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Four Papers on Monetary Policy Uncertainty and Central Bank Communication

by

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Abstract

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This thesis presents four essays on monetary policy uncertainty, expectations, perceptions, and central bank communication. The first essay develops a Twitter-based index of monetary policy uncertainty for South Africa, addressing the absence of high-frequency measures in emerging markets. Using a shock-restricted structural VAR, the analysis identifies a link between policy uncertainty and stock market volatility, that is, uncertainty shocks increase volatility in the short run, while volatility shocks also feed back into uncertainty. This provides the first high-frequency measure of monetary policy uncertainty that uses social media in South Africa.

The second essay examines the causal relationship between subjective monetary policy uncertainty and subjective stock market volatility using a novel dataset on French households. To address endogeneity concerns, the analysis applies high-dimensional instrumental variable methods, such as IV-Lasso. The results show that higher perceived monetary policy uncertainty leads to significantly higher reported stock market volatility. These findings provide micro-level evidence that uncertainty about monetary policy shapes perceptions of financial market risk, with implications for monetary policy transmission through expectation channels.

The third essay evaluates whether French households form policy rate expectations consistent with the Full Information Rational Expectations benchmark. It documents systematic deviations in the form of perception gaps and forecast errors. These biases are shown to influence household behaviour, particularly saving decisions, where larger perception gaps are associated with a lower probability of being in higher saving bands. This evidence supports theories of bounded rationality and limited attention.

The final essay applies large language models to central bank press releases and speeches to analyse the content and tone of communication. The results show that communication priorities vary across institutions and affect how policy is perceived by markets and households. This essay demonstrates that central bank communication operates as a policy tool in its own right and illustrates the potential of modern computational methods in the study of monetary policy.

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Declaration of Authorship

I declare that this thesis and the work presented in it is my own and has been generated by me as the result of my own original research.
I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. None of this work has been published before submission

Signed:.. Date:..................

Co-Authorship Statement

Chapter 5 was written with the assistance of Dr. Solo Zerbo (International Monetary Fund). My contributions to this research work are as follows:

- **Identification of research question:** Shared responsibility with co-author.
- **Literature review:** My sole responsibility.
- **Data cleaning and analysis:** My sole responsibility.
- **Manuscript preparation:** My sole responsibility.

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To my mom!

Chapter 1

Introduction

1.1 Context and Motivation

Uncertainty has long been recognised as central to economic analysis. Knight (1921) distinguished between measurable risk, where probabilities are known, and fundamental uncertainty, where the probabilities themselves cannot be quantified. Keynes (1936) similarly emphasised that uncertainty pervades investment decisions through shifting “animal spirits.” These early contributions shaped how economists think about expectations and decision-making when the future cannot be reduced to calculable risk.

The rational expectations revolution brought a different perspective by placing strong structure on beliefs. Muth (1961) and Lucas Jr (1972) formalised the full-information rational expectations (FIRE) framework, in which agents form expectations consistent with the true economic model. Under this benchmark, forecast errors are unpredictable and uncorrelated with available information. Households and firms are assumed to fully internalise the central bank’s reaction function, such that policy uncertainty only reflects the stochastic nature of shocks.

A large body of evidence accumulated in recent decades has challenged this frictionless view. Surveys of households, firms, and professional forecasters reveal systematic biases, information frictions, and persistent disagreement in expectations (Sims, 2003; Weber et al., 2022). Expectations are often dispersed and adaptive, with outcomes sensitive to the way information is presented. For example, households and firms tend to overestimate recent inflation and hold biased views about future inflation relative to official targets (D’Acunto et al., 2021). These patterns are observed across countries and are difficult to reconcile with the FIRE paradigm. Instead, they are consistent with models of bounded rationality (Simon, 1955) and rational inattention (Sims, 2003), where information processing is costly and agents rely on heuristics. Within such frameworks, even clear central bank forward guidance may not be fully absorbed, and many individuals remain inattentive or misinformed. Recent evidence shows that consumers pay limited attention to interest rates in low-inflation environments, becoming more attentive only when inflation or borrowing costs rise sharply (Coibion et al., 2023). Financial literacy and personal exposure also play a role, that is, households with adjustable-rate mortgages or higher financial literacy tend to monitor policy developments more closely (Weber et al., 2022). This evidence shows that real-world expectations depart from the frictionless benchmark and that monetary policy uncertainty (MPU), as perceived by the public, can be substantial. Understanding this uncertainty is crucial because beliefs about the future path of policy rates influence saving, borrowing, investment, and asset prices. When households or firms are unsure how the central bank will act, or hold misperceptions about current and future policy, their expectations can themselves become a source of economic fluctuations.

Over the past two decades, a sequence of crises has brought uncertainty to the forefront of both research and policymaking. The global financial crisis, the euro area sovereign debt crisis, the COVID-19 pandemic, and the recent inflation surge all generated large swings in uncertainty, reflected in volatility indices and dispersions in forecasts (Bloom, 2009; Altig et al., 2020). During these episodes, central banks adopted unconventional tools such as quantitative easing and forward guidance and placed greater emphasis on communication. While these measures aimed to stabilise expectations, they sometimes created new uncertainties regarding exit strategies and the durability of interventions. As a result, monetary policy uncertainty has become an important driver of macroeconomic and financial dynamics.

A growing literature proposes different ways to measure MPU and to examine its effects on the economy. One measure is the market-based indicator which infers uncertainty from option prices and interest rate futures (Bauer et al., 2021). These measures are high-frequency and forward-looking, but by construction they reflect the views of professional investors and therefore capture only market-implied uncertainty. Broader econometric approaches use large panels of macroeconomic data to estimate the conditional volatility of forecast errors, as in the general macro uncertainty framework of Jurado et al. (2015). In contrast, other measures such as text-based methods rely on counting policy and uncertainty terms in newspapers, with the Economic Policy Uncertainty index of Baker et al. (2016) providing a prominent example. Extensions of this approach tailor the keyword lists more specifically to monetary policy (Husted et al., 2017, 2020). Each of these proxies captures a different dimension of uncertainty, that is, markets versus households, short-term versus long-term horizons, financial risk versus policy communication. As such, conclusions about the impact of uncertainty can vary with the chosen lens. This motivates a comprehensive strategy that draws on multiple methods and sources, as adopted in this thesis.

Uncertainty does not only exist as an object of measurement, but it also propagates through the economy through several channels. For firms, the real options framework shows that when investment involves sunk costs, heightened uncertainty increases the value of waiting, which delays irreversible capital expenditure (Dixit and Pindyck, 1994; Bloom, 2009). For households, precautionary motives become stronger when future interest rates, inflation, or income are harder to predict. This encourages higher buffer stock saving and reduces current consumption (Carroll, 1996). Financial markets react immediately to changes in policy uncertainty, with higher uncertainty raising term and risk premia, lowering equity valuations, and increasing volatility (Pastor and Veronesi, 2013; Gospodinov and Jamali, 2015). Even when the policy rate itself does not change, uncertainty about its future path can widen credit spreads and unsettle asset markets. Central bank communication provides another important channel. When communication is clear and consistent, it can anchor expectations and mitigate uncertainty. However, when guidance is opaque, inconsistent, or lacks credibility, it can increase dispersion in forecasts and amplify volatility (Blinder et al., 2008; Hansen and McMahon, 2016). A well-known example is the 2013 “Taper Tantrum,” where investor uncertainty about the Federal Reserve’s exit strategy contributed to significant market turmoil.

Despite this progress, important gaps remain. Most empirical evidence on MPU concerns advanced economies, particularly the United States and the euro area. Emerging markets are underrepresented because the high-frequency financial instruments typically used to gauge uncertainty, such as interest rate options, are often thinly traded or unavailable, and historical newspaper archives or survey data are less comprehensive. While a few emerging markets such as Colombia and Mexico are now covered in the global Economic Policy Uncertainty database,[1] these indices remain exceptions rather than the rule and are mostly based on newspaper coverage of general policy uncertainty

[1] See www.policyuncertainty.com.

rather than monetary policy specifically. South Africa therefore fills a regional and methodological gap by providing one of the first African cases with a high-frequency, monetary-policy-specific uncertainty measure. The South African Reserve Bank operates an inflation-targeting regime in a volatile environment shaped by frequent external shocks, including commodity price swings and capital flow reversals, as well as domestic challenges (Redl, 2018; Kisten, 2020). Conventional MPU measures are scarce in this setting, but social media offers an alternative source of information. By drawing on Twitter data, it becomes possible to construct high-frequency indicators of monetary policy uncertainty that provide real-time signals of how the public perceives policy. Chapter 2 of this thesis develops such an index for South Africa, demonstrating how non-traditional data can extend measurement beyond the standard set of economies where traditional sources are available.

Second, household beliefs about monetary policy have received much less attention than household beliefs about inflation, even though policy rates are the direct instrument of central banks. Inflation expectations have long been monitored as a gauge of credibility, but relatively little is known about how households perceive the level and future path of policy interest rates. Do people know the current policy rate, and if so, how accurately? Are they confident in predicting where it is heading, or do they express substantial uncertainty? These questions matter because perceptions of policy rates directly shape borrowing and saving decisions. A household considering a mortgage or a car loan will take into account whether it expects interest rates to rise or remain stable. If many households misperceive the current policy rate or hold disparate views about its future path, the transmission of monetary policy to consumption and housing investment may become weaker or more uneven than standard models assume (D'Acunto et al., 2021; Weber et al., 2022). Until recently, suitable data to study household-level monetary policy uncertainty were scarce, especially within the euro area. This thesis makes use of novel survey data from French households that elicit perceptions of the current European Central Bank (ECB) policy rate and expectations of its future distribution. France provides a particularly useful case because it is a large, advanced economy where policy is set at the supranational level, which may make ECB decisions feel distant to ordinary citizens. By analysing this microdata, the thesis offers new evidence on an overlooked aspect of expectations, subjective monetary policy uncertainty at the household level. This contribution complements the well-established literature on inflation expectations by providing a parallel understanding of how people perceive and forecast interest rates.

