**0.940*** **	1.096	1.052	1.035	0.949	1.511
9m	**1.021** **	1.118	1.088	1.075	1.027	1.713
12m	**1.059*** **	1.141	1.102	1.089	1.070	1.455

*, ** and *** denote statistical significance at the 10%, 5% and 1% respectively based on the Superior Predictive Ability (SPA) test. The Null hypothesis is that the benchmark model is not inferior to the current model.

Figure 1. Term structure volatility (SLOPERV) and stock-market volatility (SP500RV).

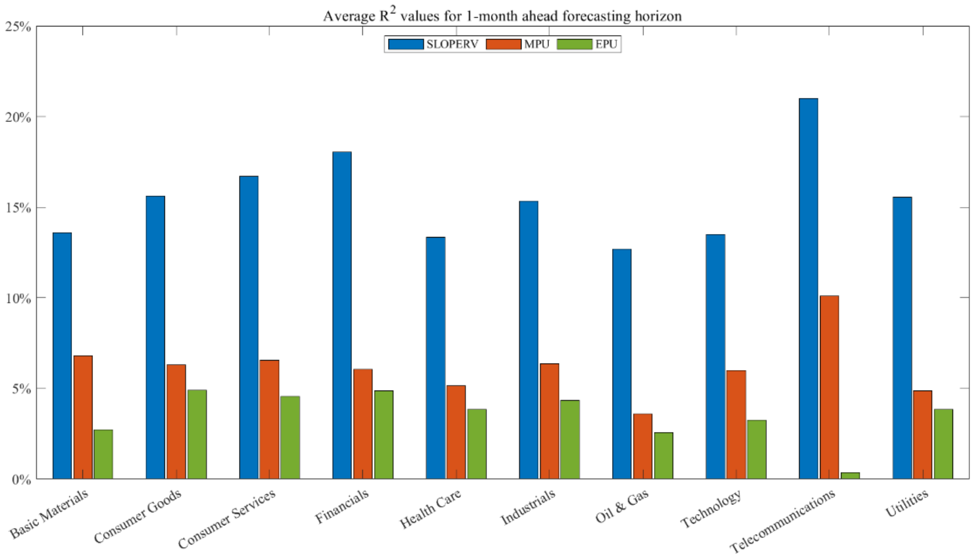


Note: The shaded areas identify NBER US recessions.

Figure 2. Volatility forecasting of S&P500 constituents with 1-month forecasting horizon (in-sample regression results)

This figure shows the sectoral averages of the R^2 values and t-statistics for the bivariate regression models (shown in Equation (3)) on the Realized Variance (RV) of the constituents of the S&P500 index, when using SLOPERV, EPU and MPU in the right-hand side of the bivariate regression equation. More specifically, in this table we report, for each industrial sector in the US stock market, the average of the R^2 values for the S&P500 constituents who belong to the same sector. Panel A reports the sectoral averages of the R^2 values, while panel B reports the respective averages of t-statistics. The t-statistics for the predictive regressions on S&P500 constituents are corrected for autocorrelation and heteroskedasticity using the Newey-West (1987) estimator. The monthly dataset for the predictive regressions on the monthly RV of S&P500 constituents spans the period from November 2002 till December 2017.

