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A NEW FINANCIAL WELL-BEING INDEX BASED ON BIG DATA

By

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Declaration of Authorship

I declare that the work in this thesis submitted by me for the degree of Doctor of Philosophy is my work and it is original, to the best of my knowledge, except where stated, referenced and acknowledged.

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Abstract

This study proposes a new Financial Well-Being (FWB) measurement methodology based on Google Trends Search (GTS). Current survey-based FWB measurement methods are lagging. Moreover, their capability to cover the multi-faceted FWB concepts is limited. On the other hand, the GTS has real-time values that could capture the multidimensions of FWB. The FWB is based on keywords extracted from the literature and processed by machine learning on constructs of unemployment, inflation, interest rate, stock index, and uncertainty that are mediated by financial behaviour. The proposed methodology involves selecting, filtering, expanding, and transforming keywords from these constructs to build an FWB index.

Consequently, the study creates an instant overarching model based on financial patterns of individual search from GTS using Partial Least Square Modelling (PLS-SEM). The GTS model keywords were transformed with several preprocessing steps, including stationarity and seasonality adjustments. The GTS model was compared with another developed model, the Alternative Proxy model, based on proxy variables data extracted from the UK. Both models had a sizeable explanatory analysis, as indicated by their large R^2 values; however, the GTS shows a few variations due to its dynamic measurements of extreme economic events over a selected period.

In contrast, all the variables in the Alternative Proxy model were significant; however, inflation was positively correlated with positive financial behaviour. The study contributes to a new FWB Index based on GTS that provides a direct instant measurement of FWB. The FWB Index is useful for financial practitioners, policymakers, and government entities. The model provides an instant measure that promptly assesses public financial sentiment, facilitating timely and informed decision-making.

Keywords: Financial Well-Being (FWB), Google Trends Search (GTS), Partial Least Square Modelling (PLS-SEM), Economic Events, Financial Behaviour, FWB Index.

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List of Synonyms and Abbreviations

Abbr./Synonym	Description
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
Alternative Proxy	Alternative model to the proposed GTS model based on published data
ARIMA	Autoregressive Integrated Moving Average
AVE	Average Variance Extracted
CFPB	Consumer Financial Protection Bureau
CPI	Consumer Price Index
CR	Composite Reliability
CVPAT	Cross-validated Predictive Ability Test
FB	Financial Behaviour
Fed	Federal Reserve
FSB	Financial Stability Board
FTSE 100	Financial Times Stock Exchange 100 Index
FWB	Financial Well-Being
GDP	Gross Domestic Product
GDPPH	Gross Domestic Product Per Head
GT	Google Trends
GTS	Google Trends Search, the model that measures Financial Well-Being
HHAFE	Real Household Actual Final Consumption Expenditure per head
HHFCE	Real Household Consumption Expenditure per head
HHI	Household Income
HHS	Household Spending
IA	Indicator Average
IAVS	Increments of Attention Volume for Stocks
INF	Inflation
INT	Interest Rate
IQR	Interquartile Range
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LM	Linear Model
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MaPS	Money and Pensions Service
NARDL	Nonlinear Autoregressive Distributed Lag
NDP	Net Domestic Product per head
NDPPH	Net Domestic Product per head
NFW	Net Financial Wealth per head
OECD	Organization of Economic Co-operation and Development
ONS	Office for National Statistics
PACF	Partial Autocorrelation Function
PE	GDP per head
PLS-SEM	Partial Least Square Modelling
PP	Perron Phillips and Perron

Abbr./Synonym	Description
QE	Quantitative Easing
RGAHDI	Real Gross Adjusted Household Disposable Income
RNHADI	Real Net Household Adjusted Disposable Income
RNNDI	Real Net National Disposable Income per head
SDG	UN Sustainable Development Goals
SEM	Structured Equation Modelling
STK	Stock Index
STL	Seasonal-Trend Decomposition Procedure Based on LOESS
SWB	Subjective Well-Being
TAIEX	Taiwan Stock Exchange Capitalization Weighted Stock Index
UNC	Uncertainty
UNE	Unemployment
VIF	Variance Inflation Factor
VIX	Chicago Board Options Exchange's CBOE Volatility Index.
WEPI	Whole Economy Production and Income

CHAPTER 1: INTRODUCTION

Well-being is a comprehensive concept that covers every aspect of life, such as financial, social, spiritual, occupational, and environmental aspects (Hooker *et al.*, 2020; Rath and Harter, 2010). Therefore, well-being intersects with sociology, economics, philosophy, and psychology (Stoll, 2014). It has two categories: objective and subjective. Objective well-being is the tangible measurement of financial status (Voukelatou *et al.*, 2021). However, individual emotions express their personal life experience with the subjective wellbeing (Diener and Suh, 1997).

According to the Consumer Financial Protection Bureau (CFPB), Financial Well-Being (FWB) is defined as "a state of being wherein a person can fully meet their current and ongoing financial obligations, where they can feel secure in their financial future, and where they can make choices that allow for the enjoyment of life" (Consumer Financial Protection Bureau (CFPB), 2015, p. 18). Therefore, the FWB expresses the individual happiness that correlates with many factors, such as employment status (Nikolova and Graham, 2012). Therefore, the FWB objective measure reflects an individual life satisfaction with tangible assets such as income, whereas the subjective dimension involves (Sorgente and Lanz, 2017). Therefore, the FWB is conceptualised based on financial literacy, financial capability and psychological factors (Mahendru, 2020). Hence, FWB could be achieved by managing debt and savings and achieving financial control, in contrast with relying solely on credit facilities (Vlaev and Elliott, 2014). Thus, prudent financial behaviours, including savings and timely bill payments, are good money management towards better FWB (Carton *et al.*, 2022). FWB represents a critical facet of comprehensive well-being of happiness and life satisfaction (Benjamin *et al.*, 2014; Jaggar and Navlakhi, 2021).

Financial capability is operationalised as combining objective financial knowledge and financial access (Birkenmaier *et al.*, 2022). Consumer financial capability, encompassing knowledge and behaviour, indicates the quality of life; therefore, policymakers prioritise initiatives to enhance consumer financial literacy (Xiao and Bialowolski, 2023). Financial capability integrates literacy and psychological aspects where an individual uses this comprehensive set of activities to achieve his financial well-being (Lučić *et al.*, 2022). This capability is assessed by synthesising objective financial knowledge and access to financial resources (Birkenmaier *et al.*, 2022). Consequently, financial capability is one factor that influences financial behaviour, which in turn is integral to the underlying economic and social policy frameworks.

1.1. Problem Statement

The FWB is a multifaceted concept; therefore, covering all aspects is challenging for a comprehensive measurement (Brüggen *et al.*, 2017). One significant aspect that adds to the complexity of FWB is Financial Behaviour (FB). FB includes, among others, education, efficacy, demographics, awareness, and understanding of human behaviour (Hira, 2012; Ingale and Paluri, 2022; Jackson, 2021; Powell *et al.*, 2023; Rahman *et al.*, 2021; Xiao *et al.*, 2006; Zulaihati *et al.*, 2020).

Surveys are standard methods for measuring FWB (CFPB, 2015) ; however, they are limited due to individual response or their design (Dalenius, 1983). If respondents fear repercussions, they might hesitate to be completely honest. (Tourangeau and Yan, 2007). Moreover, they might provide inaccurate self-reporting due to memory lapses or boredom (Alwin *et al.*, 2014). Finally, non-response bias can skew results (Coughlan *et al.*, 2009). Unlike surveys, Google Trends Search (GTS) data reflects real-time public sentiment on financial matters, a broader and potentially more honest picture of individual concerns. It eliminates social desirability bias and memory limitations often associated with surveys. Additionally, GTS data can be continuously monitored, allowing financial authorities to identify emerging trends.

Despite attempts to model FWB, the existing literature reveals a significant gap: no model comprehensively addresses FWB's complexity (Vlaev and Elliott, 2014). In addition, many FWB studies rely on datasets that might lag (such as surveys) economic and market conditions; therefore, these studies lack future financial stability (Ghosh and Renna, 2022; She *et al.*, 2023). Accordingly, lagging measures are problematic for government and policy decision-making, where current FWB are essential for informed strategies and interventions (Kaur *et al.*, 2021).

Many attempts to model FWB based on real-time data analysis, particularly in GTS, require a valuable approach that ensures accuracy, completeness, consistency, and validity (Cebrián and Domenech, 2022). The GTS captures user behaviour based on search keywords (Barros *et al.*, 2019; Wang *et al.*, 2019). According to Statista's website, the Market share of leading search engines worldwide from January 2015 to January 2024 shows Google on top with more than 90%. However, the suitable set of keywords affirms valid results of FWB measurement

(Scharkow and Vogelgesang, 2011). Figure 1.1 and Figure 1.2 show that GTS is a web tool for human keyword searches during a specific period and geographical location (Barros *et al.*, 2019). Search queries and social media discussions are used as markers of investor sentiment and attention (Gómez *et al.*, 2021).

While there are guidelines for GTS keyword selection (Mavragani and Ochoa, 2019), the absence of a methodology may result in ad hoc keyword selection strategies that jeopardise the FWB measurement. Consequently, the need for more research methods significantly constrains the depth of FWB research (Michael Collins and Urban, 2020). This research posits that GTS has sufficient information to illuminate FWB trends within the United Kingdom to bridge the identified gaps in real-time data analysis.

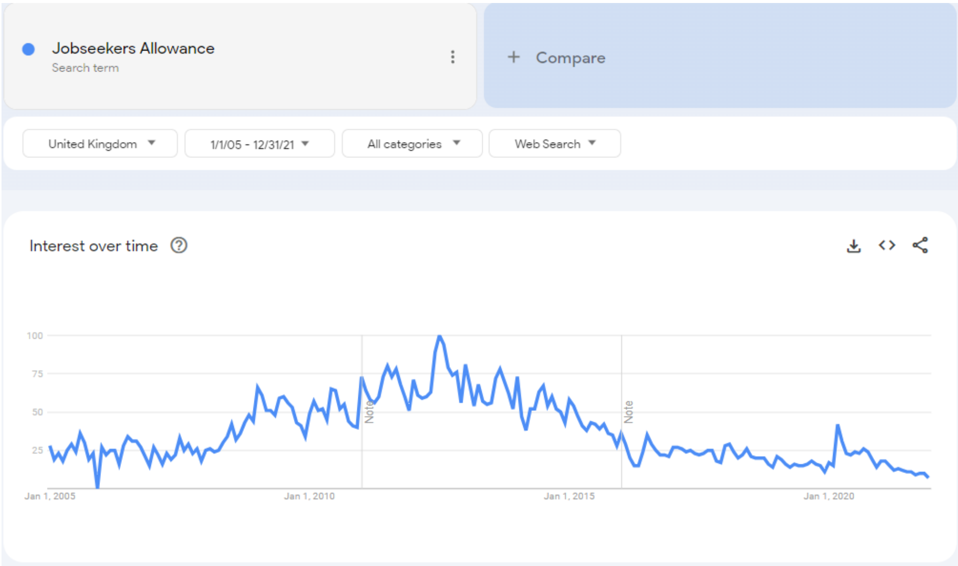


Figure 1.1: Google Trends Search Website (‘Jobseekers Allowance’ Keyword).

1.2. Research Objectives

The main goal of this research is to create an index of FWB based on big data from Google Trends. In this study, big data refers to vast datasets that reflect broad population trends and behaviours. The index allows the research community, financial practitioners, and policymakers to apply it in practical scenarios. This research develops a new approach to collecting keywords based on similar approaches discussed in the literature. Moreover, the study details the groups of keywords that measure various aspects of financial well-being.

The research aims to accomplish the following objective. The first objective is to adapt an FWB conceptual framework illustrating the relationship between several constructs under extreme events. The constructs are Financial Behaviour (FB), Unemployment, Interest Rates, Inflation, Stock Index, and Uncertainty related to FWB measurement. Based on the adapted conceptual framework, the study develops a methodology for selecting, expanding, and refining GTS keywords to measure and estimate individuals' FWB. GTS searches for topics (or terminologies) related to the proposed conceptual framework to measure the dependent variable FWB. Several keywords related to FWB measurement are extracted from the literature, while others are fine-tuned using machine learning. The adapted FWB conceptual framework is validated with two approaches: the GTS and an Alternative Proxy model. The GTS is based on Google data, while the latter is based on data extracted from the Office of National Statistics and other published data. The models should adequately include all the constructs FB has implemented to enhance FWB. In addition, the study compares its findings with statistical metrics to signify the conceptual framework's hypothesis. This objective ensures the reliability and validity of the proposed GTS model compared to the Alternative Proxy model data.

The second objective is to develop an FWB index for the UK based on the proposed GTS model. The index will be validated with published data surveys and related FWB proxies. Therefore, this objective provides an agent for policymakers and government authorities to help them frame out or apply new policies and financial interventions.

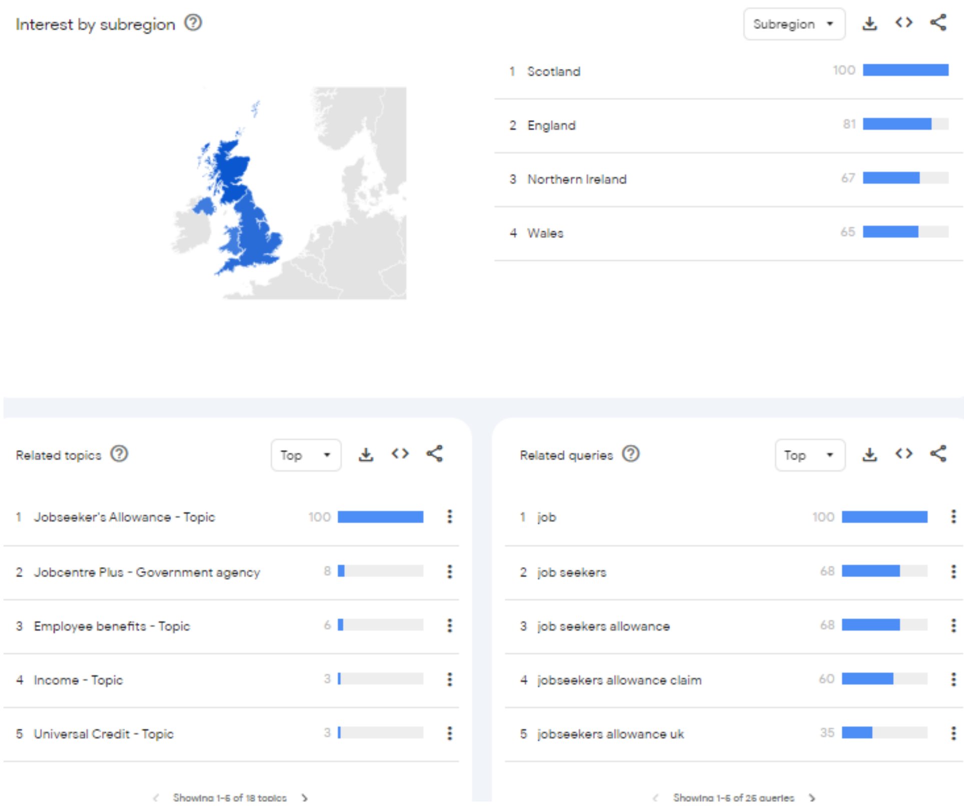


Figure 1.2: GTS Regions and Related Subtopics ("Jobseekers Allowance").

This approach uses a real-time analytical framework (Michael Collins and Urban, 2020). Therefore, it is assumed that big data sources of Google Trends have enough information to study FWB variables. It is assumed that information that is hard to extract from Google trends, such as age group, marital status, and family structure, are negligible or have minimal effect on the overall FWB index evaluation. It is also assumed that users who suffer from financial issues or do well frequently use the Google search engine as part of their financial attitudes. It is also assumed that extreme events are the primary factor of FWB; thus, only related categories of extreme events are included in this research.

1.3. Significance and Contribution of Study

The significance of this study is its new methodological approach that measures FWB through GTS big data. Moreover, it directly contributes to achieving the UN Sustainable Development Goals 2030 (SDGs 1, 3, 8,10, and 16) that recognise FWB's multifaceted aspects (United Nations, 2023). Financial well-being supports the United Nations' Sustainable Development Goals (SDGs). Financial well-being addresses SDG 1(no poverty) by increasing the financial security against economic shocks. Secondly, improved financial well-being addresses SDG 3(good health and well-being) by enabling better access to healthcare. Thirdly, financial well-being supports SDG 8 (work and economic growth) by encouraging financial education for a more skilled workforce. Furthermore, the financial inclusion of literacy programs contributes to SDG 10, which reduces inequalities where individuals are empowered to participate in the economy. Consequently, financial well-being addresses SDG 16 (peace and justice) to foster a stable society with trustworthy institutions.

Noteworthy, the proposed approach based on big data could be used to provide instant measurements as opposed to methods reliant on surveys, which lack and limit comprehensive results (Ghosh and Renna, 2022; She *et al.*, 2023). Applying the FWB index is a comprehensive measure combining two aspects. First, it considers the subjective financial abilities suggested by the GTS patterns. Second, it considers the psychological factors representing FWB's tangible and intangible elements (Birkenmaier *et al.*, 2022)Therefore, this study is significant as a tool for policymakers, financial practitioners, and the research community at large. The developed real-time FWB index can revolutionise how financial well-being is measured to achieve macroeconomic stability and individual financial security.

The study has several contributions. The study adapts a conceptual framework for FWB that builds extreme events (e.g., unemployment, interest rate, inflation, uncertainty) mediated by individual financial behaviour. The framework bridges literature gaps to understand FWB measurements. In addition, a new methodology has been established for selecting, expanding, and refining FWB-related keywords using literature, glossary terms, and machine learning algorithms. The new set of keywords could be used in similar economics studies. A new method for filtering keywords using adequate machine learning is developed using semantic similarity. An ample vector space of keywords is compared to Financial Behaviour and Financial Well-Being definitions to ensure semantic similarity. Furthermore, the study develops two FWB models, the GTS and the Alternative Proxy models, to measure the FWB of individuals in the UK. The two models were compared with statistical tests. The new FWB index is based on the proposed conceptual framework. The model hypothesis was validated to quantify and evaluate FWB.

1.4. Research Method

The research adapts a conceptual framework extracted from scoping literature, as shown in Figure 1.4. This research method develops a methodology using GTS (Scharkow and Vogelgesang, 2011). First, initial keywords sourced from the literature undergo expansion via Google's Suggestions and are refined and transformed using statistical analysis. As shown in Figure 1.3, Google Suggestions is known for its utility and effectiveness (Fattahi *et al.*, 2016).

Next, the transformation of keywords includes eliminating keywords with no frequencies in GTS and unrelated keywords to the UK and averaging the keywords for each construct. The refined keywords are Unemployment, Interest Rate, Inflation, Stock Index, and Uncertainty. These constructs represented the extreme events that mediate Financial Behaviour towards the FWB index.

Then, the time series for each construct undergoes stationarity tests to ensure the reliability of the results (Cheung and Lai, 1995; Dickey and Fuller, 1979; Kwiatkowski *et al.*, 1992; Phillips and Perron, 1988). Non-stationary time series are converted to a new time series with differencing (Brockwell and Davis, 1991). In addition, seasonality testing and adjustments are followed to complete the transformation (Pratap and Priyaranjan, 2023).

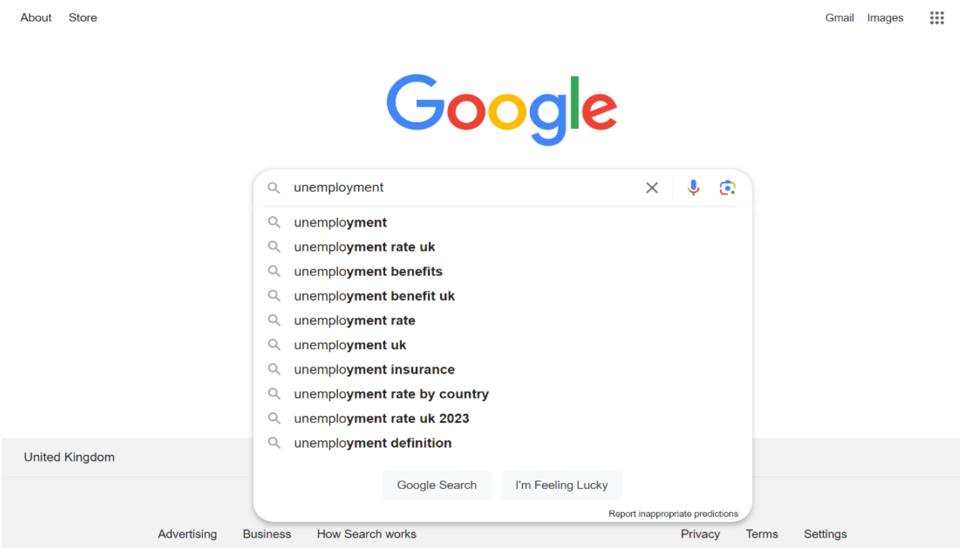


Figure 1.3: Google Suggestions (Unemployment Keyword).

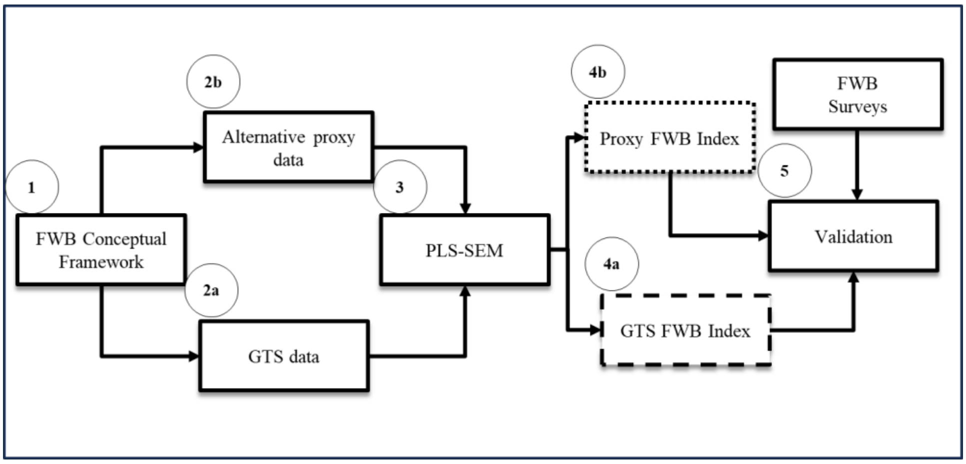


Figure 1.4: Study Framework.

The study framework was adapted with GTS keywords using Partial Least Squares Structural Equation Modelling (PLS-SEM). In contrast, the Alternative Proxy model was developed based on proxies of economics extracted from the UK Office for National Statistics and published data (Figure 1.4). Consequently, the methodology develops a dynamic FWB index and the Alternative Proxy FWB Index that are compared for validity with hypotheses testing and various statistical tests. The resulting GTS FWB index is graphically compared to absolute survey values reported in 2015 and 2018 by UK Financial Capability Surveys. The UK strategy for financial well-being is to take forward the work of the Financial Capability Strategy. The Money and Pensions Service (MaPS) is responsible for the UK Financial Well-Being Surveys and implementing the Financial Well-Being Strategy. These surveys are typically used to assess and track the financial well-being of individuals in the UK, and the data gathered is often used to inform and shape financial education and policy initiatives.

1.5. Thesis Outline

This study adapts an integrated framework of financial well-being measurement across multiple chapters. Chapter 2 (Literature Review) presents related studies of FWB and then is used in Chapter 3 to develop a conceptual framework for measuring FWB during extreme economic events. It reviews FWB during extreme economic events such as the COVID-19 pandemic and financial crisis. Building on this, Chapter 3 (Research Methodology) develops the methodology for collecting, expanding, and refining the conceptual framework's FWB keywords. It also details how the Partial Least Squares Structural Equation Modelling (PLS-SEM) develops the Google Trends (GTS) and the Alternative Proxy models. Results and

Analysis are presented in Chapter 4 following the proposed methodology. Results include graphical analysis, descriptive statistics, exploratory analysis, and empirical validation. The hypotheses developed in Chapter 3 are tested based on the developed PLS-SEM for GTS and the Alternative Proxy models are presented in Chapter 5 (Hypothesis Testing). An in-depth discussion of the research objectives is presented in Chapter 6 (Discussion). Finally, Chapter 7 concludes the study by acknowledging limitations and proposing directions for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter carries out a scoping review of financial well-being (FWB). It reviews FWB theories, dimensions of FWB, FWB measurement, and research gaps and provides a foundation to build a conceptual framework for FWB based on the revised literature in Chapter 3. The literature focuses on the effect of extreme economic events, such as the COVID-19 pandemic and financial crisis, on FWB measurement.

2.1. Background of Financial Well-Being

FWB is a topic of citizens' healthy spending and saving habits, which indicates the state of a person meeting his current and ongoing financial obligations and liabilities (Netemeyer *et al.*, 2018). Most families struggle to manage their financial resources during the economic downturn (Kim and Wilmarth, 2016) or the COVID-19 pandemic (Botha *et al.*, 2021). Moreover, poor financial well-being is associated with poor physical health (Arber *et al.*, 2014). Furthermore, the FWB has a significant and positive relationship with life satisfaction (Ngamaba *et al.*, 2020). The FWB discussion in the literature has increased recently due to many reasons, such as the decrease in household savings (OECD, 2021), issues of loan payments for young adults (Hsieh, 2004), healthcare barriers (Dorsey *et al.*, 2020), and lack of retirement funds for working-aged people (Soepding *et al.*, 2021; Suh, 2021).

Therefore, the FWB is a topic of interest to economists, social scientists, and governments. Policy-making authorities, including the UK's Money and Pensions Service (MaPS) and the American Consumer Financial Protection Bureau (CFPB), could take intervention strategies to enhance the FWB of the individuals. In this era, the G20 developed consumer financial protection based on the Organization of Economic Co-operation and Development (OECD) and the Financial Stability Board (FSB). Subsequently, financial programs and strategies are developed to enhance the FWB, such as the Australian Strategy (Muir *et al.*, 2017) and the UK FWB strategy (Money and Pensions Service, 2020).

FWB closely relates to subjective well-being (or happiness and life satisfaction), where financial security enhances life satisfaction, which influences financial decisions positively (Netemeyer *et al.*, 2018). In other words, subjective financial well-being directly impacts subjective well-being (Iannello *et al.*, 2021). For example, research shows that participation in social activities affects financial well-being (Yeo and Lee, 2019). However, it less impacts psychological well-being (Shim *et al.*, 2009). Nevertheless, the FWB is multifaceted: economic, legal, political, socio-cultural, technological, and market (Brüggen *et al.*, 2017).

Consequently, several measurement methods have been employed due to the FWB's dimensionality. Methods that measure the FWB are survey-based methodologies (Barrafrem *et al.*, 2020; Newmeyer *et al.*, 2021; Santini *et al.*, 2019), experimental research (Eberhardt *et al.*, 2021; Sarofim *et al.*, 2020), and mixed-research methods (Abrantes-Braga and Veludo-de-Oliveira, 2019). However, surveys and experimental research (using interviews, for example) are time-consuming.

As an economic effect, stock market fluctuations have tangible impacts on individual health. Market dips correlate with immediate spikes in hospital admissions, especially for psychological distress, anxiety, and panic disorder (Engelberg and Parsons, 2016)Therefore, financial loss translates into acute medical outcomes, which might have broader societal implications. A more integrated approach to FWB necessitates proper economic and health policy planning.

In addition, unconscious mental processes impact investment decisions and financial markets. Emotional finance, based on psychoanalytic theory, investigates unconscious desires, fantasies, and group dynamics that influence market behaviour (Taffler, 2018). For instance, fear and greed influence market behaviour during market bubbles and crashes. Greed can drive bubbles through irrational asset inflation, while fear incites panic selling during crashes. In addition, investors' group economic behaviour makes markets more volatile. Therefore, emotional finance uncovers physiologic forces for more resilient investment strategies.

Additionally, at the corporate level, employee mental health is directly affected by financial frictions, like difficulties refinancing debt during economic downturns (Taffler, 2018). According to their study (Taffler, 2018), the distress manifests in job losses or existing employees due to increased job insecurity and related psychological strains. The implications extend to financial well-being, as persistent workplace stress and uncertainty about job stability can lead to broader financial insecurity, influencing employees' overall financial health and decision-making capabilities.

However, the effects of intergenerational financial transfers, such as inheritances and parental cash gifts, were insignificant on Australian adults' health and well-being outcomes (Ong *et al.*, 2018). Based on their Household, Income, and Labour Dynamics in Australia (HILDA) Survey data from 2001 to 2015, no consistent evidence exists that receiving inheritances or parental cash gifts improves health or wellbeing outcomes across genders. Instead, family wealth may impact health through human and social capital rather than direct financial transfers.

This UK longitudinal yearly general health questionnaire examines the role of social capital in buffering psychological well-being during the 2008 financial crisis. Results reveal a significant drop in generalised trust across the UK, from 40% in 2007 to 32% in 2008. However, those maintaining high trust exhibited a protective effect against worsening psychological well-being. Despite increased social participation, it reduces psychological health. Therefore, strengthening social capital during an economic downturn raises trust through policy initiatives contributing to overall financial well-being.

Studying What Matters to Adults (WM2A) in Australia ensures cultural relevance and measures genuine Aboriginal and Torres Strait Islander values and preferences (Howard *et al.*, 2024). The culturally grounded well-being measures suggest that such tailored approaches can significantly enhance indigenous populations' financial well-being (FWB) by more accurately identifying and addressing their needs and perspectives. Therefore, this study is an effective intervention to improve individual life quality and economic stability.

FWB is a multidimensional concept that includes many factors, such as personal and microeconomic conditions (Bashir and Qureshi, 2023a; de Oliveira *et al.*, 2019). A study reported 13 antecedents and outcomes of financial well-being under various sub-headings (Bashir and Qureshi, 2023a). Therefore, the multifaceted FWB requires an integrated approach to policy planning to increase social trust, leading to more effective strategies.

2.2. Literature Review Approach

The financial well-being agenda acknowledges its multidisciplinary interaction with other domains (Brüggen *et al.*, 2017). The FWB has several components, such as financial behaviours (Gerrans *et al.*, 2014), literacy programs (Meier and Sprenger, 2013), personal characteristics (Fan *et al.*, 2021), and social community (Stevenson *et al.*, 2020) that might not match much of the other developing and developed countries (Karakurum-Ozdemir *et al.*, 2019).

Although many studies use Google Trends as a data source to measure many economics and related financial constructs (Algan *et al.*, 2016; Askitas and Zimmermann, 2011) to the researcher's knowledge, no specific initiative has been using big data as a source of data to measure the FWB. However, some initiatives emphasise the need for a machine learning approach to process big data from Google or social media (Algan *et al.*, 2016).

Therefore, based on the research objectives, the literature should cover the central concepts discussing FWB so that an empirical model could measure the significance of its underlying constructs. This study employs a scoping review approach to explore the literature on FWB measurement (Arksey and O'Malley, 2005; Levac *et al.*, 2010). The review analyses relevant research on FWB measurement across various disciplines. Therefore, the FWB measurements are scoped to create a new FWB Index, as outlined in the research objectives.

This study is a scoping study of FWB, where it is impractical to review all of its dimensions (Arksey and O'Malley, 2005; Levac *et al.*, 2010). The study explores FWB measurement to create a new FWB Index based on Google Trends Search (GTS). The study groups concepts with evidence from the literature to identify gaps. Furthermore, the review combines collected literature roadmaps guided by the research agendas of (Brüggen *et al.*, 2017) with expert consultation for completeness. Therefore, the methodological guidelines (Arksey and O'Malley, 2005; Levac *et al.*, 2010) are followed to identify gaps in the multidimensional aspects of FWB.

Due to the multidimensionality of FWB, the review process balances comprehensive coverage of the literature with deep analysis of FWB concepts to support a well-supported argument. Consequently, the review incorporates the theoretical frameworks of human behaviour, FWB's significant relevance to individuals, families, and communities, FWB during extreme economic conditions, and generic techniques to measure the FWB concept. Thus, the review defines the purpose and the scope, develops inclusion and exclusion criteria, and consolidates and synthesises selected literature.

The search strings were placed on Google Scholar, which has many indexed journals. Search strings include Search String 1- General FWB Constructs and Measurement: ("Financial Well-Being" OR "financial behaviour" OR "economic conditions") AND ("measurement" OR "Google Trends" OR "survey") AND ("contextual factors" OR "financial interventions" OR "personal factors"). The Search String 2- FWB, Financial Behaviour, and Economic Events: ("Financial Well-Being" OR "financial behaviour") AND (unemployment OR "interest rate" OR inflation OR "stock index" OR uncertainty) AND ("economic events" OR "financial stability"). Moreover, Search String 3- FWB Measurement and Google Trends: ("Financial Well-Being" OR "financial behaviour measurement") AND "Google Trends" AND (unemployment OR "interest rates" OR inflation OR "stock market" OR uncertainty). Finally, Search String 4- FWB Interventions and Outcomes: ("Financial Well-Being interventions" OR "financial education" OR "financial counselling") AND ("impact" OR "outcomes" OR "quality of life" OR trust OR welfare) AND ("family" OR "community" OR "extreme economic conditions").

The inclusion criteria for the critical review include articles written in English and UK government reports about financial well-being, especially those that use Google Trends. In addition, psychological theories were only considered to understand human financial behaviour in general. The final phase of the critical review consolidates and synthesises literature to construct and understand the intricate relationships among financial behaviour and extreme events (unemployment, interest rates, inflation, stock index, uncertainty) that impact FB and FWB. Moreover, a complementary study was made to find proxy constructs on UK government websites. Therefore, the study extracts themes and patterns of FWB and aligns with the GTS and its Alternative Proxy model.

2.3. Financial Well-Being Theories

FWB is conceptually correlated to psychology and other domains concerned with human well-being. Literature suggests more than 21 theories spanning individual, family, and social/community levels (Bashir and Qureshi, 2023b). Such theories encompass various aspects such as financial security, comfort, survival, and levels of well-being.

2.3.1. Individual Financial Behaviour

Notable theories in FWB include the Planned Behaviour Theory (Ajzen, 1991, 2020). The Planned Behaviour Theory is a psychological framework that examines how individual attitudes, subjective norms, and perceived behavioural control influence intentions and behaviours. For example, teenagers may perceive smoking as the norm when influenced by peer groups engaged in smoking, which can change their perception of the norm upon encountering statistics demonstrating the opposite (non-smoking) behaviour. According to systematic literature, Planned Behaviour Theory is the most used theory to understand the FWB (Bashir and Qureshi, 2023a).

Self-efficacy Theory (Bandura and Adams, 1977; Vaughan-Johnston and Jacobson, 2020; Warmath and Zimmerman, 2019) proposes that individuals believe in their ability to cope with circumstances (Bandura, 1977). It encompasses confidence in controlling one's motivation, behaviour, and social environment (Sekerdej and Szwed, 2021). Self-efficacy consists of four dimensions: mastery experiences, vicarious experiences, verbal persuasion, and physiological and affective states (Bandura, 1977). The theory emphasises one's beliefs, which affect motivation and behaviour in the financial environment (Forbes and Kara, 2010). The Self-determination Theory shows the critical roles of autonomy, competence, and relatedness in financial well-being (Limbu and Sato, 2019).

The Expectancy-Value Theory (Burcher *et al.*, 2021) and the Psychological Theory of Well-Being (Vlaev and Elliott, 2014) illustrate expected outcomes and psychological satisfaction in financial decision-making. Dominance Differentiation Theory (Painter II, 2013) and Conservation of Resources Theory (Choung *et al.*, 2023) explore how power dynamics and resource management contribute to FWB. On a broader scale, the Rational Choice Theory (Scott, 2000) merges concepts from economics, psychology, and philosophy to analyse individual behaviour based on self-interest and the pursuit of maximum benefit. This theory posits that individuals act based on self-interest, making preferred decisions that maximise their benefit.

In economics, the Prospect Theory explains how people assess gains and losses differently (Kahneman and Tversky, 1979). The theory points out that individuals tend to avoid risks when there are gains but become more willing to take risks when faced with losses. Thus, this theory impacts financial behaviours decision-making processes.

2.3.2. Family Dimension and the Individual Financial Behaviour

Family members shape an individual's financial behaviour due to resource sharing. Several theories are reported in the family dimension, including Family Resource Management Theory (Deacon and Firebaugh, 1988), Consumer Socialisation Theory (Ward, 1974), and Family Financial Socialisation Theory (Gudmunson and Danes, 2011). Family Resource Management Theory analyses resource allocation (for example, time and money) to meet their needs and make adaptations. It is also intended for decision-making adapting to family dynamics and functioning. Consumer Socialisation Theory explains how agents (for example, parents) develop the behaviour of family members (Ward, 1974). The Consumer Socialisation Theory describes the attitudes and intentions of adolescents influenced by their parents as primary influential factors (Drever *et al.*, 2015). According to the theory, parents influence the financial behaviour of adults through explicit teachings, such as managing monthly expenses, or through guidance on budgeting and financial planning (Gudmunson and Danes, 2011). The Family Financial Socialisation Theory (Danes, 1994; Gudmunson and Danes, 2011) examines how interactions and shared experiences among family members can lead to the acquisition and development of financial attitudes, skills, and knowledge.

2.3.3. Social Communities Influence on Individual Financial Behaviour

Financial Socialisation (Danes, 1994; LeBaron and Kelley, 2021) encourages learning financial knowledge, values and behaviours within social groups. Social Comparison Theory (Festinger, 1954) suggests individuals evaluate their financial situation by comparing themselves to peers, often those of similar age, income, or occupation. Social Role Theory (Eagly *et al.*, 2000; Eagly and Wood, 2016) examines how individuals exchange resources (financial or social) within communities. Social Exchange Theory (Cook and Emerson, 1987) fosters FWB by exchanging knowledge within society. Social Capital Theory (Hellerstein and Neumark, 2020) shows how relationships, people's trust, and cooperation are resources that could increase individuals' and communities' FWB. Consumer Socialisation Theory (Agnew and Cameron-Agnew, 2015; Ward, 1974) explores how social groups influence financial attitudes and behaviours. The Financial Socialisation Theory involves learning, knowledge acquisition, values advancement, and behaviours that promote financial well-being (Danes, 1994), such as children learning financial behaviours from their parents.

2.3.4. Outcomes from Financial Well-Being Theories

The scoping review of theoretical frameworks covers individuals, families, and communities, which contributes to a holistic understanding of FWB (Braun Santos *et al.*, 2016; Brown *et al.*, 2016). The Comparison Theory illustrates financial behaviours as related to social circles. Social networks and trust enhance FWB, as the Social Capital Theory explains. However, research showed that the Planned Behaviour Theory (Ajzen, 1991, 2020) is dominant among other theories (Bashir and Qureshi, 2023a). The latter theory explains that beliefs, social norms, pressure, and self-control influence financial decisions. Moreover, research suggests that combining theories increases FWB levels by increasing knowledge and decision-making skills (Thomas and Gupta, 2021).

2.4. Financial Well-Being Dimensions

The scope review analysis shows several predictors of FWB, categorised into four levels: individual, family, community, and extreme events, as guided by the FWB agenda (Brüggen *et al.*, 2017). However, this study does not list all factors exhaustively due to complexity.