Third, many text-based measures of monetary policy uncertainty rely on fixed dictionaries of keywords. For example, one approach counts occurrences of terms such as “uncertainty” in close proximity to references to the Federal Reserve in newspaper articles (Baker et al., 2016; Husted et al., 2017). While informative, these methods are limited in their ability to capture changes in language use or context and may generate spurious results if relevant words appear independently. Recent advances in natural language processing offer a richer toolkit for analysing central bank communication. Instead of simple word counts, topic models and sentiment analysis can extract structured meaning from policy documents. For instance, Hansen and McMahon (2016) apply Latent Dirichlet Allocation to statements of the Federal Open Market Committee and demonstrate that the content of communication, not just the numerical decision, affects market responses. More recent methods track how central banks shift their emphasis between objectives such as inflation and exchange rates over time (Gorodnichenko et al., 2021). Large language models represent a further step forward because they account for syntax and semantics, enabling the detection of subtle shifts in tone or priorities that dictionary-based approaches may miss. This thesis makes use of these innovations by applying machine learning to a comparative study of central bank communications. In doing so, it provides new evidence on how policy priorities are framed across countries and periods. For example, it becomes possible to identify when central banks place unusual attention on the exchange rate, or when the language used to describe inflation shifts in response to economic conditions.

Finally, the rise of social media offers an opportunity to measure policy uncertainty using timely and relatively cost-effective signals outside traditional media. Millions of users discuss economic developments on platforms such as Twitter, making it a rich, though noisy, source of data on public sentiment and uncertainty. Recent work has demonstrated the feasibility of constructing uncertainty indices from Twitter content. For example, Sagner and Becerra (2023) develop a daily Economic Policy Uncertainty index for Chile based on tweets and show that it captures real-time fluctuations in policy concerns, especially during fast-moving episodes such as the pandemic. These approaches extend uncertainty analysis to countries and periods where mainstream news coverage or financial market data are limited. In this thesis, I adopt a similar approach by creating a Twitter-based Monetary Policy Uncertainty index for South Africa. This contribution not only fills a geographic gap in the literature but also demonstrates how non-traditional data and modern machine learning techniques can be employed to measure economic phenomena in real time.

Against this background, the thesis is situated at the intersection of uncertainty measurement, expectations formation, monetary policy communication, and new data science methods. It focuses on two economies that illustrate complementary dimensions of monetary policy uncertainty. South Africa, as an emerging market with a volatile history, provides a laboratory for developing new uncertainty indicators and examining their macro-financial effects in a setting where traditional measures are scarce. France, by contrast, is an advanced economy with detailed household surveys, which make it possible to study micro-level perceptions and behaviours under a well-established monetary regime. The unifying theme across these cases is understanding how monetary policy uncertainty is formed, measured, and transmitted, from both the demand side of policy (households and markets) and the supply side (central bank communication). By combining evidence from financial markets, household surveys, and central bank messaging, the thesis seeks to provide a more comprehensive picture of monetary policy uncertainty and its economic consequences.

This thesis therefore asks four central research questions, each addressed in an empirical chapter. The first asks how monetary policy uncertainty can be measured in real time in economies where conventional market and media data are scarce. Specifically, can Twitter content be used to construct a timely index for South Africa, and what does this reveal about the relationship between uncertainty and stock market volatility in such a setting? This addresses the practical challenge of measuring uncertainty outside the data-rich environments of advanced economies, and probes whether fluctuations in uncertainty coincide with, or even anticipate, swings in financial volatility.

The second research question turns to French households. Using novel survey data, it asks how subjective monetary policy uncertainty relates to subjective stock market volatility, and whether this relationship is bidirectional. In other words, do households who feel less certain about future interest rates also expect higher stock market volatility, and do those expectations reinforce each other over time? This question builds directly on the macro-level analysis in Chapter 2 by shifting the lens from markets to households. Whereas Chapter 2 examines how uncertainty influences aggregate volatility, this chapter investigates whether households perceive similar connections in their own expectations. In doing so, it provides a micro foundation that complements the macro evidence and reveals heterogeneity that aggregate measures cannot capture. It also considers whether particular groups, such as those with more income or higher education, are more attuned to the link between policy uncertainty and market risk.

The third research question explores whether households in an advanced economy form expectations of policy rates that are consistent with the full-information rational expectations benchmark. It asks whether systematic perception gaps, such as misperceptions of the current policy rate, and forecast errors, defined as deviations of expected from realised outcomes, emerge in household data. If so, which socioeconomic characteristics help explain these deviations, and how do they shape saving and borrowing behaviour? This chapter therefore probes the validity of rational expectations at the household level. It considers whether the average household forms accurate expectations, or whether predictable biases exist, such as persistent overestimation of future rate increases. It also examines the behavioural implications of these errors. For instance, households who underestimate future rate rises may take on excessive debt, while those who overestimate may save excessively and delay investment. By documenting these patterns, the chapter provides a behavioural perspective on monetary transmission and highlights the importance of communication that reaches a broad audience (Weber et al., 2022).

The fourth research question examines how central banks communicate their policy priorities across countries, and whether modern language models can be used to detect systematic patterns in the emphasis on inflation and exchange rates. In particular, does the way priorities are framed in official statements influence subsequent exchange rate behaviour and volatility? This shifts attention to the supply side of expectations and employs natural language processing to analyse central bank communication. It considers, for example, whether central banks in emerging markets place more emphasis on exchange rate stability than those in advanced economies, and whether an increased emphasis on inflation in speeches corresponds to more anchored expectations or distinct market reactions. By applying machine learning to decades of central bank communication across countries, this chapter uncovers patterns that are difficult to detect through human reading alone. It also tests whether differences in communication, both in content and in tone, have tangible effects on market variables such as the exchange rate. In doing so, it connects the content of central bank communication to one of its key objectives of shaping expectations and behaviour in financial markets.

By addressing these questions, this thesis clarifies how monetary policy uncertainty is measured, how it is perceived by different economic agents, and how it can be managed or exacerbated through communication. Together, these chapters aim to advance understanding of MPU as both an outcome of policy actions and communication, and as a determinant of economic decisions. The work represents a systematic effort to acquire and integrate knowledge at the frontier of several fields, including monetary economics, behavioural expectations, and data science applications. Each study moves into relatively less explored territory, whether by measuring uncertainty in an emerging market using social media, examining household expectations of interest rates in detail, or applying advanced large language models to central bank communication. The remainder of this introduction turns to the theoretical underpinnings for these questions, reviews the methodologies available to measure MPU, and outlines the specific contributions of each empirical chapter and how they are interconnected.

1.2 Theoretical Background

The distinction between risk and uncertainty is foundational for the study of expectations. Knight (1921) defined risk as situations in which the probability distribution of outcomes is known, and uncertainty as situations in which these probabilities are themselves unknown or undefined. Monetary policy decisions frequently fall into the latter category. While central banks may follow reaction functions, the public cannot know with certainty how policy will respond to future economic developments, especially in unprecedented circumstances. Keynes (1936) stressed that fundamental uncertainty is a permanent feature of economic life. Agents are unable to assign exact probabilities to many macroeconomic events and instead rely on conventions or sentiments that may shift suddenly. This Keynesian perspective implies that expectations are inherently fragile and subject to swings in confidence, which can amplify business cycle fluctuations when uncertainty rises.

The rational expectations revolution offered a contrasting perspective. Muth (1961) and Lucas Jr (1972) argued that agents form expectations consistent with the true model of the economy, so that forecast errors are unpredictable and uncorrelated with available information. In such a world, monetary policy uncertainty would reflect only the inherent volatility of the economy rather than ambiguity about the central bank's behaviour. Agents would understand the policy rule and form probability distributions for future interest rates accordingly. Within this framework, credible forward guidance can in principle eliminate uncertainty about the intended path of policy, leaving only the residual uncertainty from unforeseen shocks. New Keynesian models adopt this benchmark by assuming that the public's expectations of policy rates and inflation align with the model-consistent forecast.

Over time, evidence has revealed limitations of the full-information rational expectations paradigm, leading researchers to introduce imperfect information into models of expectation formation. One strand is bounded rationality, which recognises cognitive limits. That is, rather than fully optimising, agents may rely on heuristics or rules of thumb when forming forecasts (Simon, 1955). A second strand is rational inattention, formalised by Sims (2003), which models the idea that processing and updating information is costly. In such models, agents optimally choose to pay attention to some signals and ignore others, leading to sticky or partial adjustments in expectations. For monetary policy, this implies that many individuals may not immediately notice or react to a central bank announcement if the perceived benefit in terms of decision quality is small relative to the effort required. This mechanism helps explain survey evidence showing that a large fraction of households is unaware of recent policy rate changes or cannot recall the central bank's most recent decision.

Other approaches emphasise heterogeneous information. In these models, different agents observe different signals about the economy, such as news reports or personal experiences, which leads to divergence in expectations and slows the aggregation of information into prices (Morris and Shin, 2002). Empirical studies confirm that forecast disagreement is persistent and that systematic biases are concentrated in certain groups. For example, households with lower education levels tend to expect higher inflation or interest rates than those with greater financial literacy (Weber et al., 2022). These findings are inconsistent with the notion that everyone shares the same information set and instead point towards frameworks in which expectations are updated infrequently or unevenly. The sticky-information model of Mankiw and Reis (2002) captures this by assuming that some agents continue to rely on outdated information while others adjust more quickly, producing a coexistence of old and new expectations.

In light of these theories, it is useful to define monetary policy uncertainty more formally. At the aggregate level, MPU can be understood as the conditional variance of future policy instruments as perceived by economic agents at time t. If i_{t+h} denotes the policy interest rate h periods ahead, then MPU at horizon h can be written as $Var_t(i_{t+h})$, the variance that the representative agent or market assigns to i_{t+h} given information at time t. This concept can also be expressed in terms of distributions, for instance by the width of confidence intervals around expected future rates. At the micro level, each individual has their own subjective uncertainty. Surveys often measure this by eliciting probability distributions. For example, respondents may be asked, “What is the probability that the policy rate will exceed four percent next year?” A respondent who assigns positive probability to a wide range of outcomes is inferred to have higher subjective uncertainty. Another common proxy at the micro level is disagreement across respondents. The cross-sectional variance of point forecasts can serve as an indicator of overall uncertainty in the population, though Jurado et al. (2015) caution that disagreement and uncertainty need not always coincide. Both perspectives are relevant for this thesis. Chapter 2 constructs a Twitter-based, aggregate index of monetary policy uncertainty for South Africa, while Chapters 3 and 4 analyse household-level subjective uncertainty using novel survey data that reveal heterogeneity in beliefs and perceived risks.

Theoretical models therefore illustrate why monetary policy uncertainty matters for the wider economy. In a standard New Keynesian framework, expectations of future interest rates enter directly into the consumption Euler equation and the investment condition. When uncertainty about those future rates rises, risk-averse agents with convex utility functions reduce current consumption and investment through precautionary effects. For example, if the central bank’s policy rule becomes less predictable, firms may delay expansion plans and households may postpone major purchases as they prepare for a range of possible financing costs.