Panel A



Panel B

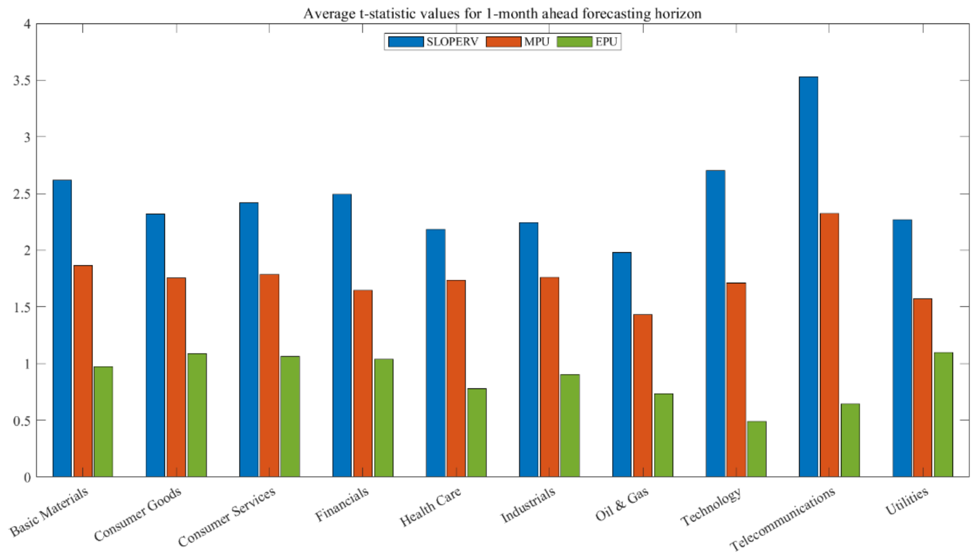


Figure 3. Forecasting the volatility of S&P500 constituents (out-of-sample regression results)
This figure shows the sectoral averages of the out-of-sample R^2 values for the bivariate regression models (shown in Equation (3)) on the Realized Variance (RV) of the constituents of the S&P500 index, when using SLOPERV, EPU and MPU in the right-hand side of the bivariate regression equation. More specifically, in this table we report, for each industrial sector in the US stock market, the average of the out-of-sample R^2 values for the S&P500 constituents who belong to the same sector. The monthly dataset for the predictive regressions on the monthly RV of S&P500 constituents spans the period from November 2002 till December 2017. For the recursive out-of-sample estimations we use an initial 5-year window as we describe in Subsection 3.4 of the paper.

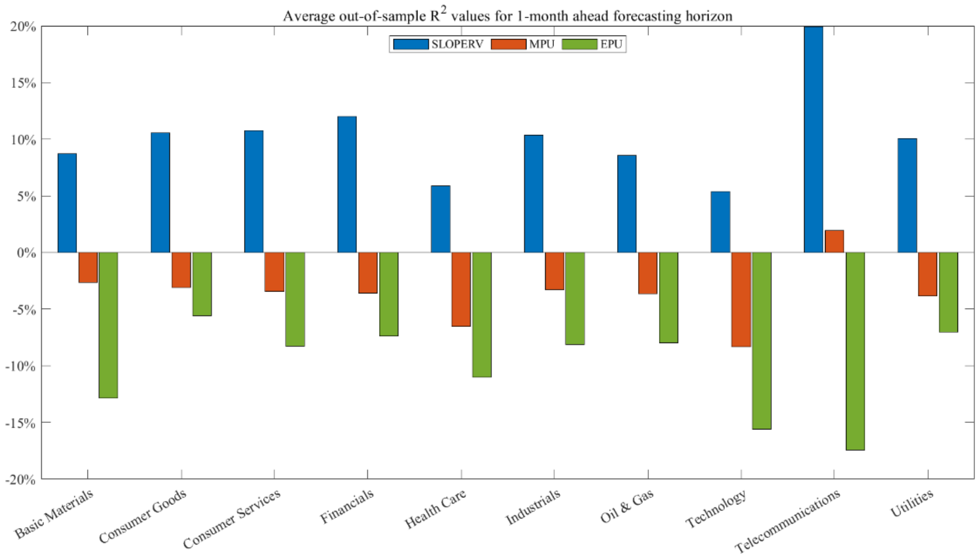
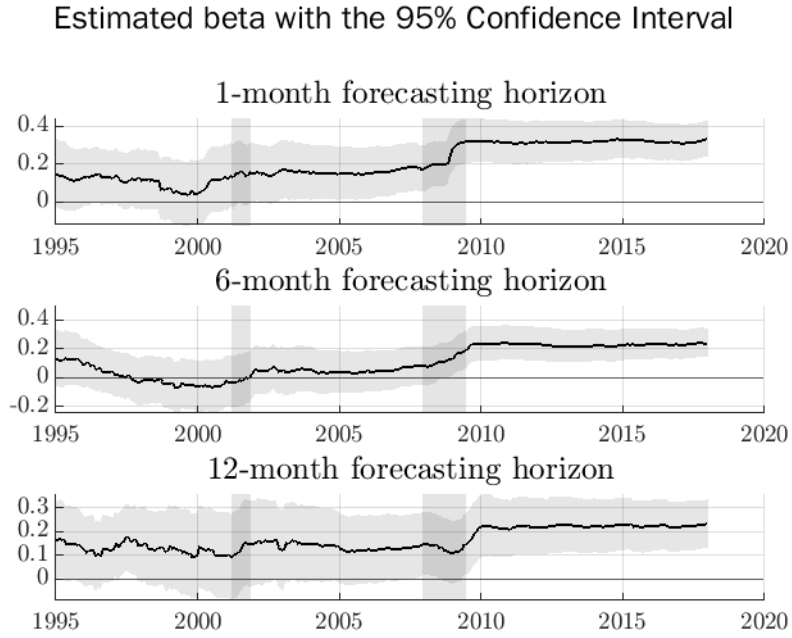