2.4.1. Individual Dimension

During an individual social life, they gain more knowledge and experience, which might influence their financial decisions to become increasingly influenced by their social capital (Michael Collins and Urban, 2020). According to Brüggen et al. FWB agenda (2017), FWB includes personal factors, such as socio-demographics, skills and attitudes, traits, practices, and life events. FWB could be predicted using various factors derived from Planned Behaviour and Self-Efficacy theories. These factors include financial knowledge (Hadar *et al.*, 2013; Losada-Otalora *et al.*, 2020; Robb and Woodyard, 2011; Warmath and Zimmerman, 2019), education (Ho and Lee, 2021; Lyons and Kass-Hanna, 2021), financial attitudes (Edwards *et al.*, 2007; Ho and Lee, 2021; Jorgensen *et al.*, 2017), financial behaviours (Suh, 2021), risk tolerance (Grable, 2000; Payne *et al.*, 2019), self-efficacy (Sabri *et al.*, 2020), self-control (Rey-Ares *et al.*, 2021; Strömbäck *et al.*, 2017, 2020), financial-literacy (Schmeiser and Seligman, 2013), and personal demographics (Fan and Babiarz, 2019; Florendo and Estelami, 2019).

An individual attitude toward money increases financial planning and decreases risk tolerance (Castro-González *et al.*, 2020). However, materialistic orientations toward money often result in less satisfaction than individuals with high conscientiousness, as socio-demographic and dispositional variables significantly influence financial attitudes (Donnelly *et al.*, 2012). Consequently, long-term financial goals require adequate financial planning and commitment (García-Mata and Zerón-Félix, 2022) and financial resilience to reduce risks and provide proactive behaviours (Klapper and Lusardi, 2020).

Moreover, research showed that financial management skills correlate positively with age and education; financial literacy is crucial to enhanced financial well-being (Yuesti *et al.*, 2020). Additionally, financial capability is seen as integrating financial literacy and behaviour, where knowledge guides suitable financial actions to achieve the desired level of financial well-being (Xiao, 2016). Therefore, financial capability combines financial access and literacy to effective financial management behaviours and enhanced financial well-being (Birkenmaier *et al.*, 2022; Khan *et al.*, 2022).

2.4.2. Family Dimension

A family's financial management satisfaction depends on the household's relative income and the individual financial satisfaction of family members. A higher household income generally contributes to better financial security, especially with positive individual attitudes towards overall family FWB (Ali *et al.*, 2015).

Moreover, the Family Management Theory indicates that FWB could be predicted with macro family factors: parental socialisation, social, family structure, and social comparisons (Antoni *et al.*, 2019; Yeo and Lee, 2019). Furthermore, the discussions and knowledge sharing boost positive financial behaviour and FWB (LeBaron and Kelley, 2021). Therefore, parental socialisation evokes emotions in family members for enhanced skills and knowledge (Antoni *et al.*, 2019; Drever *et al.*, 2015). As a result, financial behaviour and social capital provide social resources that tie and trust to enhance the quality of life (Snow *et al.*, 2017; Yeo and Lee, 2019).

Conversely, family structures bound by marriage or bloodline might impact financial well-being due to the intricacies of resource-sharing (Ahn *et al.*, 2014). One reason is the application of Social Comparison Theory, which illustrates how individuals gauge their financial behaviours by benchmarking themselves against others (Braun Santos *et al.*, 2016). However, such comparisons could escalate the risk of financial adversities (Braun Santos *et al.*, 2016) .

2.4.3. Community Dimension

The community could influence the FWB of individuals indirectly. However, the literature has limited studies in this area (Kaur *et al.*, 2021). The community dimension includes financial markets, economic and political stability, technological adoption, cultural and religious practices, and government financial aid (Sarofim *et al.*, 2020). Notably, a study shows a correlation between recurrent terrorist activities and the perception of financial well-being among attackers and their communities (Gaibulloev *et al.*, 2019). Therefore, their study suggests that feelings of economic hardship or disparity can contribute to a decline in subjective well-being. Furthermore, the Great Recession has influenced retirees' financial well-being, affecting their financial resources and subjective feelings of financial security (Donnelly and Taylor, 2019). Additionally, within online communities, the excessive use of social networking platforms for purchasing activities has been positively associated with increased buying and financial anxiety (She *et al.*, 2021).

2.4.4. Extreme Events Dimension

Extreme events, characterised by their severity, can potentially influence FWB. These events cover many scenarios, from natural disasters such as floods, earthquakes, and hurricanes to human-made crises, including wars and economic downturns (Sufi and Taylor, 2022). For instance, economic recessions can impose financial stresses that heighten consumer price awareness, which leads to sudden changes in financial behaviours (Hampson and McGoldrick, 2017). The research on the macroeconomic consequences of economic events on financial well-being remains limited due to the significance of external factors such as environmental catastrophes, fiscal contractions and surging housing costs (Barrafrem *et al.*, 2020; Kim and Wilmarth, 2016; Lee *et al.*, 2018; de Soto *et al.*, 2021). Therefore, managing financial resources reduces the FWB status of families due to unplanned financial commitments in economic downturns (Botha *et al.*, 2021; Kim and Wilmarth, 2016; Milani, 2021).

The COVID-19 pandemic triggered unemployment and disturbances in the labour market that altered working conditions (Abdull Rahman and Ahmad Shafiai, 2021). These changes are associated with a notable 29% decrease in the perceived level of financial well-being among affected populations (Botha *et al.*, 2021). As a result, significant events like COVID-19, alongside occurrences like the Brexit Referendum, have negatively influenced financial markets and heightened economic dissatisfaction (Iglesias, 2022). Cognitive biases such as exponential growth bias and flawed mental budgeting practices detrimentally impact individual financial behaviours during such times (Wahla *et al.*, 2021). Therefore, the insecurity and lack of financial knowledge exacerbated by COVID-19 affect financial behaviour (Ali and Talha, 2021). Consequently, the crisis triggered governments' intervention through policies that promote financial well-being, including investments in environmental, social, and governance initiatives (Mavlutova *et al.*, 2022).

An example of extreme events in the UK is presented in Table 2.1. The events are expected to affect the studied variables. The Global Financial Crisis of 2008-2009 impacted financial well-being in the UK, causing high unemployment rates and historically low interest rates. The 2011 Eurozone debt crisis exacerbated inflation and job insecurity. The COVID-19 pandemic from 2019-2020 further strained financial well-being, with lockdowns and unemployment.

Table 2.1: List of Extreme Events (2008-2021)

Event	Time	Description
Global Financial Crisis	2008-2009	The global financial crisis significantly impacted the UK economy, leading to a severe recession, bank bailouts, and government intervention.
Eurozone debt crisis	2011	The eurozone debt crisis affected several European countries, including Ireland, Portugal, and Spain. The crisis began in 2010 and peaked in 2011. The crisis harmed the UK economy due to its close ties to the eurozone.
London Olympics	2012	The 2012 Summer Olympics were held in London from July 27 to August 12, 2012. The Olympics positively impacted the UK economy, generating an estimated £9.9 billion in economic activity.
Oil price crash	2016	The oil price crashed from over $100 per barrel in June 2014 to below $30 per barrel in January 2016 due to oversupply, weak demand, and the strengthening of the US dollar. The oil price crash negatively impacts the energy sector in the UK.
COVID-19 Pandemic	2019-2020	The COVID-19 pandemic profoundly impacted the UK economy, leading to lockdowns, economic contractions, and government support programs.

These events were chosen for their diversity and significant impact on the UK's economy, society, and individual financial well-being. The Global Financial Crisis and the Eurozone Debt Crisis are examples of large-scale economic disruptions to global market connections. The London Olympics demonstrates how it could boost economies through tourism, infrastructure development, and job creation. The oil price crash exposes the UK to external shocks that affect industries like the North Sea oil sector while lowering consumer energy costs. Lastly, the COVID-19 Pandemic is a global health crisis with broad economic and social impacts. Examining these events provides a comprehensive understanding of how the UK's economy and financial well-being respond to different types of stress and disruption.

2.5. Classical Financial Well-Being Measurement

This section discusses classical and new real-time methods in FWB measurements.

2.5.1. Survey-based Methods

Survey research uses systematic observations and adequate measurement methods to identify associations or correlations between variables (Fan and Henager, 2022). These survey-based methodologies hinge on crafting a questionnaire to assess FWB objectively. For example, Comerton-Forde *et al.* (2018) conceptualised and developed a FWB measurement scale. Their scale was based on data from major Australian bank customers. Their model has three determinants of financial well-being: household characteristics, external conditions, and financial behaviour. The Comerton-Forde *et al.* research has a common construct with studying socioeconomic environment, knowledge, skills and experience, psychological factors, and behavioural factors (Kempson *et al.*, 2017). Their research coincides with students' financial well-being and includes financial knowledge, financial attitudes, perceived behaviour control, and subjective norms (Shim *et al.*, 2009).

Qualitative research studies human behaviour and the reasons that govern such behaviour, including in-depth interviews, focus groups, observational methods, and content analysis (Fossey *et al.*, 2002). The research includes a one-to-one semi-structured interview to analyze consumers' FWB profiles (Mahendru *et al.*, 2020). According to Mahendru et al. (2020), the FWB of consumers is affected by financial behaviour and mediated by financial knowledge, personality traits, and mindful finance. In addition, financial literacy and locus of control directly impact individual investors' financial behaviour, with financial literacy as a moderator that enhances these positive effects (Mutlu and Özer, 2022). However, survey-based expectations of FWB measurements are often biased and inefficient, attributable to data collection methods and variations in the perception of variables (Bicchal and Raja Sethu Durai, 2019).

The Global Financial Wellness Survey (Fidelity Investments, 2020) by Fidelity examines the financial well-being of working households across various countries, including the United Kingdom. The survey evaluates financial wellness based on budgeting, debt, savings, and protection dimensions. The survey combines objective, at the lower end of the metrics and subjective feelings about financial health. The survey collected data from individuals aged 20-75 with specific income thresholds and was conducted by Ipsos between March and May 2020. According to the survey, the median Financial Wellness Score was 63 for the UK, a lower end of compared countries. The Canadian Financial Well-Being Survey (Financial Consumer Agency of Canada, 2019) was conducted online for 1,935 respondents in 2018. The survey assesses financial well-being based on five categories: financial behaviours, social factors, psychological factors, economic factors, and financial knowledge and experience. The survey reveals that while many Canadians are doing reasonably well financially, a strong relationship exists between financial well-being and financial behaviours. The report indicates that active saving and avoiding borrowing for daily expenses significantly enhance financial well-being. The average Financial Well-Being Score was 66 out of 100, with 74% of Canadians scoring above 50.

The Money and Pensions Service (MaPS) consolidates the functions of The Money Advice Service, The Pensions Advisory Service, and Pension Wise, integrating debt advice, money guidance, and pension guidance. Their Adult Financial Wellbeing Survey (Money and Pensions Service, 2022) builds on previous iterations by incorporating the financial impacts of the COVID-19 pandemic, repayment holidays, and changes in bill and credit commitments. Conducted from July to September 2021, the survey involved a sample size of 10,306 respondents through a hybrid approach of online access panels and postal invitations. The questionnaire assesses current and long-term financial well-being, day-to-day financial management behaviours, planning for future financial resilience, and enablers and inhibitors of financial health, such as financial confidence, numeracy, and engagement with financial advice. Results indicate that while many UK adults effectively manage their financial commitments, there is significant variance in financial comfort and future resilience. Key data points include mean scores of 81 for meeting commitments, 61 for financial comfort, and 60 for future resilience, where strategic interventions could enhance overall financial well-being.

The sixth Financial Wellbeing Survey, conducted by YouGovGalaxy in Australia and New Zealand (Prendergast *et al.*, 2018) applied Elaine Kempson FWB model (Kempson *et al.*, 2017) to estimate financial well-being. Conducted from July to September 2021, the survey involved 3,578 adult Australians. It assessed their ability to meet financial commitments, comfort with their financial situation, and resilience to future financial challenges. The results categorised respondents into four groups: 'No worries,' 'Doing OK,' 'Getting by,' and 'Struggling,' with respective scores out of 100. Key findings revealed that active saving and avoiding borrowing for everyday expenses were critical behaviours contributing to financial well-being, accounting for 19% and 16% of the variation in scores, respectively. Socioeconomic circumstances contributed 30% to differences in financial well-being, particularly confidence in money management.

The US Federal Reserve Board 2022 survey, Survey of Household Economics and Decision-making (SHED), evaluates the economic well-being of U.S. Households for a sample of 6,595 individuals online (Board of Governors of the Federal Reserve System, 2023). Results showed that adults' financial well-being was 73%, 5% compared to the previous year. Adults spend less than their income and report increased credit card debt. They had concerns about future financial security based on adults' feelings about their retirement savings plans. However, disparities persisted based on education, with bachelor's degrees more likely to have job flexibility and telework opportunities.

The 2019 Survey of Adult Financial Literacy Competencies was coordinated by the Federal Financial Supervisory Authority to assess the financial well-being of German adults (Federal Financial Supervisory Authority, 2019). The questionnaire covers several categories, including financial knowledge, attitudes, and behaviours. According to computer-assisted telephone interviews with 1,003 respondents, most consumers adopt a cautious approach to financial management. However, respondents prefer traditional savings accounts and digital payment methods. Three-quarters of respondents compared information from different providers before selecting financial products. Notably, half of the respondents expressed doubts about the safety of their bank deposits despite existing deposit guarantees.

2.5.2. Experimental Research

Experimental research involves manipulating variables to establish cause-and-effect relationships in controlled environments (Thomas, 2021). The experimental research on FWB focuses on finding FWB constructs from existing themes in carried experiments. For example, the study (D'Agostino *et al.*, 2021) measures the FWB based on five factors: inner well-being, relative assessment, time (past and future), financial security, and financial freedom.

The exploratory study (Chauhan and Dhami, 2021) shows the effect of before-and-after financial literacy interventions among 308 working respondents on the relationship between subjective financial well-being and individuals' financial behaviours. The study found a strong correlation between financial well-being and financial behaviour and their relation to income and employment. Thereby, the study unveils the influence of financial literacy on enhancing personal economic behaviour and overall financial well-being.

Money illusion is a cognitive bias where people assess the value of money based on its nominal amount rather than its actual value. The method used controlled experiments (with a declining conversion rate technique) to study the money illusion's effect on financial decisions under different inflation scenarios. Therefore, the actual purchasing power after inflation (Cordes *et al.*, 2023). Their approach simulates the impact of inflation on nominal wealth versus real purchasing power to study the cognitive biases of investment behaviours systematically. Their index for money illusion illuminates the intricate effects of cognitive biases on financial choices to deepen the conversation about how inflation perceptions influence saving and investment decisions.

In addition, a study explored credit card debt repayment strategies through qualitative research, stakeholder engagement, and an online survey, concluding that altering the decision-making environment may be more effective than just informing about the costs of minimum payments (Adams *et al.*, 2018). Surveys were utilised to assess FWB and develop a regression model that analysed a dataset of 6,000 US households collected by the CFPB (Michael Collins and Urban, 2020). However, the reliability of these methods significantly depends on the study's sample.

2.5.3. Mixed Research Methods

Mixed-method studies combine quantitative and qualitative research techniques. Mixed methods scale the development of the FWB construct (Netemeyer et al., 2018; Rabbani et al., 2021). For example, the mixed research (Netemeyer *et al.*, 2018) is based on consumer financial narratives, surveys, and experiments, which found that FWB is related to stress and financial security. They developed a regression model with these variables: age, financial literacy, subjective well-being, demographics, resources, perceptions of financial knowledge, and nine US regional fixed effects. A latent profile analysis method categorises college students into distinct groups based on subjective, objective and comparative financial knowledge (Rabbani *et al.*, 2022). The study reveals significant differences in risk tolerance and financial education experience towards financial well-being.

The mixed method (Mattke *et al.*, 2021) explores the motivations behind individuals' investments in Bitcoin. Their study combines qualitative data from interviews with 73 participants, quantitative data from a survey of 150 individuals, and a fuzzy-set analysis of Bitcoin investment factors. Bitcoin's underlying ideology gains support through disclosed profit expectations, simplicity of acquisition, investing expertise, and a propensity for risk among its advocates. Investors seeking higher returns through Bitcoin often view it as a pathway to financial stability and future security; however, they are at a high risk of loss.

The study (Jabbi, 2022) examines the effects of the COVID-19 financial crisis on the working capital management of UK enterprises. It adopts quantitative data from a survey of 150 UK businesses with qualitative data from follow-up interviews. The study reports a significant negative impact of the pandemic on medium-sized enterprises' working capital and liquidity.

In addition, it reduces customer demand and economic uncertainty using Structural equation modelling.

2.6. Research Gaps

The scoping review of FWB literature identifies several research gaps.

2.6.1. Surveys Limitations

Surveys are a standard approach for assessing financial well-being (CFPB, 2015). However, they come with limitations due to individual responses or design issues (Dalenius, 1983). Respondents may hesitate to provide accurate answers if they fear the consequences (Tourangeau and Yan, 2007) or might inaccurately self-report due to memory lapses or boredom (Alwin *et al.*, 2014). Non-response bias can also distort survey results (Coughlan *et al.*, 2009). In contrast, Google Trends Search (GTS) data offers a real-time gauge of public sentiment on financial topics, providing a broader, potentially more accurate reflection of concerns. GTS data bypasses social desirability bias and memory issues linked to surveys and allows continuous monitoring of emerging trends in financial well-being. Most surveys are limited in it and costly. This study illustrates this issue by example. The 2015 UK Financial Capability Survey views how people manage their money based on a sample of 5,603 respondents; however, it has a few limitations. Self-reported data introduced a layer of bias, as many people might feel uncomfortable admitting poor financial habits. Therefore, results favour positive financial status over reality. Moreover, the survey also took a predominantly online approach (72%), inadvertently excluding those without regular internet access. Therefore, these groups without access often face unique financial challenges. Further, while the survey broke down results by demographic groups, the findings were usually too broad to address specific struggles distinct populations face. Lastly, the survey could not reveal how financial habits change over time. Therefore, the survey could not illustrate longer-term trends and evolving financial behaviours.

The 2018 Financial Capability Survey had a more comprehensive view of 21 components of financial well-being across the UK, with a sample of 5,974. Despite a significant participant count, the survey's effectiveness hinged on the UK's diverse demographics of specific regions or socioeconomic groups. Additionally, the survey's length of more than 100 questions introduced the risk of respondent fatigue, reducing response quality and data reliability. Despite its structured approach to measuring, it may have missed the fluidity of personal finance as economic conditions and individual circumstances changed. Moreover, the mixed modes of administration telephone, online, or face-to-face could have introduced variability in responses due to differing communication styles. Lastly, relying on self-reported data posed inherent biases. Participants could overestimate or underestimate their financial behaviours and knowledge.

2.6.2. Dynamic and Multidimensional Construct

Maintaining FWB as a multifaceted concept encompasses financial security and the liberty to pursue desired life paths (Bashir and Qureshi, 2023a) . Due to its dimensionality, there is no consensus on its scope and definitions. It is defined as an individual's self-reporting about their level of income and their financial satisfaction (Owusu, 2023; Xiao *et al.*, 2014) and as "a state of being wherein you have control over day-to-day, month-to-month finances; have the capacity to absorb a financial shock; are on track to meet your financial goals; and have the financial freedom to make the choices that allow you to enjoy life" (Consumer Financial Protection Bureau, 2019, p. 3). Other researchers define it as individuals' perceptions of financial strain and stress (Lindberg *et al.*, 2021). Netemeyer *et al.* (2018) explain the difference between "what my situation is today?" and "what I expect in the future related to my financial satisfaction." Similarly, Prawitz *et al.* (2006) defined it as how satisfied individuals are with their current financial situation and how they manage financial stress and feel about personal finances.

Consequently, a single definition of financial well-being is a substantial challenge. Current studies on financial well-being focus on developmental psychology (Sahi, 2017), consumer decision-making (Xiao and Tao, 2021), and financial planning (Castro-González *et al.*, 2020), yet there is no definite consensus on its meaning (Ali *et al.*, 2015; Botha *et al.*, 2021; Comerton-Forde *et al.*, 2020). In particular, the new FWB definitions include money management, shock absorbance, and financial freedom (Consumer Financial Protection Bureau, 2019, p. 4). On the other hand, the FWB of Brüggen *et al.* (2017, p. 229) concentrates on sustainable living standards and financial freedom. Moreover, the measurement of FWB is also considered inconsistent due to the lack of standardised research instruments on objective or subjective FWB (Michael Collins and Urban, 2020). Consequently, the measurements vary across different researchers depending on the list of identified factors in the scope of the FWB. Therefore, research is called to adopt a standard definition and find a measurement method to measure FWB based on its defined scope.

FWB has many elements at the individual, family, and community levels. At the individual level, these include factors such as financial behaviour (Riitsalu and Murakas, 2019), self-control (Strömbäck *et al.*, 2017), and financial capabilities (Warmath and Zimmerman, 2019). It has different levels of abstraction; it has core financial behaviours (Gerrans *et al.*, 2014), literacy initiatives (Meier and Sprenger, 2013), personal characteristics (Fan *et al.*, 2021), and social community (Stevenson *et al.*, 2020). The FWB family factors include parental socialisation, family parental socialisation (Zhao and Zhang, 2020), social capital (Yeo and Lee, 2019) and family structure (Wilmarth, 2021). At a higher level, the FWB community factors include the financial market (Fu, 2020), economic stability (Odekon, 2015), cultural and religious practice (Sarofim *et al.*, 2020), and technological advancement (Bayuk and Altobello, 2019; Kaur *et al.*, 2021). Moreover, FWB is also influenced by unprecedented events such as earthquakes, psychological shocks, wars, economic downturns (Kim and Wilmarth, 2016). It is also influenced heavily by health conditions that reduce effective positive decisions, such as COVID-19 (Barrafrem *et al.*, 2020; Godinic *et al.*, 2020; de Soto *et al.*, 2021). Consequently, the FWB is a multifaced construct for various dimensions: economic, legal, political, socio-cultural, technological, and market (Brüggen *et al.*, 2017).

Additionally, financial well-being varies across income levels (Botha *et al.*, 2021), demographic characteristics (Iannello *et al.*, 2021), and family financial resilience (Stevenson *et al.*, 2020). Examples include income and money management under stress (Netemeyer *et al.*, 2018; Stevenson *et al.*, 2020) and expected financial security (Chatterjee *et al.*, 2019). Therefore, FWB levels correspond to socioeconomic characteristics and country culture more than the objective measures (D'Agostino *et al.*, 2021). Consequently, FWB is difficult to measure consistently because of its complexity and multifaceted dimensions (D'Agostino *et al.*, 2021).

Another area for improvement is the divergence of the FWB across countries. According to Nanda and Banerjee (2021) critique the use of scales that measure FWB based on the presence or absence of financial stress or shocks, arguing that such measures may not accurately reflect the actual state of FWB (Lindberg *et al.*, 2021). Moreover, financial decision freedom is not fully automated; therefore, scales will have limited utility for developing countries (Kumar *et al.*, 2023; Tong and Tian, 2023). Thus, research is called to reduce the complexity of multifaced FWB.

2.6.3. Problems with Measurement Methods

Surveys could measure FWB; however, surveys pose significant challenges due to their high costs and time (Solomon, 2001). There has been little agreement on the components of subjective well-being and its predictors, which are influenced by subjective financial well-being (Ngamaba *et al.*, 2020). Subjective well-being is also multidimensional (Iannello *et al.*, 2021), and some aspects, especially pain, are difficult to capture. For example, financial satisfaction, as measured by the study (Sahi, 2017), is the subjective evaluation of one's financial situation (Fan and Babiarz, 2019). Even studies show that a single factor (i.e., knowledge) could be subjective and objective, where, for example, a risky investment increases when subjective knowledge is pursued (Hadar *et al.*, 2013).

Regression and linear measurement methods have the issue of input datasets; however, most of the published data sets are of US origin (Dorsey *et al.*, 2020). The study (Fu, 2020) compares economies (including the United Kingdom) to find how one country's FWB differs (Yáñez-Araque *et al.*, 2021). The study found differences in accessing finance resources, the disproportionate availability of financial product resources, and different consumer protection frameworks. According to a literature review study (Nanda and Banerjee, 2021) highlighted that the number of studies in the UK was limited to four studies in the marketing dimension (Arber *et al.*, 2014; Hampson and McGoldrick, 2017) compared to more than 70 studies in the US FWB marketing context.

The higher dimensionality of the construct resulted in several methods that could measure the construct based on its sources of data, such as survey methodologies (Barrafrem *et al.*, 2020; D'Agostino *et al.*, 2021; Ianole-Calin *et al.*, 2021; O'Connor *et al.*, 2019), experimental research (Eberhardt *et al.*, 2021; Sarofim *et al.*, 2020), regression analysis (Efendi *et al.*, 2019; Tharp *et al.*, 2020), and mixed methods (Abrantes-Braga and Veludo-de-Oliveira, 2019)However, surveys and experimental research are time-consuming. On the other hand, methods based on collected data expect a large dataset to generalise the model's coefficients.

2.6.4. Financial Well-Being During Extreme Events

Extreme events are uncommon events that include natural disasters such as floods, earthquakes, hurricanes and human-made crises like wars or economic downturns (Sufi and Taylor, 2022). Such events could impact the FWB because they affect individual behaviour towards planning and using money. Economic downturns bring about lasting financial and normative pressures, altering consumer behaviours (Hampson and McGoldrick, 2017). External and uncontrolled events could impact FWB more than regular events (Kim and Wilmarth, 2016; Lee *et al.*, 2018; de Soto *et al.*, 2021). Therefore, understanding how individuals manage their financial resources in response to these challenges is paramount (Botha *et al.*, 2021; Milani, 2021).

In this study, physical events are not considered; however, their potential consequences related to economic events, such as interest rate, inflation, uncertainty, unemployment, and stock index, are considered. For example, higher interest rates give lenders a more significant return, attracting foreign capital and increasing exchange rates, facilitating saving (Okechukwu *et al.*, 2019). The increase in inflation reduces the buying power as goods prices increase; therefore, it negatively impacts consumer spending and saving (Batrancea, 2021; Duca-Radu *et al.*, 2021). Also, increased economic uncertainty negatively correlates with investor confidence (Dzielinski, 2012). There are many possible events of uncertainty, such as market crisis (de la GONZÁLEZ *et al.*, 2017; Luchtenberg and Vu, 2015), inflation expectations (Benk and Gillman, 2023; Ullah *et al.*, 2020), and pandemics (Biswas *et al.*, 2020; Bulog *et al.*, 2022; Nikolopoulos *et al.*, 2021; Yang *et al.*, 2022; Yuesti *et al.*, 2020).

2.6.5. Literature Gaps Summary

These are the critical identified gaps in the literature.

1) **Methodological Shortcomings in Real-time Data Analysis:** The integrity of real-time data analysis, particularly in GTS, requires a valuable approach that ensures accuracy, completeness, consistency, and validity (Cebrián and Domenech, 2022). However, current keyword selection and filtering methods lack a literature-supported methodology for effectively measuring FWB (Symitsi *et al.*, 2022). While there are guidelines for keyword selection (Mavragani and Ochoa, 2019), the absence of an accepted method results in diverse and often ad hoc keyword selection strategies. Therefore, keyword selection and processing should have standardised keyword selection and filtering methods building on principles such as normalisation and grouping, as suggested by prior research (Höpken *et al.*, 2019).

2) **Challenges in Data Collection and Relevance**: Most studies on FWB rely on datasets that significantly lag rapidly changing economic and market conditions. For example, the UK Financial Capability Surveys administered by Money and Pensions Service (2015, 2018) show a significant disparity between current FWB and long-term financial security, where the current FWB was almost double the long-term security score. Therefore, it challenges

future economic stability (Ghosh and Renna, 2022; She *et al.*, 2023). Thus, it becomes problematic for government and policy decision-making for informed strategies and interventions (Kaur *et al.*, 2021). This situation underscores the need for real-time datasets and approaches to build relevant FWB indicators.

3) **Complexity and Incompleteness of FWB Models**: Despite the acknowledged complexity and multifaceted FWB (Brüggen *et al.*, 2017), existing theoretical models are incomprehensive and incomplete. The impact of FWB is mediated by the financial behaviour (FB) of informed financial decisions (Comerton-Forde *et al.*, 2018; Iramani and Lutfi, 2021; Kempson *et al.*, 2017; Oquaye *et al.*, 2020). Moreover, financial behaviour is also a multidimensional aspect that includes education, efficacy, demographics, awareness, and understanding (Hira, 2012; Ingale and Paluri, 2022; Jackson, 2021; Powell *et al.*, 2023; Rahman *et al.*, 2021; Xiao *et al.*, 2006; Zulaihati *et al.*, 2020). However, to the researcher's knowledge, no FWB is complete (Vlaev and Elliott, 2014). Therefore, research must develop systematic and comprehensive theoretical models for financial well-being (García-Mata and Zerón-Félix, 2022).

Consequently, the scarcity of comprehensive research tools significantly constrains the depth of FWB research (Michael Collins and Urban, 2020). Despite these challenges, this research posits that GTS harbours sufficient information to illuminate FWB trends within the United Kingdom. Thus, analysing Google Trends bridges the identified gaps in real-time data analysis and application. A new era of well-being measurement uses big data extracted from the web based on frequently used human terms. Although many studies use Google Trends as a data source to measure many economics and related financial constructs (Algan *et al.*, 2016; Askitas and Zimmermann, 2011) to the researcher's knowledge, no specific initiative has been using big data as a source of data to measure the FWB. However, some initiatives emphasise the need for a machine learning approach to deal with big data from Google or social media (Algan *et al.*, 2016; D'Agostino *et al.*, 2021).

2.7. Chapter Summary

This chapter summarises the related critical review of articles on financial well-being. As multidimensional concepts, the review includes established theories in financial behaviour and individual behaviour in the context of a family and the community. The chapter focuses on extreme economic events, which were found to focus on Unemployment, Interest Rates, Inflation, Stock Indexes, and Uncertainty. The conceptual framework has the mediator of

Financial Behaviour that mediates the extreme economic events towards overall individual financial well-being.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter aims to develop a new measure of financial well-being (FWB) using Google Trends Search (GTS) data, addressing the literature gap discussed in Section 2.6. Although surveys are standard measurement methods, they are costly, time-consuming, and have limited coverage (Solomon, 2001). Literature on FWB showed that surveys are often outdated (Kaur *et al.*, 2021).

Alternatively, GTS data is considered secondary data based on input based on human search patterns about FWB index terms. GTS captured 71.61% of the global market share with 67 million users in the United Kingdom in 2022 and a percentage market share of 92.45%, according to reports(Austin Return On Now Internet Marketing LLC, 2022). It was reported that GTS is a reliable search engine for household search behaviour (Gao *et al.*, 2020). The methodology consists of several primary steps, as illustrated in Figure 3.1. The steps are identifying the source of keywords and sampling, selecting keywords, filtering keywords and transformation, index construction, and FWB index validation. Above all, GTS is adequate to cover the limitations of surveys and the multi-faceted nature (Bashir and Qureshi, 2023a; Michael Collins and Urban, 2020) of FWB using instant and prominent topics.

GTS involves inputting specific keywords or topics into the Google Trends platform to monitor their popularity and track changes in public interest over time. GTS provides the flexibility to view results monthly, yearly, or weekly within a specified time frame. It also allows visualising results graphically or exporting them to CSV files for further analysis. The significance of GTS lies in its ability to harness big data generated by millions of users, providing valuable insights into trending topics and shifts in public interest. The GTS tool has been used in many studies, as discussed in Section 3.2.

In this methodology, the financial behaviour construct (FB) indicates how individuals manage money, make financial decisions, and engage in saving and spending habits, increasing their FWB. Unemployment is a construct influenced by political decisions or unforeseen events like the COVID-19 pandemic, which may impact financial behaviour. The Interest rate (INT) fluctuations influence financial behaviour toward saving rather than investment. Similarly, inflation (INF) affects consumer perceptions, spending decisions, and financial behaviour. The uncertainty (UNC) arising from various sources, such as market crises and pandemics, could reduce positive financial behaviour. Finally, the stock index values (STK) may trigger an individual financial behaviour. It was assumed that the development model in Section 3.1 , to model the proposed hypothesis, these constructs should be modelled following the proposed model.

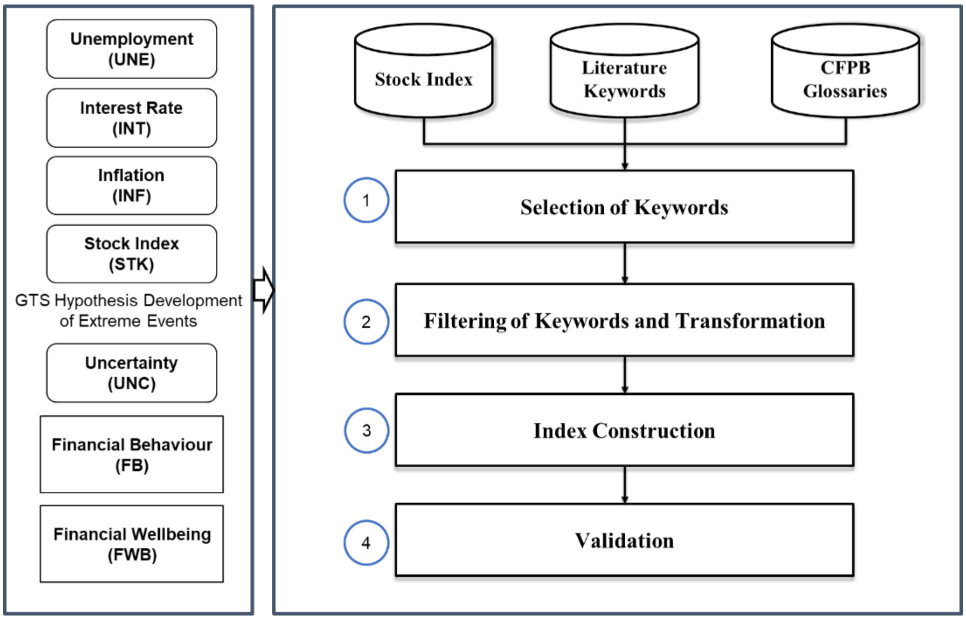


Figure 3.1: Proposed Methodology for Google Trends Search Index Building.

The frequencies of these keywords are extracted from GTS, representing related user search patterns. Next, these keywords undergo several processing steps to construct the FWB index.

3.1. GTS Hypothesis Development of Extreme Events

Based on the critical review in this study, the framework for extreme economic events is developed next.

3.1.1. Variables

The following variables are studied as they are related to extreme events of FWB, as depicted in Figure 3.2.

A. Financial Behaviour (FB)

Financial behaviour (FB) indicates how individuals make financial decisions, including engagement in saving and spending habits (Damian *et al.*, 2020; Gutter and Copur, 2011; Helm *et al.*, 2019). FB is influenced by individual demographics, socio-economic status, cultural norms, financial experiences, financial literacy, psychological and social influences, and technological factors (Goyal *et al.*, 2021). Literature shows that information transparency disseminated by the financial sector environment may impact FB. It may result in unbiased advice availability and competition, which may significantly influence financial well-being through unbiased advice availability and competition (Yáñez-Araque *et al.*, 2021). Therefore, FB factors identify the factors that mediate or affect an individual's financial situation (Vosylis and Klimstra, 2022).

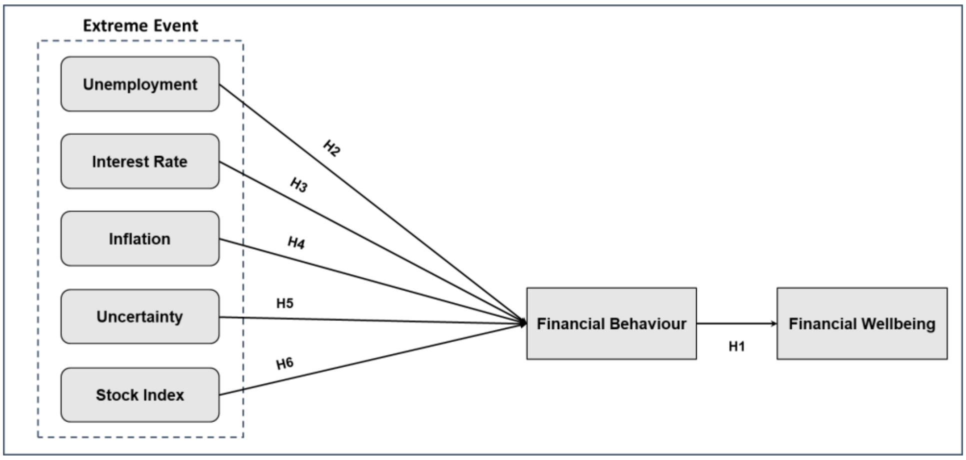


Figure 3.2: Hypothesis development (Conceptual Framework).

Therefore, financial behaviour subconstructs, such as effective budgeting and disciplined saving, enhance financial well-being (Comerton-Forde *et al.*, 2018; Utkarsh *et al.*, 2020; Wahla *et al.*, 2021). In other words, individuals who exhibit these behaviours have a sense of control over their finances, achieve their financial goals, and experience reduced financial stress (Castro-González *et al.*, 2020; Sehrawat *et al.*, 2021; Zia-ur-Rehman *et al.*, 2021).

People categorise their spending in different ways, separating necessities from non-essentials. However, they budget their money relative to their financial well-being. Accordingly, research shows that those with lower financial security tend to budget less frequently but might monitor their spending more closely (Zhang *et al.*, 2022). Conversely, poor, inadequate financial capabilities can undermine financial well-being (Xiao *et al.*, 2022). For example, impulsive spending, excessive debt accumulation, or failure to plan for future financial needs often precipitate financial instability, which declines financial well-being (Castro-González *et al.*, 2020).

A study conducted in the UK has found that among the components of financial capability (financial knowledge, behaviour, and skills), financial behaviour has the most significant impact on FWB (Xiao and Porto, 2021). his result supports the existence of a positive correlation between the subjective financial capability index and financial well-being (Xiao *et al.*, 2023).

Therefore, a hypothesis can be formulated that suggests that improving financial behaviour can mediate or enhance financial well-being (Bashir and Qureshi, 2023a; Damian *et al.*, 2020; Iramani and Lutfi, 2021; Oquaye *et al.*, 2020), Individuals would experience increased financial resources and reduced financial stress by adopting positive financial habits (Guan *et al.*, 2022) to improve their financial health (Ingale and Paluri, 2022; Mahendru, 2020). Conversely, a lack of responsible financial behaviour may lead to declining financial well-being. The hypothesis for this variable is as follows:

H0: *Financial Behaviour (FB) does not influence the Financial Well-Being (FWB).*

H1: *Financial Behaviour (FB) influences the Financial Well-Being (FWB).*

B. Unemployment (UNE)

A financial crisis or extreme events could increase unemployment rates. These events include political disruptions such as Brexit, global health issues such as the COVID-19 pandemic, economic downturns, and unforeseen repercussions of war or supply chain distractions. The Brexit event has far-reaching implications, correlating with a decreased unemployment rate (Luchtenberg and Vu, 2015; Simionescu *et al.*, 2020). The COVID-19 pandemic business shutdowns and social distancing mandates led to significant labour market shocks (Botha *et al.*, 2021). For instance, the labour market shock experienced by Australia's economy was associated with an average 29% decrease in perceived financial well-being (Botha *et al.*, 2021). The pandemic shows that the additional unpaid care work increases stress and results in lower financial well-being (Bulog *et al.*, 2022; Mihaela, 2020; Simionescu and Cifuentes-Faura, 2022a). Consequently, individuals often seek government-supported benefits for short periods until their financial status recovers.

Google data provides evidence to predict unemployment rates in different countries. Google data forecasts the unemployment rate more accurately than survey-based methods in the UK (Aaronson *et al.*, 2022; Castelnuovo and Tran, 2017; Smith, 2016). The predictive power of GTS data extends beyond the UK; for instance, the keywords "unemployment" and "job offers" research inform the formulation of effective fiscal and monetary policies in Spain and Portugal (Simionescu and Cifuentes-Faura, 2022b). Moreover, the Principal Component Analysis (PCA) is employed to forecast Spanish unemployment rates (Mulero and García-Hiernaux, 2021). In addition, a modified Kalman filter approach utilising GTS data to forecast precision for unemployment trends (Fondeur and Karamé, 2013).