Uncertainty also affects asset pricing. In models with time-varying risk premia, investors demand compensation for bearing the risk of policy surprises. Higher monetary policy uncertainty therefore translates into higher term premia on long-term bonds and a higher cost of capital for businesses. This mechanism is supported by empirical evidence showing that periods of heightened uncertainty about Federal Reserve policy are associated with increases in option-implied volatility on interest rates and higher credit spreads (Gospodinov and Jamali, 2015; Bauer et al., 2021). Equity markets respond in a similar way, a surprise increase in monetary policy uncertainty is often followed by higher stock market volatility and lower equity prices as investors reassess risk exposures (Antonakakis et al., 2013; Bloom, 2009).

Another channel operates through the anchoring of expectations. In an environment of low and stable inflation, well-anchored inflation expectations reflect the public’s confidence that the central bank will maintain price stability. Analogously, well-anchored expectations of interest rates indicate trust that policy will follow a steady course consistent with the central bank’s reaction function. When uncertainty about policy rises, for example because communication sends mixed signals, these anchors can weaken. This may lead to more volatile long-term interest rates and more erratic responses to economic news, as markets speculate about how the central bank will react. Studies have shown that when central bank communication is unclear, financial markets exhibit excess volatility relative to fundamentals (Blinder et al., 2008; Hansen and McMahon, 2016). From a welfare perspective, high monetary policy uncertainty is costly because it induces suboptimal investment and saving behaviour and weakens the transmission of policy actions.

In summary, the theoretical background suggests three points that are central to this thesis. First, rational expectations provide a useful benchmark, but real-world behaviour is shaped by information frictions and heterogeneity. Second, monetary policy uncertainty can be defined and measured in different ways, including aggregate conditional variances and micro-level measures of subjective dispersion or forecast errors. Third, uncertainty is not merely a by-product of policy but a key driver of economic outcomes through multiple channels, including investment, consumption, asset prices, and expectations anchoring. This provides the foundation for the empirical analyses that follow.

In my thesis, each chapter revisits these themes in a different setting. That is, Chapter 2 considers how uncertainty shocks influence financial volatility in South Africa and vice versa, Chapter 3 examines this relationship at a micro-level, Chapter 4 examines whether imperfect knowledge of policy leads households to make systematic forecast errors and perception gaps and links these deviations to borrowing and saving behaviour. Lastly, Chapter 5 applies large language models to central bank press releases and speeches, showing how communication priorities differ across countries.

Before turning to the individual studies, it is necessary to consider how MPU can be measured in practice. The next section reviews the main approaches in the literature, illustrating their respective strengths and limitations. This discussion sets the stage for the measures developed in Chapter 2, which constructs a Twitter-based index for South Africa, and Chapter 5, which applies language models to central bank communication, as well as for the survey-based measures analysed in Chapters 3 and 4.

1.3 Measuring Monetary Policy Uncertainty

Because uncertainty is not directly observable, economists rely on proxy measures that infer beliefs from available data. Four broad approaches have been used to quantify monetary policy uncertainty, that is, market-based measures, survey-based measures, text-based measures, and more recently, social media or other high-frequency proxies. Each approach captures a different dimension of expectations and uncertainty.

Market-based measures use financial prices to back out the perceived distribution of future policy. A leading example is the use of option prices on interest rate futures, such as futures on three-month USD Libor to calculate the implied volatility of short-term interest rates. Bauer et al. (2021) develop a model-free policy uncertainty index by extracting the risk-neutral density of future short-term interest rates from options on Eurodollar futures. The intuition is straightforward, if options that pay off in the event of large rate moves become more expensive, then the market must be assigning greater probability to those tail outcomes. Their measure produces a daily time series of monetary policy uncertainty at horizons ranging from six to twenty-four months, extending back to 1990. Notably, this series spikes during major shocks such as the global financial crisis and the COVID-19 pandemic, reflecting that investors suddenly perceived a much wider range of possible policy paths.

Another market-based approach is to examine forecast dispersion among professional traders. For example, Eurodollar futures implied rates can be compared across broker-dealers to gauge disagreement about future Federal Reserve policy. These measures have several advantages. They are timely and forward-looking, updating continuously with news and available at high frequency, sometimes intraday. They also represent stakes-based beliefs since investors put money on the line when they trade options or futures. However, their limitations are equally important. They primarily capture the views of financial market participants, who may differ systematically from households or firms. Moreover, market-based measures are risk-neutral while option-implied volatility may overstate or understate subjective uncertainty depending on risk premia.

Despite these caveats, market-based MPU indices have become widely used. The Federal Reserve now maintains an index of market-based monetary policy uncertainty derived from options, and recent research shows that uncertainty measured in this way significantly shapes the transmission of monetary shocks. For example, Bauer et al. (2021) find that when uncertainty is high, a surprise rate cut has a smaller effect on long-term yields because investors doubt how long the policy stance will persist. Conversely, clear forward guidance that reduces uncertainty can lower term premia and flatten the yield curve by more than the mechanical effect of the guidance itself.

Survey-based measures provide a more direct way to gauge expectations and uncertainty by asking households, firms, or professional forecasters to report their views. Many modern surveys elicit not only point forecasts but also density forecasts or confidence intervals. For example, the Survey of Professional Forecasters (SPF) asks respondents to assign probabilities to ranges of future interest rates or inflation. The European Central Bank's Survey of Monetary Analysts similarly collects distributional forecasts for the policy rate. These data allow researchers to compute each respondent's subjective uncertainty, such as the interquartile range of their forecast distribution, as well as aggregate measures of average uncertainty or cross-sectional dispersion.

At the household level, newer instruments such as the U.S. Survey of Consumer Expectations (SCE) and the ECB's Consumer Expectations Survey (CES) provide rich information on subjective beliefs. The CES, launched in 2020, asks euro area consumers about their expectations for interest rates one year ahead and how confident they are in those predictions. Survey-based measures offer several advantages. They capture subjective uncertainty directly and reveal heterogeneity across respondents, rather than focusing solely on market consensus. They also allow researchers to identify which groups are more uncertain. For example, households with lower financial literacy often report wider confidence intervals for future inflation or interest rates than more financially literate groups (D'Acunto et al., 2021; Weber et al., 2022). Surveys further make it possible to compare beliefs with realised outcomes, highlighting systematic biases or persistent forecast errors.

However, surveys also have limitations. Traditional instruments are often infrequent, with quarterly or monthly frequency, and sometimes cover small samples at high frequency. Until recently, few surveys focused on policy rate expectations, as most concentrated on inflation or growth. One exception was the New York Fed's Primary Dealer Survey, conducted around Federal Open Market Committee meetings, which asked institutions to provide probability distributions for future policy rates. Husted et al. (2017) show that their news-based index of monetary policy uncertainty for the United States correlates strongly with dispersion in this dealer survey, lending credibility to both measures.

This thesis builds on these developments by using novel survey data from French households that include questions on perceptions of the current ECB policy rate and expectations of future changes. Responses to these and related questions, such as those on the stock market outlook, are used to construct individual-level measures of uncertainty and to analyse their determinants. Cross-sectional disagreement, measured as the spread of responses, also serves as a proxy for aggregate household uncertainty. Recent international evidence suggests that household expectations display greater dispersion and bias than those of professional forecasters. For example, household inflation forecasts are consistently higher than realised inflation and above expert forecasts across many countries (Weber et al., 2022). Moreover, knowledge of central banks is limited among households, and those who are more informed exhibit more stable and less biased expectations. These findings motivate the analysis in Chapters 3 and 4, which examine who is informed versus uninformed, how this relates to expectation accuracy, and how misperceptions shape behaviour.

Text-based measures represent another influential approach to quantifying monetary policy uncertainty. A major breakthrough came with the work of Baker et al. (2016), who introduced the Economic Policy Uncertainty (EPU) index based on newspaper coverage. Their method counts the frequency of articles that include terms related to “economy,” “policy,” and “uncertainty” in leading newspapers and then normalises and aggregates those counts into a monthly index. Building on this idea, subsequent studies developed variants tailored to monetary policy. For example, Husted et al. (2017) construct a U.S. Monetary Policy Uncertainty index by searching the New York Times, Wall Street Journal, and Washington Post for articles that simultaneously mention “uncertainty” or “uncertain,” monetary policy terms such as “interest rate” or “Fed funds rate,” and references to the Federal Reserve or the FOMC. The number of such articles is then scaled by the total volume of Federal Reserve–related articles and standardised. Their measure spikes around well-known episodes such as the 2008 global financial crisis, the 2013 tapering discussions, and other periods of heightened uncertainty about Federal Reserve actions. Importantly, Husted et al. validate their automated index by comparing it with a hand-coded index constructed from thousands of articles and find a strong correlation between the two. They also show that their measure diverges sensibly from the generic EPU index. For example, during the 2013 government shutdown, general policy uncertainty was elevated but monetary policy uncertainty did not increase as much.

An advantage of text-based measures is that they can often be constructed retrospectively over long historical periods wherever newspaper archives exist.

For example, Scotti (2016) develops a historical monetary policy uncertainty index for the United Kingdom back to the nineteenth century. Similar approaches have been applied in other countries by searching local news sources, often in the domestic language, to create country-specific indices. These measures can also be tailored to particular policy areas, with categorical EPU indices focusing on monetary, fiscal, or trade policy by applying targeted keyword sets. More sophisticated approaches build on this foundation by using natural language processing tools that go beyond simple keyword counts. Contextual sentiment analysis can, for example, identify when an article's tone about policy is uncertain, while topic models or word embeddings allow more flexible detection of evolving concepts such as "quantitative easing," which would not appear in dictionaries fixed before 2008.

Nevertheless, dictionary-based approaches face limitations. They are susceptible to noise if keywords appear in unrelated contexts, and they may struggle to keep pace with changes in language over time. This has led to the adoption of more advanced tools. Hansen and McMahon (2016) and Gorodnichenko et al. (2021), for instance, demonstrate that topic models can extract systematic information from central bank documents that influence market responses. More recently, large language models have expanded the frontier by capturing syntax and semantics, enabling the detection of subtle shifts in tone or emphasis that keyword methods would miss.

In this thesis, Chapter 5 extends text-based analysis by applying natural language processing to central bank communications themselves (speeches, press releases, and policy statements), rather than to newspaper reports. This approach focuses on the supply of information, identifying how central banks frame their policy priorities and the degree of uncertainty they communicate. By moving beyond word counts to contextual analysis, it becomes possible to distinguish whether references to uncertainty concern forecasts of inflation or uncertainty about the policy reaction function. Large language models are particularly well suited to this task because they can detect conditional phrasing or expressions of concern that may signal heightened uncertainty. By systematically comparing communications across countries, the thesis constructs novel indicators such as an "exchange rate focus index" and an "inflation priority index." These indicators trace how central bank emphasis changes over time and examine whether such shifts are associated with movements in financial markets.