Figure 4. Dynamic recursive R^2s and beta coefficients for the bivariate regression model using SLOPERV as predictor of stock-market volatility.

The initial 5-year estimation window spans the period from January 1990 to December 1994, hence the first dynamic recursive R^2 and beta (b_1) coefficient is estimated in January 1995. Panel A presents the dynamic recursive R^2s, and Panel B shows the beta coefficients used for the out-of-sample stock market volatility forecasts for the bivariate regression model shown in equation (3).

Panel A: Estimated beta (b_1) coefficient with 95% confidence intervals



Panel B: Estimated R^2 adjusted values

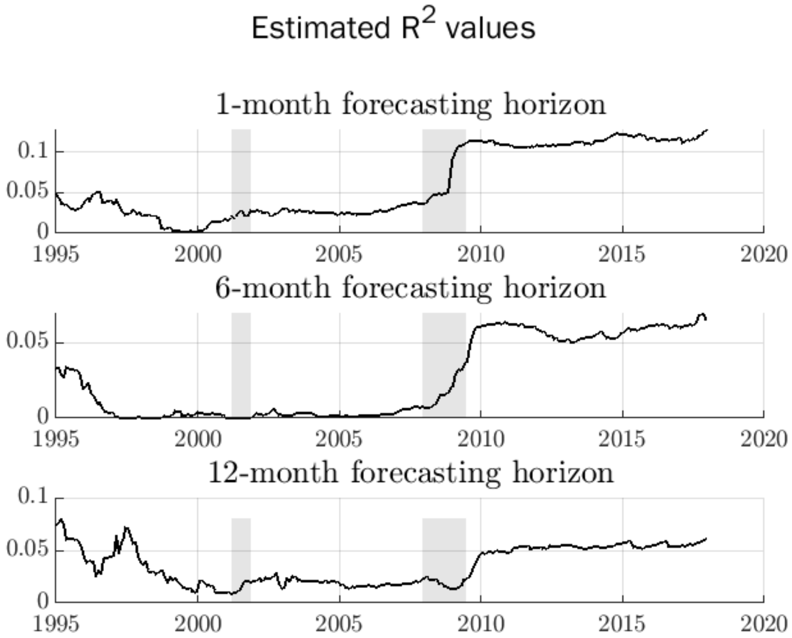


Figure 5. Impulse Response Functions of the 6-factor VAR model

This figure reports the estimated orthogonalized Impulse Response Functions of SLOPERV and SP500RV to one standard deviation shocks in SLOPERV and SP500RV respectively. The grey shaded areas show the corresponding bootstrapped confidence intervals with 1000 repetitions.