The predictive utility of GTS is further evidenced in the Visegrad Group region, forecasting unemployment rates (Pavlicek and Kristoufek, 2015). Despite the success, it is essential to note that nowcasting models of unemployment rates using GTS data yield mixed results, varying from one country to another (Pavlicek and Kristoufek, 2015). Moreover, GTS was employed to predict unemployment rates and potentially enhance market trading strategies in the US (Bock, 2018; Caperna *et al.*, 2022). However, other studies show that GTS has a limited contribution to predicting unemployment rates in the US (Nagao *et al.*, 2019). GTS forecasts the Indonesian unemployment rates during the COVID-19 pandemic (Fajar *et al.*, 2020).

Therefore, despite a few mixed outcomes, GTS has proven to enhance forecasting employment growth and labour market conditions substantially (Borup and Schütte, 2022). Based on this understanding, hypotheses regarding Unemployment and its impact on Financial Behaviour are formulated as follows:

***H0**: Unemployment (UNE) does not influence financial behaviour (FB).*

***H2**: Increased Unemployment (UNE) impacts financial behaviour (FB).*

C. Interest Rate (INT)

Central banks like the Federal Reserve (Fed) and the Bank of England adjust interest rates to control inflation and stimulate economic growth. The increase in interest rates cools down the economy while their decrease encourages spending and investment (Papadamou *et al.*, 2020). In particular, the Quantitative Easing (QE) monetary policy in the UK is directed at reducing interest rates in the long term (Lima *et al.*, 2016). However, higher interest rates raise businesses' capital costs, making investing in borrowing less attractive. Consequently, higher rates decrease business investment and economic growth (Alzoubi, 2022). Simultaneously, borrowing is more expensive when interest rates rise, discouraging consumer spending. In turn, it reduces the overall demand in the economy (Grodzicki *et al.*, 2023; Liñares-Zegarra and Wilson, 2014).

Interest rates influence stock prices because interest rates affect the present value of future cash flows. Higher rates decrease the value of the future cash flows companies are expected to generate, influencing their stock prices (Campbell, 2015; Huang *et al.*, 2016). Historical data from China indicates that higher interest rates generally lead to lower stock prices (Gu *et al.*, 2021). Consequently, interest rates can discourage investment in the stock market, impacting overall economic activity. In addition, when a country's interest rates are higher compared to others, it can attract foreign investment seeking better returns. Nevertheless, a stronger currency may render the country's exports less competitive globally (Okechukwu *et al.*, 2019).

Interest rate fluctuations influence savings and debt patterns. Higher rates incentivise saving as the return on savings instruments increases (Felici *et al.*, 2023; Staal, 2023). As a result, financial institutions benefit from higher interest rates, allowing them to charge more for loans and enhancing profitability (Guttman-Kenney *et al.*, 2023). Conversely, indebted households may experience difficulties servicing their debt with rising interest rates (Michail, 2021). However, indebted consumers prioritise debt repayment and adjust spending over saving during such periods, reflecting a risk-averse approach (Xiao *et al.*, 2006).

However, prolonged low-interest rates can adversely affect bank earnings (Borio and Gambacorta, 2017). Therefore, policymakers must carefully manage interest rate adjustments, as increasing rates can control inflation and risk slowing economic growth. The Quantitative Easing (QE) programs reduce long-term interest rates and stimulate economic activity and asset prices (Lima *et al.*, 2016). However, crafting monetary policy requires balancing rate adjustments with other strategies to ensure macroeconomic stability, especially for developing economies (Ha *et al.*, 2022; Khumalo *et al.*, 2017).

Therefore, given the intricate ways interest rates influence financial behaviour (saving, spending, investments), it is crucial to examine how individuals adjust their financial behaviours in response to changes in interest rates and how these adjustments impact their overall financial well-being. The hypotheses are formulated as follows:

H0: *Interest Rate (INT) does not influence financial behaviour (FB).*

H3: *Increased Interest Rate (INT) influences financial behaviour (FB).*

D. Inflation (INF)

Inflation is a multiform trend that varies across sectors and economic agents (Tissot, 2013). Individuals perceive inflation as changing prices of food, goods, and services. The increase in inflation reduces the buying power of consumers; therefore, it negatively impacts consumer spending and saving (Batrancea, 2021; Duca-Radu *et al.*, 2021). A study in Switzerland indicates that immediately following the COVID-19 lockdown, prices decreased by approximately 0.4%, thereby influencing inflation and shaping consumers' long-term expectations (Alvarez and Lein, 2020). During the COVID-19 pandemic, the Indonesian Composite Stock Price Index was significantly impacted by inflation rates (positively) and bank interest rates (negatively), both exerted 94.9% (Nurmasari and Nur'aidawati, 2021).

Investor confidence is due to cost-push inflation, which will cause price rises (Rawlins *et al.*, 1985).

Many countries have their own methods; however, CPI is the most common way to measure inflation in China (Funke *et al.*, 2015), India (Bhattacharya and Kapoor, 2020; Goyal and Parab, 2021; Misra, 2018), and Switzerland (Alvarez and Lein, 2020; Khumalo *et al.*, 2017). Public opinions from Google trends on price dynamics can also forecast the CPI as a proxy for inflation prediction (Li *et al.*, 2015). The study (Li *et al.*, 2015) uses a set of positive and negative keywords ("rise" and "decrease") sub-terms to express sentiment towards food or goods increasing/decreasing in a specific time. Twenty-one keywords were grouped with PCA, and only correlated with CPI were used in the study. In addition, inflation is forecasted using mathematical models (Hassani and Silva, 2018; Jha and Sahu, 2020; Perano *et al.*, 2018) or machine learning (Aras and Lisboa, 2022; Kar, 2021). It was reported that survey measures of inflation expectations are biased and inefficient because not enough data is collected and the perceived variables in the study (Bicchal and Raja Sethu Durai, 2019).

Individuals' perceptions about inflation could influence price changes due to supply and demand and their economic behaviour of saving and spending (Ranyard *et al.*, 2008). Moreover, studies show that inflation expectations are sensitive to news and user sentiment on the internet (Saakshi *et al.*, 2020). For example, political shocks and the Russian invasion increased short-run inflation expectations, heavily affected by the Ukraine war due to fear regarding supply chain effectiveness (Gründler *et al.*, 2022).

Additionally, research suggests a connection between inflation and online searches. A Google Trends index reports a correlation between inflation and consumption (Bleher and Dimpfl, 2021). Google Trends study shows that inflation is coupled with consumer price limits and future expectations (i.e., inflation) (Bleher and Dimpfl, 2021). Their study (Bleher and Dimpfl, 2021) develops an index for GTS prices, which reports a correlation between inflation and consumption (Bleher and Dimpfl, 2021). Simultaneously, when consumers expect inflation to rise, they often forecast lower real consumption growth (D'Acunto *et al.*, 2022). However, they might still maintain a positive outlook towards purchasing durable goods, planning their spending with the anticipation that interest rates will increase (Ryngaert, 2022).

As inflation increases, individuals' savings become more challenging to maintain as their capital value is reduced over time (Vanlaer *et al.*, 2020). Therefore, inflation may also result in poor self-control (Netemeyer *et al.*, 2018) and degraded investment behaviour (Rehman *et al.*, 2019). Consumers may save more to compensate for the decrease in purchasing power. However, there are challenges associated with saving during inflation, and some strategies may be more effective than others, such as prioritising saving in assets that can potentially outpace inflation, such as real estate or certain commodities (Scott *et al.*, 2023). Moreover, investors may hesitate to commit capital to long-term investments if they anticipate inflation eroding potential returns. The variability in inflation rates encourages adaptive financial management, which leads to financial growth (Mandeya and Ho, 2022).

Consequently, rising inflation leads to a perceived decrease in purchasing power among consumers due to the increasing prices of goods and services, influencing their financial behaviour (Batrancea, 2021; Duca-Radu *et al.*, 2021). Subsequently, consumers adjust their saving and spending habits (Ranyard *et al.*, 2008). They might save more to compensate for the declining value of their money (Scott *et al.*, 2023). Additionally, news and online sentiment influence inflation expectations, which might impact long-term investment decisions (Saakshi *et al.*, 2020). For instance, investors may hesitate to commit capital if they anticipate inflation eroding potential returns (Mandeya and Ho, 2022). Consequently, the inflation impact on consumer financial behaviour is hypothesised to:

H0: *Inflation (INF) does not influence financial behaviour (FB).*
H4: *Increased Inflation (INF) influences financial behaviour (FB).*

E. Stock Index (STK)

Various factors influence the stock market, including investor sentiment and information demand.

(1) The Impact of Information Demand on Market Dynamics and Investor Behaviour

The GTS is employed in stock market analysis. It is utilised to forecast and predict stock market movements, which shapes investors' decisions through bibliometric analysis (Jain and Chhabra, 2022). Increased pandemic uncertainty reflected in rising GTS can lead to higher volatility and lower liquidity across the G7 countries (Dash and Maitra, 2022). However, other research suggests combining GTS with historical data and social media information could predict market prices (Pai *et al.*, 2018). A high GTS can be associated with negative stock returns, which indicate a short-term effect (Bijl *et al.*, 2016).

GTS impacts predicting stock market volatility, especially when combined with other macroeconomic variables such as quarterly GDP (Xu *et al.*, 2019). Investor attention, possibly shown in GTS or other social media, increases market volatility in the short term; however, in the long term, investor attention is likely to reverse (Said and Slim, 2022). The investors' attention on the stock market was quantified using a new measure called Increments of Attention Volume for Stocks (IAVS) based on collective attention from stock trading platforms (Yang *et al.*, 2017). The results demonstrated a significant correlation between IAVS and stock market movements in 2014 and 2015, indicating its significance compared to the GTS and Baidu proxy indices.

The literature explores investor behaviour reflected in information demand. Financial news predicts stock market volatility (Atkins *et al.*, 2018). The relationship between investor behaviour and stock market volatility is studied with a focus on the role of information demand (Vlastakis and Markellos, 2012). Unlike traditional research examining news and announcements' impact on the markets, internet search volume surrogates information demand. The findings correlate increased market volatility with increased trading volume of information demand. Additionally, the study finds that investors intensify their information-seeking behaviour when they feel more risk-averse.

A new GTS keyword filtering method based on the trading volume of stocks from the Dow-Jones and NASDAQ100 indices addresses the challenge of noisy tickers (Arditi *et al.*, 2015). This discovery of a correlation between search volume index and trading volume indicates that increased trading and search interest coincide with new information about a company. Hence, the study identifies 13 tickers with a correlation coefficient greater than 0.1. This selective group notably excludes tickers with generic or identical company names. Therefore, the revised focus on these 13 tickers shows that information demand impacts stock market volatility for better risk management and investment decision-making.

(2) Influence of Google Search Volumes on Stock Prices and Returns

Stock market values often correlate positively with the volume of GTS data. However, the strength of this association can vary depending on the specific stock. For instance, the global nature of the NYSE index weakens the correlation between its price and localised search trends (Bozanta *et al.*, 2017). In contrast, the volume of GTS shows a statistically significant positive correlation with major indices like the S&P 500 and Dow Jones while displaying a negative correlation with the volatility index (VIX) (Poutachidou and Papadamou, 2021). The study (Salisu *et al.*, 2021) shows consistent negative correlations of GTS with stock returns across different sectorial stocks. The study (Audrino *et al.*, 2020) shows that while Google is a potential signal for stock market movement (e.g., S&P 500), the signals depend on the sentiment (positive/negative) of the adopted investor attention keywords.

(3) Impact of Global Extreme Events on Stock Market Fluctuations

The effects of pandemics, inflation and disasters are evident in the literature. The average stock prices from 58 nations from five continents dropped 6.57% in the first week and 6.43% in the second week, which indicates a positive relationship between COVID-19 news and the drop in stock price (Arendt and Mestas, 2021). The stock market shows a significant movement of stock liquidity and return with investing behaviour GTS data revealed from the Turkish stock market (Duz Tan, 2022). Therefore, the trader sentiment based on the put-call ratio and trading volume positively correlates with the stock return (Bui and Nguyen, 2019; Vasileiou and Tzanakis, 2022).

Literature reports that inflation impacts stock prices negatively (Upadhyay *et al.*, 2022). However, the literature reports mixed results regarding GTS with stock returns in different countries. The average returns of the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) are positively correlated with GTS (Shen *et al.*, 2019). In India, the study (Jain and Biswal, 2019) shows a bidirectional causality between GTS volume and both the Indian equity index (NIFTY) and the Indian exchange rate against the US dollar. For Indian companies, increased GTS positively relates to future excess stock returns, liquidity, and volatility (Aziz and Ansari, 2021). The study on the Jordan stock market shows that the increase in interest rates or CPI would reduce prices in the stock market by 5% and 1.6%, respectively (Alzoubi, 2022). In Norway, GTS is not correlated with stock returns; however, increased Google searches predict increased volumes (Kim, Lučivjanská, *et al.*, 2019). For Pakistan stock markets, high GTS is associated with high and positive stock returns (Kim, Lučivjanská, *et al.*, 2019). GTS volume data proved to have a bidirectional spillover towards stock market volatility (Škrinjarić and Čižmešija, 2019).

A study for NASDAQ100 and DJIA30 from 1999 to 2016 found that inflation rates negatively impact stock prices, and a positive relationship exists between stock prices and actual interest rates. The fluctuation of interest and inflation rates causes a significant change in stock prices (Eldomiaty *et al.*, 2020). In the Nigeria stock market during the period 1995-2014, it was found that the inflation rate and exchange rates positively impact stock market returns, while interest rates negatively impact stock market returns, resulting in stock market return volatility

(Okechukwu *et al.*, 2019). The US real interest rate negatively impacted S&P 500, DJIA, and NASDAQ stock returns from 2003 to 15 (Huang *et al.*, 2016).

Movements in production and interest rates have a relatively similar effect on stock returns (1969-2012) for the UK, France, and Germany (Peiró, 2016). A strong bidirectional simultaneous interaction exists between the bond interest rate and stock return, especially during the crisis (Jammazi *et al.*, 2017). The stock returns of the Korean and Japanese stock markets are significantly affected by exchange rates and interest rates during volatility. However, during high volatility, the Korean stock market is unaffected by interest or exchange rates, whereas Japanese stock returns are positively correlated with exchange rates and negatively correlated with interest rates (Kim, Kim, *et al.*, 2019).

Liu *et al.* (2020) analyse the effects of disaster events on company stock prices using the GTS and Baidu Index. Their study analyses the relationship between the search volume data and public attention during disasters towards the impact on stock prices. The findings suggest that disaster events have a significant influence on stock prices.

(4) Investor Financial Behaviour and Market Movements

The relationship between financial behaviour and stock market movement is related to investor psychology. For example, investors in Europe favour familiar and well-known stocks during investment decisions, potentially neglecting other crucial factors like market uncertainty (Lobão *et al.*, 2017). Therefore, familiarity and uncertainty are potential drivers of investment decision-making. The relationship between financial behaviour variables and stock indices was analysed, focusing on the political impact on the stock market (Pereira *et al.*, 2018). The study (Pereira *et al.*, 2018) analysed the cross-correlations between the "Donald Trump" occurrence in GTS and stock market volatilities and returns. The study reveals moderate to weak effects with positive correlations on the volatilities of stock exchanges in Mexico, Japan, Australia, and Brazil. However, there were weak to moderate positive effects on the North American stock exchange and a weak negative impact on Mexican stock exchanges. Therefore, the "Trump Effect" is valid in the global financial markets.

Similarly, machine learning models show a relationship between GTS and stock market behaviour (Lobão *et al.*, 2017). Their regression model on 77 stock markets generates an index related to the stock market. The study finds that their index reflects an uncertainty narrative and closely aligns with established measures of market uncertainty. Furthermore, the index approximates and predicts stock market drivers and volatility.

Consequently, there is a positive relationship between GTS and stock returns and liquidity (Adachi *et al.*, 2017), strongly correlated with volume (Takeda and Wakao, 2014), and weakly positive for stock returns. The FTSE 100 experiences increased volatility, affecting financial behaviour, during times of heightened investor attention and volatility, as observed in the short-term component's negative impact (Said and Slim, 2022).

(5) Stock Index Hypothesis

The previous sections show the influence of information demand, Google Trends search volumes, extreme events, and financial behaviour on stock market dynamics. It demonstrates that investor behaviour has a significant role in influencing market volatility and returns. The evidence suggests a complex relationship between stock indices and financial behaviours, warranting further investigation. Given the insights provided, the study proposes the following hypotheses for exploration:

H0: *Stock index (STK) does not influence financial behaviours (FB).*
H5: *Financial behaviours (FB) are influenced by stock index (STK) values.*

F. Uncertainty (UNC)

This analysis illustrates how fluctuating economic conditions influence households' financial behaviour and well-being, including crises, inflation expectations, and pandemics. There are many possible ways of uncertainty, such as market crisis (González-Fernández and González-Velasco, 2018; Luchtenberg and Vu, 2015), inflation expectation (Benk and Gillman, 2023; Ullah *et al.*, 2020), and pandemics (Biswas *et al.*, 2020; Bulog *et al.*, 2022; Nikolopoulos *et al.*, 2021; Yang *et al.*, 2022; Yuesti *et al.*, 2020). For readability, the uncertain construct is divided into subtopics.

(1) Market Crises and Investor Confidence

Households use their skills and knowledge to cope with a changeable financial environment. Financial experience and work status correlate with meeting financial commitments (Mekonen *et al.*, 2022). However, the increased uncertainty about the state of the economy is negatively correlated with investor confidence (Dzielinski, 2012). Hence, bank deposit outflows as a personal financial behaviour are significantly and negatively correlated to financial crisis sentiment due to depositors' fear (Anastasiou and Drakos, 2021; Konstantakis *et al.*, 2021) or financial market uncertainty (Bilgin *et al.*, 2019). Consequently, building an index is a valuable outcome in decision-making. For example, based on a few keywords, the Google Trends index constructs a general stock market-related index that peaked around significant events.

(2) Inflation Expectations

Uncertainty is also due to consumer expectations about inflation. Hostile measures of investor confidence are due to cost-push inflation for land and raw materials that will eventually affect the consumers, or the demand inflation will result in price rises (Benk and Gillman, 2023; Husaini and Lean, 2021; Rawlins *et al.*, 1985). In addition, the inflation expectations due to events such as the Brexit referendum (Breinlich *et al.*, 2022) or COVID-19 (Tran *et al.*, 2022) result in increased consumer financial stress, which will reduce the FWB (Ozyuksel, 2022). Therefore, inflation may result in poor self-control and investment behaviour (Rehman *et al.*, 2019). Literature reported that financial stress negatively impacts the FWB (Fan and Henager, 2022). As a result, income shock had a negative association with FWB and financial and personal resilience, with economic resources showing a stronger positive association with FWB than personal resilience (Kulshreshtha *et al.*, 2023).

(3) Pandemics and Economic Behaviour

Individuals invest in the stock market to enhance their financial well-being. However, increased uncertainty and market instability in volatility, liquidity, and price range may impact financial behaviour and household return over time (Qi *et al.*, 2022). For example, Brexit's impact on the UK and the global financial markets emphasises increased instability and uncertainty (Belke *et al.*, 2018). It affects stock returns, interest rates in the UK, and the economies of Greece, Ireland, Italy, Portugal, and Spain. However, a study shows a limited impact of Brexit on the financial market before the Brexit process; however, markets were stable in the long run during the Brexit process (Breinlich *et al.*, 2018). On the other hand, the US stock market has a significantly positive relationship with GDP and the industrial production index, while it has a negative relationship with unemployment and interest rates (Jareño and Negrut, 2016).

(4) Uncertainty and Financial Behaviour

Several studies use GTS to measure economic policy uncertainty (Weinberg, 2020). The GTS study (Weinberg, 2020) develops an uncertainty index to gauge economic policy uncertainty across major EU economies, which strongly correlates with official financial volatility measures. High GTS is negatively related to stock due to agents' increased uncertainty (Anastasiou and Drakos, 2021). The uncertainty about the economy increases the demand for information and is negatively correlated with measures of investor confidence, resulting in low stock returns in the upcoming week and reversal the following week (Dzielinski, 2012).

There is a close relationship between the well-being of households, financial income, economic behaviour, and property-related assets. Instability and economic turbulence of the economy will result in degrading households' financial well-being due to the economic environment and behaviour factors such as COVID-19 and consumer reflection (Voznyak *et al.*, 2022). There is also a moderate relationship between financial behavioural aspects and socioeconomic conditions (Voznyak *et al.*, 2022). The GTS shows that the COVID-19 pandemic had a direct and indirect hype effect on the stock market, where the hype sometimes recedes from the actual unsolved coronavirus-related issues (Nepp *et al.*, 2022). The uncertainty of the Brexit referendum policy will continue to cause instability in vital financial markets (Belke *et al.*, 2018).

Moreover, investor sentiment, economic factors, and social media influence stock markets (Nti *et al.*, 2020). In addition, the market's volatility is directly impacted by news (Atkins *et al.*, 2018; Lee, 2020). Moreover, the COVID-19 pandemic's higher uncertainty is significantly associated with the drop in China's composite index (Liu *et al.*, 2021). Generally, a decline in well-being in the UK was observed during the lockdown period in March 2020 (Murphy and Elliot, 2022).

(5) Uncertainty Hypothesis

This literature analysis shows how uncertainty stemming from economic downturns, inflation, and global health crises affects financial behaviours and well-being. The evidence underscores strategies for financial uncertainties for informed decision-making during economic turbulence. Therefore, research anticipates a negative relationship between increased uncertainty and financial behaviour as follows:

H0: U*ncertainty (UNC) does not influence financial behaviour (FB).*

H6: *Increased Uncertainty (UNC) impacts financial behaviour (FB).*

3.2. Google Trends Search

Financial Well-being measurement could use the Google Trends Search datasets, particularly keywords to analyse user search patterns (Barros *et al.*, 2019) or a recommender system (Wang *et al.*, 2019). This study uses Google Trends Search (GTS) to develop the Financial Well-Being (FWB) index because of its numerous advantages over traditional survey methods and its practical usage in many research areas. Surveys, while commonly employed in FWB research, suffer from several limitations, including high costs, time-consuming processes, and data that are often outdated by the time it is analysed (Bashir and Qureshi, 2023a; Kaur *et al.*, 2021; Michael Collins and Urban, 2020). Thus, surveys restrict the ability to provide timely actions to decision-makers, especially during periods of significant economic volatility or crisis. On the other hand, GTS utilises real-time data based on human search patterns, allowing it to capture financial behaviours and sentiments as they occur. Therefore, by monitoring search frequencies of concepts that represent Financial Well-Being using GTS, a responsive FWB index can be constructed to adjust to real-time fluctuations in economic variables, which track public interest in monthly intervals. Moreover, the multi-step process of selecting, filtering, and transforming keywords ensures the creation of a robust and precise FWB index.

3.2.1. Google Trends Usage

The Google Trends Search is an online public individual search of user patterns that could be used for analysing various domains (Yakubu and Kwong, 2021). GTS is an easy-to-use tool developed by Google that could be grouped into topics, terms, products, or events (Jun *et al.*, 2018). The search queries are time-series across geographical locations, with a normalised score (0-100) of search volume relative to the popularity within a specific timeframe.

GTS allows for the analysis of search trends from daily to yearly. Therefore, seasonal patterns or sudden spikes due to specific events could be visualised. Moreover, GTS could be used to simultaneously compare the search volume of multiple keywords. Therefore, this feature uncovers correlations between various search terms and time trends. For instance, comparing "inflation" and "gold" could visualise the investor's behaviour during rising inflation. It could also indicate increased investor interest in safe-haven assets as a hedge against inflation risk. In addition, the GTS supports search across countries, regions, or cities. Therefore, researchers use GTS to uncover localised trends or cultural influences.

Several experts adopt GTS analysis: investors, financial analysts, marketing business analysts, content creators, journalists, and marketing managers. The GTS studies investors' behaviour by analysing search trends for specific investment instruments (Wuoristo, 2012). For instance, an increase in searches for "gold" might indicate a potential shift towards safe-haven assets during periods of market uncertainty. Financial analysts utilise the GTS capacity as an early indicator of market sentiment. Marketing business research identifies consumer interest trends to understand customer searches (Ayers *et al.*, 2013; Chumnumpan and Shi, 2019). Content creators utilise GTS to identify popular topics and keywords to enhance content relevance (France *et al.*, 2021).

Moreover, GTS is used by journalists to track topic and story popularity over time (Ørmen, 2016). For example, the analysis for the terms "stock market crash" or "recession" could be used to identify periods of market fear or anxiety. In addition, marketing managers use GTS to assess the effectiveness of their marketing campaigns by tracking search volume for their brand name or product keywords before and after a campaign launch (Demirel, 2020). Therefore, GTS applicability domains ensure its utility for various business operations.

However, GTS has a few limitations. The GTS search volume does not necessarily equate to actual behaviour or investment decisions. Additionally, GTS could be influenced by other factors, such as media coverage or search engine optimisation strategies.

3.2.2. Google Trends Keywords

GTS-related keywords are used to build models; however, the model's accuracy depends on effect keywords. Keyword databases are one of the adopted GTS sources. For example, the OECD Better Life Index Online Database and the American Time Use Survey extract keywords related to job and financial security, leisure determinants, and family life (Algan *et al.*, 2016). In another study, the American Time Use Survey keywords seed Google Correlate to identify associated search terms (Baker and Fradkin, 2017). Furthermore, a list of keywords extracted from a charity short message system was used to determine online salience for charitable donations (Perroni *et al.*, 2022).

The second source or keywords are used in literature based on common sense on a particular topic. For example, predefined lists of cryptocurrencies and their concepts were employed to assess investor attention in cryptocurrency investment (Smales, 2022). Additionally, major US technology brands are used as keywords for GTS to analyse the users' attitudes towards their products (Liu *et al.*, 2021).

3.2.3. Expansion Techniques of Keywords

Keyword expansion is used to get broader data on public interest and sentiment related to specific concepts. The expansion involves various methods for keyword screening and verification. Several studies utilised brainstorming and screening techniques to create a list of keywords pertinent to COVID-19 cases (Amelia and Syakurah, 2020; Jurić, 2021). Furthermore, statistical correlation analysis filters correlated keywords related to the topic of interest (Bustamante *et al.*, 2019). Therefore, GTS-related keyword expansion techniques are instrumental in the prediction. In practice, GTS keywords were used to predict suicide rates in Ireland by combining search query data with unemployment to facilitate risk assessments (Barros *et al.*, 2019).

Additionally, many studies have employed dictionary-based or tool-based keyword expansion to enhance their original keywords. Google's Keyword Planner discovers additional related keywords (Symitsi *et al.*, 2022). For example, expanding "jobs" resulted in 172 terms to forecast employment growth (Borup and Schütte, 2022).

3.2.4. Google Trends Pattern Analysis Methods

The search queries and social media discussions are used as markers of investor sentiment and attention (Gómez *et al.*, 2021). Their trading algorithm (Gómez *et al.*, 2021) searches specific keywords in GTS to make informed decisions in live futures trades based on search patterns of the stock market. Similarly, social media extends keyword search patterns to analyse stock performance (Six *et al.*, 2022), predict exchange rates (Bulut, 2018), predict medical conditions (Liu, Schally, *et al.*, 2022), and forecast consumption rates (Woo and Owen, 2019). Therefore, keyword pattern analysis has a broad potential for various purposes.

The GTS patterns are based on time; therefore, time series analysis models are applicable. Time series models of keywords such as inflation correlate with GTS patterns to analyse the supply of goods or food items within specific periods (Li *et al.*, 2015). Researchers have grouped keywords into patterns using the Principal Component Analysis (PCA) to reduce dimensionality (Mishra *et al.*, 2017; Xiao *et al.*, 2014). PCA clusters keywords based on their strong correlation with key indicators like the Consumer Price Index (CPI) (Chen *et al.*, 2013). The Investor attention was deduced by combining internet search queries and social media discussions to identify the relationship between information demand and volatility of the stock market (Vlastakis and Markellos, 2012)Therefore, the study suggests selecting appropriate keywords and analysing the relevance of search queries of stock market volatility models; therefore, it could enhance risk assessment for better investment decisions.

Accordingly, the GTS encapsulates public concerns about health and the economy (Voukelatou *et al.*, 2021). Consequently, integrating data from news, crowdsourcing, and call detail records provides a comprehensive view of well-being indicators. The flexibility and convenience of web search query data enable the assessment of specific user interests, which contributes to understanding health, employment opportunities, socio-economic progress, safety, and political aspects of well-being. Therefore, GTS is a pattern detector for happiness associated with job security, financial security, leisure determinants and family life (Algan *et al.*, 2016). In addition, the GTS applications extend beyond personal well-being to predict economic indicators like grain prices, stock market, unemployment and job finding (Baker and Fradkin, 2017; Gómez *et al.*, 2021).

Google Trends Search is seen as a utility. It is used to develop a metric for the United States' subjective well-being (Algan *et al.*, 2016). Furthermore, it is used to monitor the impact of sports events like cycling tours on community engagement (Genoe *et al.*, 2021). Furthermore, Google Trends Search analysis is adopted to forecast COVID-19 incidences (Jurić, 2021), analysing trends or cases (Amelia and Syakurah, 2020; Dey *et al.*, 2021; Niu *et al.*, 2021), monitoring pharmaceuticals (Batistic *et al.*, 2021; Bragazzi *et al.*, 2017; Sycinska-Dziarnowska *et al.*, 2021), and investigating medical terminologies (Tejada-Llacsa *et al.*, 2021). Consequently, GTS is useful for analysing economic trends and societal preferences for a better data-driven decision-making utility.

3.3. Source of Keywords and Sampling

Selecting appropriate keywords is crucial to confirm the validity of the outcomes obtained from GTS (Scharkow and Vogelgesang, 2011). Furthermore, selected keywords should not suffer from limitedness or coverage. Therefore, this research's baseline of keyword selection is based on previously collected keywords from the literature or related web.

3.3.1. Source of Keywords

The source of keywords is critical to GTS as it represents developed (Algan *et al.*, 2016) Other alternatives might be dictionaries or website content (Algan *et al.*, 2016). However, the dictionaries could be large enough to select a suitable subset of keywords representing the constructs of interest. On the other hand, websites could be biased towards their developers: often target programs to FWB initiated by governments or other related authorities.

A. Source of Unemployment, Inflation, Interest Rates, Uncertainty, and Stock Index

The gap analysis of this study showed that it could be the first to use GTS as its source of information. The exception in the table was using stock index (STK), ticker names that represent companies because they are country-dependent (Ding and Hou, 2015; Duan *et al.*, 2018; Shen *et al.*, 2019).

Consequently, this study adopts literature keywords because they are validated by academia and consistent with previous studies in the area shown in Table 3.1 for five constructs (Unemployment, Inflation, Interest Rate, Uncertainty, Stock Index).

B. Source of Financial Behaviour and Financial Well-Being

To the best of the author's knowledge, the FB construct has no keywords used in literature; therefore, an alternative was chosen. The source of these variables was The Consumer Financial Protection Bureau (CFPB) glossary, which is similar to dictionaries used in similar studies(Gao *et al.*, 2020). Financial glossaries have been used with other models to enhance comprehension and effective communication of audit risks in financial statement audits (Smith, 2023). The CFPB glossary is essential for high school students as it provides a comprehensive reference of financial terms, enabling them to understand and make informed financial decisions (Mandell, 2008). The use of the CFPB's glossary has several reasons: (1) The CFPB is an authoritative government agency responsible for consumer financial protection with accurate and reliable glossary concepts; (2) The glossary supports financial education in various covering topics, including banking, budgeting, credit, debt, and investing. Therefore, it is considered a valuable resource for individuals' knowledge in topics related to financial well-being; (3) The CFPB maintains its educational resources and updates them regularly. Therefore, the information evolves with new financial concepts and extreme events or programs related to this study concepts, and (4) The CFPB glossary is a reliable governmental entity dedicated to safeguarding consumer financial interests.

Finally, the keywords of FWB were based on the significant constructs of extreme events (Unemployment, Inflation, Interest Rate, Uncertainty, Financial Behaviour) using a machine learning approach similar to FB with the same threshold. As discussed earlier, the FWB is a multifaceted concept; therefore, it is not practical to use a large set of keywords that could cover many dimensions for many reasons: (1) an extensive list of keywords processing is computationally expensive and might have noise keywords that are hard to eliminate statistically, (2) to the author knowledge, no FWB keywords' source exists that could be used directly or customised for extreme events, and (3) The primary objective of this study is to assess the impact of extreme events on FWB. Extreme events such as the financial crisis in 2008 have evidence to affect human Google search behaviour (Gao, Ren and Zhang, 2020).

Therefore, the set of FWB keywords is specifically tailored to include terms directly relevant to extreme events.

Initially, the keywords of FB and their respective definitions are extracted into an Excel file prepared from the original set of terms from the CFPB glossary website. A pre-trained model of Google's Universal Sentence Encoder (GSE) is used to extract word embeddings of each financial term: the concept from the glossary and the definition of financial behaviour (from the literature). The GSE is one of the best machine learning models (Cer, Yang, Kong, Hua, Limtiaco, John, Constant, Guajardo-Cespedes, Yuan, Tar, Sung, *et al.*, 2018). The glossary Excel file containing the keywords is read, and each keyword's definition is embedded into the pre-trained model. This process generates a comprehensive vector that captures the semantic meaning of each concept's definition. Subsequently, the similarity between each keyword's definition and the topic of financial behaviour is assessed, typically employing techniques such as cosine similarity. Then, based on the higher similarity score (>0.6), each keyword is considered as part of the FB list of neglected, as depicted in Figure 3.3.

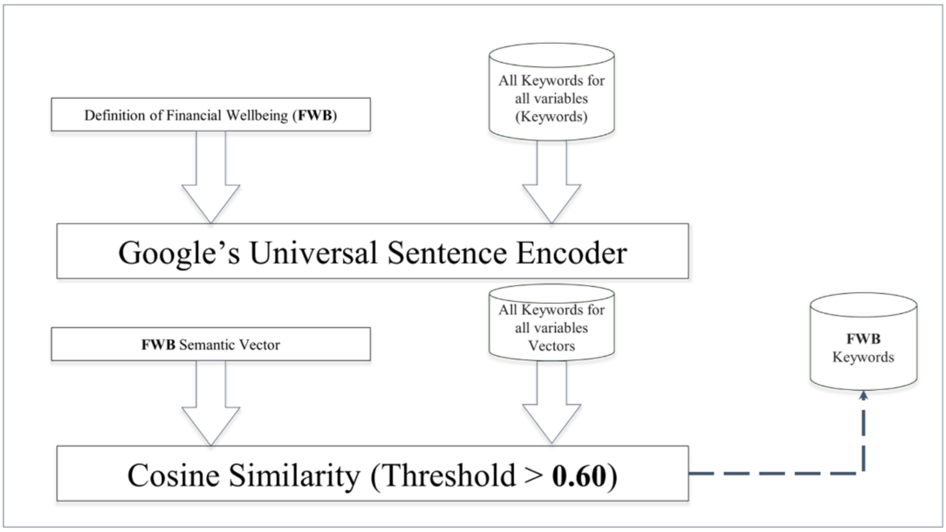


Figure 3.3: Proposed Semantic Similarity of Financial Well-Being and the Consumer Financial Protection Bureau Glossary.

The GSE generates semantic vectors that could be used mathematically to find similarity (often cosine, as shown in the equation (3.1)) similarity. A mathematical calculation is used to find similarities between CFPB terms and the definition of FB. The cosine similarity between -1 and 1 indicates whether terms are related. To this end, a threshold value of 0.60 ensures alignment with the FB construct.

$$\mathrm{Sim}(\mathrm{E\_FB},\ \mathrm{E\_Key}) = (\mathrm{E\_FB} \cdot \mathrm{E\_Key})/(||\mathrm{E\_FB}|| \cdot ||\mathrm{E\_}Key||), \tag{3.1}$$

where the '·' is the dot product, and the $||\mathrm{E\_FB}||, ||\mathrm{E\_}Key||$ denotes are the Euclidean norm (magnitude) of the vectors of word embeddings of FB definition and list of keywords. Note that $\mathrm{Emb\_FB}$, $\mathrm{Emb\_Key}$ are calculated using GSE pre-trained language models with only providing relevant text as input.

Furthermore, extending the methodological rigour to FWB, the approach mirrored the FB construct but had a different focus. Instead of exclusively relying on the CFPB glossary, the study incorporated keywords initially designated for constructs (Unemployment, Inflation, Interest Rate, Uncertainty, Financial Behaviour).

Table 3.1: Keywords Collected from the Literature (Examples).

Construct	Sources	Model	Country
Unemployment	Matias (2013)	Regression	UK
	Borup and Schütte (2022)	Word expansion	US
	McLaren and Shanbhogue (2012)	Regression	UK
	Smith (2016)	Regression	UK
	Simionescu *et al.* (2020)	Regression	UK
	Onorante and Koop (2016)	Time Regression	US
	Perano et al. (2018)	Dynamic model Averaging	UK
Inflation	Bicchal et al. (2019)	Auto regressive	India
	Li *et al.* (2015)	Mixed data sampling	China
	Chen *et al.* (2013)	Granger	China
	Onorante and Koop (2016)	Time Regression	US
	Perano *et al.* (2018)	Dynamic model Averaging	UK
Interest Rate	Weinberg (2020)	ARIMA	Europe
	Onorante and Koop (2016)	Time Regression	US
	Perano *et al.* (2018)	Dynamic model Averaging	UK
Uncertainty	Bilgin *et al.* (2019)	VAR	Turkey
	Maneejuk and Yamaka (2019)	ARMAX	UK, US
	Castelnuovo and Tran (2017)	VAR	US, AUS
Stock Index	Individuals could use ticker names to get information about market trends, stock performance, and economic conditions directly impacting their financial well-being. Therefore, the data enables investors to make informed decisions and capitalize on investment opportunities. An example is the books(Castelnuovo and Tran, 2017) that enhance precision and consistency in GTS analysis. Authentic glossaries are accurate representations that could facilitate reproducible research.		
Financial Well-Being	The source of this construct is taken by considering all keywords in these constructs (UNE, INF, INT, UNC, FB) due to the unavailability of keywords for FWB in the literature. Moreover, the study aims to focus on keywords related to extreme events.		

Note: ARIMA: Autoregressive Integrated Moving Average, ARIMAX: Autoregressive Integrated Moving Average with Explanatory Variable

C. Keywords Expansion (Sampling)

The number of keywords initially collected from the previous section is further expanded to increase the search space of each construct. There are many approaches for expanding keywords, as discussed in Section 2.3.2.C; however, this study uses Google's suggestion.

Google suggestions, known for their utility and effectiveness (Fattahi *et al.*, 2016), offer a dropdown menu with suggested search queries as users begin typing in the Google search bar. These suggestions are based on popular or frequently searched terms, aiding users in completing their queries quickly. The effectiveness of suggested keywords is determined by the relevance between suggested keywords and the relationship between suggested keywords and retrieved items (Fattahi *et al.*, 2016) and user patterns that represent their behaviour (Mccallum and Bury, 2013). The number of keywords that might be considered for each suggestion is not countable; however, the study uses ten top keywords for each recommendation based on the conversion that users often do not look down in the list for other terms that might not be highly relevant. At the end of this process, the sample spans from January 2005 through December 2021 and has a monthly frequency of GTS. GTS frequencies of a keyword ($\mathrm{GTS}_i^t keyword$) for country (i) and time (t) could be expression as in equation (3.2). In the equation, the volume search is ${GTS_V}_i^t Keyword$ is normalized by the volume search ${GTS_V}_i^t$, the $C_i Keyword$ is a constant to normalize the values between 0 and 100.