A recent frontier in the measurement of uncertainty makes use of alternative data sources such as social media posts, internet search queries, or the volatility of asset prices around policy events. The underlying idea is that public concern or attention can be inferred from online behaviour. Twitter-based indices of uncertainty have now been developed for several countries. Becerra and Sagner (2020) construct a daily index for Chile by collecting tweets from key accounts, including major newspapers, financial analysts, and opinion leaders, and counting those that discuss economic policy uncertainty. Their measure correlates strongly with news-based indices but is available at much higher frequency, even intraday, making it useful for monitoring sudden changes. For example, it captured real-time spikes in uncertainty during the COVID-19 pandemic and during episodes of political instability in Chile. Extending this approach, Behera and Rath (2022) show that a Twitter-based uncertainty index for the G7 economies has significant spillovers to global stock market volatility. During the initial outbreak of the pandemic in March 2020, Twitter-based uncertainty measures surged to record highs across countries in tandem with financial market volatility.

Another high-frequency proxy relies on the behaviour of market volatility around policy events. For instance, one can examine the change in interest rate futures volatility immediately after a central bank meeting. A large, unexpected fall in volatility would imply that the meeting resolved uncertainty, whereas a rise would suggest that it created new uncertainty. Altig et al. (2020) show that news-based, market-based, and other measures of uncertainty tended to co-move and reached unprecedented levels during the COVID-19 crisis, suggesting that they capture a common underlying factor.

Social media measures are not without limitations. They can be noisy, subject to shifts in platform usage, and may over-represent particular groups such as journalists or academics. Nevertheless, they offer a valuable complement to traditional approaches, particularly in countries where conventional data are sparse or delayed. In this thesis, Chapter 2 develops a Twitter-based index of monetary policy uncertainty for South Africa. This contribution demonstrates how non-traditional data sources can be harnessed to extract meaningful signals about policy uncertainty in real time. The index is constructed using keyword filtering and volume counts from Twitter data. Its usefulness is evaluated by testing whether movements in the index correlate with financial outcomes such as stock market volatility and bond yields. In addition, Chapter 2 analyses the dynamic interaction between monetary policy uncertainty and market volatility using structural econometric techniques to assess causality and feedback. In this way, the chapter contributes to the emerging literature that combines text-based methods with financial econometrics to understand how

uncertainty is transmitted to markets.
Each measurement approach therefore sheds light on different aspects of monetary policy uncertainty, and there is no single definitive measure of an unobservable concept such as uncertainty. A central theme of this thesis is that combining approaches yields deeper insight. Chapters 2 and 5 employ text-based methods, drawing respectively on Twitter data and official central bank communications. Chapter 3 relies on survey evidence from households, while all chapters analyse financial market reactions. By triangulating across these sources, it becomes possible to validate findings. For example, if both news-based and market-based measures indicate a spike in uncertainty at a particular moment, this strengthens the inference that it reflected a genuine and significant event. Similarly, if households report heightened uncertainty at the same time that newspaper indices rise, it points to a broad-based phenomenon rather than something confined to professional traders.
In this sense, measurement is both critical and non-trivial. It demands creativity as well as rigour, particularly when data are sparse or when traditional measures fall short. Advances in data science and computing power over the past decade have significantly expanded the available toolbox, enabling economists to harness large-scale textual and high-frequency data to quantify elusive concepts like uncertainty (Gorodnichenko et al., 2021; Becerra and Sagner, 2020; Sagner and Becerra, 2023). This thesis builds on these advances by adopting new measurement strategies in several chapters, demonstrating how the application of modern methods can generate novel outlook into how monetary policy uncertainty is formed, transmitted, and perceived.

1.4 Transmission Channels of Monetary Policy Uncertainty

Having discussed what monetary policy uncertainty is and how it can be measured, the next step is to consider how it matters: the transmission channels through which uncertainty affects real economic activity and financial conditions. Understanding these channels provides the foundation for the empirical strategies adopted in later chapters and informs the interpretation of the results.
A first channel operates through firms' investment decisions. The real options framework of Dixit and Pindyck (1994) shows that when investment entails sunk costs, greater uncertainty increases the value of waiting before committing resources. In other words, when firms are unsure about future demand, costs,

or policy, they may delay investment because postponing allows them to avoid costly mistakes should conditions turn unfavourable. Monetary policy uncertainty contributes to this mechanism by increasing uncertainty about financing costs and broader macroeconomic conditions. For example, if firms are unsure whether the central bank will raise rates sharply to contain inflation, they may postpone borrowing for expansion until that uncertainty is resolved. Empirical evidence supports this channel. Bloom (2009) shows that uncertainty shocks, proxied by spikes in stock market volatility, cause immediate declines in investment and hiring as firms adopt a "wait-and-see" posture.

In emerging markets, such as South Africa, these effects may be particularly pronounced. Firms operate in already volatile environments, facing exchange rate swings, political risk, and external shocks. Additional policy uncertainty, for instance, around elections or changes in central bank priorities, can further dampen private investment. Moreover, the cost of capital in such markets often carries an uncertainty premium. Kisten (2020) finds that rising economic uncertainty in South Africa, measured by a news-based index, is associated with declines in industrial production and exports, as well as increases in long-term government bond yields and currency depreciation. The latter result indicates that investors demand higher returns to hold domestic assets when uncertainty is elevated, raising financing costs for both firms and the government. Chapter 2 of this thesis examines a related dynamic by focusing on the interaction between monetary policy uncertainty and stock market volatility in South Africa. If uncertainty shocks cause firms to delay investment, stock markets should reflect these expectations through higher volatility and lower returns as investors reassess growth prospects. This chapter tests for such effects using a structural VAR framework, providing evidence on how uncertainty shapes financial conditions in an emerging market setting.

A second channel operates through household behaviour, particularly in consumption and saving decisions. Households are typically sensitive to interest rates through borrowing costs on mortgages and consumer loans, as well as through the returns on savings. When there is uncertainty about the path of future interest rates, households may respond in precautionary ways. One response concerns consumption: a more uncertain outlook for rates, often accompanied by uncertainty about income or employment, can induce households to postpone durable purchases or to reduce discretionary spending and increase saving. This precautionary saving motive is formalised by Carroll (1996), who shows that when households cannot predict future financing conditions with confidence, they maintain larger buffers of liquid assets to insure against adverse scenarios.

For example, if a household is unsure whether its mortgage will reset to a much higher rate, it may cut current consumption in order to strengthen its balance sheet.

A second response concerns portfolio and borrowing choices. Risk-averse households facing greater policy uncertainty may prefer fixed-rate debt to hedge against unexpected rate increases, or they may reduce leverage altogether. Periods of elevated uncertainty are often associated with a shift from adjustable-rate to fixed-rate borrowing, or with a slowdown in credit growth as both lenders and borrowers turn more cautious. In some cases, expectations of rising rates may even encourage households to borrow pre-emptively, but because uncertainty implies that outcomes are not known with confidence, caution tends to dominate. Survey evidence confirms that households with higher subjective uncertainty or economic pessimism tend to cut back on spending (Bachmann et al., 2013).

These mechanisms are examined in later chapters of this thesis. Chapter 3 uses French household survey data to test whether individuals who perceive higher monetary policy uncertainty also report greater willingness to save or lower consumption of discretionary goods. Chapter 4 goes further by linking households' perception gaps and forecast errors to their actual financial choices. For instance, households who underestimate future rate hikes may accumulate more debt or maintain lower savings than those who correctly anticipate policy moves. If systematic, such patterns could pose risks for financial stability, as large segments of the population may take on excessive debt in response to misperceived monetary policy conditions.

Household attention plays an important mediating role in these dynamics. Many households do not follow monetary policy closely in normal times (Coibion et al., 2018). Those with greater exposure, such as mortgage holders on variable rates or those with higher financial literacy are more attentive to interest rate developments and respond more strongly when uncertainty rises. Evidence from the ECB's Consumer Expectations Survey shows that mortgage borrowers and financially literate households track interest rate news more closely and express narrower forecast distributions (Lane, 2025). This suggests that the transmission of monetary policy uncertainty is heterogeneous. More attentive households, who are often better educated and higher income, adjust their behaviour quickly in response to rising uncertainty, whereas inattentive households may only react after policy changes materialise. Chapter 4 examines these differences by exploring which demographic and financial characteristics are associated with larger perception gaps and by linking these to observed patterns in saving and borrowing behaviour.

Financial markets provide an immediate barometer of uncertainty, as policy ambiguity is rapidly priced into asset values. One important channel operates through risk premia. Investors demand higher returns to hold assets that are exposed to monetary policy decisions when those decisions are uncertain. This can elevate bond yields and depress equity valuations, since the discount rate incorporates an additional premium. Pastor and Veronesi (2013) demonstrate theoretically that equity prices fall when policy uncertainty rises, even if the expected policy path itself does not change, because investors require compensation for bearing the extra variance in outcomes.

A second channel works through volatility. When uncertainty is elevated, traders interpret each new piece of information as potentially altering the future policy stance. This tendency can amplify short-term reactions, leading to excess volatility in stock and bond markets. Empirical evidence confirms this mechanism: Gospodinov and Jamali (2015) find that monetary policy uncertainty in the United States contributed to higher volatility in Treasury yields and equity prices in the run-up to Federal Open Market Committee announcements. In emerging markets, these dynamics can be even more pronounced. Uncertainty surrounding U.S. monetary policy often spills over internationally, increasing volatility and risk premia in emerging market bonds and currencies. For instance, episodes where the Federal Reserve signalled possible rate hikes without clear guidance generated sharp movements in exchange rates and capital flows to emerging economies. Chapter 2 of this thesis examines whether similar dynamics occur in South Africa by testing whether episodes of elevated monetary policy uncertainty, as measured by the Twitter-based index developed in that chapter, coincide with spikes in equity market volatility. Evidence of such effects would align with the international literature and highlight the importance of communication in stabilising financial conditions.

A further mechanism runs through the credit channel. When uncertainty about the policy outlook rises, banks and other lenders often tighten credit standards, reflecting their own concerns about interest rate risk and broader macroeconomic conditions. This tightening can appear in higher spreads on loans, reduced lending volumes, or shorter maturities that allow repricing when conditions change. By raising the cost of borrowing and restricting access to credit, this behaviour transmits monetary policy uncertainty into lower consumption and investment. While this thesis does not directly test bank behaviour, household survey data analysed in Chapter 3 may provide indirect evidence of such effects. Households with outstanding debt often report greater concern about their financial position when policy uncertainty rises, suggesting that tighter credit conditions or perceived riskiness of debt obligations play a role in shaping household responses.

Exchange rates provide another important channel through which monetary policy uncertainty is transmitted, particularly in small open economies or in emerging markets with substantial external debt. When markets perceive that a central bank is less firmly committed to its inflation target, or may tolerate a depreciation of the domestic currency, uncertainty can translate directly into exchange rate volatility or depreciation pressure. Conversely, if the central bank's willingness to defend the currency is unclear, investors may test this commitment, producing bouts of self-fulfilling volatility. Evidence from South Africa supports this view: Redl (2018) finds that uncertainty shocks were associated with a depreciation of the rand and higher exchange rate volatility, illustrating how fragile expectations can amplify financial instability.

Volatility in the exchange rate also feeds back into the real economy. A weaker or more volatile currency raises import prices, thereby fuelling inflation, and can disrupt growth through trade channels. Recognising these risks, many emerging market central banks place explicit emphasis on the exchange rate in their public statements, often signalling readiness to act against "excessive" movements. Whether such communication reduces or increases uncertainty depends on consistency. When central banks stress their commitment to defending the currency, market participants may gain confidence and volatility may subside. By contrast, mixed or changing messages can exacerbate uncertainty, creating greater swings in the foreign exchange market.

Chapter 5 of this thesis investigates these dynamics systematically by studying how central banks prioritise and communicate their exchange rate and inflation objectives, and whether differences in emphasis affect market outcomes. Cross-country evidence indicates that central banks operating under pegged regimes communicate differently from those with floating regimes, devoting more attention to exchange rate developments, and often mentioning the dollar explicitly (Husted et al., 2020). Such variation reflects the underlying policy framework: where the exchange rate is effectively a target, credibility requires that it be addressed in communications. Finally, it is important to note that a country's own monetary policy uncertainty does not exist in isolation. International spillovers matter, and global factors such as U.S. policy uncertainty or worldwide uncertainty indices can shape domestic exchange rate dynamics. This external dimension is therefore incorporated into the analysis that follows.

Central bank communication forms an increasingly important transmission channel of monetary policy uncertainty. Communication is both a policy tool in its own right and a vehicle through which uncertainty can either be mitigated or amplified. When a central bank explains its reaction function and policy outlook clearly, it reduces uncertainty by coordinating expectations and narrowing the range of beliefs about future interest rates. Forward guidance is a prominent example: when the Federal Reserve stated in 2011 that it anticipated keeping policy rates near zero for two years, the aim was to reduce uncertainty about the expected policy path. At the same time, communication can also create uncertainty if messages appear inconsistent or if decisions deviate from earlier guidance, undermining credibility (Blinder et al., 2008).

Credibility is central to the effectiveness of communication. Hansen and McMahon (2016) show that Federal Open Market Committee statements convey multiple dimensions of information, including tone and forward-looking language, and that financial markets respond to these nuances. If the tone of communication is unexpectedly hawkish or dovish compared with prior signals, it can alter market perceptions of future policy and thereby raise or lower uncertainty. Related evidence from sentiment analysis suggests that confident and consistent communication tends to reduce market volatility, while ambiguous or cautious statements often increase it.

Communication also shapes expectations at the household level. Coibion et al. (2023) demonstrate that when households are provided with clear and accessible central bank statements, their inflation expectations shift and often become more accurate, although the effects may fade unless reinforced. This shows that central bank communication is part of the broader information set influencing how uncertainty is perceived.

In Chapter 5, communication is examined directly. The chapter analyses the content of official central bank statements across countries to identify patterns in how policy priorities are framed and whether these patterns affect the anchoring of expectations. Particular attention is paid to how often central banks stress inflation or exchange rate concerns, and whether greater clarity and consistency reduce the degree of uncertainty priced into financial markets. Evidence from recent cross-country work suggests that some emerging market central banks communicate with sharper focus on inflation and in clearer language than certain advanced-economy counterparts, which may help to explain stronger anchoring of expectations in those settings (Nagy Mohácsi et al., 2024). At the same time, there is concern that many central banks adopt a reactive style, discussing inflation risks only after they have materialised, thereby missing the chance to guide expectations more effectively. The analysis in Chapter 5 will assess the consequences of these differences for both credibility and market outcomes.

In summary, the transmission of monetary policy uncertainty operates through multiple reinforcing channels: real options effects on investment, precautionary savings effects on consumption, risk premium and volatility effects in financial markets, credit tightening effects, and communication feedback effects. These channels rarely act in isolation. For example, a spike in uncertainty might simultaneously cause firms to delay investment, households to cut spending, and investors to sell stocks, a combination that can produce a meaningful macroeconomic slowdown. The effects also tend to be state-dependent. That is, uncertainty is especially potent during downturns or crises when confidence is already fragile (Bloom, 2014). Throughout the empirical chapters, we will see manifestations of these channels. Chapter 2's finding that a policy uncertainty shock leads to higher stock market volatility in South Africa would align with the risk premium channel. Chapters 3 and 4 will reveal how household behaviour (e.g. saving rates or debt choices) varies with their perceived uncertainty, displaying the micro underpinnings of the precautionary channel. Chapter 5 will tie into the communication channel by showing how different emphasis in central bank talk is associated with market reactions, including exchange rate moves. Recognizing these channels also has a normative aspect as it suggests why policymakers care about managing uncertainty. A central bank that minimizes unnecessary uncertainty (for instance, by providing clarity when possible and avoiding abrupt, unexplained shifts) can likely achieve better outcomes in terms of stable investment and consumption, as well as avoid unintended spikes in risk premia. At the same time, central banks must be aware that too much certainty can also be risky. If they commit and then circumstances change, breaking the commitment can be even more disruptive. Thus, the art of central banking involves balancing commitment with flexibility, and communication is the tool to navigate that balance. This thesis, by studying uncertainty and communication together, ultimately speaks to that challenge.

In summary, monetary policy uncertainty is transmitted through several interlinked channels that reinforce one another. Firms facing irreversible investment may delay commitments when financing costs are unclear, households may increase precautionary saving or adjust their borrowing choices, financial markets may reprice assets through higher risk premia and volatility, credit may tighten as lenders charge more for uncertainty, and communication can either calm or exacerbate these dynamics. These channels rarely act in isolation. A surge in uncertainty can lead firms to defer expansion, households to cut back on consumption, and investors to withdraw from risky assets at the same time, producing a meaningful slowdown in activity. The effects are also state-dependent as they are most pronounced during downturns or crises, when confidence is already weak (Bloom, 2009).

The empirical chapters of this thesis examine these mechanisms in different settings. Chapter 2 shows how uncertainty shocks in South Africa affect stock market volatility and equity prices, consistent with the risk premium channel. Chapters 3 and 4 provide household-level evidence from France, linking subjective perceptions of uncertainty to saving and borrowing behaviour and thereby illustrating the microeconomic underpinnings of precautionary responses. Chapter 5 turns to communication and demonstrates how the way central banks frame their priorities in official statements shapes expectations and exchange rate dynamics. This chapter is co-authored. I was responsible for preprocessing the communication data, developing the classification algorithm, and carrying out the empirical analysis. My Co-author contributed to the theoretical framing and offered expertise on specific central banks. They also collected the data. In this way, Chapter 5 extends the perspective of the thesis. While the earlier chapters analyse monetary policy uncertainty from the standpoint of those receiving or reacting to policy, Chapter 5 examines the signals created by policymakers themselves. The coherence of the thesis therefore rests on studying monetary policy uncertainty from both sides and at several levels, from macroeconomic outcomes to household behaviour and central bank communication.

The final chapter of the thesis (Conclusion) synthesises the findings and reflects on their implications for theory and policy. It shows how the four studies together advance understanding of monetary policy uncertainty. Chapter 2 develops new measures in an emerging market context. Chapters 3 and 4 examine perceptions and behaviour at the household level in a developed economy. Chapter 5 explores how communication by central banks shapes uncertainty across countries. The conclusion draws out common themes, such as the central role of information and credibility, and shows how the chapters form a connected narrative. Each addresses a different part of the uncertainty problem, and combined they cover both its causes, such as shifts in communication, and its consequences, such as delayed investment or altered saving decisions. The final chapter also identifies directions for future work. For example, there is scope to integrate heterogeneous expectation frameworks into macroeconomic models, and to evaluate whether central banks could adopt new communication strategies, including those informed by textual analysis, to manage public expectations more effectively. The overall message is that monetary policy is conducted under conditions of uncertainty, and that managing this uncertainty has become a central part of the policymaking process.

In summary, the thesis represents a systematic effort to acquire and apply knowledge across several fields. It contributes to research in monetary economics by studying expectations and policy transmission, to behavioural economics by examining household biases, and to data science by showing how non-traditional data such as Twitter posts and machine learning techniques can be used to measure economic phenomena. The four studies are connected in that each chapter builds on the findings of the previous one. Methods and results developed in one setting motivate the questions addressed in the next. By combining these perspectives, this thesis offers a broad and integrated account of monetary policy uncertainty, showing that it is shaped as much by information and perceptions as by economic fundamentals.

Furthermore, recognising these channels also carries a normative dimension. Central banks have strong incentives to manage uncertainty, since providing clarity and avoiding abrupt, unexplained shifts can support stable investment and consumption and reduce excess risk premia. At the same time, too much certainty can also be problematic, that is when circumstances change, breaking earlier commitments can damage credibility and create fresh volatility. Effective policy therefore requires balancing commitment with flexibility, and communication is the main instrument through which that balance is struck. By analysing uncertainty and communication together, this thesis contributes to understanding how central banks can navigate that challenge.

1.5 Contributions to the Literature

This thesis contributes to the growing body of work on monetary policy uncertainty and expectations in several distinct ways.

First, it develops a new measure of monetary policy uncertainty for South Africa based on Twitter data. By doing so, it extends the literature on uncertainty measurement beyond the advanced economy focus of most existing studies (Baker et al., 2016; Husted et al., 2017; Jurado et al., 2015). The contribution lies not only in applying social media data in an emerging market context, but also in validating that the resulting index captures meaningful dynamics by linking it to stock market volatility within a structural VAR framework.

Second, the thesis advances the understanding of household-level expectations by analysing novel French microdata on perceptions and expectations of policy rates. Much of the existing literature has concentrated on inflation expectations with far less attention been given to how households perceive policy interest rates, despite their central role in monetary transmission (Weber et al., 2022; D'Acunto et al., 2021). This thesis documents systematic perception gaps and forecast errors, explores their determinants, and shows how they affect saving and borrowing choices. In doing so, it adds a behavioural perspective to the literature on rational expectations and rational inattention.