All keywords for each construct were saved in a separate CSV file. Next, a python script was executed to get the frequency of each keyword per month based on the Pytrends library. The results were saved in a new file for each construct, where rows represented a year and month, and the columns represented each keyword. In contrast, each cell represented the actual GTS frequency extracted from January 2005 until December 2021. Finally, keywords are ready for the next step, as in equation (3.2).

$$GTS_i^t Keyword = \frac{{GTS_V}_i^t Keyword}{{GTS_V}_i^t} \cdot C_i Keyword \, \epsilon [0,100] \qquad (3.2)$$

3.4. Keywords' Filtering and Transformation

The previous section illustrates the list of keywords that might be considered in subsequent steps; however, it is critical to use the keywords that are effective, useful, and significant for the upcoming steps. Time series cleaning and filtering techniques are crucial in extracting high-quality and reliable temporal data, enabling precise analysis, forecasting, and decision-making (Box *et al.*, 2015).

3.4.1. Keywords' Filtering

Effective keyword filtering is a pivotal aspect of building successful models. Relevance filtering directs keywords to the research topic to uphold the data's pertinence (Castelnuovo

and Tran, 2017). For instance, specific country-related keywords, such as "unemployment in US/US unemployment," are excluded from consideration (Perano *et al.*, 2018) to map the context of this study. Simultaneously, excluding noise keywords becomes imperative, as they might introduce distortions during analysis (Algan *et al.*, 2016). Another critical tactic involves time frame selection to capture trends most pertinent to the study's context. However, using prominent Google keywords may result in a model with high explanatory power but low predictive ability, while too many keywords lead to poor predictions (Algan *et al.*, 2016).
Following much previous research, the Geographic Specification was only for the UK, and the Time-Based Filtering includes the period from Jan-2005 until Dec-2021 with monthly data that maps to existing reported data time frames. Despite many methods to group keywords, they were already categorised from the beginning as they were based on the literature. However, within the scope of this study, specific keywords that have null frequencies in GTS due to time constraints are removed because they render them unhelpful and noisy. Specifically, keywords with a similarity threshold of 0.60 with FB definition are considered for FB. This study uses a 0.60 correlation threshold, which was also used by (Chen *et al.*, 2013).

3.4.2. Keywords Transformation

The range for average is between 0 and 100, the range of each keyword search in GTS. The exact formula or algorithm used by Google Trends is proprietary and not publicly disclosed. Some studies use complex normalisation formulas or time series processing (Adu *et al.*, 2023; Huang *et al.*, 2020). However, the search interest in a particular term or topic changes over time compared to the total volume of Google searches. First, the average of nonempty keywords was computed for each construct. For each construct, the average of all keywords is calculated. Compared to studies that use max values (Pratap and Priyaranjan, 2023). , the usage of average is considered. The maximum value tends to consider outliers and variability within the dataset, while the average value provides a measure of central tendency that outliers may affect to a lesser extent. Furthermore, subsequent steps in the transformation include the traditional stationarity tests and analysis for the averaged values of each construct's list of keywords. Any construct: Financial Behaviour (FB), Inflation (Inf), Interest Rate (Int), Uncertainty (Unc), Stock Index (STK), Unemployment (UnE), and Financial Well-being (FWB) is considered a time series as expressed as in equation (3.3).

$$\mathrm{Y_t} = f(\mathrm{Y_{(t-1)}},\ \mathrm{Y_{(t-2)}},\ \mathrm{Y_{(t-p)}}, \varepsilon_t), \mathrm{Y_t} \in [FB, Inf, Int, Unc, STK, UnE, FWB], \qquad (3.3)$$

where, Y_t is the value of the time series at the time t, f is some function representing how the current value Y_t depends on its previous values $Y_{(t-1)} .. Y_{(t-p)}$ and potentially an error term ε_t, and the lagged values of the time series $Y_{(t-1)}$, $Y_{(t-2)}$, $Y_{(t-p)}$ up to some order p, indicating dependencies on past values.

A. Stationarity tests

A stationarity time series data is a statistical property where the statistical properties, such as mean, stay constant throughout the time series (Gimeno *et al.*, 1999). Stationarity tests are commonly used in time series transformations (Li *et al.*, 2015; Nti *et al.*, 2020; Perano *et al.*, 2018).

The stationary checking formally includes examining the properties of the time series data using statistical tests. The existence of a unit root in a time series indicate a non-stationarity series, where processing is required to infer or predict data. Often, the Augmented Dickey-Fuller (ADF) test (Cheung and Lai, 1995; Dickey and Fuller, 1979) is used. Researchers often transform the time series to make it stationary (Agiakloglou and Newbold, 1992).

In some cases, one might use another famous test: the Phillips and Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al.*, 1992). In PP or ADF analysis, autocorrelation (serial correlation) is used to regress the differenced series. While the PP test disregards serial correlation, the ADF employs autoregression to model the error structure. The KPSS test, unlike ADF, focuses on testing the null hypothesis that the data is stationary around a deterministic trend.

This study uses three tests to confirm the constructs' properties.

1) Augmented Dickey-Fuller Test

The ADF test equation is shown in equation (3.4):

$$\Delta Y_t = \alpha + \beta t + \gamma y_{(t-1)} + \delta_1 \Delta y_{(t-1)} + \delta_2 \Delta y_{(t-2)} + \delta_p \Delta y_{(t-p)} + \varepsilon_t \qquad (3.4)$$

where ΔY_t is the first difference of the time series Y_t. α is the constant that is the intercept constant value, βt is the time trend, and ε_t refers to the residual errors. In the null hypothesis ($\text{Ho}: \gamma = 0$, nonstationary data (unit root)) or an alternative hypothesis ($\text{Ho}: \gamma = 0$, stationary time series). The critical values of the t-statistic following (Paparoditis and Politis, 2018) is adopted. If the t-statistic reports less than a critical value, it is concluded that the unit root is not present, and the null hypothesis is rejected.

2) Phillips and Perron Test

The Phillips-Perron (PP) test (Phillips and Perron, 1988) is an alternative stationarity test based on the unit root test. The PP test is based on the equation (3.5).

$$\Delta Y_t = \alpha + \rho y(t-1) + \varepsilon_t \tag{3.5}$$

where ΔY_trepresent the difference of a time series, α is the constant, and ρ is the coefficient of the nonparametric correction and heteroscedasticity in the white noise error term (ε_t). Like in the ADF test, when the null hypothesis ($\mathrm{H0}: \gamma = 0$) is considered, it implies that a unit root exists in the time series, suggesting non-stationarity. If the t-statistic leads to the rejection of $\mathrm{Ho}: \gamma = 0$, then the alternative hypothesis $\mathrm{H1}: \gamma = 0$ is favoured, indicating that the time series is stationary without a unit root.

3) Kwiatkowski-Phillips-Schmidt-Shin Test

In contrast, the KPSS test offers a different perspective on stationarity. The KPSS test accepts or rejects the null hypothesis (stationary around a deterministic trend). Mathematically represented as shown in equation (3.6):

$$\mathrm{Y_t} = \alpha + \delta t + \mathrm{x_t} + \varepsilon_t \tag{3.6}$$

Where $\mathrm{Y_t}$ is the time series under consideration, α is the intercept term, δt represents the deterministic trend component, $\mathrm{x_t}$ captures the stochastic trend or the random walk component and ε_t denotes the error term. Unlike the ADF test, the KPSS test the null hypothesis of existing stationary time series. So, practically, the p-value interpretations are just opposite of each other.

B. Seasonality Adjustments

The seasonal decomposition of the time series data reveals patterns that recur periodically, often annually (Proietti and Pedregal, 2023). Decomposition facilitates anomaly detection and understanding (Wen *et al.*, 2020). A consistent seasonality suggests that certain times of the year are predictably associated with variations in the economic indicators under study, which can influence FWB. If there is a seasonal trend, it must be adjusted to provide a better analysis (Ollech, 2021).

After establishing the presence of seasonality, the study applies the Seasonal Decomposition Procedure Based on LOESS (STL) (JE and Terpenning, 1990)This step isolates the genuine effects of the economic indicators on FWB from the predictable seasonal fluctuations. The adjustment method is guided by the strength and nature of the seasonal patterns identified in the decomposition phase. Therefore, removing seasonal distortions increased the accuracy of FWB indicator relationships.

C. Transformation

In general, a non-stationary time series lacks reliable results; therefore, mathematical calculations are applied to transform the series to be stationary. A commonly employed technique is differencing, which involves taking the difference between consecutive observations. Several other techniques include logarithmic transformations (Abonazel and Abd-Elftah, 2019; Kim, Lučivjanská, *et al.*, 2019) and Box-Cox transformations (Ollech and Bundesbank, 2023). Additionally, more robust models concentrate on time and simplicity, such as the Adaptive DC (Direct Current) technique (Musbah *et al.*, 2023). The DC is an approach that removes non-stationary features from time series data. It transforms the data into a stationary domain. The technique divides the data into groups, calculates the mean of each group, and subtracts the mean from the corresponding points. The Adaptive DC technique achieves stationarity from the first step, while the differencing technique may require multiple steps. Another research has done early transformation of Google data based on a set of keywords and a baseline keyword before removing trending and seasonality(Pratap and Priyaranjan, 2023).

Nevertheless, this study uses differencing. Differencing is preferred in time series analysis because it is a simple and effective method to achieve stationarity by removing trends and making the series more predictable, as shown in (3.7) and (3.8). It is straightforward to interpret and implement, making it a convenient choice. This study prefers the ADF test for its robustness, simplicity, ability to handle time trends, and established statistical power. However, multiple tests can be used for more confidence in the results. While the ADF test might be old, it is commonly used for stationary checking in time series analysis (Benlagha and Hemrit, 2023; Kristoufek, 2013; Park *et al.*, 2017; Salisu *et al.*, 2020; Yu *et al.*, 2019). Moreover, the ADF has been employed in recent studies (Qin *et al.*, 2023; Syamsuddin *et al.*, 2020). Along ADF, PP and KPSS are reported for reference with their leggings. Similarly, the PP and KPSS are used in many studies.

$$\Delta Y_t = Y_t - Y_{t-1}, \tag{3.7}$$

$$\Delta^2 \mathrm{Y}_t = \Delta Y - (Y_{t-1} - Y_{t-2}), \tag{3.8}$$

The implementation of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests was carried out using Python. The ADF test, accessed through the “statsmodels” library in Python, assesses tests for a unit root in a univariate time series. As discussed earlier, the “adfuller” function reports critical values and p-values for result interpretation for null and alternative hypotheses. If the original series fails the ADF, PP, or KPSS test, attempts are made to achieve stationarity through first and second differences. The first difference computes the variance between consecutive observations, and the second difference applies this operation to the first difference series. It is important to note that differencing, being based on successive values, results in a reduction in the number of values.

Next, the study uses a systematic approach to account for seasonality in economic indicators to ascertain their impact on Financial Well-Being (FWB). The process begins with the already tested series and stationary adjusted, followed by a seasonal decomposition. The study employs methods that disaggregate the data into trend, seasonal, and residual components from Python's 'Time Series Analysis' package. The decomposition allows the visual examination of the data to identify and confirm recurring seasonal patterns. Then, seasonality adjustment was carried out to provide better model accuracy.

During validation at a later stage, the values of the constructs are converted to be compatible for comparison with values from the surveys. The collected survey points for FWB were in 2015,2018 with values in the range of 0 to 10; therefore, the FWB is converted to 0 to 10 after processing (dividing by 10).

3.5. Index Construction and Assessment Approach

The study aims to use the FWB index for quick use by individuals or organisations.

3.5.1. Financial Well-Being Building

After acquiring the correlated keywords, the subsequent step involves modelling the FWB conceptual framework proposed in Section 3.13.1. The study adopts the use of Structural Equation Modelling (SEM) due to these reasons: (1) the proposed conceptual framework has the FB as a mediator variable, which is not possible to measure with linear regression models (Hair *et al.*, 2019), (2) SEM has been used in many areas of financial and economic studies (Hair *et al.*, 2019, p. 7) and (3) the capital structure analysis discussed in the literature shows that the Partial Least Squares-Structural Equation Modelling (PLS-SEM) is suitable when it examines multiple indicators for each construct, handles multi-collinearity, and analysis of multiple paths of measurement constructs (Ramli *et al.*, 2018, pp. 200–201). PLS-SEM was used in many studies for FWB indexes for many countries, such as India (Mathew and Kumar, 2022; Sehrawat *et al.*, 2021), Pakistan (Hashmi *et al.*, 2021), the US (Gerrans *et al.*, 2014; Owusu *et al.*, 2023) The Iceland's (Gardarsdóttir and Dittmar, 2012; Powell *et al.*, 2023), and others (Owusu *et al.*, 2023; Rahman *et al.*, 2021).

There are many tools for SEM modelling; however, this study uses SmartPLS (Ringle *et al.*, 2022), a Partial Least Squares-Structural Equation Modelling (PLS-SEM) software (version 4). The software is robust, with an easy-to-use and intuitive graphical user interface. The uses the recommended bootstrapping technique with a sample size of 10,000 (Becker *et al.*, 2023). The bootstrapping process involves generating subsamples at random to increase the number of samples for the SEM model. This study used a bootstrapping of 10,000 to ensure robust analysis. The PLS-SEM is the only way to handle this research's mediator construct (FB).

3.5.2. Partial Least Squares-Structural Equation Modelling

The study proposes to use two models based on the GTS data used to build the FWB index and the second one based on data on various government sites, such as the Office for National Statistics (ONS) data, as a proxy to validate the built FWB. For simplicity, the first model is called the GTS model, and the latter is called the Alternative Proxy model.

A. Google Trends Search Partial Least Squares-Structural Equation Modelling

The GTS model includes the dependent variable FWB, a mediator variable FB, and the independent variables INT, INF, UNC, UNE, and STK. The model could be expressed as in questions (3.9) and (3.10).

$$\mathrm{FB} = \beta 01 + \beta 11 \times \mathrm{Inf} + \beta 21 \times \mathrm{Int} + \beta 31 \times \mathrm{Unc} + \beta 41 \times \mathrm{STK} + \beta 51 \times \mathrm{UnE} + \varepsilon_1, \qquad (3.9)$$

where FB is the financial behaviour (mediator) variable. The Inf, Int, Unc, STK, and UnE . The independent variables are Inflation, Interest Rate, Uncertainty, FTSE 100 (stock index), and unemployment. $\beta 01$ is the intercept of FB varaibel. The $\beta 11$, $\beta 21$, $\beta 31$, $\beta 41$, and $\beta 51$ are the coefficients representing the effects of the respective independent variables on FB. Then, the predicted FWB is as shown in the equation (3.10).

$$\mathrm{FWB} = \beta 02 + \beta 12 \times \mathrm{FB} + \varepsilon_2, \quad (3.10)$$

where $\beta 02$ is the intercept of the outcome-dependent variable FWB, and $\beta 12$ is a coefficient representing the effect of FB on FWB.

B. Alternative Proxy Partial Least Squares-Structural Equation Modelling Model

In time series analysis, alternative approaches can be employed when no data for the dependent variable is available. One option is to use proxy variables (Atalay and Edwards, 2022; Wooldridge, 2009) that closely relate to the dependent variable, serving as substitutes to analyse its relationship with independent variables. This approach is valid as actual variables data is not reported with enough data. It also serves as a cornerstone to validate the original proposed model. The best-performing (GTS) model is compared with actual proxy data (i.e., the Alternative Proxy model). The raw data for the seven variables is selected from various government websites, shown in Table 3.2 Data is published on different websites in the UK. Having an alternative model enables the author to validate the proposed GTS model.

Three key considerations guided the selection of proxy variables in the Alternative Proxy model. Firstly, each proxy was carefully chosen based on its alignment with the definition of the respective construct, as discussed in Section 2.5, ensuring that the proxies accurately capture the essence of the constructs under investigation. Secondly, the robust and reliable source of the published data further validated the selection, as data from authoritative governmental sources enhances the credibility and transparency of the study. Lastly, the consistency of each proxy with the specific research objectives ensured that they directly contributed to the study's focus, enhancing the precision and relevance of the analysis. Therefore, such considerations contribute to the validity and reliability of the chosen proxy variables.

Table 3.3: Real Published Data for Study Variables.

Variable	Data Source
Financial Well-Being	UK Household Income and Whole Economy Production and Income
Financial Behaviour	UK Household Spending
Unemployment	The UK unemployment information on the labour market.
Interest Rates	Bank of England's official rate history
Inflation	CPI annual rate.
Stock Index	The Financial Times Stock Exchange 100 Index
Uncertainty	UK Monthly EPU Index

3.5.3. Financial Well-Being Index

The FWB index is a graphical representation of the FWB compared to actual survey values. The FWB index could represent numbers during the study inclusion period (2005-2021). The average FWB projected from the previous model in Section 3.1 is used to compare survey values reported by the UK government. Next, the errors between predicted values with GTS and survey values are compared.

Each model that satisfies the p-value and R-squared metrics was used to predict the FWB values. However, the FWB actual survey scores are only reported in three periods as it takes time to collect and analyse data. The actual FWB scores reported in the surveys are for the years 2015 (Money Advice Service, 2019), 2018 (Money Advice Service, 2020), and 2021(on hold). According to the financial well-being report, the FWB for 2015 has a mean of 7.5 and 6.8 for 2018, as shown in the UK Data Service website. The absolute error between the model's predictions and the survey scores is reported.

Table 3.4: Descriptive analysis Formulas

Method	Description
Observation	Total number of rows in each time frame.
Mean	Determines the central tendency of constructs.
Standard Deviation	Measures the constructs discrepancies.
Skewness	Indicates the symmetry of data; $Sk = 0$ suggests normal distribution, $Sk > 0$ implies positive skewness, and $Sk < 0$ implies negative skewness.
Kurtosis	Reveals data shape and departure from normal distribution; $K > 3$ is leptokurtic, $K < 3$ is platykurtic, and $K = 3$ is mesokurtic.
Max and Min	Identifies the highest and lowest data values, indicating volatility in index returns.
Pearson Correlation	Measures the linear relationship between two variables: ranges from perfect negative correlation (-1) to perfect positive correlation (1), with 0 indicating no correlation.

3.5.4. Assessment Approach

This section discusses the approach used to assess the proposed models and the statistics metrics used to describe the models.

A. Descriptive Analysis Approach

The study uses a graphical analysis of constructs, showing each variable as related to the dependent variable FWB. Graphical analysis would show the FWB as compared to the survey values. Moreover, all variables would be compared to their associated proxies used in the Alternative Proxy model. This research focused on how extreme events, encompassing natural and human-made crises, can significantly impact FWB. The next chapter will detail the metrics of studied data, including the ones presented in Table 3.4.

B. Model Assessment and Comparison Approach

The two models (GTS and the Alternative Proxy model) undergo multiple statistical tests, including hypotheses testing for direct and indirect effects with a p-value cutoff of 0.05. Additionally, this study evaluates the model's explanatory power using R-squared values, following (Hair Jr *et al.*, 2021) to assess a model's explanatory power (the proportion of variance in the dependent variable explained by the independent variables, as described in the equation (3.11). Furthermore, this study reports the F-Square for interpreting the effect sizes of each construct, in line with (Cohen, 2013), as explained in the equation (3.12).

Moreover, this study assesses multicollinearity via the Variance Inflation Factor (VIF), as shown in the equation (3.13), to maintain predictor variables' independence and thus ensure parameter estimates' stability. This study follows the recommended threshold of 5 (Diamantopoulos and Siguaw, 2006).

This study has gone a step ahead by validating the proposed model's predictor ability using the Cross-validated Predictive Ability Test (CVPAT) as suggested by (Sharma *et al.*, 2023). Therefore, GTS and the Alternative Proxy model results are testified for robust assessment and generalizability on any potential new data. The CVPAT implementation of SmartPLS (the PLSpredict results report) used out-of-sample prediction techniques utilizing k-fold cross-validation (standard 10) and repetitions for stable estimates of predictive performance. The test assesses whether the PLS-SEM's average loss is significantly lower than benchmark models' average loss values, indicating better predictive capabilities.

$$R^2 = 1 - SSR/SST, \tag{3.11}$$

where SSR is the sum of residual errors and SST is the total sum of squares.

$$F^2 = R^2/(1 - R^2), \tag{3.12}$$

$$VIF = 1/(1 - R_i^2), \tag{3.13}$$

where VIF is calculated with a standard threshold of 5.

3.6. Chapter Summary

This chapter describes building and validating Financial Well-being (FWB) based on Google Trends Search (GTS) data and FWB-published data (called the Alternative Proxy model) on government authorities' websites. Both models are based on the relationship between these constructs: Financial Behaviour (FB), Inflation (INF), Interest Rate (INT), Uncertainty (Unc), Stock Index (STK), Unemployment (UNE), and Financial Well-being (FWB). Consequently, the hypothesis development shows that Financial behaviour could be influenced positively by an increased Stock Index and negatively by Unemployment, Interest Rate, Inflation, and Uncertainty. However, Financial Behaviour is hypothesised to increase the dependent variable in both ways. The GTS model follows these steps: identifying source keywords, selecting and filtering keywords, index construction, and FWB validation. The study uses literature to source keywords. The keywords are expanded with Google suggestions and filtered to extract high-quality data. Stationarity tests, including Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). Non-stationarity tests are transformed (with differencing) until they become stationary. After subsequent seasonality adjustment, the study builds the FWB index construction using Structural Equation Modelling (SEM). The GTS and the Alternative Proxy model are validated for reliability using the Cross-validated Predictive Ability Test (CVPAT). Finally, the FWB index is constructed graphically and validated against actual survey scores.

CHAPTER 4: RESULTS AND ANALYSIS

This chapter provides a detailed analysis of the results, which includes graphical analysis, descriptive statistics, exploratory analysis, and empirical validation of the proposed model presented in Chapter 3. The GTS data used for this study is a sample of the monthly frequency of keywords from January 2005 through December 2021. The proposed methodology proposed in the previous chapter is followed in steps: Step 1 (Section 3.1), Step 2 (Section 3.2), Step 3 (Section 3.3). Following Step 1, the source of keywords is shown in Table 4.1 (1,465 keywords). Next, following Step 2, the filtering and transformation of keywords, the results are shown in Table 4.2.

Table 4.1: Total Initial Keywords for Each Construct.

Variable	Code	Approach of Collection	Total Keywords
Unemployment	UNE	Literature	89
Inflation	INF	Literature	197
Interest Rate	INT	Literature	51
Stock Index	STK	The study uses the FTSE 100. The Financial Times Stock Exchange 100 Index (FTSE 100) includes companies from various categories of industries, including technology, retail, automotive, telecommunications, utilities, finance, mining, pharmaceuticals, and more. Individuals could use ticker names to get information about market trends, stock performance, and economic conditions directly impacting their financial well-being. Therefore, the data enables investors to make informed decisions and capitalise on investment opportunities.	101
Uncertainty	UNC	Literature	98
Financial Behaviour	FB	The Consumer Financial Protection Bureau's (CFPB) glossary uses a machine learning approach.	598 (later filtered to 140 keywords)
Financial Wellbeing	FWB	All keywords in these constructs (UNE, INF, INT, UNC, FB) were filtered with a machine learning approach.	2,412 (later filtered to 789)
Total Initial Keywords			1,465

Table 4.2: Keywords after expansion with Google Suggestion.

Construct	Code	Before Expansion and Cleaning	After Expansion and Cleaning
Financial Wellbeing	FWB	2,412*	789+
Financial Behaviour	FB	598	140+
Unemployment	UNE	89	459
Interest Rate	INT	51	242
Inflation	INF	197	690
Stock Index	STK	101	101
Uncertainty	UNC	98	322
Total Keywords After Expansion		3,546	2,743

*Keywords depend on the previous set of keywords (FB, UNE, INT, INF, UNC)
+Keywords within a threshold of 0.6 similarity with definitions of FWB or FB were only included.

4.1. Graphical Analysis

This section visually presents the time trends of various constructs and their relationships with FWB. Graphical analysis illustrates time trends of various constructs and their relationships to identify potential trends and fluctuations, especially during extreme events. Figure 4.1 shows a declining trend from 2005 to 2008, followed by a general upward trend from 2008 onwards, with fluctuation during extreme events. Figure 4.2 shows trends of other constructs. The financial Behaviour displays a similar trend. The Unemployment construct exhibits different trends, influenced notably by extreme events; it is downward from 2005 to 2008 and from 2013 to the end of 2021, with an increase observed between these periods, aligning with the aftermath of the 2008 financial crisis and the subsequent recovery phase. The Interest Rate construct shows a significant decline from 2005 to a bottoming out around 2011, then fluctuates with relative steadiness till 2021.

The Inflation construct follows a decline from 2005 to 2008, then fluctuates with a slight upward trend from 2011 to 2021, with more variability during extreme events. The figure indicates that inflation does not simply exhibit a slight upward trend but rather a series of peaks and troughs that correlate with these extreme events. The Stock Market Index, represented by FTSE, experiences volatility around extreme events but maintains a generally upward trajectory, which is especially noticeable from 2013 to 2021. Additionally, the Uncertainty construct appears to trend with the FTSE, with both experiencing similar fluctuations, except those of the Uncertainty construct had little volatility between 2008 and 2010. Analysing each construct alongside FWB, it can be inferred that FB and FWB move in the same direction with a slight increase in their difference after 2011, suggesting that high positive financial behaviour could lead to increased FWB, as shown in Figure 4.3. Similar relationships are observed for Unemployment, Interest Rate, and Inflation, shown in the exact figure. Notably, the gap between Interest Rate and FWB increased after 2020. However, FTSE and Uncertainty move in tandem with FWB, with a gap in the performance of each construct, indicating a potential low impact on FWB.

As discussed in Chapter 2, extreme events are the cornerstone for the deviation of FWB. The impact of extreme events on the examined constructs is outlined as follows. The Global Financial Crisis (2008-2009) and the Eurozone debt crisis (2011) correspond with spikes in FWB and FB at the beginning of each event, indicating increased search behaviour or concern. The UNE is sensitive to all extreme events with spikes. During the financial crisis, there was a decrease in INT followed by a spike in 2009, contributing to a reduction in INF. The COVID-19 Pandemic (2020-2021) also shows an increase in INT rates as the Oil Price Crash (2016) aligns with reverse fluctuating INF rates, as reflected in the data.

The analysis of Interest Rate and Inflation shows some contracting results. The financial crisis (2008-2009) precipitated a sharp increase in INT, followed by a recovery period. The Eurozone debt crisis (2011-2012) resulted in a decline, then a sharp increase, before levelling off. The Olympics (2012-2013) had a negligible impact on INT. During the COVID-19 Pandemic (2020-2021), there was a decrease in INT, with a notable recovery peak in early 2021. The oil price fluctuations (2016-2017) caused a brief dip in INT, with recovery observed in mid-2016.

On the other hand, the Eurozone debt crisis, the oil price crash, and COVID-19 led to an initial increase in INF, followed by a sharp decline in the mid-period and then a recovery. The Olympics did not significantly affect INF. The COVID-19 Pandemic initially caused an increase in INF, with a peak in early 2020, aligning with a subsequent recovery period. The oil price shifts increased INF, followed by a marked decrease in late 2016 before recovery.

The stock market FTSE 100 index and Uncertainty variables trend in tandem. The Global Financial Crisis (2008-2009) and the Oil Price Crash (2016) caused significant fluctuations in the FTSE. The Eurozone debt crisis (2011) and the Olympics (2012-2013) also negatively affected the FTSE. During the COVID-19 pandemic and mid-2020, a decline followed by a sharp recovery in the FTSE was observed, which is indicative of market resilience similar to the uncertainty index.

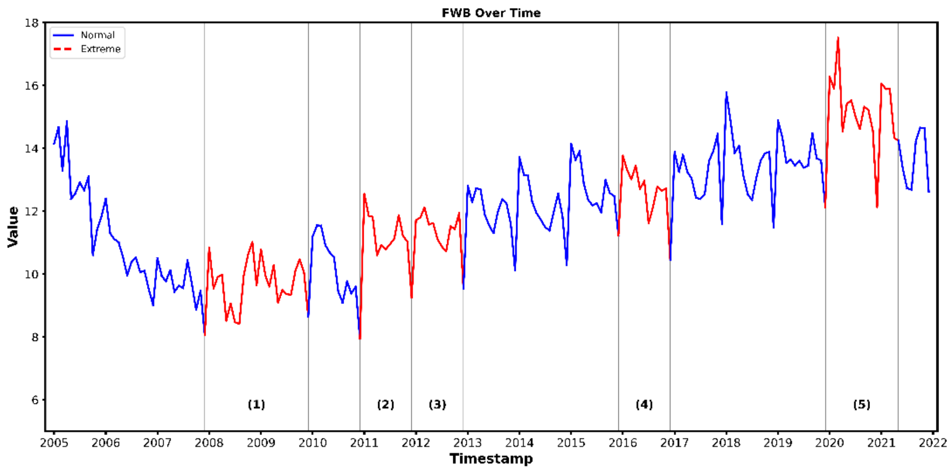
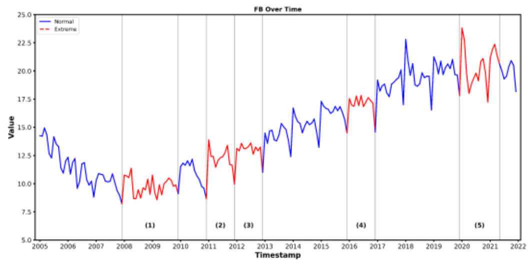
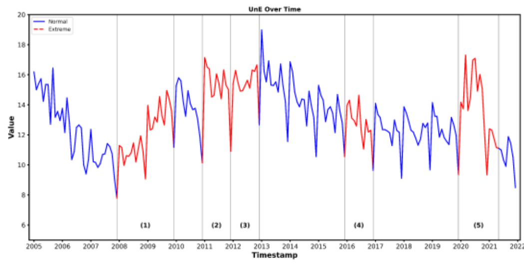


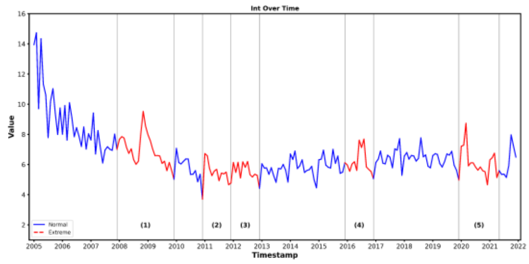
Figure 4.1: Financial Well-Being 2005-2021- (1) Financial Crisis, (2) Eurozone Debt Crisis, (3) London Olympics, (4) Oil Price Crash, (5) COVID-19 Pandemic.



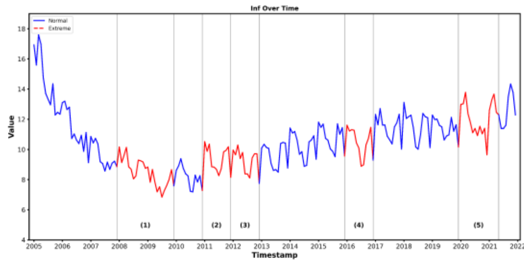
Financial Behaviour



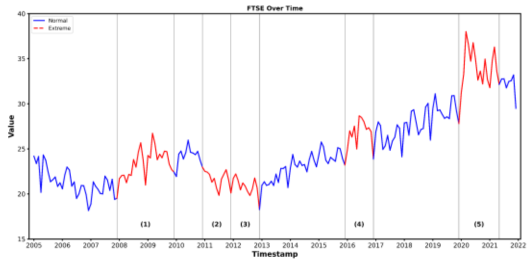
Unemployment



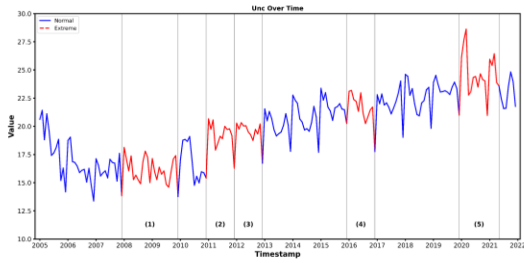
Interest Rate



Inflation

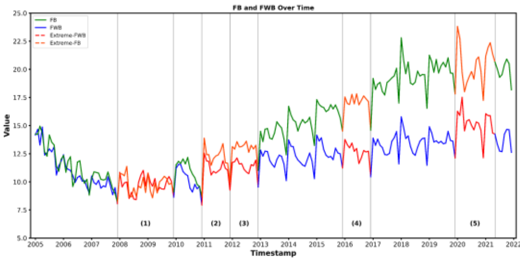


Stock Index

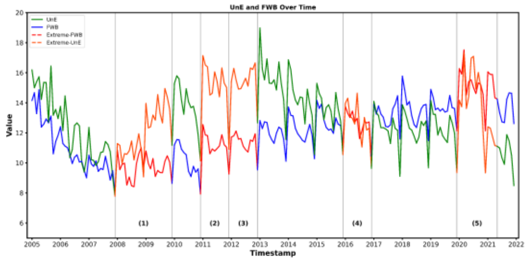


Uncertainty

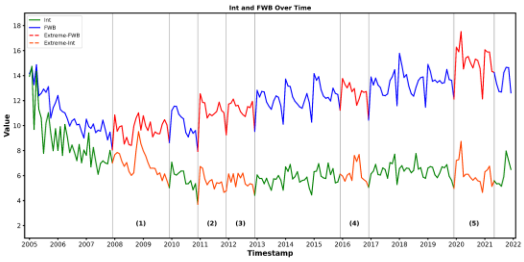
Figure 4.2: Mediator and Independent Variables 2005-2021- (1) Financial Crisis, (2) Eurozone Debt Crisis, (3) London Olympics, (4) Oil Price Crash, (5) COVID-19 Pandemic.



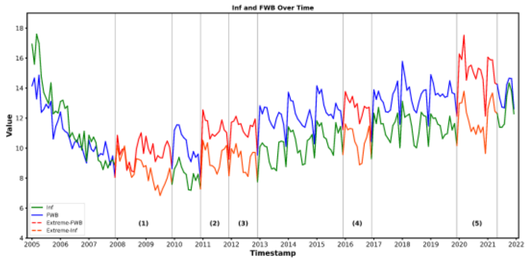
Financial Well-Being with Financial Behaviour



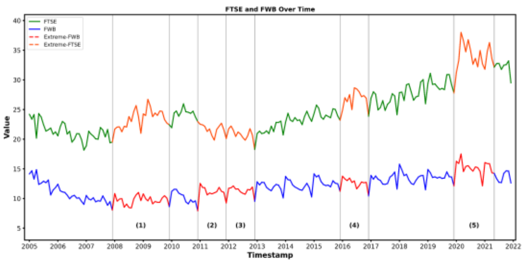
Financial Well-Being with Unemployment



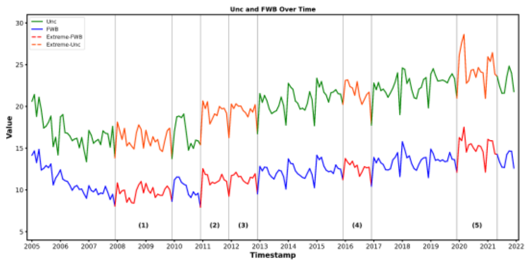
Financial Well-Being with Interest Rate



Financial Well-Being with Inflation



Financial Well-Being with Stock Index



Financial Well-Being with Uncertainty

Figure 4.3: Relationship between Financial Well-Being and Other Constructs-- (1) Financial Crisis, (2) Eurozone Debt Crisis, (3) London Olympics, (4) Oil Price Crash, (5) COVID-19 Pandemic.

4.2. Descriptive Statistics

Table 4.3 shows the economic variables throughout the sample period. The FWB has a mean value of 12.02%, extending from 7.94% to 17.52%. Financial Behaviour follows, exhibiting a mean of 14.80% and a broader range from 8.22% to 23.82%. Unemployment shows a mean value of 13.15%, fluctuating between 7.79% and 18.98%. The Interest Rate has the lowest mean of 6.61% and demonstrates substantial variability within a range of 3.71% to 14.73%. Inflation maintains an average rate of 10.53%, with its values spanning from 6.83% to 17.59%. The Stock Index has the highest mean of 24.95% and varies from 18.17% to 38.01%. Lastly, Uncertainty has a mean value of 19.91% and a range from 13.39% to 28.63%.

Table 4.4 shows the Pearson correlation coefficients between variables and their significance levels. The FWB significantly correlates with Financial Behaviour, Inflation, Stock Index, and Uncertainty. However, it has an insignificant relationship with INT and a relatively low correlation with UNE. Conversely, FB's relationship with Unemployment is not statistically significant and negatively correlated with Interest Rate (INT) (-0.1402, $p = 0.045$). Therefore, the correlation between INT and FB suggests that interest rate fluctuations may slightly influence financial behaviours. FB also correlates positively with Inflation (0.5725, $p < 0.01$) and more intensely with Stock Index (0.7815, $p < 0.01$), implying that financial behaviours are reflective of inflation levels and stock market performance. INT shows a weak negative correlation with Stock Index (-0.1311, $p < 0.1$), indicating that stock market performance may decline as interest rates increase. Meanwhile, INF and UNC show moderate to strong positive correlations with Stock Index (0.409, $p < 0.01$ and 0.574, $p < 0.01$, respectively). In addition, Stock Index has a strong positive correlation with Uncertainty (0.7306, $p < 0.01$), reinforcing the relationship between market performance and economic uncertainty. These findings elucidate the complex web of relationships between individual financial metrics and broader economic indicators, underscoring the importance of a comprehensive approach to economic analysis.

Table 4.3: Data Statistics for Google Trends Search.

	Obs.	Mean	Min	Max	Dev.	Skew.	Kurt.
Financial Wellbeing	204	12.02	7.94	17.52	1.89	0.16	-0.47
Financial Behaviour	204	14.80	8.22	23.82	3.98	0.20	-1.18
Unemployment	204	13.15	7.79	18.98	2.09	0.00	-0.54
Interest Rate	204	6.61	3.71	14.73	1.58	2.29	7.83
Inflation	204	10.53	6.83	17.59	1.88	0.71	1.14
Stock Index	204	24.95	18.17	38.01	4.20	0.98	0.35
Uncertainty	204	19.91	13.39	28.63	3.13	-0.01	-0.70

Table 4.4: Correlation between Constructs in the Google Trends Search Model.

	1	2	3	4	5	6	7
1. Financial Wellbeing	1						
2. Financial Behaviour	0.900***	1					
3. Unemployment	0.332***	0.079	1				
4. Interest Rate	0.105	-0.140**	-0.006	1			
5. Inflation	0.742***	0.572***	0.117*	0.550***	1		
6. Stock Index	0.723***	0.781***	-0.056	-0.131*	0.409***	1	
7. Uncertainty	0.935***	0.928***	0.265***	-0.114	0.574***	0.730***	1

Note: *** p<0.01, ** p<0.05, * p<0.1

4.3. Exploratory Analysis

Explanatory analysis in economics aims to understand and explain the causal relationships between economic variables (Cleff, 2014). The study analyses relations between variables as an economic phenomenon by integrating the detailed Pearson correlation coefficients with the trend and stationary analyses (Phillips, 2005).

4.3.1. Trend Analysis

Trend components of a time series could be visualised with smoothing data. Moving averages reduce short-term fluctuations and highlight longer-term trends by averaging data points within a specified time to reduce irregularities (Zakamulin and Giner, 2020). After smoothing the data with moving averages (period =12), the study analyses the study's variables using trend analysis and scatter plots. The analysis of the trend component shows the series' long-term directions (Stock and Watson, 1988) and could be used to study independent cyclical fluctuations (Stock, 1994). Additionally, regression analysis with time as an independent variable can be employed (Mills and Markellos, 2008) to ascertain the trend's statistical significance and slope(Dewick, 2022). It could be used to study the discernment of secular growth or decline within the data to understand financial development assessments and policy decisions.