Third, by directly linking households' perceptions of monetary policy uncertainty with their expectations of stock market volatility, the thesis builds a bridge between macro-level findings that policy uncertainty raises financial volatility (Bloom, 2009; Altig et al., 2020) and the micro-level evidence on individual beliefs. This contribution provides a new foundation for understanding how aggregate volatility can emerge from dispersed household perceptions.

Finally, the thesis contributes methodologically to the literature on central bank communication. By applying modern natural language processing methods, including large language models, to a broad cross-country corpus of central bank statements and speeches, it offers new evidence on how policy priorities are framed and how these framings influence exchange rate dynamics. This goes beyond traditional keyword or dictionary-based approaches, showing the value of richer text analysis in understanding the expectations channel of monetary policy.

As such, these contributions show how monetary policy uncertainty can be measured across contexts, how it shapes beliefs and behaviour at the household level, and how it is influenced by the way central banks communicate. They demonstrate originality in both substance and method, placing the work at the frontier of research in monetary economics, behavioural expectations, and computational text analysis.

1.6 Roadmap of the Thesis

The remainder of the thesis is structured as follows. Chapter 2 develops a new Twitter-based index of monetary policy uncertainty for South Africa and analyses its relationship with stock market volatility in a structural VAR framework. Chapter 3 turns to French household survey data to examine perceptions of policy rates and their connection to subjective stock market volatility. Chapter 4 investigates whether household expectations of policy rates conform to the rational expectations benchmark, introducing the concepts of perception gaps and forecast errors and linking them to saving and borrowing behaviour. Chapter 5 shifts the focus to central banks themselves, applying large language models and sentiment analysis to study how policy priorities are communicated and how they affect exchange rate dynamics across countries. The concluding chapter draws the findings together, reflects on their theoretical and policy implications, and suggests directions for future research.

This structure ensures that the four papers form a coherent body of work. Each addresses a different dimension of monetary policy uncertainty, yet they are connected by the common aim of understanding how uncertainty is formed, measured, transmitted, and managed. The thesis therefore contributes to both academic debates and practical policy discussions at a time when uncertainty has become a defining feature of the global economy.

Chapter 2

Harnessing the power of Big Data: The relationship between stock market volatility and monetary policy uncertainty in South Africa

2.1 Introduction

In an era of growing global economic uncertainty, central banks play a pivotal role in stabilizing economies. Thus, monetary policy has become a key component in controlling the economy, more especially in the aftermath of the 2008 global financial crisis and during subsequent periods of economic turbulence. During this period, central banks played a pivotal role in stabilizing financial markets and managing inflation whilst maintaining stable economic growth. However, as global economic shocks such as the COVID-19 pandemic and geopolitical tensions become more frequent, uncertainty about the future path of monetary policy has grown significantly. This uncertainty often leads to heightened market volatility and reduced investor confidence, which poses risks not only for advanced economies but also for developing nations.

South Africa, like many economies worldwide, uses monetary policy to manage inflation and guide economic growth through the South African Reserve Bank (SARB). By controlling the money supply, the SARB is able to influence borrowing costs in the economy, thus ensuring better control over economic growth, unemployment rates, and inflation. Since the 2008 global crisis, central banks around the world have become more transparent about the rationale behind the policy rates set and the likely future course that these rates will take through the release of minutes and transcripts of monetary policy committee meetings. Developing economies, including South Africa, often experience more pronounced market volatility and are more susceptible to policy changes due to structural factors such as less developed financial markets and higher political risk. Therefore, despite SARB's transparent monetary policy framework, uncertainty about future interest rate paths persists, particularly for borrowers, investors, and market participants. This ongoing uncertainty, amplified by unique structural vulnerabilities in developing economies, is a key driver of stock market volatility, as shown by previous studies such as Kaminska and Roberts-Sklar (2018). However, the impact of this uncertainty on markets in developing economies such as South Africa remains under explored. Previous studies, such as Gospodinov and Jamali (2015), that use market-based proxies, found that monetary policy uncertainty increases stock market volatility. However, the methodologies used have been subject to some scrutiny, particularly in relation to the reliability of market-based measures (Husted et al., 2020). As an alternative, some researchers have suggested using text-based measures, such as newspaper data, to assess monetary policy uncertainty (Arbatli et al., 2017; Baker et al., 2016). However, most of these textual-based indices have been developed for advanced economies, while similar measures for developing economies, including South Africa, remain scarce. More recently, researchers have turned to social media platforms like Twitter (now known as X) to create real-time, high-frequency indices of policy uncertainty. For example, Sagner and Becerra (2023) developed a Twitter-based economic policy uncertainty index for Chile, while Baker et al. (2021) constructed a similar index for the United States. Despite the different methodologies used, both studies demonstrated the potential of social media data in capturing policy uncertainty at a higher frequency. Given the lack of a readily available monetary policy uncertainty index for South Africa, constructing one using Twitter data offers a promising alternative. Although newspaper-based approaches such as Baker et al. (2016) have been widely applied, their direct implementation in the South African context is limited by the availability and structure of source material. Digital archives of major newspapers are incomplete, formats differ across publications, and historical text data are not always accessible for automated processing. In addition, overall newspaper circulation in South Africa is relatively low compared with the size of the country's active Twitter user base, and the demographic profiles of the two groups differ significantly.[1] The median newspaper reader is

[1] Evidence on South African media consumption shows a sustained decline in print circulation and readership, with industry reports documenting closures, consolidation, and

older and less urban, whereas the median Twitter user is younger, urban, and more engaged with real-time policy discussion. This makes newspapers a less suitable high-frequency source for capturing immediate reactions to monetary policy communication.

Moreover, the existing South African Policy Uncertainty Index (PUI) developed by Raymond Parsons (Parsons and School, 2016) at North-West University is quarterly, combines business-survey assessments with newspaper coverage, and measures broad policy uncertainty rather than monetary-policy-specific uncertainty. The Twitter-based approach adopted here complements this work by providing a higher-frequency, publicly available, and policy-specific indicator that captures near-real-time shifts in attention to monetary policy decisions and communication, thereby extending existing newspaper-based indicators to a higher-frequency, publicly generated information source.

Therefore, extensive research in this area is needed, especially in developing countries where the newspaper-based monetary policy uncertainty index is not readily available and the Twitter-based measure could be easily computed at a higher frequency.

The objective of this paper is to fill this gap by developing a Twitter-based monetary policy uncertainty index for South Africa, addressing the lack of existing high-frequency data in developing economies. Using this newly constructed index, the paper then explores the causal relationship between monetary policy uncertainty and stock market volatility in South Africa. The direction of this relationship has been a topic of debate in the literature, as there is no consensus on whether uncertainty drives market volatility or vice versa (Ludvigson et al., 2021). In addition, previous research has explored whether central banks should incorporate financial stability as a key policy objective. Cecchetti (2000) advocated for pre-emptive action to prevent asset bubbles, while Greenspan (1997) and Bernanke (2002, 2009) preferred minimal intervention, emphasising that the focus should be on price stability while maintaining stable growth. Should South Africa include financial stability as one of its key objectives? To address this challenge and answer these questions, we employ a shock-restricted structural VAR (SVAR) method developed by Ludvigson et al. (2021), which allows a more precise analysis of the causality between

falling print engagement across major titles. The Reuters Institute's Digital News Report for South Africa further shows that print audiences are disproportionately older and less urban, while online and social-media news users are younger and more urban. DataReportal's Digital South Africa and Meltwater's Social Media Statistics South Africa indicate that social media use continues to expand, with platforms such as Twitter (X) attracting a large, digitally engaged urban user base.

uncertainty and market volatility. By understanding this relationship, policy makers can better navigate the balance between stabilising inflation and minimising financial market disruptions. Our analysis includes stock market volatility data from the Johannesburg Stock Exchange, industrial production, and the newly developed Twitter-based monetary policy uncertainty index. To ensure the robustness of our results, we perform stationarity tests on the data variables before conducting the VAR analysis to avoid spurious regressions. The results suggest that a positive shock in monetary policy uncertainty initially leads to an increase in stock market volatility, although this effect dissipates over time. Furthermore, we find that an increase in stock market volatility raises monetary policy uncertainty, indicating a bidirectional relationship between the two variables.

This paper therefore contributes to the literature in two-fold. First, we construct a novel Twitter-based monetary policy uncertainty index for South Africa, providing a much-needed tool for assessing uncertainty in a developing economy. Second, we add to the literature on policy uncertainty by analysing the causal relationship between monetary policy uncertainty and stock market volatility using a cutting-edge SVAR methodology. These findings have significant implications for policy makers in South Africa, as they offer meaningful contributions to understanding monetary policy uncertainty and market behaviour. For central banks like the SARB, effectively managing public expectations and reducing monetary policy uncertainty is crucial to maintaining economic stability. Uncertainty about the future path of interest rates can lead to market overreactions, increased volatility, and reduced investment. By developing a Twitter-based uncertainty index, this research provides policymakers with a real-time, high-frequency tool that can track sentiment shifts in the market and help central banks fine-tune their communication strategies to minimise economic disruption.

Developing economies often face more pronounced market volatility and greater sensitivity to policy changes. The absence of reliable uncertainty measures tailored for emerging markets like South Africa means that policymakers are operating with incomplete data. This paper bridges that gap by constructing a Twitter-based uncertainty index that is both more reflective of real-time sentiment and easily adaptable to the conditions of emerging markets. For South African policymakers, this tool offers a novel approach to monitoring market conditions, which improves their ability to stabilise the economy during periods of uncertainty.

In today's global economy, increasingly characterised by sudden shocks and crises, timely decision-making is essential for mitigating the negative effects of uncertainty. By utilising a high-frequency Twitter-based index, central banks like the SARB can better monitor and respond to changes in market sentiment. This proactive approach enables policymakers to adjust monetary policy more quickly, providing clearer guidance to financial markets and potentially reducing the impact of speculative behaviours during periods of uncertainty.

Moreover, high levels of monetary policy uncertainty can destabilize financial markets, leading to increased stock market volatility and influencing broader economic outcomes such as investment and consumer confidence. By analysing the causal relationship between monetary policy uncertainty and stock market volatility, this research helps central banks understand the risks posed by uncertainty to financial stability. Armed with this knowledge, policymakers can take pre-emptive actions to stabilise markets and mitigate the risk of sudden economic shocks.