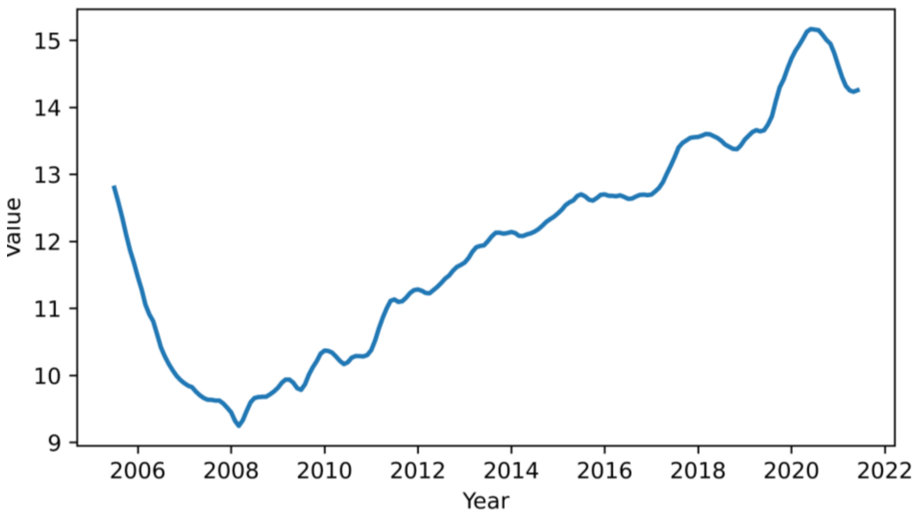


Figure 4.4: Trends Components of Financial Well-Being.

A. Trend Components

The time series trend components of the dependent and independent variables are depicted in figures (Figure 4.4 and Figure 4.5, respectively). The trends demonstrate financial trends and their response to extreme economic events. The upward trend in the FWB and Financial Behaviour variables suggests a growing economy; however, this ascent is interspersed with significant volatility corresponding to economic events. For example, the Global Financial

Crisis of 2008-2009 is sharp dips in figure trends reflecting mirrored trends due to economic distress. Conversely, the London Olympics 2012 reflects a noticeable boost of FWB as a positive economic stimulus. The ongoing climb in FWB and FB series also implies a recovery post-crisis, with intermittent dips, such as the slight decline during the Eurozone debt crisis in 2011 and the drop during the 2016 oil price crash. However, FB and FWB generally increased sharply after 2011 due to many reasons after recovery, such as the digital technology and the rise of fintech companies making financial services more accessible (Arner *et al.*, 2015; Gabor and Brooks, 2020), government significant change in financial regulation and policy aimed at encouraging responsible lending, borrowing, and investing (Dolan *et al.*, 2012).

The unemployment variable showcases the vulnerability of the labour market to external shocks and the corresponding economic resilience. Unemployment is reflected by a stark increase during the Global Financial Crisis due to its immediate and severe impact on employment. The series followed by a period of recovery until the subsequent peak in 2011 of the Eurozone debt crisis, indicating the interconnectivity with broader European financial health. A significant spike in 2020 indicates the profound impact of the COVID-19 pandemic that led to an abrupt and steep rise in unemployment.

Interest rates and Inflation variables show varied patterns. The decline in interest rates post-2008 reflects a monetary response to stimulate the recession-hit economy. Next, it was stabilised as the economy entered a period of relative calm. Inflation trends initially downwards, indicating adequate inflation controls. However, it starts gradually rising, potentially due to the gradual strengthening of the economy and commodity price shifts.

The trend analysis of the Stock Index and the Uncertainty reveals synchronous patterns. Both variables demonstrate an overarching upward trend, indicative of a robust stock market and escalating economic uncertainty over the long term. The Stock Index retreated due to the Global Financial Crisis and the 2016 oil price crash. However, it bounces back during the 2012 London Olympics. The Uncertainty mirrors previous movements relatively; however, it got an acute ascent amid the COVID-19 pandemic, which also catalysed a dramatic rise in unemployment as the interplay with the market performance.

Figure 4.5: Trends Components of Independent Variables.

B. Constructs Relationships (Scatter Plots)

Scatter plots are used to understand how variables are related and have been widely used time series techniques for a long time (Hyndman and Athanasopoulos, 2018; Mills, 1990). The scatter plots are depicted in Figure 4.6. The scatter plots and regression analysis for FB versus FWB demonstrate a notable positive linear relationship, with a regression coefficient of 0.43. This relationship is reinforced by the Pearson correlation coefficient of 0.900***, suggesting a strong and significant connection where improved FB is associated with substantial increases in FWB. A positive but weak relationship exists between UNE and FWB. The regression coefficient of 0.30 is coupled with a Pearson correlation of 0.332***, confirming that the degree of impact is weak. The scatter plot of Interest Rate suggests a weak positive relationship (0.13 coefficient), which aligns with the Pearson correlation coefficient, which is non-significant (0.105). This discrepancy could indicate that the direct impact of interest rates on FWB is limited or overshadowed by other economic factors. The INF construct shows a significant positive relationship with FWB, with a regression coefficient of 0.74 and a Pearson correlation of 0.742***. This relationship indicates that inflation levels substantially correlate with FWB, yet other variables could influence this correlation, highlighting the complex nature of inflation's impact on financial well-being.

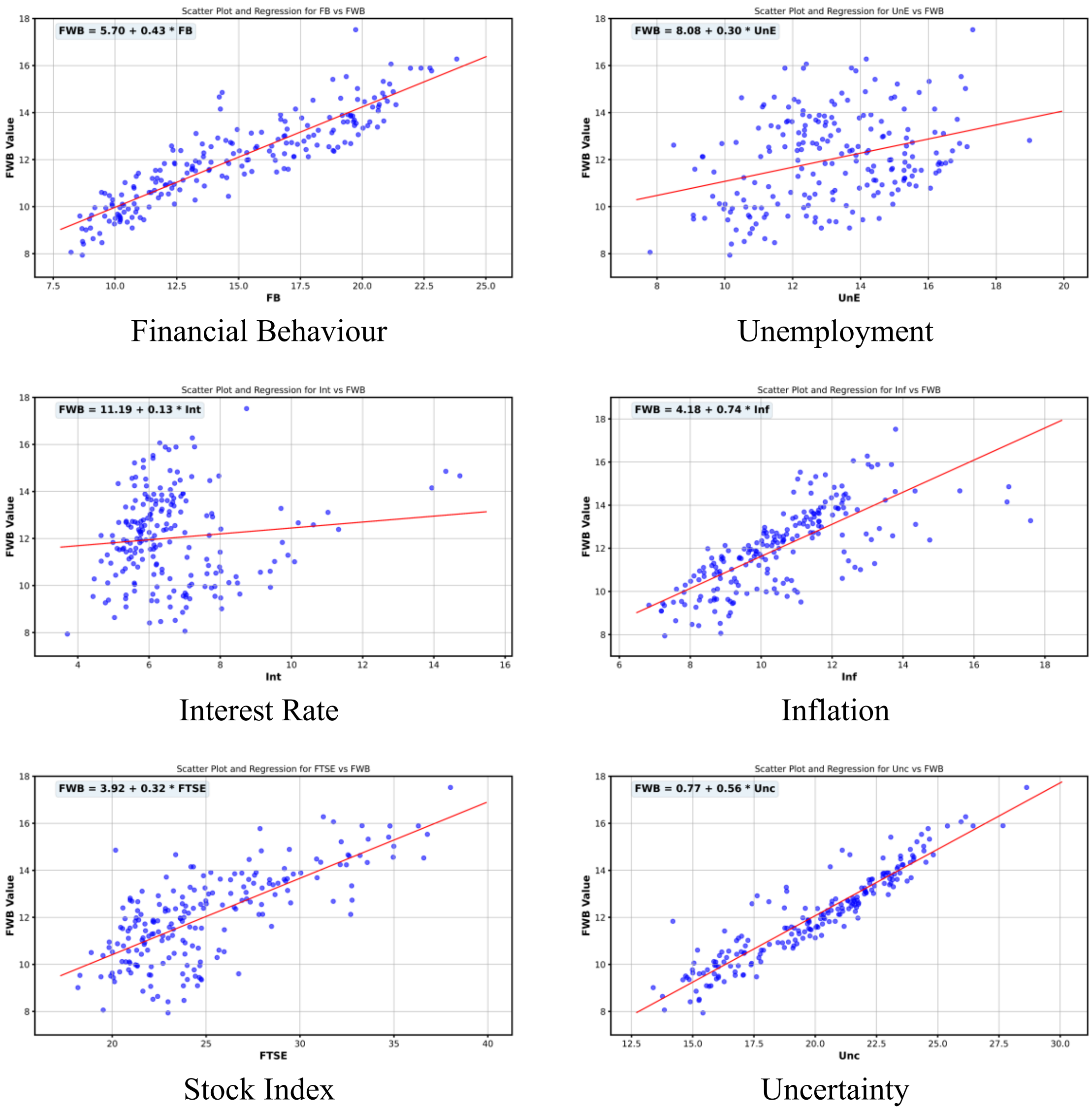


Figure 4.6: Linear Relationship Between Constructs and Financial Well-Being.

As measured by the Stock Index, the Stock Market's performance exhibits a positive correlation with FWB, evidenced by a regression coefficient of 0.32 and a Pearson correlation of 0.723***. The relationship suggests that a rising stock market is associated with increased FWB, likely reflecting the broader wealth effect and the perceived financial security during bullish market conditions (Baker and Wurgler, 2007; Barber and Odean, 2013). Uncertainty is strongly correlated with FWB, demonstrated by a regression coefficient of 0.56 and a very high Pearson correlation of 0.935***. This unexpectedly strong positive correlation may suggest that during times of uncertainty, individuals engage in financial behaviours that inadvertently bolster their financial well-being.

4.3.2. Stationarity and Seasonality

The independent and the dependent variables plotted in the previous section show a trend and possible seasonality. Therefore, trends and seasonality should be adjusted to provide better analysis (Ollech, 2021).

A. Stationarity Testing

This study adopts tests of the Augmented Dickey-Fuller (ADF) test (Cheung and Lai, 1995; Dickey and Fuller, 1979), Phillips-Perron (PP) test (Phillips and Perron, 1988) and the Kwiatkowski-Phillips-Schmidt-Shin (Kwiatkowski *et al.*, 1992).

The analysis employs a significance level of 0.05 (alpha = 0.05) to assess stationarity, a common practice in many domains (Kim and Choi, 2017). The time series were initially evaluated for stationarity using the ADF, PP, and KPSS tests. If any time series was found non-stationary for any test, a differencing operation, commonly employed in transformation, was applied to all variables to ensure consistency (Liu, Wu, *et al.*, 2022). A second differencing operation was performed if the first differencing operation did not result in a stationary series (Hans Franses and Taylor, 2000). Consequently, all series were differenced twice to achieve stationarity.

The stationarity assessment for constructs is shown in Table 4.3. The ADF test points to non-stationarity for FWB, yet the PP test deems it stationary; however, the KPSS test suggests non-stationarity at a 5% level. FB and UNE exhibit non-stationarity in the ADF tests but stationarity in the PP tests, with the KPSS tests confirming non-stationarity. INF and FTSE follow a similar pattern of non-stationarity in the ADF tests and stationarity in the PP tests, but KPSS tests indicate non-stationarity. Conversely, INT is stationary according to the ADF and PP tests, with KPSS tests suggesting non-stationarity. UNC's ADF test indicates non-stationarity, unlike stationarity suggested by the PP and KPSS tests. The discrepancy among the results of ADF, PP, and KPSS tests highlighted the need to ascertain the stationarity of economic time series for robust econometric modelling and informed policymaking.

Table 4.5: Stationarity test for The Google Trends Search Model After Differencing.

Variable	Augmented Dickey-Fuller t-stat	Phillips-Perron t-stat	Kwiatkowski-Phillips-Schmidt-Shin t-stat
Financial Wellbeing	-4.105***	-35.04***	0.070*
Financial Behaviour	-4.551***	-33.21***	0.410***
Unemployment	-4.569***	-33.71***	0.047*
Interest Rate	-4.802***	-7.866***	0.057*
Inflation	-13.26***	-87.59***	0.052*
Stock Index	-4.547***	-22.66***	0.141*
Uncertainty	-6.064***	-35.92***	0.090*

Note: *** p<0.01, ** p<0.05, * p<0.1

The post-differencing stationarity tests for the GTS model are outlined in Table 4.5. After differencing, all variables demonstrate strong stationarity at the 1% significance level in the ADF and PP tests. The KPSS test, however, shows that FB is not stationary. The Financial Well-Being, Unemployment, Interest Rate, Inflation, Stock Index, and Uncertainty show that KPSS does not reject the null hypothesis of stationarity at the 5% level, indicating they are trend stationary. The stationarity of the variables is shown in Figure 4.7 and Figure 4.8.

The KPSS test rejected the null hypothesis of stationarity for the FB series at the 5% level, indicating non-stationarity post-differencing. The analysis showed that the KPSS was coupled with persistent ‘Interpolation Warnings’ and challenges in selecting an appropriate number of lags (lags) for FB, which raises reliability for the reported p-value (according to Python's out-of-the-box implementation of KPSS). Moreover, the potential structural breaks in the FB series further complicated the situation as the KPSS test assumes a consistent structure throughout the series. These issues led to the consideration of alternative methods for assessing stationarity. The Range Unit-Root (RUR) test (Aparicio *et al.*, 2006) Also, similar errors were found for all variables except FB and FTSE. The Zivot-Andrew’s test (Zivot and Andrews, 2002; Baum, 2015) was inconsistent with the ADF and PP tests. Therefore, only ADF and PP tests were used for the FB series.

B. Seasonal Decomposition

Although extreme events remain beyond individual control, systematic seasonality analysis through time series studies can provide predictive capabilities. The seasonal decomposition of the time series data reveals patterns that recur periodically, often annually (Proietti and Pedregal, 2023). Decomposition facilitates anomaly detection and understanding (Wen *et al.*, 2020). A consistent seasonality suggests that certain times of the year are predictably associated with variations in the economic indicators under study, which can influence FWB.

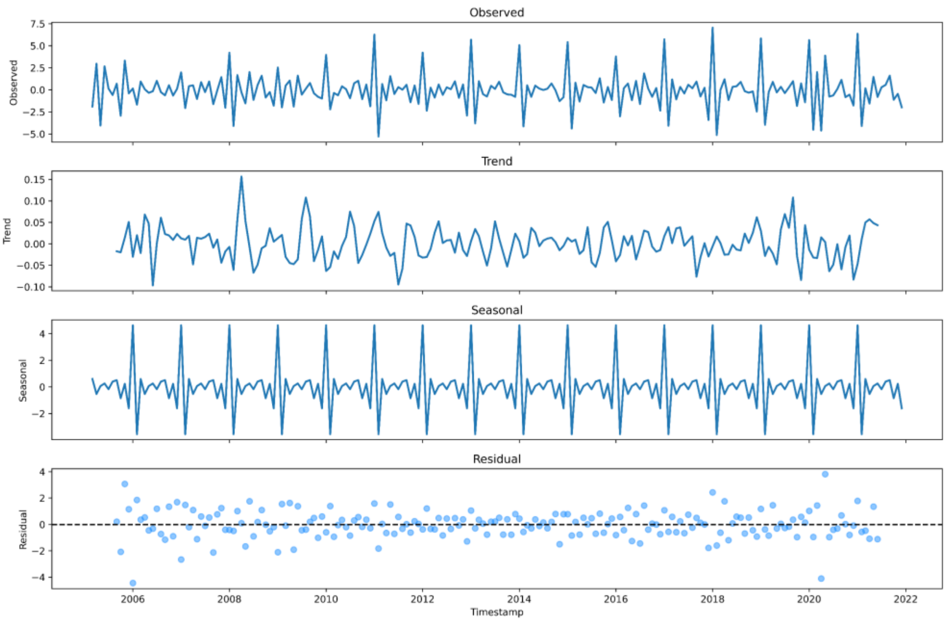
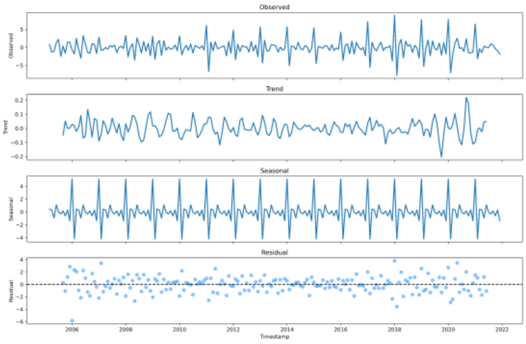
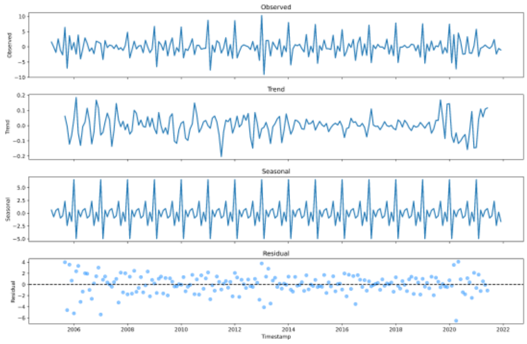


Figure 4.7: Seasonal Decomposition of Financial Well-Being After Stationary Differencing.

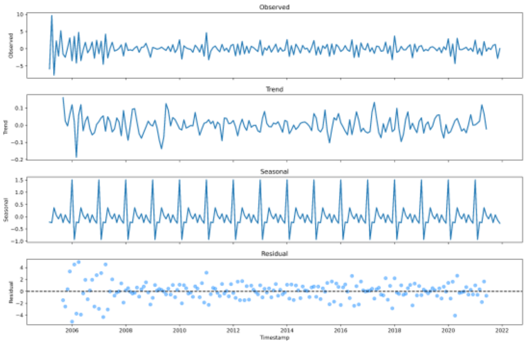
A yearly seasonal pattern for FB may emerge due to holiday spending surges or tax season individuals engage more actively with their finances. A cyclical FB underscores the importance of timing in financial planning and policy implementation, as there are discernible periods when financial behaviours are more pronounced. The UNE trends are likely to mirror the economic cycles of hiring, which can fluctuate seasonally due to factors like seasonal industries requiring more labour at specific times of the year or retail sectors hiring temporarily during the holiday season (Marshall, 1999). INT patterns may reflect central bank policy changes, which often follow a regular schedule, or could be influenced by seasonal variations in borrowing, where certain times of the year see an uptick in loans and mortgages due to consumer behaviour or business investment cycles.



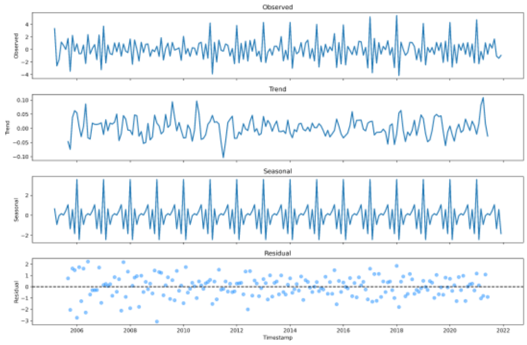
Financial Behaviour



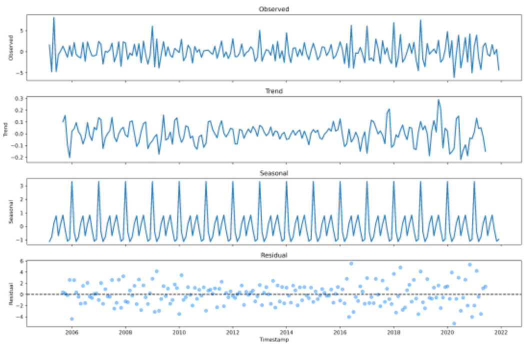
Unemployment



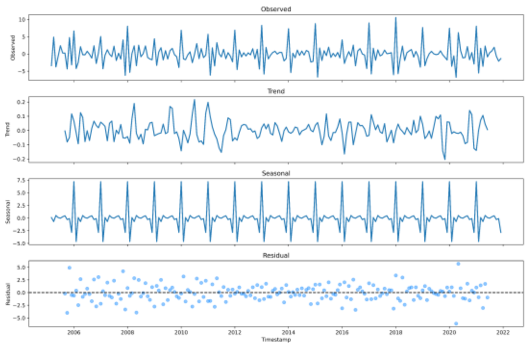
Interest Rate



Inflation



Stock Index



Uncertainty

Figure 4.8: Seasonal Decomposition of Independent Variables After Differencing.

Inflation seasonality might be driven by fluctuations in demand for goods and services throughout the year. The INF seasonality could be influenced by holiday seasons, energy price cycles, or agricultural production patterns, leading to periodic inflation spikes or dips. The FTSE index is correlated to investor behaviour, especially in seasons of the "January effect" trends (Haug and Hirschey, 2006; Moller and Zilca, 2008). During January, stock prices tend to increase following the sell-off in December or summer due to waning trading volumes. Lastly, UNC exhibits seasonal patterns corresponding to economic policy announcements or regular fiscal reports that can cause market sentiment and economic outlook fluctuations.

Therefore, FWB ebbs and flows with independent variables. Consequently, recognising seasonality can be invaluable in crafting financial well-being strategies.

The seasonality decomposition of this study of independent variables (IV): Financial Behaviour (FB), Unemployment (UNE), Interest Rate (INT), Inflation (INF), Stock Index (STK, FTSE), and Uncertainty (UNC) reveals consistent patterns that will result in fluctuations of FWB. This study's autocorrelation analysis comprehends the relationships within the constructs and their lagged time gaps to identify potential patterns and cyclic behaviours. The Autocorrelation Function (ACF) measures the correlation between a construct data and its lagged values. At the same time, the Partial Autocorrelation Function (PACF) is calculated after removing the effect of intermediate lag values, which could detect direct relationships between specific time points. The ACF and PACF are commonly used in economics to discover seasonality and autocorrelation between lags (Wang and Yildirim, 2022). The figures for financial well-being and its independent variables are shown in (Figure 4.9 and Figure 4.10).

The ACF figures show negative ACF values at specific lags of 11 and 13, which could signal irregular cyclical behaviours or the presence of external influences that disrupt the usual seasonal patterns. For instance, an 11-month lag could be associated with delayed effects of policy changes or market adjustments that do not conform to the standard calendar year. Similarly, a 13-month lag might hint at an annual event's influence that shifts slightly each year, such as a fiscal policy that varies in its implementation date. Figures suggest that the upward movement in FWB is particularly notable around the start of the year, which could be reflective of the "January effect," a phenomenon where financial market gains are often seen in January (Haug and Hirschey, 2006; Moller and Zilca, 2008). Moreover, extreme events explained earlier show their direct effect on figures trends.

Applying ACF and PACF analyses to the financial series yields a spectrum of seasonality and correlation strengths, each necessitating a tailored analytical approach. The findings emphasise the importance of model selection that is cognizant of the underlying seasonal characteristics, ensuring that economic forecasting and modelling are robust and contextually informed.

Consequently, seasonal patterns align with increased economic activity following the holiday or year-end financial adjustments and new investment inflows. Therefore, further adjustments are carried out to provide a better, reliable series.

The trend and seasonal decomposition have several relations with previous descriptive discussions. For example, the scatter plot for FB vs FWB reveals a strong positive linear relationship, suggesting that FWB tends to increase as financial behaviours improve or become more prevalent (Figure 4.3). The findings are corroborated by the high Pearson correlation coefficient observed, which implies that interventions to enhance financial behaviours might positively influence overall financial well-being.

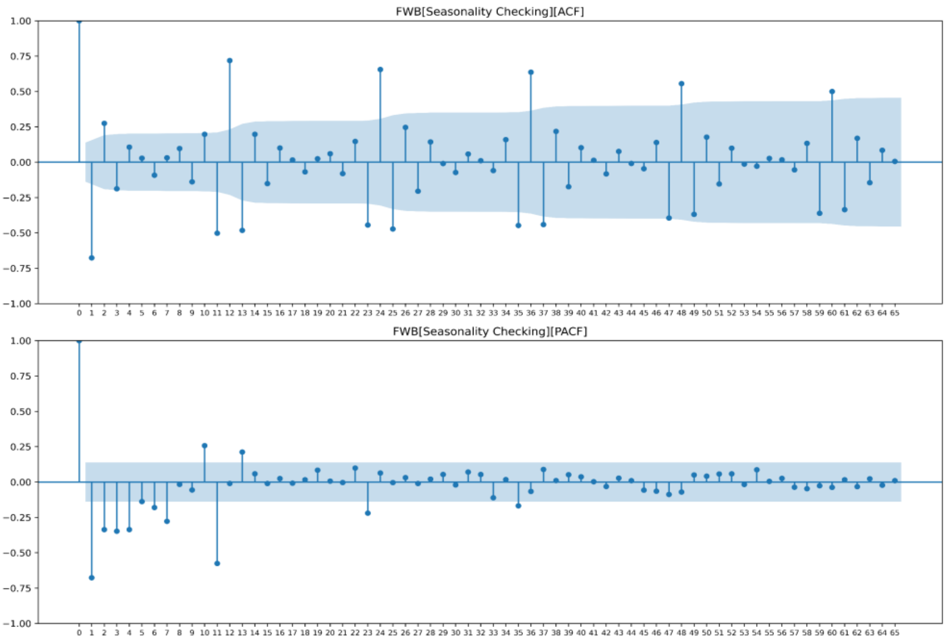


Figure 4.9: The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of Financial Well-Being (Before Adjustment).

All variables exhibit strong seasonality, with ACF values exceeding 0.5, suggesting the presence of regular seasonality, particularly at 12-month intervals. On the other hand, the FTSE presents weak seasonality, indicated by ACF values below 0.3. However, the figures indicate little evidence for a correlation between PACF values.

The ACF and PACF plots for Unemployment, Interest Rates, and Stock indexes structure a temporal behaviour. The unemployment contract's ACF plot tails off, which indicates a trend affecting unemployment rather than clear-cut seasonality. In contrast, the Interest Rate ACF plot shows distinct periodic spikes suggesting seasonal variations, potentially due to economic policies or market expectations over time. Finally, the Stock Index's ACF plot displays a less definitive seasonal pattern due to irregular economic events or annual reports influencing the stock market.

C. Seasonality Adjustment

Seasonality adjustments are used to create a new series that eliminates seasonal effects (Lin *et al.*, 2020). Seasonal adjustment is applied to consistent patterns over set intervals, such as months or quarters, to filter out periodic fluctuations and cycles inherent in the data.

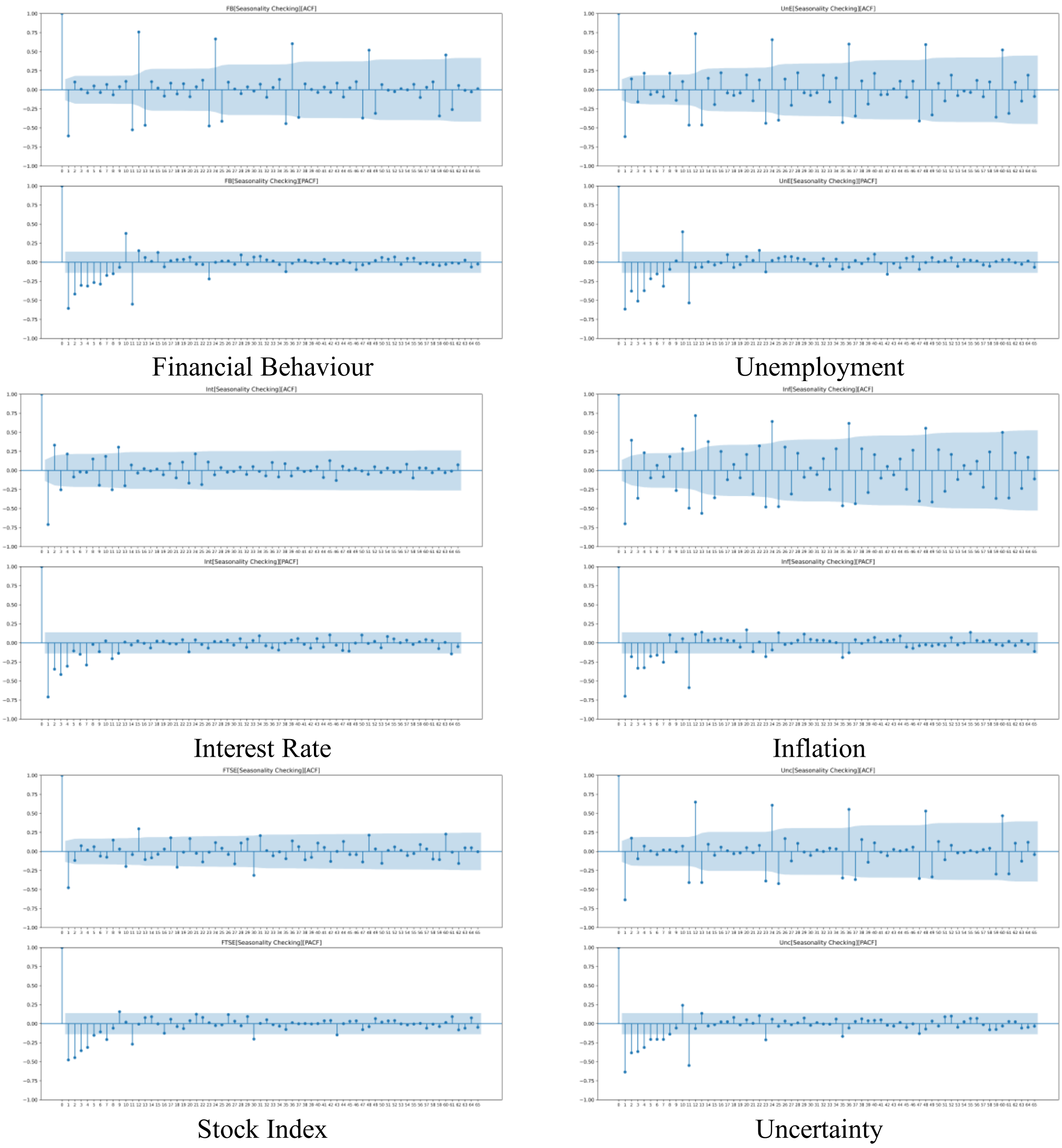


Figure 4.10: The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of Independent Variables (Before Adjustment).

The study performs such adjustments (using the Python ‘statsmodels’ package) on monthly data by adopting an additive model, a common approach when seasonal variations are relatively constant over time, irrespective of the level of the time series. The package extracts the 12-month seasonal component inherent in the data and subtracts this component to eliminate predictable seasonal variations. Following the stationarity adjustment discussed in the results in Table 4.5, the study carried out a seasonality adjustment, as shown in (Figure 4.11 and Figure 4.12) for FWB and Independent Variables, respectively.

As a result, selecting an appropriate seasonal period is crucial for accurate decomposition and forecasting. The studies try different seasonality adjustment patterns of 11,12 and 13 as indicated by ACF and PACF plots. Through this investigative process, 12 months emerges as the most fitting for seasonal adjustment. This preference is based on several critical insights gleaned from the data. Primarily, the 12-month period aligns closely with the annual economic cycle, capturing the comprehensive effects of significant economic events such as budgetary enactments, regular market cycles, and policy implementations that characteristically influence FWB. Furthermore, while the autocorrelation analysis detected lingering effects of certain events up to 13 months, these are generally considered outliers rather than the norm. Therefore, the 12-month adjustment period, the seasonal model, is more likely to mirror the authentic economic rhythms.

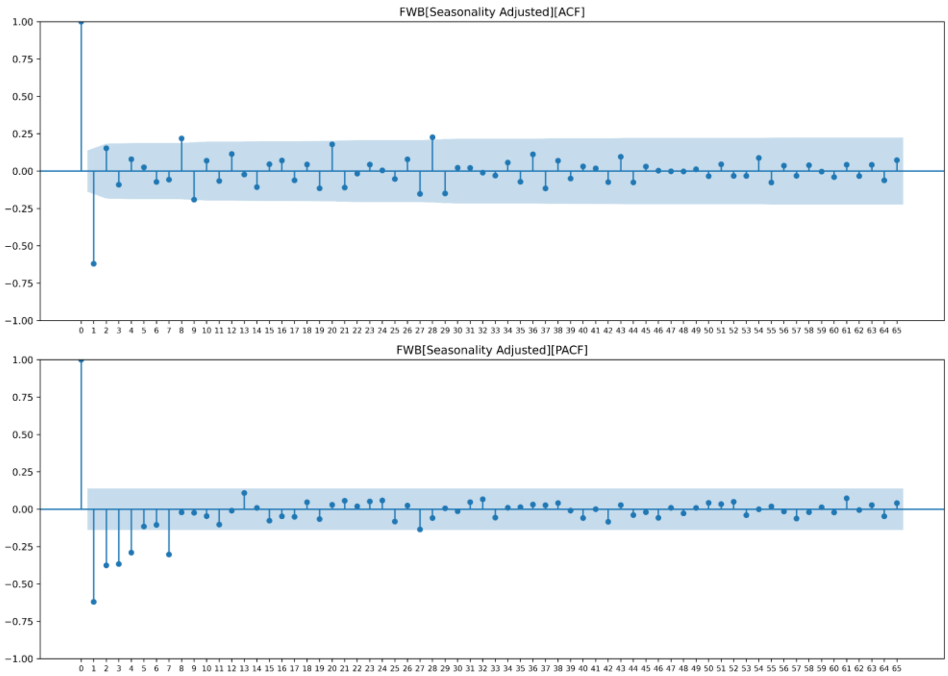


Figure 4.11: Financial Well-Being Seasonal Adjustment (period =12).

Furthermore, applying standard seasonal decomposition and Seasonal-Trend Decomposition using LOESS (STL)(JE and Terpenning, 1990) reaffirmed a seasonal pattern over a 12-month cycle. The STL decomposition method isolates the seasonal component while considering irregularities and trends. Consequently, adopting a 12-month cycle for seasonal adjustment emerges as a representative approach for analysing the relationship between financial constructs and FWB remains attuned to real-world economic rhythms.

Therefore, a 12-month cycle captures extended economic cycles and the overlapping effects of extreme events. Hence, the period adjustment enhances the model's explanatory power and aligns with real-world economic phenomena. The new series that passes through the transformations is presented in Figure 4.13 and Figure 4.14.

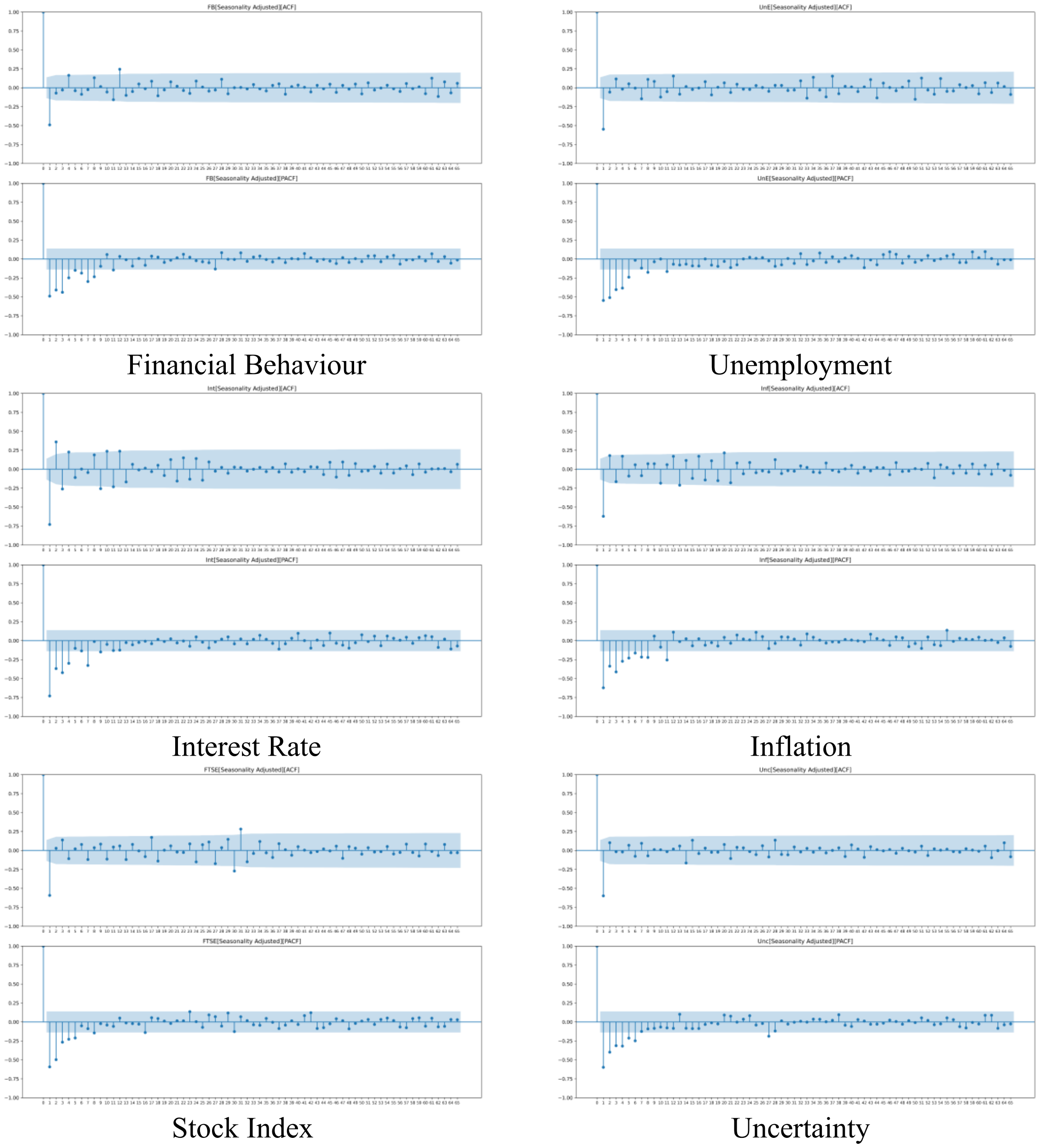


Figure 4.12: Seasonal Adjustment of Independent Variables (period=12).

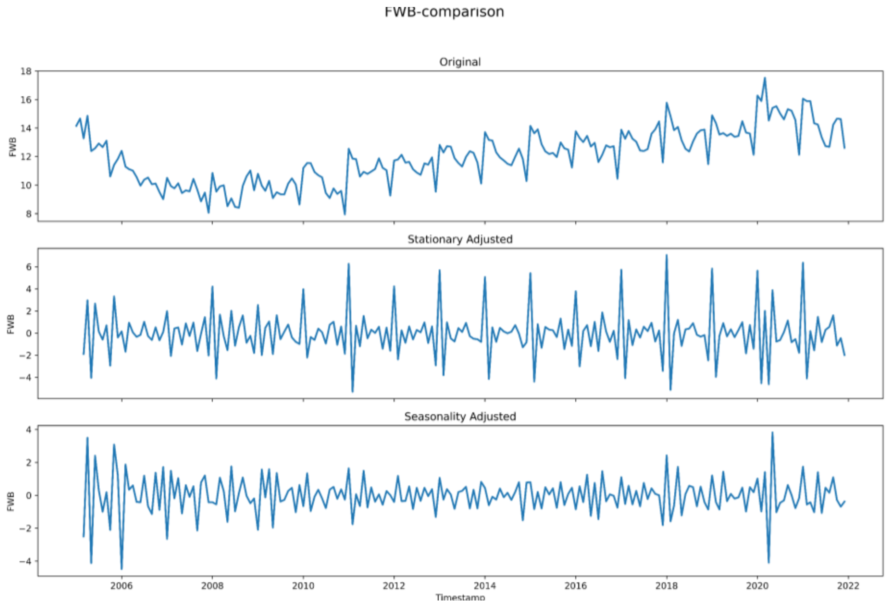
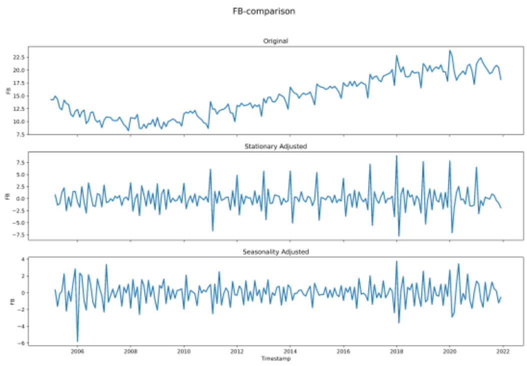


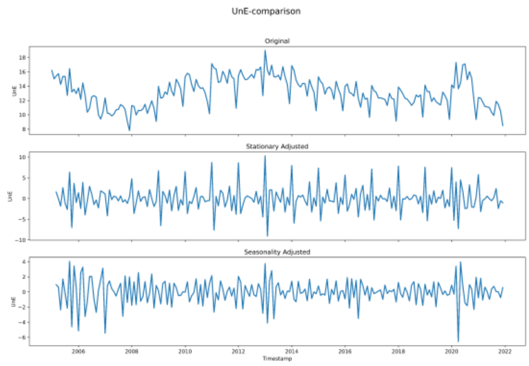
Figure 4.13: Financial Well-Being over the Transformation Process.