This paper thus contributes to academic debates while offering practical guidance for policymakers. A clearer understanding of the relationship between monetary policy uncertainty and stock market volatility will help central banks, especially in developing economies, improve decision making, refine communication strategies, improve financial stability, and ultimately stabilise the economy in times of uncertainty. Furthermore, this research not only fills a critical gap in the South African context but also contributes to a growing global discussion on the importance of policy uncertainty in emerging markets.

The rest of the paper is organized as follows: Section 2.2 reviews the literature, 2.3 constructs the twitter-based Monetary Policy Uncertainty Index, Section 2.4 discusses the methodology and data. Section 2.5 details the results and finally Section 2.6 concludes.

2.2 Review Of Literature

This paper is related to the literature on policy uncertainty and its effects on the economy. Monetary policy uncertainty refers to the unpredictability or ambiguity surrounding future actions or decisions by central banks regarding monetary policy, such as adjustments to interest rates, inflation targets, or the money supply. This uncertainty can arise due to unclear communication from central banks, rapidly changing economic conditions, or differing interpretations of economic data.

The literature suggests that monetary policy uncertainty can have several adverse effects on the economy, including reductions in output, interest rates, inflation, and investment (Balcilar et al., 2017; Husted et al., 2017). These findings show the importance of further research on monetary policy uncertainty, given its potential to negatively impact economic performance.

The literature, however, disagrees on the various methods used to measure monetary policy uncertainty. Since uncertainty is not directly observable, economists have developed several proxies to capture and quantify the uncertainty perceived by policymakers, market participants, professional forecasters, and the media. These measures are forward-looking and have the advantage of capturing sudden economic shocks, in contrast to backward-looking measures derived from statistical models that utilize lagged data.

Consequently, research on economic uncertainty has employed data with short lags and real-time information to measure uncertainty effectively and capture sudden economic shocks that larger lagged data sets might overlook. Although there are a variety of uncertainty measures within the literature, most focus on general economic uncertainty, with only a limited number specifically targeting monetary policy uncertainty. However, due to the lack of direct comparability among these measures, the use of different methods to capture uncertainty raises concerns about the reliability of the results obtained from empirical analyses. This section reviews the various measures of uncertainty available in the economic literature.

2.2.1 Measures of Monetary Policy Uncertainty

In the existing literature, market-based, survey-based, and text-based proxies are commonly used to measure monetary policy uncertainty. Market-based proxies measure uncertainty through realized volatility from interest rate futures and implied volatility from interest rate options (Swanson, 2006; Kishor and Marfatia, 2013; Kontonikas et al., 2013; Gospodinov and Jamali, 2015; Bauer et al., 2021). Realized volatility is defined as the scaled sum of squared daily returns (Andersen et al., 2003), although intraday returns are also frequently employed. The advantage of realized volatility lies in the availability of large time series data, making it a robust tool for analysing historical financial uncertainty. However, its backward-looking nature limits its ability to capture real-time economic shocks, which is a critical limitation for policymakers. Another key market-based measure is the VIX, which captures U.S. stock market uncertainty. It is calculated as the weighted average price of out-of-the-money S&P 500 options that expire between 23 and 37 days (Britten-Jones and Neuberger, 2000). While the VIX is forward-looking and effective at detecting sudden economic shocks, it primarily measures financial rather than monetary policy uncertainty.

Swanson (2006) offers a more specific market-based proxy for monetary policy uncertainty by calculating the standard deviation of 90-day Eurodollar options with six-month expiration dates, sampled around Federal Open Market Committee (FOMC) meetings. While this method provides a more focused approach to monetary policy, its reliance on interpolated data to maintain a consistent forecast horizon raises concerns about the reliability of the results, as interpolation may not always accurately reflect market conditions.

Moreover, Swanson adjusts the measurement to avoid misinterpretations during periods of low interest rates. Yet the method may still face issues of endogeneity, as monetary policy might respond to stock market fluctuations. These limitations suggest that Swanson's measure, despite its contributions, does not fully overcome the challenge of measuring monetary policy uncertainty independently.

Although using high-frequency data, such as daily or intraday data, could address some of these shortcomings, the limited availability of data and shorter time series for implied volatility continue to pose challenges. Bauer et al. (2021) improve upon previous market-based measures by introducing a model-free approach that incorporates a wider range of strike prices and uses exchange-traded prices instead of over-the-counter quotes.

Despite these advancements, market-based proxies may still fall short of accurately capturing monetary policy uncertainty, as financial market volatility could be driven by factors unrelated to policy uncertainty, such as time-varying risk aversion (Jurado et al., 2015; Husted et al., 2020).

Nevertheless, while market-based measures have certain advantages, they are not without significant drawbacks. One major criticism is that such measures tend to capture financial market reactions, which might be influenced by factors unrelated to monetary policy, such as changes in investor sentiment or external economic shocks. As a result, there is a growing consensus that market-based proxies, although useful, may not be sufficient to fully understand monetary policy uncertainty.

Jurado et al. (2015) propose a model-based measure to overcome some of these limitations by focusing on the unforecastable component of macroeconomic data. Their approach aggregates individual uncertainty measures, offering a forward-looking perspective that is able to capture sudden shocks more effectively. This model also addresses a key criticism of market-based proxies such as their failure to remove forecastable variations from uncertainty measures, leading to potential overestimations of uncertainty. While this model-based approach provides a more comprehensive understanding of macroeconomic uncertainty, it is not without its limitations. For instance, it is available only at a monthly frequency and focuses predominantly on interest rate-based uncertainty, thereby excluding other monetary policy tools.

Uncertainty in economics is also measured using information from newspaper articles (Azzimonti, 2018; Husted et al., 2017; Baker et al., 2016). Monetary policy uncertainty is often gauged using newspaper-based indexes. For example, Husted et al. (2017) developed a monetary policy uncertainty index from newspaper articles, arguing that market-based proxies fall short because they only account for interest rate uncertainty, excluding other monetary policy tools. Furthermore, market-based measures primarily capture uncertainty as perceived by households active in the options market, thus failing to offer a more representative sample. There is also the possibility that market-based proxies might be driven by time-varying risk aversion or state-dependent marginal utility rather than true economic uncertainty.

To address these limitations, Husted et al. (2017) constructed a newspaper-based monetary policy uncertainty index using articles that contain specific keywords related to monetary policy and uncertainty. Their approach builds on Baker et al. (2016), who created a general economic policy uncertainty index. The advantage of newspaper-based measures is that they are forward-looking and can capture sudden shocks in the economy. However, this measure reflects uncertainty as perceived by the media, which may not necessarily align with the views of the general public.

Finally, survey-based measures of uncertainty offer another approach, capturing ex-ante uncertainty through subjective assessments by businesses, professional forecasters, households, and market participants. For example, Scotti (2016) measures macroeconomic uncertainty by using squared deviations of data release surprises from Bloomberg survey expectations, while Altig et al. (2022) examine firms' one-year-ahead uncertainty concerning sales and employment. Survey-based measures are beneficial in that they can specify the segments of the population experiencing uncertainty and are precise in terms of the time horizon of uncertainty.

In recent years, Twitter-based measures of policy uncertainty have emerged as a modern approach. Twitter, with its large platform and real-time, high-frequency data, provides a cost-effective method for capturing public perceptions of economic uncertainty. Unlike newspaper-based measures, which are often influenced by editorial biases, Twitter-based measures are more likely to

reflect the general public's views. Additionally, the presence of retweets allows for the creation of weighted indices of monetary policy uncertainty. Despite these advantages, Twitter-based measures have limitations. For instance, the platform only began in 2006, meaning that no historical data exists prior to this time. In developing countries, limited internet access makes Twitter less representative of the broader population. Baker et al. (2021) and Becerra and Sagner (2020) have applied Twitter data to develop economic policy uncertainty indices for the United States and Chile, respectively. However, Becerra and Sagner (2020) reliance on tweets from major broadcasters and newspapers may introduce bias, as it might not fully capture the views of the general public. Nonetheless, Twitter-based measures offer an improvement over newspaper-based approaches by providing real-time data that can capture sudden economic shocks. However, it remains noteworthy that, to date, no Twitter-based measures have been created specifically for monetary policy uncertainty, especially in developing economies like South Africa.
As such, while newspaper-based measures provide a forward-looking approach to measuring monetary policy uncertainty, they are limited by their reliance on media perceptions, which may not always reflect the views of the broader population. Survey-based measures offer more specific insights into different segments of society and time horizons but are limited by their subjective nature and lack of representativeness. Twitter-based measures, while offering high-frequency real-time data, are restricted by their limited historical data and accessibility issues in certain regions.

2.2.2 Effects of Policy Uncertainty

Although measures of uncertainty remain subject to debate, there is consensus in the literature that uncertainty impacts the economy. Numerous studies have investigated the causal relationship between macroeconomic uncertainty and economic activity, yielding conflicting results. One strand of literature states that low economic activity is caused by uncertainty, examining both the demand-side and supply-side effects. On the demand side, uncertainty has been studied through both firm-level and household-level approaches. At the household level, scholars such as Carroll (1996) and Romer (1990) observed that when households face uncertainty regarding the labour market or their future income, they tend to increase precautionary savings. This precautionary behaviour, aimed at building a buffer of savings to mitigate future income shocks, leads to a decline in consumption during periods of heightened uncertainty.

At the firm level, the real options theory explains the countercyclical behaviour of uncertainty, particularly regarding the irreversibility of investment decisions (Bernanke, 1983; Dixit and Pindyck, 1994). According to this theory, increased uncertainty prompts firms to delay investment and hiring decisions, resulting in a decrease in both investment and employment. As uncertainty recedes, firms resume these activities, potentially leading to economic growth and an overshooting effect. A seminal contribution in this area is Bloom (2009) analysis of macroeconomic uncertainty. Using the real options theory, Bloom explored the “wait-and-see” effect of uncertainty through a Real Business Cycle (RBC) model with frictions in capital and labour. In this framework, uncertainty about technological innovation disrupts real economic activity, leading to declines in output.

Furthermore, the supply-side channel of uncertainty has been explored in several studies. Bentolila and Bertola (1990) argued that high adjustment costs in the labour market increases the negative effects of uncertainty on hiring plans. Similarly, Bloom (2009) noted that uncertainty may cause firms to delay hiring decisions, and Disney et al. (2003) highlighted that firms may be hesitant to enter new export markets during times of uncertainty, limiting the efficient allocation of resources and reducing overall supply.