4.4. Empirical Validation

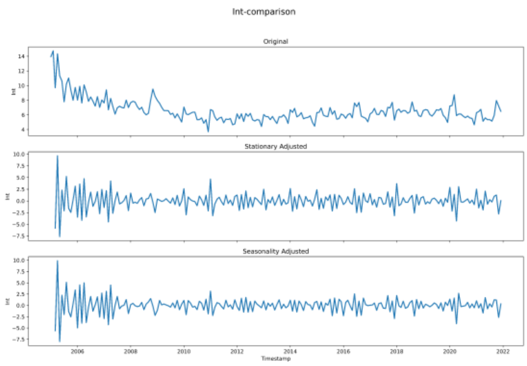
In time series analysis, alternative approaches can be employed when no data for the dependent variable is available. One option is to use proxy variables (Atalay and Edwards, 2022; Wooldridge, 2009) that closely relate to the dependent variable, serving as substitutes to analyse its relationship with independent variables. The GTS time series is compared with actual proxy data (called the Alternative Proxy model). The raw data for the seven variables is selected from various government websites, as shown in Table 3.2. The two models (GTS vs the Alternative Proxy model) are visually compared for each concept. Next, the Mean Absolute Error (MAE) compares the errors between the GTS and the Alternative Proxy model. MAE is a statistical method that represents the positive magnitude between actual and predictive values (Karunasingha, 2022), and it is also used in time series forecasting models (Chen and Lee, 2015). Therefore, the Alternative Proxy model is assumed to have the actual values, while the GTS has the predictive ones.



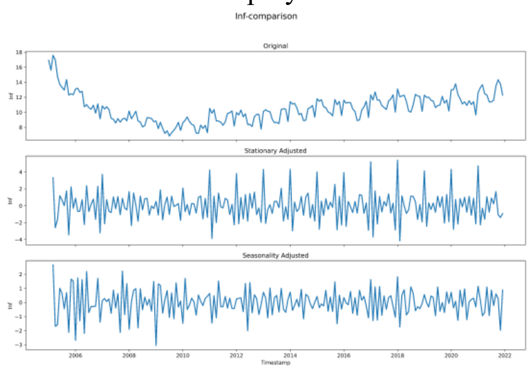
Financial Behaviour



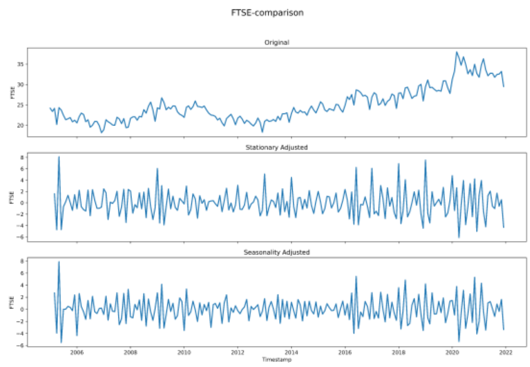
Unemployment



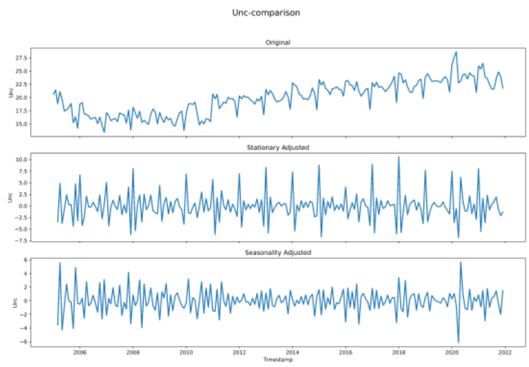
Interest Rate



Inflation



Stock Index



Uncertainty

Figure 4.14: Variables Over Transformation Process.

According to the collected data in Table 3.2, not all constructs have a clear-cut proxy or limited data. Missing data is a crucial aspect of imputing values that are not available (Ribeiro and Castro, 2022). Therefore, the study depends on data available from 2008. Also, when data was unavailable for a few months, months were imputed with the same values as the previous ones (Phan *et al.*, 2020). In this approach, the filling of missing data ensures that data is filled with data instead of being scattered and avoids any potential incorrect values that the government did not report (Ribeiro and Castro, 2022).

It is assumed that the individuals will depend on the latest values, such as interest rate, even if it spans a few months. Moreover, the data were normalized for each construct k, for each data point ($\text{Norm\_Construct}_k(i)$), the following equation (4.1), which was adopted from ideas of equation 7 and equation 8 of the reference (Lima and Souza, 2023). The normalisation is done as per the data of the proxy data range so that the reader will see the data in the range of actual proxy variables (Phan *et al.*, 2020). Readers should note that some proxies combine more than one actual sub-proxy; therefore, aggregated values were reported, as will be detailed in the hypothesis testing chapter.

$$\mathrm{N\_Construct_k}(i) = \min(\mathrm{Prxy}_k) + \left(\frac{(\mathrm{Constr}_k(\mathrm{i}) - \min(\mathrm{Constr}_k)) \times (\max(\mathrm{Prxy}_k) - \min(\mathrm{Prxy}_k))}{\max(\mathrm{Constr}_k) - \min(\mathrm{Constr}_k)} \right) \tag{4.1}$$

Where the $\mathrm{Construct_k}(i)$, is the construct k for the i$^{\text{th}}$ month, the Prxy_k is the proxy for construct k, and min and max functions to get the minimum and maximum values of the input series.

The proxy data spans from 2008 to the end of 2019 and includes a comprehensive set of economic indicators such as Unemployment, Inflation, Interest Rates, Uncertainty, Stock Index (FTSE), and variables about financial behaviour and financial well-being (FB and FWB). A comparative analysis reveals the movement of these indicators in tandem with their proxies, indicating a generally reliable representation of economic trends. However, notable discrepancies could be linked to extreme economic events such as shocks and the importance of robust policy measures to mitigate these effects.

The FWB and FB proxies show a consistent trend with similar behaviour capturing the downturn during the financial crisis (Figure 4.15 and Figure 4.16, respectively). However, the proxy variables disregard the impact on financial behaviour and well-being during the Eurozone debt crisis.

The Unemployment data indicate fluctuations corresponding to major economic events (Figure 4.17). During the financial crisis 2008, a spike in Unemployment was evident with significant fidelity as the proxy. However, the proxy's representation became less aligned during the Eurozone debt crisis. Notably, a dramatic rise in unemployment was observed, which the proxy did not reflect clearly. The discrepancy may stem from a lag in reporting unemployment statistics or immediate government intervention programs that temporarily influenced the labour market, delaying the manifestation of the full impact on the proxy measures. Conversely, the GTS sharply reflects the rise in unemployment concerns, likely capturing the real-time public reaction to the job market.

The Interest Rate (INT) construct alongside their proxies in Figure 4.18 shows discrepancies during extreme economic events. The INT aligns with the post-2008 decline in the GTS model due to the Bank of England's aggressive rate cuts to recover from the recession. Following this period, the proxy enters a phase of relative stability. The consistent static representation of stability potentially overlooks the subtler policy manoeuvres during less turbulent times. However, the proxy has further mirrored limitations to the real-time economic conditions, with a slight decrease before recovery. The disparities between the actual interest rates and the proxy during economic calls for a more adaptable Alternative Proxy model.

The Inflation rate and its proxy (Figure 4.19) display a consistent pattern, with the proxy tracking the actual inflation rate closely over time. The proxy indicates an appropriate response to the financial and subsequent debt crises, with inflation rates reflecting cost-push inflationary pressures. Nonetheless, the proxy slightly diverges, possibly due to the proxy not fully accounting for the rapid changes in consumer behaviour and supply chain disruptions.

The stock index proxy (Figure 4.20) closely tracks the FTSE, reflecting the market's volatility through the financial and debt crises. However, the proxy failed to capture the sharp market drop and subsequent rapid recovery, suggesting that it may not be as responsive to sudden market sentiments driven by global crises.

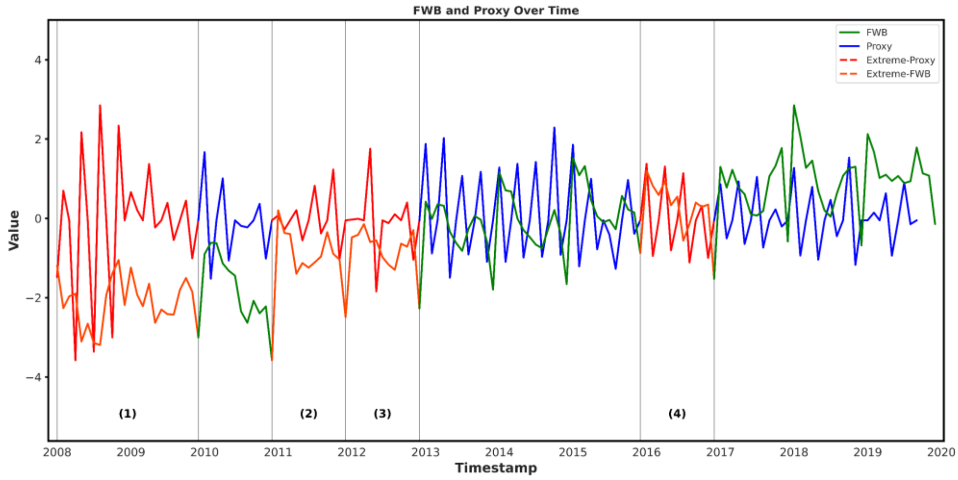


Figure 4.15: Financial Well-Being (GTS vs Proxy) Over Time.

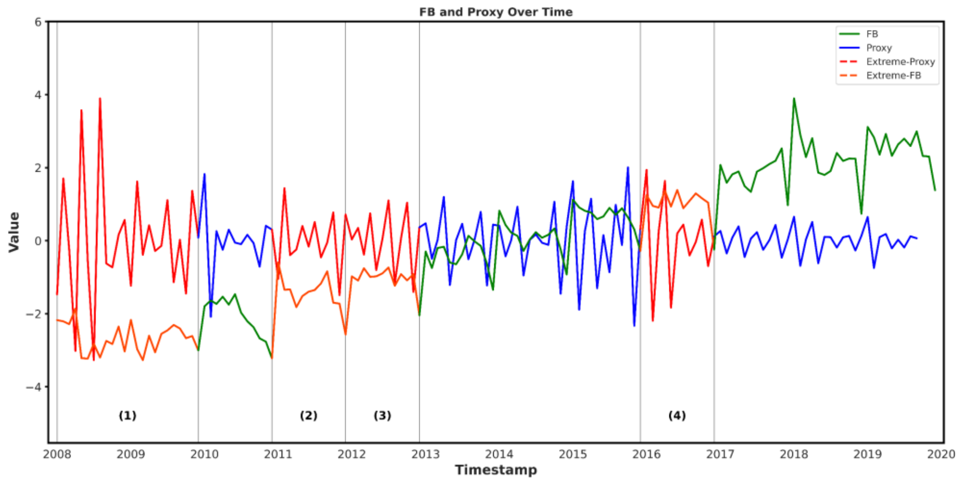


Figure 4.16: Financial Behaviour vs its Proxy Over Time.

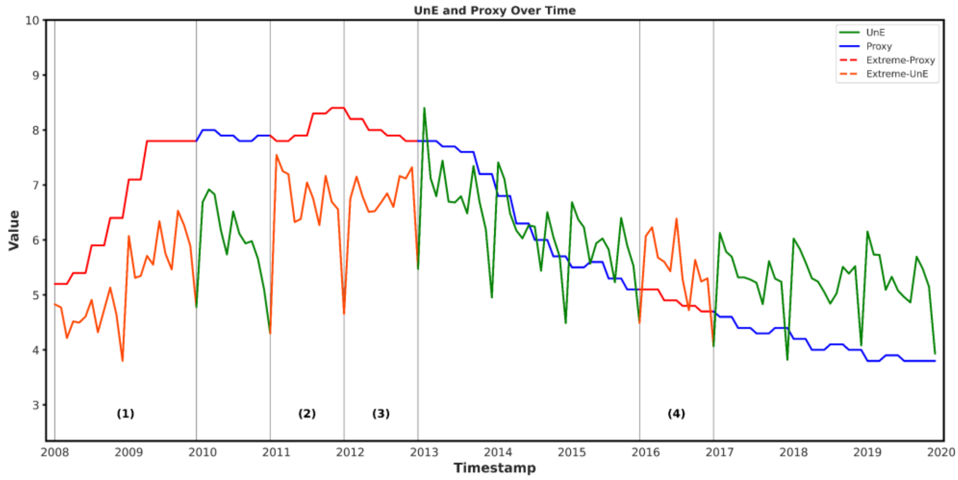


Figure 4.17: Unemployment vs its Proxy Over Time.

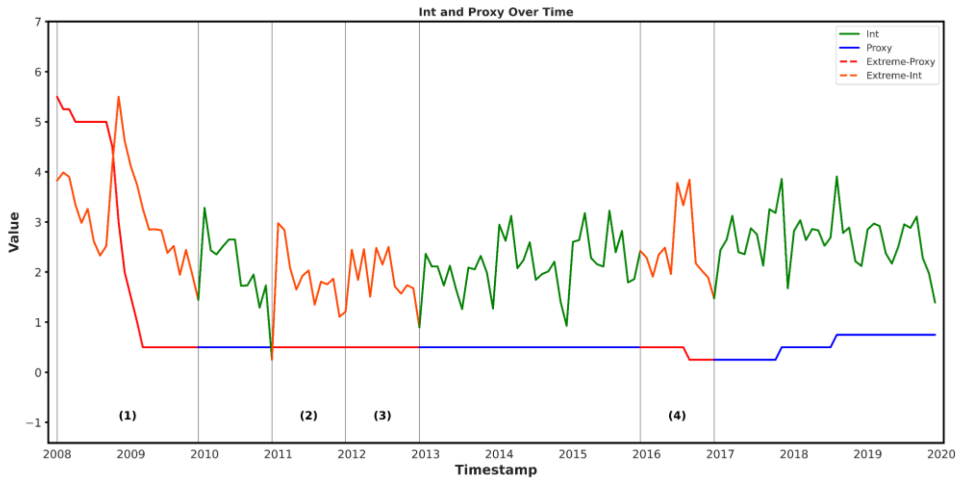


Figure 4.18: Interest Rate vs its Proxy.

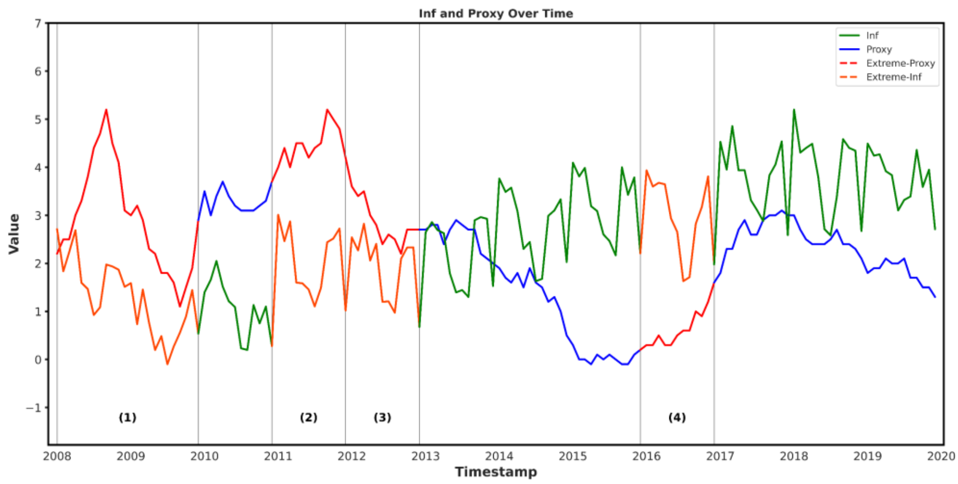


Figure 4.19: Inflation vs its Proxy.

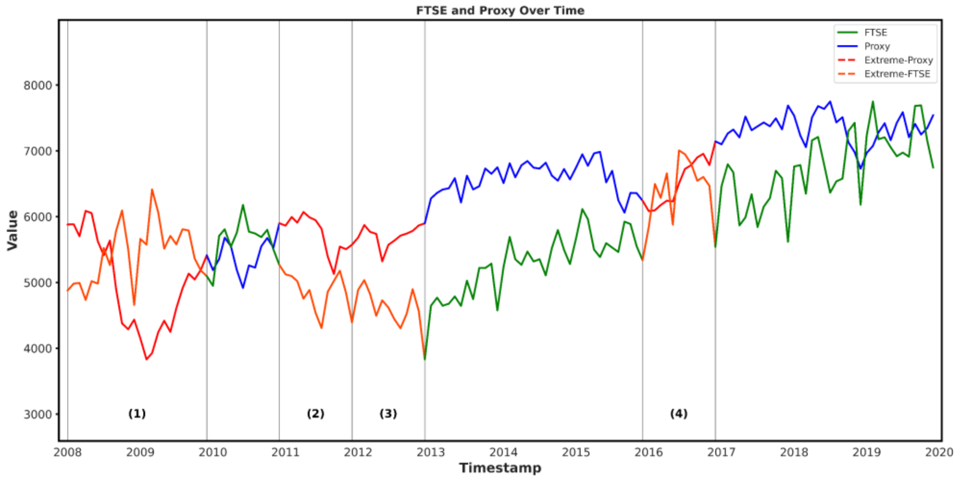


Figure 4.20: Stock Index (FTSE) vs its Proxy.

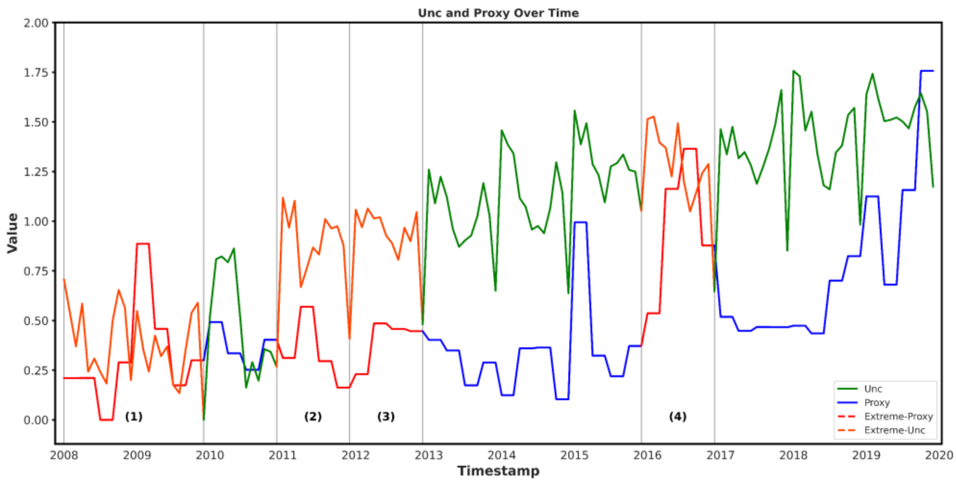


Figure 4.21: Uncertainty vs its Proxy.

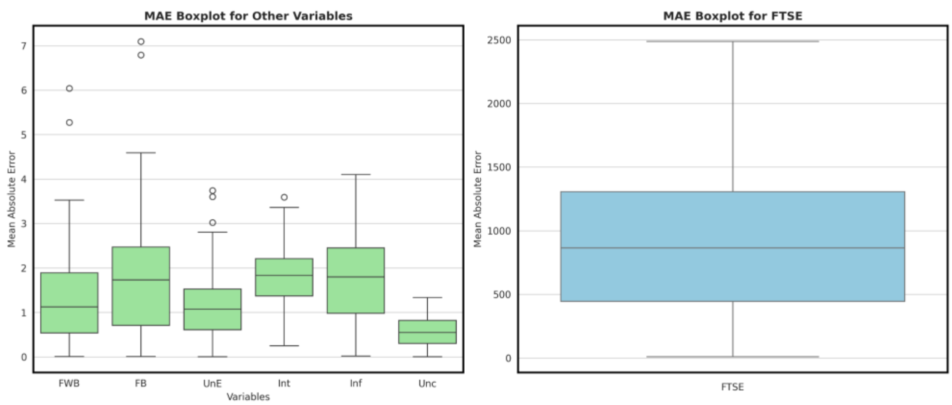


Figure 4.22: Mean Absolute Error (MAE) for Variables.

Finally, uncertainty in economic conditions is intrinsically challenging to quantify, yet the proxy for Uncertainty shows a general trend that aligns with major economic shifts (Figure 4.21). The graph captures the surge in uncertainty during the financial crisis and the oil price shocks, with noticeable peaks that coincide with these periods of economic turmoil. Nevertheless, there was a marked discrepancy during crisis; while the actual uncertainty levels rose sharply, the proxy did not fully mirror this escalation. The results could indicate that the model generating the proxy may not have been calibrated to account for such an extraordinary and rapid increase in economic uncertainty, highlighting a gap in the proxy's ability to reflect sudden and novel economic disruptions.

One way to visually present the comparison between the MAE of different variables is using boxplots. Boxplots illustrate the median as a central tendency (central line within the box) unaffected by extreme values. The box, the Interquartile Range (IQR), represents the middle 50% of the data. This range is represented by whiskers extending from the box, typically set at 1.5 times the IQR above and below the box. Points lying beyond the whiskers are often considered outliers, indicating instances of significant deviation from typical error values.

A larger IQR indicates more significant variability among the middle half of the data, suggesting inconsistencies in model predictions. Conversely, a smaller IQR implies more consistent performance. A more extended whisker range indicates a broader spread of data points, reflecting greater extremes in prediction errors. Outliers indicate instances of significant deviation from typical error values. Additionally, if the median is not centred within the IQR, it suggests a skewness in the error distribution, indicating a tendency for the model to overpredict or underpredict. The IQR details are detailed in Table 4.6. The IQR data for the GTS model vary across variables. The FWB and FTSE have the most comprehensive range, which indicates diverse constructs. The FTSE index spans 9.53 to 2486.92, with quartiles from 444.02 to 1306.49. Therefore, the FTSE demonstrates the most substantial variation, implying that the index fluctuates over time.

Table 4.6: Interquartile Range (IQR) for the Google Trends Model

Variable	Min	Q1	Median	Q3	Max
Financial Wellbeing	0.006	0.536	1.126	1.891	6.041
Financial Behaviour	0.009	0.705	1.733	2.472	7.095
Unemployment	0.002	0.608	1.073	1.524	3.743
Interest Rate	0.250	1.371	1.834	2.207	3.594
Inflation	0.019	0.978	1.796	2.449	4.100
Stock Index	9.53	444.02	864.37	1306.49	2486.92
Uncertainty	0.002	0.300	0.550	0.821	1.333

The MAE between the economic proxies and their respective variables are shown in Figure 4.22, respectively. From the boxplots, it is observed that variables such as Inflation, Uncertainty, Unemployment, Interest Rate, Financial Behaviour, and Financial Well-Being show a relatively tight grouping of MAE values, with most data points clustering close to the median, indicating a moderate level of error and thus a reasonably good proxy performance for these variables. Notably, the boxplot for the Stock Index (FTSE) reveals a higher range of MAE values with a more extensive spread, suggesting that the proxy for FTSE may not capture the actual market movements as closely as the other proxies do for their variables. The errors could be due to the volatile nature of stock markets or the proxy not accounting for all influential market factors. Outliers in the data indicate instances where the proxy significantly deviates from the actual values, which could be attributed to extraordinary economic events or changes not captured by the model.

Consequently, proxies present a reliable yet imperfect mirror of economic indicators, capturing overall trends but occasionally diverging in the face of complex and rapid changes in the financial landscape. Extreme economic events show a critical impact on economic indicators.

4.5. Chapter Summary

This chapter explores economic trends of Financial Behaviour (FB), Unemployment (UNE), Interest Rate (INT), Inflation (INF), Stock Index (FTSE), and Uncertainty (UNC) as related to the dependent variable Financial Well-being (FWB). The chapter uses Google Trends data from January 2005 to December 2021, comprising 1,465 keywords. Graphical representations delineate clear trends and correlations, particularly in the post-2008 financial crisis. The statistical method incorporates several elements, including seasonal adjustment with a 12-month cycle, justified by the impacts of recurring economic events and financial activities. Empirical validation is conducted through proxy comparisons, indicating generally reliable economic trend representations and uncovering discrepancies. The Mean Absolute Error (MAE) analysis shows moderate proxy performance for most variables, with the FTSE proxy indicating more significant errors.

CHAPTER 5: HYPOTHESIS TESTING

This chapter describes the hypothesis of the conceptual framework (Figure 3.2) for Google Trends Search (GTS) and the Alternative Proxy models. The conceptual framework has the following variables: Financial Well-Being (FWB), Financial Behaviour (FB), Unemployment (UNE), Interest Rate (INT), Inflation (INF), Stock Index, and Uncertainty (UNC). The FWB is the dependent variable, the FB is the mediator variable, and the others are independent variables. The study also uses FTSE as a representative of the STK.

As discussed in Chapter 3, the data preprocessing for GTS follows keyword selection, expansion, and filtering; therefore, the average keywords per construct is used for GTS modelling. On the other hand, the Alternative Proxy model has data from UK government websites that can be mapped to the GTS constructs. Figure 5.1 summarises the hypotheses investigated in GTS and the Alternative Proxy model.

Financial Well-Being (FWB): Dependent Variable

Financial Behaviour (FB): Mediator	**Unemployment (UNE)**
H0: *FB does not influence the FWB.* ***H1:*** *FB influences the FWB.*	***H0:*** *UNE does not influence FB.* ***H2:*** *Increased UNE impacts FB.*
Interest Rate (INT)	**Inflation (INF)**
H0: *INT does not influence FB.* ***H3:*** *Increased INT influences FB.*	***H0:*** *INF does not influence FB.* ***H4:*** *Increased INF influences FB.*
Stock index (STK)	**Uncertainty (UNC)**
H0: *STK does not influence FB.* ***H6:*** *FB are influenced by STK values.*	***H0:*** *UNC does not influence FB.* ***H5:*** *Increased UNC impacts FB.*

Figure 5.1: Hypotheses of the GTS Financial Well-Being Conceptual Framework.

5.1. Adopted Approach

As discussed in Chapter 3 (3.5), this study uses Structural Equation Modelling (SEM). This section explains Partial Least Squares SEM (PLS-SEM), its configuration, and the metrics used to evaluate GTS and the Alternative Proxy models.

5.1.1. PLS-SEM Approach

The study found that the PLS-SEM is the most suitable model for GTS and the Alternative Proxy model for these reasons: (1) Linear regression models could not measure mediator variables (Hair *et al.*, 2019); therefore, this option was eliminated because the conceptual framework has a mediator construct (Financial Behaviour), (2) It is valid to use PLS-SEM in economics as well as many areas of financial studies (Hair *et al.*, 2019, p. 7) some of them for FWB (Mathew and Kumar, 2022; Sehrawat *et al.*, 2021), and (3) PLS-SEM has usage evidence in the capital structure where it handles multicollinearity and is capable of analysing multiple paths of several constructs (Ramli *et al.*, 2018, pp. 200–201).

5.1.2. PLS-SEM Configuration

The PLS-SEM is implemented in SmartPLS version 4 (Ringle *et al.*, 2022). First, the data for the GTS and the Alternative Proxy models are uploaded without additional vector weighting. Next, the maximum number of iterations is set to 3,000 with a stopping criterion of 10^{-7} of convergence. Following SmartPLS, the path weighting scheme is used with the standardised data.

The number of GTS data samples is relatively low, so bootstrapping is implemented. Bootstrapping creates simulated samples from the original data. Five thousand bootstrap samples are drawn with a fixed random seed to ensure reproducibility. The significance level was set at 0.05, and a two-tailed test was applied to determine the p-values. Therefore, SmartPLS ensures that the calculation is statistically significant.

5.1.3. Evaluation Metrics

The study evaluates the developed Partial Least Squares Structural Equation Modelling (PLS-SEM) models using these metrics to ensure robustness and model validity: R-squared (R^2), F-squared (F^2), and the Variance Inflation Factor (VIF). Additionally, the study employs path analysis to examine the strength and significance of the relationships between constructs. Moreover, the Cross-validated Predictive Ability Test (CVPAT) tests the models for predictive validity.

The R-squared (R^2) shows the proportion of variance in the dependent variable explained by its independent variables (Hair *et al.*, 2019). Hair *et al.* (2019) state that R^2 has a scale of 0.25, 0.50, and 0.75, representing minor, moderate, and substantial effects, respectively. The F-squared (F^2) scores indicate the individual predictor variables' impact on the endogenous constructs, according to Cohen (2013). According to Cohen, common interpretations include 0.02: Small effect size, indicating 2% of variance explained by the predictor variable; 0.15: Medium effect size, indicating 15% of variance explained; and 0.35: Large effect size, indicating 35% of variance explained. A highly correlated predictor could suffer from multicollinearity (James et al., 2023); therefore, it should be tested and reduced. The Variance Inflation Factor (VIF) assesses the presence of multicollinearity, where a value below five indicates no multicollinearity concern; a value between five and ten indicates potential multicollinearity, while a value above ten calls for model revision. The Cross-validated Predictive Ability Test (CVPAT) tests a model's generalizability on unseen data (Sharma *et al.*, 2023). The CVPAT repeatedly divides the data, building the model on one part and predicting on the other. Consequently, the average prediction loss error across these partitions estimates the model's generalizability. The CVPAT compares the average loss error against two critical benchmarks: Indicator Averages (IA) and Linear Model (LM). The IA prediction is based on average values of indicator variables, whereas LM builds a linear regression for prediction using all exogenous variables (FB, FWB). According to Sharma *et al.* (2013), the optimal case is that PLS-SEM predictions are significantly better than IA and LM ('strong predictive validity'). If IA values are not significant, it indicates that the model has 'no predictive validity', while if the IA is significant, LM is not ('predictive validity). Therefore, the CVPAT method extends beyond mere error quantification, providing a comparative analysis that assesses whether the PLS-SEM model surpasses predictive methods. Hence, CVPAT is used to enhance model understanding and bolster confidence in its generalizability.

5.2. Google Trends Search Model

As depicted in Figure 5.1. The independent variables Unemployment, Interest Rate, Inflation, Stock Index, and Uncertainty affect the mediator variable, Financial Behaviour, which reflects its effect on Financial Well-being.

Next, a detailed investigation into the direct and indirect effects and measures of reliability is conducted. This analysis is accompanied by the influence of extreme events and Alternative Proxy model data to understand these variables comprehensively.

5.2.1. Direct Effect of the Google Trends Search Model

The hypotheses of the proposed conceptual framework are H1 to H6, as shown in the first column Table 5.1. The direct effects of constructs are detailed as follows.

Table 5.1: Hypothesis Testing of the Google Trends Search Model (Direct Effect).

Hypo.	Direct Relationships	Std. *Beta*	Std. Error	T Values	p Values
H1	Financial Behaviour ➔ Financial Well-being	0.883	0.028	31.709	0.000
H2	Unemployment ➔ Financial Behaviour	0.242	0.075	3.228	0.001
H3	Interest Rate ➔ Financial Behaviour	-0.006	0.057	0.097	0.923
H4	Inflation ➔ Financial Behaviour	0.311	0.060	5.172	0.000
H5	Stock Index ➔ Financial Behaviour	0.021	0.047	0.443	0.658
H6	Uncertainty ➔ Financial Behaviour	0.377	0.076	4.982	0.000

A. H1: Financial Behaviour (FB) and Financial Well-Being (FWB)

The analysis rejects the null hypothesis (H0) that financial behaviour does not influence financial well-being, evidenced by a significant Beta coefficient of 0.883 and a p-value of 0.000. Therefore, the research findings accept the alternative hypothesis (H1) that financial behaviour positively influences financial well-being. The accepted hypothesis (H1) resonates with financial behaviour's role in enhancing financial well-being (Bashir and Qureshi, 2023a; Damian *et al.*, 2020; Gerrans *et al.*, 2014; Iramani and Lutfi, 2021; Oquaye *et al.*, 2020). Moreover, the relationship between financial behaviour and financial well-being(Figure 4.6 and Figure 4.3) corresponds with the solid visual correlation between them, especially for years after 2011, due to the rise of fintech companies making financial services more accessible (Arner *et al.*, 2015; Gabor and Brooks, 2020), and government financial regulation encouraging responsible lending, borrowing, and investing (Dolan *et al.*, 2012).

Generally, financial behaviour and financial well-being are in tandem; however, a broader model could investigate the role of sub-constructs of financial behaviour, such as self-efficacy (Forbes and Kara, 2010), knowledge, self-control (Rey-Ares *et al.*, 2021; Strömbäck *et al.*, 2017, 2020), financial-literacy (Schmeiser and Seligman, 2013), and personal demographics (Fan and Babiarz, 2019; Florendo and Estelami, 2019), especially during crises, as highlighted by the trends observed in Figure 4.15 and Figure 4.16. The findings underscore the need for future research to explore broader models and incorporate more robust measures during such critical junctures.

B. H2: Unemployment (UNE) and Financial Behaviour (FB)

The literature reports that the relationship between unemployment and financial behaviour has long been assumed to be negative (Luchtenberg and Vu, 2015; Simionescu *et al.*, 2020). However, the GTS model reveals a surprising finding: a positive Beta coefficient of 0.242 with a statistically significant p-value of 0.001, indicating rejection of the null hypothesis (H0) that

UNE does not influence FB. This unexpected outcome contradicts the assumption (H2) that unemployment leads to financial strain (Mihaela, 2020; Bulog et al., 2022; Simionescu and Cifuentes-Faura, 2022b). Figure 4.17 supports this counterintuitive finding, depicting the unemployment trend's sensitivity to extreme events like the 2008 financial crisis and the COVID-19 pandemic.

The positive correlation between UNE and FB could be attributed to several scenarios. Unemployment might make people more cautious by reducing spending and better budgeting on non-essentials to improve their financial stability. These findings coincide with a recent study report that the relationship between job loss and subjective financial well-being is insignificant but not prominent (Roll *et al.*, 2022). The recent labour market analyses in the UK reveal a positive trend between unemployment and financial prudence (Görtz *et al.*, 2023). This trend identifies significant changes in consumption behaviour during unemployment. Their study found that individuals tend to cut spending and use their savings more strategically to manage reduced income, highlighting adaptive financial strategies in response to employment uncertainties. Therefore, the findings indicate that unemployed individuals adopt a more conservative approach to spending and engage in proactive financial planning beyond the immediate effects of income loss (Ganong and Noel, 2019).

These behaviours align with the broader patterns the Office for National Statistics reported. Pre-pandemic, average weekly expenditure stood at £587.90. However, during the first year (ending March 2021), spending plunged by 18% (£106.40), impacting discretionary spending. While spending partially recovered to £528.80 in the year ending 2022, it remained 10% lower than pre-pandemic levels, suggesting a cautious approach to financial management amid uncertainty. Literature shows a decrease in household spending (Blom and Perelli-Harris, 2021) and standards (Blom and Perelli-Harris, 2021) due to unemployment.

During the furloughed period, individuals improve their budgeting skills with financial literacy and planning skills (Kurowski, 2021; Xiao and Meng, 2023); however, this improvement is more evident for self-employed individuals (Annink *et al.*, 2016; Ćumurović and Hyll, 2019). Individuals generally reduce debt and increase savings against financial depletion (Mamatzakis *et al.*, 2023).

Government assistance programs are significant in maintaining financial stability during unemployment (Brewer and Tasseva, 2021; Cassim *et al.*, 2020). However, short-term reliance on government benefits or credit could create long-term debt challenges. Additionally, individuals with diverse financial backgrounds may exhibit varied financial behaviours in response to unemployment.

Therefore, while the relationship between unemployment and financial behaviour is positive, more profound research is needed to understand these findings across various demographic groups.

C. H3: Interest Rate (INT) and Financial Behaviour (FB)

Prior studies, like Alzoubi (2022), suggest a link between INT and FB; however, an initial analysis presented in Table 5.1 yields unexpected results. The table reports a non-significant Beta coefficient (-0.006) and p-value (0.923), indicating statistically insufficient evidence to conclude the significant influence of INT on FB. Therefore, the findings accept the null hypothesis (H0) that INT does not impact FB.

The discrepancy suggests that while interest rate adjustments stimulate economic growth and attract foreign investment, their direct influence on individual financial behaviour might be less immediate than traditionally perceived. High-interest rates can restrain economic growth, increase debt burdens, and impact asset values, potentially discouraging saving and influencing financial behaviour, especially in an environment with elevated inflation (Molyneux *et al.*, 2022). The GTS model, focusing on public sentiment during significant economic events, is more dynamic and comprehensive than the traditional static interest rate proxy. The initial analysis (Figure 4.46) shows that the static proxy fails to link INT to FB conclusively. While it reflects the Bank of England's (BoE) rate cuts post-2008, it does not account for subsequent economic events like the Euro Debt Crisis (2011) and the Olympics (2013), nor does it fully represent the impact of other government interventions.

Dynamic financial markets and individual financial decisions suggest that the relationship between INT and FB extends beyond the direct changes in BoE's policy rates (Reeves and Sawicki, 2007). Moreover, individual risk-aversion strategies and broader economic events could affect this relationship (Breuer *et al.*, 2014). After the 2008 financial crisis, the Bank of England's strategic reduction of interest rates to 0.5% in March 2009 and 0.25% in August 2016 significantly altered individual financial behaviour. These historically low rates, designed to stimulate economic activity, appear to have had a dual effect: a decrease in the propensity to save immediately following the crisis, with the Office for National Statistics reporting a saving ratio that surged to 10.6% in 2009 but then fell to 3.9% by Q1 2017. However, the pandemic saw this ratio dramatically increase to 27.4% in Q2 2020, highlighting the variability of individual financial responses to economic pressures (Office for National Statistics, 2022).

Concurrently, the BOE observed a slowing in household debt growth from approximately 9% to 2.4% over the decade, indicating a more prudent borrowing behaviour amidst these changing interest rates (England, 2022). Therefore, low interest rates have been associated with increases in household wealth, challenging traditional expectations of savings declines in such environments (De Bonis and Marinucci, 2023). The results highlight a shift in individual financial planning for retirement, emphasising the need to adapt strategies in the face of prolonged low-interest rates and increased life expectancy (An Chen and Sørensen, 2023).

Moreover, the low-interest-rate period has a shift in investment behaviour, with individuals seeking higher yields turning to stock markets and property investments, thus increasing their exposure to potentially higher-risk assets (Advani *et al.*, 2021; Olbrys, 2022). The slight uptick in rates to 0.75% in August 2008 signalled the onset of a potential reorientation towards more conventional savings behaviour as individuals began to recalibrate their financial strategies in anticipation of further normalisation of interest rates (Shaukat *et al.*, 2019). Additionally, research suggests that the relationship between stock returns and interest rate differentials varies between high and low-interest-rate environments (Salisu and Sikiru, 2023). Therefore, interest rate differentials influence investment decisions in different economic contexts.

The GTS model challenges the interpretation of interest rate influence on financial behaviour. The study underscores the need for dynamic, granular models incorporating individual risk tolerance, psychological factors, and financial literacy to understand better how interest rates shape financial choices.

D. H4: Inflation (INF) and Financial Behaviour (FB)

The findings reject H0, with a significant Beta of 0.311 and a p-value of 0.000, supporting the alternative hypothesis (H4) that inflation significantly influences FB. However, traditional literature suggests a negative impact of inflation on financial behaviour (Batrancea, 2021; Duca-Radu *et al.*, 2021). Furthermore, the positive trendline in Figure 4.19 could indicate the proactive measures individuals take in response to inflation, such as seeking wage adjustments or adopting cost-saving strategies, which are not always immediately evident in traditional economic models (Fröhlich, 2023). On the other hand, the proxy inflation variable takes time to reflect individual behaviour, such as the oil price crash in 2016, where the static proxy did not fluctuate too much compared to the GTS model during that period. The GTS model's sensitivity to short-term behavioural responses to inflationary trends, as opposed to long-term investment strategies, typically analysed in traditional studies, might capture this dual aspect more effectively (Arpaci *et al.*, 2024; Venkataramani and Kayal, 2023; Warrington *et al.*, 2023). That indicates that individuals feel increased inflation and adjust to rapid economic changes, compared with government-reported inflation rates often lagging behind these adjustments (Zhu *et al.*, 2021).

This discrepancy may be reconciled by considering the dual behaviour of inflation's impact: while it typically erodes purchasing power and can lead to financial stress, it also acts as a catalyst for positive financial behaviours, such as increased budgeting and prioritisation of essential needs, as individuals respond to rising prices (Ardogan and Yilmaz, 2021; Hall *et al.*, 2023; Menyhert, 2023). Therefore, during varied inflation rates, central banks consider macroeconomic and financial market variables when setting policies and underline the impact of financial conditions on macroeconomic volatility (Melolinna and Tóth, 2016). Inflation in the UK influences individual financial behaviour, leading to diverse consumer responses. The CPI annual report shows the oscillation of inflation rates during 2008-2020. It peaked at 5.2% in 2008 to a phase of deflation in 2015 and a resurgence of up to 3.1% by the end of 2017. The results exemplify the need for a multifaceted exploration of how inflation influences financial choices.

While traditional views of inflation focus on its negative impact through the erosion of purchasing power, the 'price-informative role' and the 'investment spending channel' imply that inflation can guide individuals to make informed financial choices, stimulating proactive behaviours such as strategic investment and spending (Mandeya and Ho, 2022). The variability in inflation rates encourages adaptive financial management, which leads to financial growth (Mandeya and Ho, 2022). During COVID-19, household and company balance sheets were substantially managed to provide a more strategic approach to investment and spending (Haldane, 2021). In the long term, individuals seek effective retirement financial planning (Mustafa *et al.*, 2023; Neville *et al.*, 2021).

Individuals have demonstrated resilience and financial acumen, employing adaptive strategies such as stringent budgeting, prioritising essentials, and exploring proactive financial strategies like seeking higher-yielding investments or debt consolidation (Scott *et al.*, 2023). Therefore, individuals manage inflation challenges proactively during economic stress (Macqueen *et al.*, 2022). Also, the research found that individuals use coping mechanisms by examining how consumers adapt their behaviour, like increasing price sensitivity, and exhibit increased consumer anticipated guilt and savvy shopper self-perception in response to economic crises that affect their financial status (Hampson and McGoldrick, 2017).

Consequently, the study acknowledges inflation's dual capacity to challenge and stimulate positive financial behaviour. Moreover, the findings highlight the value of the GTS model's dynamic and real-time insights, especially in capturing responses to unforeseen economic events. Future research should disaggregate financial behaviour into specific actions like saving, spending, investing, and debt management to segregate the dual effect of inflation on financial behaviour. Moreover, examining how individual characteristics, including financial literacy, risk tolerance, income level, and age, influence the inflation-FB connection would further enrich our knowledge.

E. H5: Stock Index (STK) and Financial Behaviour (FB)

In this study, the Stock Index is represented by the FTSE 100, which serves as a potential indicator of the UK's economic health. The relationship between STK and FB had a Beta of 0.021 and a p-value of 0.658, which does not lead to rejecting H0, indicating that the stock index does not significantly influence FB. The GTS model is shown in Figure 4.20: Stock Index (FTSE) vs its Proxy., representing the stock index and its proxy, shows that GTS could effectively track overall market trends and volatility during financial crises. However, the outcome of the hypothesis testing adds to the complex discourse on the relationship between stock market indices and individual financial behaviour (Jain and Chhabra, 2022).

Despite the sensitivity of FTSE to diverse factors like monetary and fiscal policies, Brexit, and global market integration (Ben Ameur and Louhichi, 2022), its influence on individual financial behaviour appears limited. This phenomenon can be attributed to several factors. Firstly, individual investors suffer from information overload in dynamic markets that could surpass investors' analytical capabilities. This phenomenon often exceeds their capacity for analytical processing, particularly in market synchronicity behaviour (Zhao and Gan, 2024). Therefore, information could deteriorate investors' decision accuracy (Aljanabi, 2023; Zer et al., 2023), such as panic buying (Aljanabi, 2023). Therefore, their ability to translate market movements into actionable decisions becomes compromised (Willows and Richards, 2023; Zhao and Gan, 2024).

Secondly, In the UK, like other European countries, demographics, education, risk aversion, cognitive abilities, trust, and sociability significantly influence an individual's decision to participate in the stock market (Kaustia *et al.*, 2023). Finally, even when individuals perceive wealth accumulation as linked to the stock market, they may not readily modify their financial behaviour due to psychological factors like loss aversion illusion (Merkle, 2020).

Consequently, the findings have a distinct perspective where GTS shows a highly coherent correlation with the FTSE proxy, as visualized in Figure 4.20. It contradicts previous literature that finds negative returns correlated with high Google search volumes (Bijl et al., 2016). This difference might be attributed to the short-term focus of the GTS model, capturing individual FB in real-time. Unlike traditional research that examines long-term investment decisions, individuals might react differently to short-term market fluctuations.

F. H6: Uncertainty (UNC) and Financial Behaviour (FB)

The study rejects H0 based on a Beta of 0.377 and a p-value of 0.000, affirming H6 that increased uncertainty correlates with changes in FB. However, the finding diverges from existing literature that associates increased economic uncertainty with negative impacts on financial well-being and investor confidence. The finding is inconsistent with the literature that income shock had a negative association with FWB and financial and personal resilience (Kulshreshtha *et al.*, 2023) and the increased uncertainty about the state of the economy is negatively correlated with investor confidence (Dzielinski, 2012). However, the proxy data for uncertainty (Figure 4.21) aligns with major economic shifts but underrepresents spikes in uncertainty during unprecedented events.

One possible explanation for this divergence might be the uncertainty captured by GTS, which taps into broader societal and economic uncertainties individuals encounter daily. First, GTS might capture short-term uncertainties more effectively than long-term trends, leading to increased savings, investment diversification, or seeking financial advice (Agunsoye and James, 2023; Stolper and Walter, 2017; Zakeri *et al.*, 2022). Second, the increased access to emerging intelligent financial systems enables financial behavioural adjustments during uncertainties. Therefore, individuals make more informed decisions when exploring new investment opportunities or debt consolidation (Arner *et al.*, 2015; Gabor and Brooks, 2020; Hikida and Perry, 2020). Lastly, evolving financial literacy and risk perception lead to proactive or resilient behaviours in uncertain times (Bekaert *et al.*, 2022; Shear *et al.*, 2021). However, further exploration into different types of uncertainty could measure FB more comprehensively.

5.2.2. Indirect Effects of the GTS Model

The mediation effects of FB are presented in Table 5.2. This analysis delves into how one variable may influence another through an intervening variable or mediator (i.e., FB).

Table 5.2: Hypothesis Testing of the GTS Model (Indirect Effect).

Hyp.	Indirect Relationships	Std. *Beta*	Std. Error	T Values	p Values
H2b	Unemployment ➔ FB ➔ Financial Well-being	0.214	0.068	3.157	0.002
H3b	Interest Rate ➔ FB ➔ Financial Well-being	-0.005	0.050	0.098	0.922
H4b	Inflation ➔ FB ➔ Financial Well-being	0.274	0.051	5.395	0.000
H5b	Stock Index ➔FB ➔ Financial Well-being	0.018	0.041	0.445	0.656
H6b	Uncertainty ➔ FB ➔ Financial Well-being	0.333	0.068	4.914	0.000

A. H2b: Unemployment → Financial Behaviour → Financial Well-Being

The substantial Beta value of 0.214 and a p-value of 0.002 suggest that Unemployment has a significant indirect effect on FWB through FB. The result implies that unemployment rates might alter financial behaviours, subsequently influencing overall financial health. This finding dovetails with the direct effects analysis, increasing the impact of Unemployment on financial well-being.

This dual pathway of the unemployment construct indicates complex individual behaviour during extreme external economic conditions. External extreme economic factors can significantly shape the progression from unemployment to financial behaviour changes and, ultimately, to overall financial health. It could be deduced that unemployment might make people more financially cautious due to economic concerns (Görtz *et al.*, 2023). Therefore, the findings could help policymakers and economists address the economic fallout of unemployment and reinforce the importance of robust social safety nets in mitigating its broader impact on financial well-being.

B. H3b: Interest Rate → Financial Behaviour → Financial Well-Being

The negligible Beta of -0.005 and a p-value of 0.922 indicate that interest rates have a minimal indirect effect on FWB via FB. The value findings align with the direct effects analysis, suggesting that interest rates may not be a significant determinant of financial well-being through financial behaviour in the context of this study. The findings affirm that individual risk-aversion strategies towards money management are likely affected by economic events (Breuer *et al.*, 2014).

The findings are particularly relevant in the current economic GTS model, which suggests a limited role of INT in shaping individual FB that leads to overall FWB. Such findings could prompt a re-evaluation of the traditional economic models that often emphasise INT, guiding policymakers and financial analysts to consider alternative factors of decision-making processes based on fluctuations of extreme economic events.

C. H4b: Inflation → Financial Behaviour → Financial Well-Being

A significant Beta of 0.274 and a p-value of 0.000 demonstrate a notable mediation effect of inflation on FWB through FB. The result underscores the role of inflation in shaping financial behaviours, which in turn impacts financial well-being.

The finding contrasts with the direct effects analysis, where inflation's impact on financial decisions and well-being appeared in a different direction. Such divergence emphasises inflation's intricate and diverse function as it affects individual behaviours. Therefore, inflation exerts a broader economic influence, comprehensive economic policies and financial strategies intricate inflation towards personal finance and financial health (Coppola, 2021).

D. H5b: Stock Index → Financial Behaviour → Financial Well-Being

The Beta of 0.018 and a p-value of 0.656 indicate a limited mediation effect of the stock index on FWB via FB. Therefore, the result suggests that stock market fluctuations might not significantly impact financial well-being through changes in financial behaviour. The hypothesis also is in tandem with H5, where H0 was accepted.

The findings underscore the potential disconnect between stock market performance and personal financial health, implying that individual financial decisions and well-being may be more resilient or less directly tied to stock market variations than commonly presumed. It points towards the need for a broader understanding of the factors influencing financial well-being beyond stock market indices.

E. H6b: Uncertainty → Financial Behaviour → Financial Well-Being

With a Beta of 0.333 and a p-value of 0.000, economic uncertainty has a pronounced indirect effect on FWB through FB. The substantial indirect influence suggests a more intricate relationship between UNC and FWB than previously understood regarding how UNC can reshape financial behaviours. However, the analysis contrasts with the initial hypothesis that increased UNC negatively impacts FB. This divergence from existing literature and initial expectations about the negative implications of uncertainty underscores the complexity of UNC's impact that may influence financial behaviours differently than income fluctuations.

5.2.3. Evaluating the Google Trends Search Model

This section evaluates the GTS model based on R-squared, F-squared, and the Variance Inflation Factor (VIF).

A. R-Squared Analysis

The R^2 analysis of the GTS model is shown in Table 5.3. The FB has an R^2 of 0.741, which indicates that the model explains approximately 74.1% of the variance in FB. The adjusted R^2 value of 0.734 confirms the robustness of this explanation.

Table 5.3: R-squared and R-squared adjusted for the Google Trends Search Model.

Latent Variables	R^2	R^{Adj2}	**Effect Size**
Financial Behaviour (FB)	0.741	0.734	Moderate
Financial Well-Being (FWB)	0.779	0.778	Large

On the other hand, the R^2 for FWB has a notable value of 0.779, which implies that about 77.9% of the variance in FWB is explained by the other variables. This high value indicates a robust model fit, signifying that critical determinants of FWB are well-represented in the model.

B. F-Square Analysis

The FB significantly influences FWB, with an F^2 value of 3.532, which draws upon the underlying equations presented in the guidelines calculating the F^2 values (Selya *et al.*, 2012). This large effect size underscores FB as a critical and dominant predictor of FWB within the model.

Several variables exhibit a medium effect on FB. Inflation (F^2 = 0.122), Uncertainty (F^2 = 0.162), and Unemployment (F^2 = 0.067) each exhibit a moderate effect on financial behaviour, signifying their significant but comparatively moderate roles in influencing Financial Behaviour. In contrast, the Interest Rate and Stock Index show minimal impact on FB, as indicated by their F^2 values. These small effect sizes suggest that changes in interest rate and stock market fluctuations slightly influence FB, aligning with the previously discussed hypothesis for Interest Rate and Stock Index (H3 and H5, respectively).

Table 5.4: F-Square for the Google Trends Search Model (Direct Effects).

Latent Variables	F^2	Effect Size
Financial Behaviour ➔ Financial Well-being	3.532	Large Effect
Unemployment ➔ Financial Behaviour	0.067	Medium Effect
Interest Rate ➔ Financial Behaviour	0.000	Small Effect
Inflation ➔ Financial Behaviour	0.122	Medium Effect
Stock Index ➔ Financial Behaviour	0.001	Small Effect
Uncertainty ➔ Financial Behaviour	0.162	Medium Effect

C. Variance Inflation Factor Analysis

The VIF values for key predictors in the model are appropriately presented in studied. Table 5.5, with each falling below the multicollinearity threshold: Four (Fox, 2015) or five (Hair and Sarstedt, 2019), ensuring their independent contribution to Financial Behaviour (FB). The absence of VIF values for FB and FWB is per standard statistical procedures; FB acts as a mediator, not an independent predictor, and FWB is the outcome variable. This focused VIF analysis ensures the clarity and reliability of the mediation model by confirming that multicollinearity does not confound the relationships being studied.

Table 5.5: Variance Inflation Factor for the Google Trends Search Model.

Constructs	VIF
Financial Behaviour (FB) ➔ Financial Well-Being (FWB)	1.000
Unemployment (UNE) ➔ Financial Behaviour (FB)	3.359
Interest Rate (INT) ➔ Financial Behaviour (FB)	1.385
Inflation (INF) ➔ Financial Behaviour (FB)	3.064
Stock Index (STK) ➔ Financial Behaviour (FB)	1.313
Uncertainty (UNC) ➔ Financial Behaviour (FB)	3.378

D. Predictability of the Google Trends Search Model

CVPAT compares the PLS-SEM against indicators average (IA) and Linear Model (LM) benchmarks, as shown in Table 5.6. The IA measures current conditions or economic trends, while the LM is a linear model between the Financial Well-Being and the independent variables. For the IA comparison, the results show that the PLS-SEM model has weak predictive validity for Financial Behaviour and Financial Well-Being constructs. The finding is evidenced by the average loss differences being negative and statistically significant, indicating the model's predictions are more accurate than if one were to predict using the average of observed values. In contrast, for the LM comparison, the PLS-SEM model displays a positive average loss difference, failing to meet the criteria for predictive solid validity criteria (Liengaard *et al.*, 2021). Therefore, the overall analysis, encapsulating both FB and FWB, maintains this trend of negative values against IA and positive values against LM, indicating an acceptable predictive model given the constraints of the current model.

Table 5.6: Cross-validated Predictive Ability Test (CVPAT) for the Google Trends Model

Construct	PLS-SEM vs IA		PLS-SEM vs LM	
	Average Loss Difference	**P Value**	**Average Loss Difference**	**P Value**
Financial Behaviour	-4.020	0.000	0.000	0.925
Financial Well-Being	-3.551	0.000	0.289	0.000
Overall	-3.786	0.000	0.144	0.000

While aligning with general trends, the empirical validation using GTS data reveals discrepancies and gaps with Alternative Proxy data, especially during crises and rapid economic changes, as discussed in the previous sections. Therefore, CVPAT for the alternative model should also be used to confirm how GTS and Alternative Proxy models compare regarding validity.

5.3. Alternative Proxy Model

The second model is the Alternative Proxy model based on static proxies of economic indicators illustrated in Table 5.7 originally extracted from the UK Office for National Statistics. The selected sub-items within the constructs of ‘Household Income’ (HHI), ‘Whole Economy Production and Income’ (WEP), and ‘Household Spending’ (HHS) are conceptualised as reflective constructs rather than formative constructs for robust theoretical and methodological reasons. In the ‘Household Income’ (HHI) construct, the ‘Real Household Actual Final Consumption Expenditure per head’ (HHAFE) and ‘Real Household Consumption Expenditure per head’ (HHFCE) are considered reflective due to their interchangeability, wherein changes in the latent variable of overall household consumption expenditure are expected to be consistently reflected in both sub-items.

Similarly, the sub-items within the ‘Whole Economy Production and Income’ construct: ‘Gross Domestic Product’ (GDP), ‘Gross Domestic Product Per Head’ (GDPPH), ‘Net Domestic Product per head’ (NDP), ‘GDP per head’ (PE), and ‘Real Net National Disposable Income per head' (RNNDI), collectively reflect the common factor of economic production and income, exhibiting the characteristics of reflective measurement models. Finally, in the 'Household Spending' (HHS) construct, 'Real Gross Adjusted Household Disposable Income' (RGAHDI) per head and 'Real Net Household Adjusted Disposable Income' (RNHADI) per head are deemed reflective due to their theoretical foundation, representing distinct aspects of the latent variable of adjusted disposable income for households.

5.3.1. Reliability and Validity Analysis of the Alternative Proxy Model

The reliability and validity testing maintain credible research findings (Hair *et al.*, 2017). Consistent results over repeated experiments indicate 'reliability' (Nunnally and Bernstein, 1994). On the other hand, capturing the represented concept accuracy is 'validity' (Carmines and Zeller, 1979).

This research examines the Alternative Proxy model that has zero-order and second-order constructs. The zero-order constructs represent measured variables directly, while second-order constructs are derived from aggregating related zero-order constructs (Chin, 1998; Cronbach, 1951).

Several statistical tests validate the zero-order and second-order constructs of the Alternative Proxy model. Cronbach's Alpha testing assesses the internal consistency of a group of items (Bagozzi and Yi, 1988). However, it has limitations and can underestimate reliability (Bagozzi and Yi, 1988). Therefore, this research utilises Composite Reliability (CR) (Hair *et al.*, 2017). In addition, the Alternative Proxy model is tested with the Average Variance Extracted (AVE) and the factor loading. The AVE calculates the proportion of variance a latent construct captures from its indicators (Fornell and Larcker, 1981a). On the other hand, the factor loadings represent the correlations between observed variables and their latent constructs (Hair et al., 2017). The factor loading and AVE should exceed 0.5 (Bagozzi et al., 1988), while the Alpha and CR must be higher than 0.7 (Gefen *et al.*, 2000).

Table 5.7: Alternative Proxy Model's Constructs

Variables	Data Source	Items
Financial Well-Being	• Household Income (HHI). • Whole Economy Production and Income (WEPI). • Net Financial Wealth per head (NFW)	• Real Household Actual Final Consumption Expenditure per head (HHAFCE) • Real Household Consumption Expenditure per head (HHFCE) • Gross Domestic Product (GDP) • Gross Domestic Product Per Head (GDPPH) • Net Domestic Product per head (NDPPH) • GDP per head (PE) • Real Net National Disposable Income per head (RNNDI)
Financial Behaviour	Household Spending (HHS).	• Real Gross Adjusted Household Disposable • Income per head (RGAHDI) • Real Net Household Adjusted Disposable Income per head (RNHADI)
Unemployment	The UK Unemployment on the Labour Market, Young People and Workless Households.	UK Unemployment Information
Interest Rate	Bank of England's Official Rate History	Bank of England Official Rate History
Inflation	CPI annual rate (Source dataset: consumer price inflation time series)	CPI Annual Rate
Stock Index	The Financial Times Stock Exchange 100 Index (FTSE 100) Stock Index	FTSE 100 Stock Index
Uncertainty	UK Monthly EPU Index	UK Monthly EPU Index

Table 5.8 provides an overview of outer loadings, Alpha, CR, and AVE for the Alternative Proxy model. For discriminant validity, this study used Fornell Lacker's method (Fornell and Larcker, 1981b). In the Fornell Lacker method, each construct's AVE's square root should be greater than its coefficient's correlation (Table 5.9 and Table 5.10 for zero and second-order constructs, respectively).

The comprehensive analysis presented in earlier tables confirms the robustness of the measurement models, laying a solid foundation for the study's empirical findings. Its sound statistical analysis indicates its credibility and reliability for the next phase.

Table 5.8: Reliability and Validity Analysis (Z: Zero and S: Second order)

Construct	Items	Loading >0.5	Alpha >0.7	CR >0.7	AVE >0.5
Household Income (HHI) (Z)	HHAFCE	0.997	0.961	0.981	0.962
	HHFCE	0.997			
Whole Economy Production and Income (WEPI) (Z)	GDP	0.995	0.985	0.988	0.943
	GDPPH	0.992			
	NDPPH	0.977			
	PE	0.928			
	RNNDI	0.962			
Household Spending (HHS) (Z) (FB)	RGAHDI	0.984	0.994	0.997	0.994
	RNHADI	0.978			
FWB (S)	HHI	0.926	0.948	0.967	0.906
	Net Financial Wealth per head (NFW)	0.957			
	WEPI	0.972			

Table 5.9: Discriminant Validity (Fornel Larcker) for Zero-order Construct.

Constr.	1	2	3	4	5	6	7	8	9
1. HHS	**0.997**								
2. HHI	0.881	**0.981**							
3. WEPI	0.981	0.845	**0.971**						
4. NFW	0.898	0.807	0.923	**1**					
5. UNE	-0.960	-0.848	-0.935	-0.788	**1**				
6. INT	-0.102	-0.240	-0.130	-0.452	-0.100	**1**			
7. INF	-0.450	-0.622	-0.456	-0.530	0.456	0.289	**1**		
8. FTSE	0.832	0.662	0.887	0.864	-0.729	-0.266	-0.363	**1**	
9. UNC	0.400	0.321	0.349	0.388	-0.368	-0.038	-0.176	0.168	**1**

Note: Values on the diagonal (bold) are the extracted average-variance square root.

Table 5.10: Discriminant Validity for Proxy Variables (Fornel Larcker)

Constructs	1	2	3	4	5	6	7
1. FB	**0.997**						
2. FWB	0.920	**0.952**					
3. Unemployment	-0.960	-0.902	**1**				
4. Interest Rate	-0.102	-0.283	-0.100	**1**			
5. Inflation	-0.450	-0.560	0.456	0.289	**1**		
6. Stock Index	0.832	0.848	-0.729	-0.266	-0.363	**1**	
7. Uncertainty	0.400	0.371	-0.368	-0.038	-0.176	0.168	**1**

5.3.2. Direct Effect of the Alternative Proxy Model

This study applied the PLS-SEM technique and used SmartPLS software version 4 (Ringle *et al.*, 2022) following the settings presented in Section 5.1. The results of direct effects are shown in Table 5.11.

A. H1: Financial Behaviour (FB) and Financial Well-Being (FWB)

The analysis rejects the null hypothesis (H0) that FB does not influence FWB, evidenced by a significant Beta coefficient of 0.968 and a p-value of 0.000. Therefore, the research findings accept the alternative hypothesis (H1) that FB positively influences FWB. This finding resonates with the arguments regarding the role of FB in enhancing FWB discussed with the GTS model and with the literature (Bashir and Qureshi, 2023a; Damian *et al.*, 2020; Iramani and Lutfi, 2021; Oquaye *et al.*, 2020). The proxy variables FB and FWB, harmonised with these findings, are shown in Figure 4.43 and Figure 4.44. The findings underscore that the GTS presented earlier relatively matches the actual proxy alternative model's direction and strength.

Table 5.11: Direct Effect of the Alternative Proxy Variables.

Hyp.	Direct Relationships	Std. *Beta*	Std. Error	T Values	p Values
H1	Financial Behaviour ➔ Financial Well-Being	0.968	0.006	170.201	0.000
H2	Unemployment ➔ Financial Behaviour	-0.835	0.027	31.35	0.000
H3	Interest Rate ➔ Financial Behaviour	-0.147	0.023	6.437	0.000
H4	Inflation ➔ Financial Behaviour	0.054	0.017	3.143	0.002
H5	Stock Index ➔ Financial Behaviour	0.193	0.027	7.178	0.000
H6	Uncertainty ➔ Financial Behaviour	0.064	0.012	5.547	0.000

B. H2: Unemployment (UNE) and Financial Behaviour (FB)

Contrary to the GTS model's findings, the Alternative Proxy model reveals a strong negative association between Unemployment and FB (Beta = -0.835, p-value=0.000). Therefore, the results suggest that higher unemployment rates significantly alter financial behaviours, leading to more conservative financial practices like increased saving (Botha *et al.*, 2021). This divergence from the GTS model's expectation of a positive impact could be attributed to the GTS model's sensitivity to specific economic contexts like the 2008 financial crisis, as discussed with the GTS model hypothesis testing.

C. H3: Interest Rate (INT) and Financial Behaviour (FB)

Interest Rates exhibit a moderate negative influence on FB in the Alternative Proxy model (Beta = -0.147, supporting H3), aligning with a cautious approach in financial behaviour as interest rates rise. The result is a deviation from the GTS model, where the impact was insignificant, indicating that real-world economic fluctuations captured by the Alternative Proxy model might differ from the trends observed in online search data.

D. H4: Inflation (INF) and Financial Behaviour (FB)

Inflation shows a moderate positive influence on FB in the Alternative Proxy model (Beta = 0.054, accepted H4), similar to the positive impact observed in the GTS model (Beta = 0.311 for H4). These findings suggest that public concerns about inflation, as reflected in online searches, moderately steer financial behaviours, impacting decision-making processes. Moreover, it shows that both models deviate from the traditional literature, which indicates a negative impact of Inflation on FB (Batrancea, 2021; Duca-Radu *et al.*, 2021). That shows that individuals feel increased inflation and adjust to rapid economic changes, compared with government-reported inflation rates, often lagging these adjustments (Zhu *et al.*, 2021).

E. H5: Stok Index (STK) and Financial Behaviour (FB)

The Stock Index exhibits a slight positive influence on FB (Beta = 0.193, supporting H5), indicating that stock market fluctuations, as reflected in the Alternative Proxy model's trends, marginally affect financial behaviour. However, the results are mixed with previous literature that finds negative returns correlated with high Google search volumes (Bijl et al., 2016) and adds to the relationship complexity and individual financial behaviour (Jain and Chhabra, 2022). The result mirrors the public's adaptive financial planning in response to stock market dynamics.

F. H6: Uncertainty (UNC) and Financial Behaviour (FB)

The analysis shows a statistically significant though relatively small positive association between Uncertainty and FB, with a Beta coefficient of 0.064 supported by a T-value of 5.547 and a p-value of 0.000. In the analysis of H6 within the Alternative Proxy model, the null hypothesis (H0), that Uncertainty does not influence FB, is rejected. The findings indicate that increased uncertainty affects financial behaviour, albeit subtler than expected. Therefore, the results suggest that uncertainty has a noticeable influence on increased financial awareness and engagement.

Nevertheless, the GTS model positively correlates with Uncertainty and FB, with a modest Beta of 0.377. The findings of the GTS model might be explained by societal and economic uncertainties, where individuals might adapt their financial behaviours more significantly than the Alternative Proxy model indicates. However, GTS and the Alternative Proxy model's findings diverge from the literature that increased economic uncertainty yields adverse financial behaviour effects (Dzielinski, 2012; Kulshreshtha *et al.*, 2023). These contrasting results from both models call for more research for better decision-making processes.

5.3.3. Indirect Effect of Alternative Proxy Model

The mediation effects of FB are presented in Table 5.12. The table shows that all effects are significant with p <0.000.

Table 5.12: Indirect Effect of Alternative Proxy Variables.

Hypo.	**Indirect Relationships**	**Std. *Beta***	**Std. Error**	**T Values**	**p Values**
H2b	Unemployment ➔ FB ➔ FWB	-0.808	0.026	30.883	0.000
H3b	Interest Rate ➔ FB ➔ FWB	-0.143	0.022	6.59	0.000
H4b	Inflation ➔ FB ➔ FWB	0.052	0.017	3.153	0.002
H5b	Stock Index ➔ FB ➔ FWB	0.187	0.026	7.209	0.000
H6b	Uncertainty ➔ FB ➔ FWB	0.062	0.011	5.579	0.000

A. H2b: Unemployment (UNE) → FB → FWB (Strong Negative Influence)

The Alternative Proxy model shows a substantial negative indirect effect of unemployment on FWB through FB (Beta = -0.808), contrasting with the GTS model’s positive influence (Beta = 0.214). Results suggest that in the Alternative Proxy model, higher unemployment rates lead to changes in financial behaviour that negatively impact FWB.

B. H3b: Interest Rate (INT) → FB → FWB (Moderate Negative Influence)

The Alternative Proxy model shows a moderate negative indirect effect (Beta = -0.143) of INT on FWB through FB. On the other hand, in the GTS model, the impact of INT on FB leading to FWB is not statistically significant, suggesting that changes in interest rates do not significantly influence financial well-being through financial behaviour within the GTS data context. The results imply that, according to the Alternative Proxy model, higher interest rates lead to more conservative financial behaviours, which negatively affect financial well-being.

C. H4b: Inflation (INF) → FB → FWB (Slight Positive Influence)

Inflation exhibits a slight positive indirect effect on FWB through FB (Beta = 0.052), similar to the GTS model's significant positive effect (Beta = 0.274). It could be implied that inflationary trends influence financial behaviours in a way that positively impacts financial well-being, albeit weakly.

D. H5b: Stock Index (STK) → FB → FWB (Slight Positive Influence)

The Alternative Proxy model shows a slight positive indirect effect (Beta = 0.187) of the stock index on FWB through FB. In contrast, in the GTS model, the indirect effect of the STK on FWB through FB is minimal and insignificant. Therefore, according to the proxy data, stock market fluctuations have a moderate impact on FWB through changes in FB.

E. H6b: Uncertainty (UNC) → FB → FWB (Slight Positive Influence)

Mirroring the GTS model (Beta=0.333), the Alternative Proxy model shows a slight positive significant indirect effect of economic uncertainty on FWB via FB (Beta = 0.062). As a result, it could indicate that increased uncertainty can subtly positively influence financial behaviours, leading to a marginal improvement in financial well-being.

5.3.4. Evaluating the Alternative Proxy Model

This section evaluates the Alternative Proxy model based on commonly used metrics of PLS-SEM, which are R-squared, F-square, and VIF.

For FB, an R^2 of 0.978 (with an adjusted R^2 of 0.977) signifies that the model's predictors explain nearly 97.8% of its variance, illustrating an excellent model fit. Similarly, for FWB, the R^2 value is 0.938 (with an adjusted R^2 of 0.937), meaning that about 93.8% of its variance is accounted for by the variables in the model, indicating a robust representation of the critical factors affecting FWB. In the Alternative Proxy model, the F2 values reveal the impact sizes ranging from small to large, as shown in Table 5.14.

A considerable effect size is observed for the relationship between FB and FWB ($F^2 = 15.035$), highlighting FB as a dominant factor influencing FWB compliance with value ranges (Selya *et al.*, 2012). Unemployment also significantly affects FB ($F^2 = 7.996$), indicating its significant influence on FB within the Alternative Proxy model. Other variables like the Interest Rate and STK demonstrate large effects on FB ($F^2 = 0.586$ and 0.544, respectively), suggesting their considerable impact on FB. In contrast, Inflation and Uncertainty exhibit more minor effects on FB ($F^2 = 0.087$ and 0.149, respectively), indicating a less pronounced but still relevant influence on financial behaviour.

Table 5.13: R^2 and R^{Adj2} for the Alternative Proxy Model

Latent Variables	R^2	R^{Adj2}	Effect Size
Financial Behaviour (FB)	0.978	0.977	Large
Financial Well-Being (FWB)	0.938	0.937	Large

Table 5.14: F^2 Effect for the Alternative Proxy Model.

Latent Variables	F^2	Effect Size
Financial Behaviour ➔ Financial Well-Being	15.035	Large Effect
Unemployment ➔ Financial Behaviour	7.996	Large Effect
Interest Rate ➔ Financial Behaviour	0.586	Large Effect
Inflation ➔ Financial Behaviour	0.087	Small Effect
Stock Index ➔ Financial Behaviour	0.544	Large Effect
Uncertainty ➔ Financial Behaviour	0.149	Small Effect

The VIF is examined as shown in Table 5.15. The values that did not exceed the threshold of five (Hair and Sarstedt, 2019) indicate that multicollinearity is not a concern in this study. Therefore, each construct contributes independently to Financial Behaviour (FB), thus validating the analysis. Notably, the low VIF values for Inflation, Interest Rate, and Uncertainty demonstrate their distinct influences on FB. Even for constructs like FTSE and Unemployment, which have relatively higher VIF values, they remain within acceptable limits even with tighter limits of score four (Fox, 2015), indicating no significant multicollinearity issues. The lack of multicollinearity in the model enhances the reliability of the analysis and conclusions drawn.

Table 5.15: Variance Inflation Factor of the Alternative Proxy Variables

Constructs	VIF
Financial Behaviour (FB) ➔ Financial Well-Being (FWB)	1.000
Unemployment (UNE) ➔ Financial Behaviour (FB)	3.936
Interest Rate (INT) ➔ Financial Behaviour (FB)	1.672
Inflation (INF) ➔ Financial Behaviour (FB)	1.522
Stock Index (STK) ➔ Financial Behaviour (FB)	3.091
Uncertainty (UNC) ➔ Financial Behaviour (FB)	1.234

The CVPAT for the Alternative Proxy model, presented in Table 5.16, assesses the model's predictive relevance using the PLS-SEM approach (Sharma *et al.*, 2023). The test compares the PLS-SEM results against IA and LM benchmarks for FB and FWB constructs. The IA comparison indicates a 'predictive validity' of the Alternative Proxy model, with negative and statistically significant average loss differences (FB = -0.993, FWB = -0.849), suggesting that the model's predictions are more accurate than simple average-based predictions. This trend is observed across the board, with overall average loss differences being negative (Overall = -0.885), reinforcing the model's predictive capability regarding IA.

In contrast, the LM comparison shows a positive average loss difference for FWB (0.088), but the overall figure remains low (Overall = 0.066), and FB shows no difference (0.000). Therefore, it indicates that while the model performs better than a basic linear model for FWB, it does not significantly outperform it for FB. The positive values, however, do not meet the criteria for strong predictive validity. Therefore, the model has limited predictive validity when evaluated against IA and LM benchmarks.

Notably, the results coincide with the GTS predictability, with slightly similar results, concluding that both models are comparable and feasible.

Table 5.16: Cross-validated Predictive Ability Test of the Alternative Proxy Model.

Construct	PLS-SEM vs IA		PLS-SEM vs LM	
	Average loss difference	p Value	Average loss difference	p Value
Financial Behaviour	-0.993	0.000	0.000	0.942
Financial Well-Being	-0.849	0.000	0.088	0.000
Overall	-0.885	0.000	0.066	0.000

5.4. Models Compared: Google Trends Search and Alternative Proxy Models in Predicting Financial Well-Beig

This section concludes the impact of economic variables on financial behaviour and well-being for GTS and the Alternative Proxy models. The GTS model is a real-time approach that captures public economic sentiments. This approach reflects immediate financial attitudes and priorities, as indicated by its high R^2 values for FB and FWB. However, the model has a 'predictive validity' as suggested by CVPAT analysis and requires careful selection of keywords to represent the constructs effectively.

On the other hand, the Alternative Proxy model is based on published government data that is more stable and comprehensive for long-term studies. Its R^2 values are similarly high, indicating a robust explanatory similar to the GTS model. In addition, one significant difference is that the Alternative Proxy model explains Unemployment and Interest Rates differently than the GTS model. It shows a significant negative relationship between Unemployment and FB and a moderate negative influence of Interest Rates on FB. Therefore, it suggests that higher unemployment and interest rates lead to conservative financial behaviours, which aligns with the literature. However, like the GTS model, the Alternative Proxy model has 'predictive validity' as shown by its CVPAT analysis. Consequently, the GTS and the Alternative Proxy models are indispensable for economic forecasting with comparable results; however, the GTS is more dynamic.

5.5. Chapter Summary

This chapter develops the Google Trends Search (GTS) and the Alternative Proxy models using Partial Least Squares Structural Equation Modelling (PLS-SEM) based on the established conceptual framework presented in Chapter 3. The models analyse the role of Financial Behaviour (FB) as a mediator influencing Financial Well-Being (FWB). Both models had a sizeable explanatory analysis, as indicated by their large R^2 values (0.779 for GTS and 0.938 for the Alternative Proxy model). However, the GTS model shows a few contradictions in the literature; increased unemployment and inflation rates result in positive financial behaviour, while the stock index and interest Rates are insignificant. In contrast, all the variables in the Alternative Proxy model were significant; however, inflation was positively correlated with positive financial behaviour. The results from GTS are due to individual financial decisions affected by the dynamic economic conditions, which lead to personal adaptive financial behaviours during uncertainties. Therefore, the GTS model's agility in capturing evolving economic sentiments complements the Alternative Proxy model and provides earlier dynamic findings. However, the results indicate further research on the multifaced complexities of related constructs.

CHAPTER 6: DISCUSSION

The study of Financial Well-Being (FWB) is critical for the government and individuals to handle inadequate long-term financial planning and low saving rates (Brüggen *et al.*, 2017). FWB includes managing debt and savings and achieving financial control (Carton *et al.*, 2022), which allows a person to make affirmed financial decisions to enjoy life (CFPB, 2015). The government cares for FWB to ensure their residents' highest living standards (Blom and Perelli-Harris, 2021; Patsios *et al.*, 2017). This research creates an index of FWB based on big data from Google. The index allows the research community, financial practitioners, policymakers, and government entities to apply it in practice.

The study identifies a few limitations of FWB measurement, discussed in Chapter 2. Despite the existing set of models that measure FWB, no model is considered complete due to the multifaced complexity of Financial Well-Being Components, as highlighted by the road to FWB measurement (Brüggen *et al.*, 2017). Therefore, the review lacks a standardised definition and measurement method (Bashir and Qureshi, 2023a; Michael Collins and Urban, 2020). On the one hand, the classical way of collecting and interpreting data using surveys and interviews lags due to economic market trends and unprecedented extreme events (Kaur *et al.*, 2021). On the other hand, dynamic models based on instant data from the web, such as Google Trends Search (GTS), lack proper construction, keyword selection, and refinement (Symitsi *et al.*, 2022). Therefore, limited research instruments are a significant issue of the little research on the FWB (Michael Collins and Urban, 2020).

Chapter 3 adapts a conceptual framework that shows how FWB could be measured with a focus on extreme economic events. As a result, the framework shows Unemployment, Interest Rate, Inflation, Stock Index, and Uncertainty that influence the Financial Behaviour towards the FWB. The conceptual framework elucidates the consequences of extreme events such as health issues (COVID-19), economic shocks, and rising housing prices on an individual Financial Well-being (Barrafrem *et al.*, 2020; Kim and Wilmarth, 2016; Lee *et al.*, 2018; de Soto *et al.*, 2021).

The study adapts the conceptual framework into two models using Partial Least Squares Structural Equation Modelling (PLS-SEM): The GTS model, which is based on Google trends data and the Alternative Proxy model, which depends on proxy data from the UK government website of the Office for National Statistics. The models are accompanied by hypothesis testing and statistical validation. The reliability and validity of the GTS model were achieved using statistical methods and compared with the Alternative Proxy model. Therefore, the second significant contribution of this study is the creation of an empirically driven FWB index for the UK context based on a new methodology. The results show promising results for GTS compared to the Alternative Proxy model, which mainly provides an instant measure of FWB during extreme events.

This research shows the relationship between FWB and its influencing constructs. In addition, this study proposes a keyword selection and refinement methodology using Google Trends Search. Consequently, one significant contribution of this study is the creation of an empirically driven FWB index for the UK context.

6.1. Discussion of Objective 1

The first research objective discusses adapting a conceptual framework that shows the relationship between FWB: financial behaviour, unemployment, interest rate, inflation, stock index, and uncertainty.

The initial study of the foundation paper (Brüggen *et al.*, 2017) shows that FWB is a multidimensional concept and acknowledges the need for multidisciplinary research. Therefore, the literature covers the central concepts discussing FWB. Hence, this research follows a critical review to interpret existing literature on FWB measurement.

The critical review collects and synthesises related literature about FWB constructs, especially during economic events. According to Brüggen, the roadmap of FWB has five dimensions: contextual factors, financial well-being interventions, financial behaviour, personal factors, and the consequences of financial well-being (Brüggen *et al.*, 2017). The contextual factors encompass economic, legal, political, socio-cultural, technological, and market influences. The financial well-being interventions involve educational initiatives, counselling services, and structural interventions.

The core dimension is financial behaviour, which focuses on promoting financially sound behaviours and providing stability during critical situations. The consequences of financial well-being pertain to individual, organisational, and social aspects, including factors such as quality of life, trust, and welfare. Therefore, the scope of the literature covers these aspects.

However, the review focuses less on objective financial well-being, such as personal factors and FWB consequences. Therefore, the scope includes theories of financial behaviour as it indicates how individuals make decisions regarding their financial situation. In addition, the review consists of studies on financial commitment and behaviour with a family group or community or during extreme economic events. Furthermore, the critical review also includes studies that show how keywords are collected, filtered and refined. Finally, standard time series model preprocessing articles and statistical tests for model validity and creditability were included.

The search strings were placed on Google Scholar, which has many indexed journals. Some of the key search strings include: ("Financial Well-Being" OR "financial behaviour" OR "economic conditions") AND ("measurement" OR "Google Trends" OR "survey") AND ("contextual factors" OR "financial interventions" OR "personal factors"). In addition, the inclusion criteria for the critical review include articles written in English and UK government reports about financial well-being. More focus was retained on FWB measurements, especially those that use Google Trends. Moreover, papers that discuss machine learning methods were eliminated. In addition, psychological theories were only considered to understand human financial behaviour in general. Lastly, papers that were less than five pages were eliminated.

The final phase of the critical review consolidates and synthesises literature to construct and understand the intricate relationships among financial behaviour and extreme events (unemployment, interest rates, inflation, stock index, uncertainty) that impact the FWB. However, a heightened emphasis is placed on papers with keywords pertinent to FWB constructs to be used in the Google Trends Search model. Moreover, a complementary study was made to find proxy constructions on UK government websites. Therefore, the study extracts themes and patterns of FWB and aligns with the GTS and its Alternative Proxy model. The ideas from several measurement models grasp the focus of the study to stay on extreme events only. As a result, Chapter 3 developed the conceptual framework grounded in literature with six hypotheses.

In the conceptual framework outlined in Chapter 3, the hypothesis development shows how extreme events impact FWB through the multifaceted mediator variable financial behaviour. The hypotheses postulate the significant influence of financial behaviour, unemployment, interest rates, inflation, stock index, and uncertainty on FWB. For instance, the assumption that "Financial Behaviour (FB) positively influences the Financial Well-Being (FWB)" (H1) is supported by the literature indicating that responsible financial behaviour, characterised by effective budgeting, disciplined saving, and prudent spending (Comerton-Forde *et al.*, 2018; Utkarsh *et al.*, 2020; Wahla *et al.*, 2021). Similarly, the relationships between Unemployment, Interest Rates, Inflation, and Uncertainty are hypothesised to influence Financial Behaviour negatively through H2, H3, H4, and H6, respectively. On the other hand, the Stock Index is hypothesised to influence Financial Behaviour positively (H5). The hypothesis is developed based on previous literature. For example, increased stress due to COVID-19 could increase uncertainty, resulting in negative financial behaviour (Bulog *et al.*, 2022; Mihaela, 2020; Simionescu and Cifuentes-Faura, 2022a). In addition, inflation fluctuations adversely affect consumer spending and saving (Batrancea, 2021; Duca-Radu *et al.*, 2021). These hypotheses cover the FWB's multidisciplinary concept amidst economic volatility.

The conceptual framework develops a mediator (Financial Behaviour), because it is the only driving force towards an individual FWB (Brüggen *et al.*, 2017). The constructs include budgeting, saving, and investing, which impact individuals' financial stability (Damian *et al.*, 2020; Gutter and Copur, 2011; Helm *et al.*, 2019). Moreover, the hypothesis development indicates that FB significantly influences FWB by transferring personal financial capabilities into financial health (Bashir and Qureshi, 2023a; Damian *et al.*, 2020; Iramani and Lutfi, 2021; Oquaye *et al.*, 2020). Therefore, the conceptual framework for extreme economic events is considered comprehensive.

The research addresses the limitations of survey methods, which often are time-consuming and potentially outdated. The proposed GTS is a real-time alternative that covers the conceptual framework's constructs with individual public sentiment of financial behaviours related to FWB. Literature shows that Google Trends explores happiness associated with job security, financial security, leisure determinants and family life (Algan *et al.*, 2016). Similarly, Trends were also used in other areas, such as predicting grain prices (Gómez *et al.*, 2021), forecasting the stock market, unemployment and job-finding (Baker and Fradkin, 2017). Therefore, Google Trends as big data is a cost-effective alternative, particularly given the multi-faceted and multi-dimensional concept of FWB (Solomon, 2001; Kaur et al., 2021).

The objective also discusses the identification of keywords from existing literature for the proposed conceptual framework. Therefore, the initial set of keywords ensures the validity and credibility of the keywords grounded in academic research; hence, the predictability of the FWB index is enhanced. In addition, the additional keywords ensure their coverage for GTS constructs of unemployment, inflation, interest rate, stock index, and uncertainty. The study found that some keywords were repeated, while some studies were based on a few words, and some of them were only one keyword (Borup and Schütte, 2022). Therefore, a seed of literature sets a solid foundation for the integrity of the conceptual framework (Scharkow and Vogelgesang, 2011).

The study found that the list of keywords was limited due to the study's wide range of sub-topics and the novelty of this study, which uses GTS for financial well-being. For example, the current set of keywords of the OECD study was related to well-being in general (Algan *et al.*, 2016); therefore, filtering these keywords might be subjective and inefficient. One reason is that if keywords of OECD were filtered, the study might be biased toward generic well-being rather than the research objective focusing only on keywords related to extreme events.

Addressing this objective, expanding the initial set of keywords through Google's suggestion introduces more comprehensive and relevant terms reflective of typical human behaviour. The process imputes potential effective (missing) keywords not included in previous studies and reduces noise due to less frequent usage of keywords (Fattahi *et al.*, 2016). One main issue was the non-existence of any initial keywords for financial behaviour and well-being; therefore, an alternative method was utilised. The keywords for FB were chosen from The Consumer Financial Protection Bureau (CFPB) glossary and selected based on their similarity to the definition of financial behaviour. Moreover, the glossary is a reliable and regularly updated financial decision literacy source.

In contrast, the keywords (Financial behaviour, Unemployment, Inflation, Interest Rate, Uncertainty) were combined to generate FWB keywords; therefore, FWB keywords adhere to the scope of the study regarding extreme events. This study used a machine learning approach to semantically compare keywords to the definition of concepts (FB, FWB using Google's Universal Sentence Encoder (GSE)). As a result, the approach contributes to automated keyword filtering for more efficient and accurate selection. Consequently, the approach minimises subjective bias in keyword selection.

The Structural Equation Modelling (SEM) approach measures the conceptual framework variables, which was selected due to its applicability. The study develops the GTS and the Alternative Proxy models using the Partial Least Squares Structural Equation Modelling (PLS-SEM). The selection of PLS-SEM because it supports complex relationships between FWB and its determinants, including media examination effects of FB. Moreover, the PLS-SEM tests the hypotheses, which reflect a commitment to methodological excellence (Hair, Risher, et al., 2019).

The FWB model is validated by comparing the GTS model against the Alternative Proxy model based on government data. This comparative analysis ensures GTS credibility and predictability using R-squared values, effect sizes, and the CVPAT tests. Therefore, measuring financial well-being using GTS data addresses a significant gap in the literature and sets a new standard for empirical studies.

The objective addresses the significance of the conceptual framework constructs using the GTS model. The hypothesis testing revealed that FB positively influences FWB. However, there was an unexpected positive correlation between Unemployment and FB. Unemployment might make people more cautious by reducing spending and better budgeting on non-essentials to improve their financial stability (Ganong and Noel, 2019; Görtz *et al.*, 2023; Roll *et al.*, 2022). The discrepancy between interest rates in the literature (negative) and the insignificant result of the GTS model suggests that the Interest Rate construct has a low direct influence on individual financial behaviour and might be less immediate, challenging traditional expectations of savings declines in such environments (De Bonis and Marinucci, 2023).

Similarly, the discrepancy between perceived literature that indicated a negative aspect of inflation on FB versus a positive significant relationship indicates a dual behaviour of Inflation construct impact: while it typically erodes purchasing power and can lead to financial stress, it also acts as a catalyst for positive financial behaviours, such as increased budgeting and prioritisation of essential needs (Ardogan and Yilmaz, 2021; Hall *et al.*, 2023; Menyhert, 2023). The influence of Stock index returns appears to have a limited impact on individual financial behaviour due to information overload that deteriorates investors' decision accuracy (Aljanabi, 2023; Zer *et al.*, 2023). However, the Uncertainty seems to be positive, albeit there is negative evidence in the literature due to the increased access to emerging intelligent financial systems that enable financial behavioural adjustments during uncertainties (Arner *et al.*, 2015; Gabor and Brooks, 2020; Hikida and Perry, 2020). However, Uncertainty influences other factors; an increase in uncertainty leads to a fall in output growth and an increase in inflation (Pratap and Priyaranjan, 2023).

The objective addresses the significance of the conceptual framework constructs using the GTS model. The hypothesis testing revealed that FB positively influences FWB. Contrary to the GTS model's findings, the Alternative Proxy model shows a strong negative association between Unemployment and more conservative financial practices like increased saving (Botha *et al.*, 2021). In addition, Interest Rates exhibit a moderate negative influence on FB in the Alternative Proxy model, aligning with a cautious approach to financial behaviour. However, the Inflation shows a mild positive influence on FB, similar to the positive impact observed in the GTS model. Contrary to the GTS model, the Stock Index exhibits a slight positive influence on FB, indicating that stock market fluctuations affect the FB construct marginally. The analysis shows a statistically significant though relatively small positive association between Uncertainty and FB; however, the values were below 0.1.

Nevertheless, the R^2 analysis of the GTS model explains approximately 74.1% of the variance in FB, with a large effect size as indicated by a high F^2 value and a low multicollinearity as indicated by a VIF value below 5. On the other hand, the Alternative Proxy model had an R^2 value above 90% and a high effect size, with an acceptable multicollinearity below the threshold. However, both models show a 'predictable validity' as the CVPAT test indicates. Therefore, the GTS model is sufficient to represent actual proxies described and disseminated on the UK government websites. However, the significant difference between these models is the automation of the GTS model, which can be executed at any time to describe new financial behaviour and financial well-being, particularly during a crisis.

6.2. Discussion of Objective 2

The research objective addresses the main contribution of the GTS model. The GTS model was developed with PLS-SEM due to its complexity with a mediator variable for FB and to ensure its credibility through statistical methods. In addition, the GTS model is compared with the estimated FWB scores published by the government's websites (in the UK) and its Alternative Proxy model. The GTS model is grounded in hypothesis testing that reflects public sentiment on financial decision concerns. Consequently, the FWB scores of the GTS data are compared with FWB scores derived from established survey methodologies during the research study period from 2008 to 2019. However, the UK government revealed only two values during this period, which were in 2015 and 2018. Therefore, the study also compared the Alternative Proxy model to make the analysis more comprehensive.

A. Comparison Process

The validation process has the following steps: (1) FWB's average raw underlying keywords are used for comparison. (2) The medians for GTS and Proxy models are used as representatives for each year due to the availability of the FWB survey year-wise and to avoid monthly fine-grain comparisons. The GTS and the Proxy models' scores are converted between 0 and 10, the scale used by the UK government FWB measures using the equation (4.1) presented earlier, (3) visualise the findings and choose the metric to compare values of FWB scores.

Consequently, the study considers the Wilcoxon signed-rank test (Woolson, 2007) preferred over alternatives like the paired t-test, which requires normal distribution and invalidates the assumption of incomplete Proxy data. The Wilcoxon test, in contrast, accommodates non-normal distributions and evaluates both the direction and magnitude of differences; however, this test might not provide credible results for only two survey values of FWB in 2015 and 2018. Therefore, the Wilcoxon signed rank is used only to test the FWB Index of the GTS model and the FWB index based on the Proxy model. Therefore, the study used an alternative suitable for small data items, the Mean Absolute Percentage Error (MAPE). MAPE is a standard statistics metric used in finance forecasting (McKenzie, 2011). The MAPE assess the accuracy of the GTS models' FWB index compared with the FWB Index estimated by the UK government. It is calculated as the average of the absolute differences between the predicted (FWB Index) and actual (FWB government index) values, divided by the actual values, expressed in percentage terms. For readability, FWB-Index refers to the FWB index calculated by the GTS model, and FWB-Proxy refers to the FWB calculated by the Alternative Proxy model. At the same time, FWB-Current and FWB-Long are the current and long FWB values calculated by the UK government.

B. Actual United Kingdom Financial Well-Being Measurement (Surveys)

The UK Strategy for Financial Wellbeing (2020-2030) aims to transform financial health nationwide with five ambitious goals. It targets two million individuals in four distinct areas: enhancing financial education for children and young people, encouraging working-age individuals to save regularly, reducing the reliance on credit for essentials, and increasing access to debt advice. Additionally, it aims to improve the understanding of financial planning of 5 million individuals for planning in and later life.

In 2015, the Money Advice Service conducted the Adult Financial Capability Survey in the UK, including behaviours, enablers, inhibitors, and demographic factors influencing financial well-being. The survey was conducted using 3,500 interviews with a representative sample of the UK population. The survey refined its conceptual financial capability model with drivers and barriers and profiling groups by their financial well-being and resilience levels. The UK's 2015 Financial Capability Survey revealed significant findings regarding the current financial well-being versus longer-term financial security. The analysis showed that individuals find managing present financial needs more feasible than planning for the future, as evidenced by the average scores across all adults. The "current financial well-being" score was higher at 7.5 compared to a lower average of 3.8 for longer-term financial security. Therefore, results indicate that surveyed individuals consider securing future financial stability challenging. In contrast, the GTS FWB-Index 2015 median value is 12.53 or 4.44 on a scale between 0 and 10.

In 2018, the UK Financial Capability Survey revealed distinct differences in "current financial well-being" and longer-term financial security. According to the survey findings, adults generally reported higher levels of "current financial wellbeing", with a mean average score of 6.8 out of a possible ten compared to low long-term financial security of 4.7. Therefore, similar to the 2015 survey results, individuals try to balance immediate financial management with future financial security (Ghosh and Renna, 2022; She *et al.*, 2023). In contrast, the GTS FWB Index's median value in 2018 was 13.73, or 5.23, on a scale of 0 to 10.

C. Financial Well-Being Index Comparison

Figure 6.1 shows the proposed FWB index calculated by the GTS model, the FWB index calculated by the Alternative Proxy model and current and long-term FWB values estimated by the UK government in 2015 and 2018. The figure includes years from 2008 until 2019, when proxy data was available. The GTS model ranges from 11.24 to 14.15 in 2015 with an average of 12.72, with an increase in 2018 range from 11.47 to 15.78 with an average of 13.54. The UK government's data for these years indicate more conservative current and long-term FWB scores of 7.5 and 3.8 for 2015 and 6.8 and 4.7 for 2018, respectively.

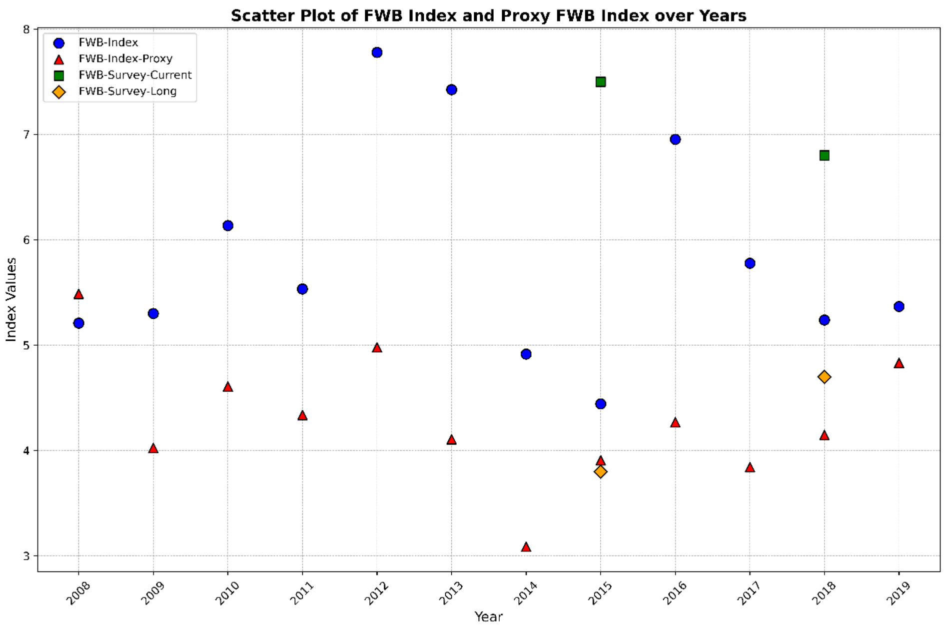


Figure 6.1: The FWB Indexes Compared with Estimated Survey Scores.

The FWB-Index exhibits higher values than the Alternative Proxy FWB index, except for 2008. It is also below the government's current FWB scores for 2015 and 2018 scores. The government's current FWB values were higher than those for FWB-Proxy and the GTS FWB index. Nevertheless, the FWB-Proxy indicates a trend consistent with the FWB-Index, yet with distinct differences in specific years. This observation is statistically supported by the Wilcoxon signed-rank test, yielding a statistic of 1.0 and a p-value of less than 0.001. Hence, the divergence in results from the GTS model is significantly distinct from random occurrence, which indicates that the relationship between the FWB-Proxy and FWB-Index measures is relatively different. The GTS model's particular sensitivity to extreme economic events is further evidenced by its differentiated reflection of collective economic sentiment and individual financial health.

A deeper analysis of the UK government's data for 2015 and 2018 reveals variations for several reasons. The scope of FWB in the GTS model covers extreme economic events of: Unemployment, Interest Rate, Inflation, Stock Index, and Uncertainty compared to survey results based on relatively different components. The MAPE values between GTS and FWB reported by the government were 14% in 2015 and 10% in 2018 in the long term. The errors indicate that individuals may find it challenging to plan for long-term financial stability compared to their current financial needs. Therefore, the proposed aggregated GTS Index provide a more generalised view of financial well-being than those from government surveys. Furthermore, results indicate that GTS has the implication of community-wide sentiment over personal financial experiences. The GTS is seen as more reactive to extreme events, as evidenced in Chapter 4. Consequently, the GTS model is a valuable supplement to traditional surveys and provides immediate scores for informed, responsive policy-making and financial education efforts. It could indicate that individuals are more realistic in the long run than the current FWB. It could suggest that by the time individuals gain more experience, the GTS will have lower MAPE errors given the unprecedented upcoming extreme events. This means people have a more accurate understanding over time than the current FWB. This suggests that as people gain more experience, the GTS will likely make fewer mistakes, mainly when predicting unexpected extreme events.

6.3. Contribution to Theory and Literature

This study contributes to the body of literature on Financial Well-Being (FWB) by introducing a novel approach to measuring FWB using Google Trends Search (GTS) data (Scharkow and Vogelgesang, 2011). It creates an empirically and theory-based FWB index that provides an alternative measurement of FWB to survey-based methods, addressing gaps identified in previous literature, such as real-time analysis (Cebrián and Domenech, 2022; Symitsi *et al.*, 2022), and future financial stability (Ghosh and Renna, 2022; She *et al.*, 2023). Moreover, the proposed framework aligns with and builds upon critical theories of financial behaviour (Brüggen *et al.*, 2017) and the potential of economic studies on big data (Michael Collins and Urban, 2020). The study's methodology combines machine learning techniques for keyword selection and PLS-SEM for model validation, opening new avenues for future research in financial behaviour modelling and real-time financial well-being assessment.

Additionally, this study incorporates the Prospect Theory (Kahneman and Tversky, 1979), which explores how individuals evaluate potential losses and gains under uncertainty, emphasising the cognitive biases that influence decision-making. Furthermore, it utilises the Theory of Planned Behaviour (Ajzen, 1991), which examines how attitudes, subjective norms, and perceived behavioural control shape financial behaviour. In addition, the study also leverages the Self-Efficacy Theory (Bandura and Adams, 1977; Vaughan-Johnston and Jacobson, 2020; Warmath and Zimmerman, 2019), while Social Capital Theory (Hellerstein and Neumark, 2020) shows how individuals seek knowledge and support online, reflecting collective behaviours and sentiments about economic conditions.

6.4. Chapter Summary

A critical literature review adapts the conceptual framework grounded in literature with six hypotheses regarding Financial Behaviour, Unemployment, Interest Rate, Inflation, Stock Index, and Uncertainty. The Google Trends Search (GTS) model uses keywords from the literature to ensure the integrity of the conceptual framework. Two exceptions for the keywords were the Financial Behaviour and the Financial Well-Being constructs. FB keywords were seeded from the CFPB glossary, a reliable source using a semantic similarity approach from machine learning. Consequently, a similar semantic approach minimises subjective bias and effectively captures FB and FWB keywords.

Consequently, FWB was generated by combining keywords (Unemployment, Inflation, Interest Rate, Uncertainty, and Financial Behaviour) after passing the similarity threshold with machine learning. In addition, there was a significant difference between the GTS and the Alternative Proxy model regarding a few hypotheses, especially during extreme economic events, as indicated by some mixed literature. In addition, the analysis correlates the FWB index with the UK government's measured value. Hence, GTS could imply planning for policy changes that affect financial well-being and complement financial well-being measurement among the UK population. In addition, the GTS model fills gaps left by traditional survey methods, particularly regarding timeliness and granularity. The GTS model provides near-real-time scores of financial well-being on the fly.

CHAPTER 7: CONCLUSION, LIMITATIONS and FUTURE WORK

This research presents a new method for measuring individuals' Financial Well-Being (FWB) based on big data extracted from Google Trends. The study adapts a conceptual framework of extreme economic events: Unemployment, Interest Rate, Inflation, Stock Index fluctuations, and Uncertainty. The literature found that these events influence Financial Behaviour towards saving, budgeting, or investing (Damian *et al.*, 2020; Gutter and Copur, 2011; Helm *et al.*, 2019). Consequently, the study adapts a new model called Google Trends Search (GTS) based on the underlying conceptual framework of FWB. The GTS model is considered an automated dynamic model for public financial sentiments. In addition, it is distinct from traditional lingering methodologies such as surveys and interviews.

Consequently, the GTS contributes a new FWB Index that could automate the FWB measurement based on keyword frequencies. The Index is validated against a Proxy model derived from UK government data, the Adult Financial Capability Survey (2015), and the UK Financial Capability Survey (2018). Results show the Index's reliabilities and capabilities as a utility tool that is a primary supplementary to the FWB assessment measure. Therefore, the Index enhances policy response during economic uncertainties.

7.1. Conclusion

While Google Trends supports this requirement, carefully selecting terms and keywords is essential for establishing a reliable FWB Index. The research collected several keywords from the literature; however, the completeness of the keywords was challenging due to the unavailability of keywords that cover all broad FWB-related concepts (Brüggen *et al.*, 2017), even in the study focusing on extreme economic events. Therefore, the study concludes by merging keywords, removing repetition, and keeping keywords with a frequency above zero magnitude on Google Trends. In addition, the keywords were collected considering they are targeting the UK; however, other research might collect other related keywords. Furthermore, the keywords were expanded with additional keywords, considering how often users select keywords in search engines. Therefore, keywords were broadened to include the top ten Google suggested search terms per keyword.

When no keywords exist in previous literature, an alternative financial glossary of terms is used. The Consumer Financial Protection Bureau (CFPB) glossary was used to collect keywords related to the Financial Behaviour concept, similar to dictionaries used in similar studies (Gao *et al.*, 2020). However, as the keywords were prominent, machine learning was adopted to filter only keywords aligned with the Financial Behaviour definition using the semantic similarity of Universal Sentence Encoder (GSE), developed by Google (Cer, Yang, Kong, Hua, Limtiaco, John, Constant, Guajardo-Cespedes, Yuan, Tar, Sung, *et al.*, 2018). GSE's approach reduces bias and allows for automated selection, given its accuracy reported in the literature (Cer, Yang, Kong, Hua, Limtiaco, John, Constant, Guajardo-Cespedes, Yuan, Tar and others, 2018). However, the generation of FWB keywords was more difficult. Despite existing keywords such as those in the Organization of Economic Co-operation and Development (OECD) for well-being (Algan *et al.*, 2016). the study decided not to use them to avoid overfitting and deviating from the research objective by focusing only on extreme economic events. Finally, semantic similarity filtered the Financial Well-Being keywords similarly to the Financial Behaviour construct approach.

It is concluded that not all keywords are relevant, and some might decrease the model performance. Therefore, in contrast with other studies that use only a few terms (Castelnuovo and Tran, 2017; Eichenauer *et al.*, 2022), this study uses several credible keywords. Thus, the study balances comprehensively with accuracy, removing additional noise that might result due to the multidimensional nature of FWB (Algan *et al.*, 2016). This Big data approach addresses the limitations of conventional surveys that lag financial well-being in years. Thus, a real-time FWB assessment of individuals becomes available to navigate financial decisions amidst economic uncertainties.

The study used Structural Equation Modelling (SEM) to build the conceptual framework, which was the only valid approach in the existence of a mediator variable (Financial Behaviour with its determinants) that influences the FWB. The GTS model and the Alternative Proxy are designed using the same PLS-SEM approach. In practice, the GTS model was developed with SmartPLS software to visualise the adopted PLS-SEM approach with a wide range of the latest statistical testing methods. However, the Alternative Proxy model is built with several levels of the underlying FWB concepts extracted from the UK government websites, such as ‘Household Income’, ‘Whole Economy Production and Income’, and ‘Household Spending’. The comparison of the GTS model with a Proxy model validates the GTS model’s credibility and predictability. The GTS and the Proxy models had a sizeable explanatory analysis, as indicated by their large R^2 values (0.779 for GTS and 0.938 for the Proxy model). However, the GTS model shows a few contradictions in the literature; an increased level of Unemployment or Inflation Rates results in positive Financial Behaviour, while the Stock Index and the Interest Rate are insignificant.

In contrast, all the variables in the Alternative Proxy model were significant; however, Inflation was positively correlated with Financial Behaviour. The results from GTS are due to individual financial decisions affected by the dynamic economic conditions, which lead to personal adaptive financial behaviours during uncertainties. Furthermore, there were discrepancies concerning the direction of Unemployment towards Financial Behaviour, which was positive for GTS and negative for the Proxy model. These findings challenge traditional assumptions and contribute to the dynamic relationships between economic conditions and financial well-being.

Additionally, validating the proposed FWB Index against established survey data demonstrates its applicability to FWB. The Mean Absolute Percentage Error (MAPE) between the GTS Index and the scores of the FWB reported by the government were 10% in 2015 and 14% in 2018 in the long-term FWB. The MAPE discrepancies indicate that individuals learn to manage long-term financial needs more effectively than they do due to accumulated experiences (Heald and Hodges, 2020). However, the FWB has a few variations, as indicated by MAPE, compared to survey data due to its responsiveness to extreme economic events. Therefore, the FWB Index could inform policymaking for financial institutions.

In conclusion, this research introduces the GTS as a dynamic tool for assessing financial well-being. It addresses the limitations of traditional survey methods and enriches the understanding of financial well-being. The findings underscore the importance of agile, big data-driven approaches for improving financial well-being during evolving economic events.

7.2. Implications

This section discusses the implications of this study in theory and practice.

7.2.1. Theoretical and Methodological Implication

The research significantly advances FWB theoretical frameworks. It is one of the first studies integrating big data of Google Trends; therefore, it provides current theories with an immediate and comprehensive viewpoint on FWB based on large numbers of public financial users' sentiments. The new framework transcends traditional survey-based assessments and acknowledges FWB's complexity, aligning with the agenda of previous studies (Brüggen *et al.*, 2017). The study incorporates current theories with extreme economic conditions on individual FWB, mediated by financial behaviour but with dynamic sentiments. Therefore, the study enriches academic discourse with FWB as an interdisciplinary concept.

The study adopts the Partial Least Squares Structural Equation Modelling (PLS-SEM) to construct the GTS and the Alternative Proxy models, triangulating its validation methodology with several sound statistical analysis methods. This study enhances the reliability of FWB assessment tools and demonstrates the efficacy of using real-time data for economic and financial studies. The keyword selection and refinement process represent a significant methodological advancement based on pre-trained machine learning models. Consequently, the collection of keywords is a dynamic alternative to conventional data collection methods that enrich the FWB assessment methods.

7.2.2. Practical Implication

The FWB Index is useful for financial practitioners, policymakers, and government entities. The model provides an instant measure that promptly assesses public financial sentiment, facilitating timely and informed decision-making. In addition, the GTS's public reaction to economic events is a critical adjunct for traditional surveys as a predictive model. In addition, the FWB Index helps the financial practitioner develop targeted financial products and services according to the financial needs of the country of interest (e.g., the UK population). Furthermore, the FWB Index empowers policymakers to design evidence-based financial regulations, interventions, and public awareness campaigns. They can tailor strategies to address the most pressing financial event (concern) facing citizens. In addition, the Government entities could use the FWB Index to assess the effectiveness of existing financial well-being initiatives and identify areas for improvement.

7.3. Limitations

Despite the automation and real-time assessment of the proposed GTS model, the study acknowledges a few limitations. The reliance on Google Trends data may not fully capture the Financial Well-Being (FWB) for aged people or for those who do not use the internet. Google Trends reflects public search behaviour which could change based on personal financial situations, potentially introducing biases linked to the demographic and geographic distribution of internet users. Moreover, the study’s concentration on extreme economic events may restrict its relevance during more stable periods. Moderate or stable economic conditions might reduce individual financial behaviour which might become less volatile and more consistent.

The set of keywords was focused on the UK, which may indicate potential biases due to differences in human behaviour from one country to another. Human financial behaviour is directly related to financial literacy, risk propensity, and even access to digital services (Lučić *et al.*, 2022). Therefore, results should be carefully interpreted in the context of the multi-dimensional FWB and as a singular model for the UK population. While the number of keywords was carefully selected, expanded and filtered, further keywords, such as new government programs, might emerge and should be included in a comprehensive model. Finally, the study consists of the period from 2005 to 2021, with a few selected economic events; however, several other economic events might emerge over time and might have different human behaviour as opposed to COVID-19, resulting in more financial resilience due to the events that increased loss of jobs and lives at the same time.

7.4. Generalisability Across Regions

This study applies the framework of Institutional Economics (North, 2005) to examine the generalisability of the Financial Well-Being (FWB) Index across different regions. Its methodology accounts for the variability in institutional structures, financial systems, cultural norms, and welfare provisions to adapt to diverse global contexts. The FWB Index has the potential to be generalised beyond the UK to various international regions. This section explores how the FWB Index can be adapted to market-driven economies, high-saving economies, emerging markets, resource-based economies, robust welfare systems, and transitional economies.

In market-driven economies like the US and Australia/New Zealand, financial behaviour is heavily influenced by investment in stock markets, household debt, and housing market dynamics. For example, in the US, consumer debt (credit cards, mortgages) and retirement savings like 401(k)s have a significant role in financial well-being (Lusardi, 2019; Lusardi and Tufano, 2015). Similarly, Australia has one of the highest household debt levels globally, driven by the housing market (OECD/Australia, 2017).Consequently, to apply the FWB Index in these regions, additional keywords related to consumer credit, housing markets, and retirement savings should be integrated to develop a tailored index.

In high-saving economies like Japan and China, the financial well-being landscape differs. Japan has high saving rates, low personal debt, and long-term employment security (Horioka, 2006). In contrast, in China, financial well-being is influenced by demographic shifts such as rising elder dependency and the evolving retirement system. As capital markets develop, the financial decisions of Chinese seniors are increasingly impacted by the rapidly changing economy (Cai *et al.*, 2010). Therefore, in both countries, financial behaviour is influenced by savings, job security, and digital payment platforms. Consequently, to generalize the FWB Index in these economies, it should focus on constructs such as savings rates, digital financial behaviour, and employment stability, while China additionally requires an emphasis on social credit scores and urban-rural financial disparities.

The informal economy is crucial to financial well-being in emerging markets like India, Southeast Asia, and Sub-Saharan Africa. In India, government initiatives such as the Kisan Credit Card and Pradhan Mantri Jan Dhan Yojana have significantly promoted financial inclusion, particularly in rural areas (Malladi *et al.*, 2021). However, despite progress, financial disparities between urban and rural populations remain, and efforts to fully include the rural population are still developing (Pushp *et al.*, 2023). Similarly, cash transactions and informal savings mechanisms are common in Southeast Asia, while in Sub-Saharan Africa, mobile money platforms like M-Pesa are transforming financial access (Siddika and Sarwar, 2024). Thus, to adapt the FWB Index for these markets, the model should focus on digital inclusion, mobile banking, regional economic disparities, remittances, and agricultural income.

In resource-based economies like the Middle East and Latin America, financial behaviour is heavily influenced by factors such as oil wealth, political instability, and reliance on the informal economy. In the Middle East, financial behaviour is strongly influenced by Islamic banking principles, particularly in family businesses, where religious beliefs and compliance with Sharia law guide financial decisions (Bizri *et al.*, 2018). In contrast, in Latin America, high inflation, economic instability, and significant income inequality influence financial well-being, particularly in Argentina and Brazil (Alvaredo *et al.*, 2018). Thus, to generalise the FWB Index for these regions, additional constructs such as Islamic finance, political stability, currency fluctuations, and informal economies should be considered.

In regions characterised by strong welfare systems and transitional economies, such as the European Union and Russia/Eastern Europe, financial well-being is shaped by unique factors. Germany and France benefit from extensive social safety nets, while countries like Spain and

Italy face higher unemployment rates and economic disparities (Neubourg *et al.*, 2007). In Russia financial behaviour is still shaped by the transition from centrally planned to market economies, with high wealth inequality and economic volatility (Dabrowski, 2023). Consequently, applying the FWB Index should account for welfare systems, cross-border financial behaviour, and political/economic instability.

Consequently, the FWB Index can be adapted for regions globally by incorporating localised economic and cultural factors through specific keywords for each construct. A focus on consumer credit and housing markets is critical in market-driven economies. In the high-saving economies, savings rates and employment stability have a more significant role. Emerging markets require attention to digital inclusion and informal economies, while resource-based economies demand consideration of currency fluctuations and political stability. Lastly, welfare systems and transitional economic factors are key to understanding financial well-being in developed welfare economies.

7.5. Future Work

This research opens new future opportunities, as highlighted.

Integrating Additional Data Sources: Future studies should explore integrating the current GTS dataset with additional real-time data sources like Twitter. The starting point towards FWB measurement using Twitter could be the work that has evaluated the Italian subjective financial well-being in different regional areas (Iacus *et al.*, 2022). Their work focuses on eight dimensions under three main areas: personal well-being, social well-being, and well-being at work, which have aspects like emotional balance, life satisfaction, and trust to enhance financial behaviour. However, for this integration, advanced machine learning algorithms should be used to select and refine keywords based on Twitter's discourse. Hence, such data provides additional individual sentiment towards events, especially in countries that use Twitter as a primary platform, such as the KSA (e.g., Alshahrani *et al.*, 2018).

Expanding Geographical Regions: While the study was focused on the UK as a case study, including additional geographical regions, allows for examining FWB Index performance across economic systems and societies. A suitable starting point could be the study highlighting the roles of community, trust, and broader geographical areas (Obster *et al.*, 2024). Expanding the study would facilitate a comprehensive evaluation of the FWB Index's efficacy across varied economic systems and cultural settings to discern regional variances in financial well-being. However, careful grouping and multi-group analysis might be required to differentiate the performance of the FWB Index in each respective region.

Longitudinal and Cross-Cultural Studies: Further studies could conduct longitudinal studies to track changes in financial well-being over time. However, it should be accompanied by cross-cultural and demographic comparative analyses for long-term validity. Such studies could assess the impact of policy changes and global economic trends on individual financial behaviour. Future research could analyse the systematic review that analyses longitudinal methods of financial well-being (Sorgente *et al.*, 2022), which shows research diffusion, data collection methods, and the FWB definition and operationalisation. This approach demonstrates the potential of integrating longitudinal studies with cross-cultural and demographic analyses to track and understand both subjective and objective aspects of financial behaviour comprehensively. However, integrating both longitudinal and cross-cultural comparative analyses challenges the methodology of process, data comparability, and the interpretation of results across diverse contexts.

Exploring Sub-Constructs of Financial Behaviour and Psychological Factors: While the study covers only extreme economic events, sub-constructs of financial behaviour could be helpful. The research findings indicate some dual behaviour of some contracts; therefore, additional factors, such as financial literacy or self-efficacy, and psychological factors like risk aversion, could indicate the combined effects of Financial Behaviour on financial well-being. Future research could use the comprehensive, integrated conceptual model (Kaur and Singh, 2024), which combines the theory of planned behaviour and social comparison theory. This model has comprehensive components such as financial knowledge, behaviours, attitudes, social comparison, self-efficacy, and cultural values, incorporating a gender perspective. However, integrating these factors requires a fine-grained research design grounded in literature to better understand individual traits and learning experiences.

Assessing the Impact of Government Policies and Technological Advancements: As the government measures the FWB Index, evaluating the effectiveness of financial regulations and policies accompanied by technological advancements could be informative. For example, fintech companies (through services) and digital currencies are concerned with future financial behaviour and investment decisions. Future research could explore the study (Kumar *et al.*, 2023), which assesses the roles of skills, digital financial literacy, and financial autonomy in making financial decisions during a crisis like COVID-19 or access to financial services of fintech companies. This work underscores digital financial literacy as a direct influence and mediator in financial decision-making and well-being to develop gender-specific policies and practices in response to technological shifts and socio-economic pressures. However, deciphering regulatory frameworks and technological progress fosters multidimensional research on financial access and the macroeconomic implications.

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