Contrary to these findings, some theories propose that uncertainty can actually increase economic activity. This perspective draws on the “growth options” theory, which suggests that firms may increase hiring and investment in response to increased uncertainty, as they seek to capitalize on potential upside gains while the downside risk remains bounded (Kraft et al., 2018; Segal et al., 2015). This theory has been used to explain phenomena like the dot-com boom, where heightened uncertainty did not lead to a contraction but rather an expansion in economic activity as firms pursued new growth opportunities.

Therefore, the literature on the theoretical underpinnings of uncertainty presents multiple interpretations regarding whether uncertainty causes or reacts to economic fundamentals and whether its impact is negative or positive. Furthermore, theoretical models do not provide clear identifying restrictions on which empirical studies can base their work. In the macroeconomic literature, structural vector autoregression (SVAR) models are often used to analyse causal relationships. However, given the theoretical ambiguity regarding the sign of the relationship between uncertainty and economic fundamentals, traditional SVAR models (identified through sign restrictions, zero-frequency restrictions, or recursive identification schemes) are limited in their effectiveness (Ludvigson et al., 2021). In response to these challenges, Ludvigson et al. (2021) propose a novel identification strategy that combines narrative restrictions with external variables. This approach provides a more robust framework for analysing the complex relationships between monetary policy uncertainty, stock market volatility, and real economic outcomes. Using this method, this paper aims to offer clearer understanding of the causal mechanisms at play and overcome the limitations of previous empirical models.

2.2.3 The relationship between Policy Uncertainty and Stock Market Volatility

Lastly, we explore the literature on policy uncertainty and stock market volatility. Several authors have analysed the nexus between policy uncertainty and the stock market, employing various measures of uncertainty to examine this relationship. On the one hand, much of the literature has focused on market-based proxies. For instance, Gospodinov and Jamali (2015), using data from the United States, investigated how stock market volatility responded to futures-based monetary policy shocks. Their sample period spanned from 1990 to 2007, and through a bivariate VAR-GARCH model, they concluded that monetary policy uncertainty led to a significant surge in stock market volatility. Similarly, Kishor and Marfatia (2013) measured monetary policy uncertainty using federal funds futures prices and found that during economic downturns, stock markets in the U.K. and U.S. responded negatively to U.S. monetary policy surprises, whereas stock markets in other parts of the world responded more positively. They suggested that this behaviour could be due to the perception in the U.S. and U.K. that unforeseen and significant cuts in policy rates might signal economic distress. Kontonikas et al. (2013) also support Kishor and Marfatia (2013)'s findings. They used federal funds rate futures as a proxy for monetary policy uncertainty and found that U.S. stock prices reacted positively to monetary policy uncertainty in periods outside of financial crises. However, Wang and Zhu (2013) argued against the impact of unanticipated monetary policy actions, contending that the effect size may be too small to meaningfully alter the correlation structure of foreign stock markets.

In addition, Ludvigson et al. (2021) adopted a model-free uncertainty measure from Jurado et al. (2015) as a proxy for macroeconomic and financial uncertainty. They examined the direction of causality between output and uncertainty using a shock-restricted structural vector autoregressive (SVAR) model. Their findings revealed that during economic downturns, increased macroeconomic uncertainty often emerges as a response to output shocks, while output fluctuations are driven by financial uncertainty.

Despite the prevalence of market-based measures as a proxy for policy uncertainty, these measures have the limitation of only capturing uncertainty surrounding the path of interest rates, without considering other monetary policy tools. To address this limitation, several studies have developed newspaper-based uncertainty indices to explore the relationship between stock market volatility and policy uncertainty. For instance, Mei et al. (2019) used the newspaper-based policy uncertainty index constructed by Baker et al. (2016) to examine the impact of economic and monetary policy uncertainty on oil market volatility. Their findings suggested that an increase in the uncertainty of monetary policy contributed to a higher volatility in the oil market and helped forecast oil volatility. Similarly, Clance et al. (2020) used a newspaper-based index to investigate whether stock market volatility could be predicted using U.S. monetary policy uncertainty. They demonstrated that monetary policy uncertainty could indeed forecast both implied and realised stock price volatility.

Likewise, Husted et al. (2020) constructed a monetary policy uncertainty index using information from newspaper articles and employed it to analyse its effects on the U.S. economy. Their results indicated that increased monetary policy uncertainty led to wider credit spreads and reduced investment and output. Cevik and Erduman (2020) also used a newspaper-based monetary policy uncertainty index and analysed its impact on the Turkish economy, finding that monetary policy uncertainty had a negative effect. Despite the improvements that newspaper-based uncertainty indices represent over market-based proxies, they remain susceptible to potential biases, as the uncertainty captured may reflect media perceptions rather than those of the general public.

To conclude, various measures of uncertainty have been developed, each with its own strengths and limitations. Recently, sentiment analysis has gained prominence as a forward-looking tool for capturing policy uncertainty, offering high-frequency data capable of reflecting sudden economic shocks. However, a critical shortcoming of the existing body of research is that most textual measures of uncertainty are concentrated in developed economies and predominantly focus on economic policy uncertainty, rather than monetary policy uncertainty. For example, Husted et al. (2020) and Baker et al. (2021) developed indices for the US, while Manela and Moreira (2017) and Arbatli et al. (2017) constructed similar indices for Belgium and Japan, respectively. This regional and thematic concentration leaves a significant gap in the literature, particularly in relation to developing economies. Addressing this gap is a key motivation of this research.

Secondly, this research explores the relationship between monetary policy uncertainty and stock market volatility in South Africa, an area that remains largely under-researched. Given the importance of stock markets in developing economies as vehicles for economic growth and capital allocation, understanding how monetary policy uncertainty affects market stability in these contexts is critical. To my knowledge, no similar studies have been conducted in South Africa, further highlighting the novelty and relevance of this work.

Moreover, while existing theoretical frameworks offer varied and sometimes conflicting perspectives on the relationship between uncertainty and macroeconomic performance, particularly regarding whether the effect is positive or negative, they often fall short in providing clear identifying restrictions for empirical testing. This study contributes to this ongoing debate by empirically investigating the causal relationship between monetary policy uncertainty and the broader economy in a developing country context, thereby addressing a vital gap in both the theoretical and empirical literature. In doing so, it aims to shed light on how monetary policy uncertainty influences economic outcomes in emerging markets, with implications that may extend beyond South Africa to other developing economies facing similar challenges.

2.3 Constructing The Monetary Policy Uncertainty Index

This paper creates a Twitter-based monetary policy uncertainty (MPU) index that shows the degree of uncertainty at which the South African public perceives the decisions taken by the South African Reserve Bank (SARB). The tweets are collected using the Twitter API for academic research archive provided by Twitter.

Twitter is beneficial as it has a large platform that provides high-frequency, real-time data at a low cost. Unlike newspapers, which mostly capture the opinions of the media, Twitter reflects the perceptions of the general public more directly. In addition, the existence of retweets makes it possible to create weighted indices of monetary policy uncertainty. Despite these advantages, Twitter also has shortcomings. It does not provide any data prior to 2006, when it was first launched, and it may not be representative of certain social groups such as the less wealthy, less educated, or older populations. Furthermore, the platform's content can be influenced by automated accounts, coordinated posting, or temporary surges in activity around specific events. To reduce these effects, the analysis aggregates tweets at a monthly frequency and relies on a broad, policy specific keyword set rather than user level sentiment, which helps smooth out extreme bursts of activity or manipulation by a small group of users. A manual inspection of random tweet samples confirmed that most posts relate to genuine policy commentary rather than automated content, although a small share of noise cannot be ruled out. In addition, engagement on social media is inherently time varying periods of intense debate may reflect attention rather than true uncertainty. These limitations are acknowledged, and the results are interpreted as capturing public attention and perceived monetary policy uncertainty rather than the objective unpredictability of policy outcomes. Nonetheless, Twitter continues to expand and is likely to reach a broader user base in the future, particularly in developing countries such as South Africa, where technological capabilities are still growing.

To construct the MPU index, we start by counting the frequency of tweets that relate to monetary policy uncertainty in South Africa. Specifically, we adopt the methodology outlined by Husted et al. (2017) and identify key search terms that capture relevant discussions. The following search criteria are employed to extract tweets:

TABLE 2.1: The Search Criteria for Extracting Tweets

a)	**b)**	**c)**
Uncertainty	Monetary Policy	South African Reserve Bank
Uncertain	Interest rate	SA Reserve Bank
Uncertainties	Policy rate	SARB
Concern	Bank rate	
	Monetary easing	
	Inflation target	
	Price target	
	Quantitative easing	
	Unconventional monetary policy	
	Asset Purchases	

Notes: The table lists the keyword groups used to extract tweets related to monetary policy uncertainty in South Africa. Tweets were selected if they contained at least one term from each column, ensuring that the final corpus captured discussions linking uncertainty, monetary policy, and the South African Reserve Bank.

We search for tweets containing the triple of (a) “uncertainty” or “uncertain,” (b) “monetary policy(ies)” or “interest rate(s)” or “policy rate” and (c) “South African Reserve Bank” or “SA Reserve Bank” or “SARB”. The set of keywords was developed through iterative searches of South African monetary policy tweets, reference to established uncertainty dictionaries, and manual screening for contextual relevance based on random tweet samples. Words that consistently appeared in policy discussions, such as “concern” and “uncertain,” were retained, while those that generated unrelated or highly emotive content, such as “worry,” were excluded. This filtering process ensures that the index reflects discussions of policy ambiguity rather than general anxiety or sentiment. The focus throughout is on language that signals doubt or unpredictability about monetary policy decisions, allowing the index to capture genuine uncertainty rather than shifts in sentiment or mood.

This refinement also distinguishes between vocabulary that signals uncertainty about the policy path and terms that primarily shift the overall level or mean of sentiment. In the tweet corpus, words such as “concern” typically appear in contexts where views on forthcoming policy decisions diverge, whereas “worry” is largely used in relation to issues unrelated to monetary policy, such as load shedding, crime, or political developments. Prioritising terms linked to uncertainty rather than mean-shifting sentiment ensures that the index captures variation in perceived policy ambiguity rather than movements in general mood.

This search is conducted monthly from January 2017 to December 2020, allowing for an analysis of trends over a significant period. This approach ensures that we capture a comprehensive range of sentiments and discussions surrounding monetary policy uncertainty in South Africa, thereby allowing for a robust analysis of the data. Based on this search criteria, a total of 4186 tweets were extracted.

After extracting tweets, we perform a thorough data cleaning process, which includes:

- **Removing duplicates:** This ensures that each tweet is unique.
- **Lowercasing:** This standardizes the text for consistency in analysis.
- **Tokenization:** This breaks down tweets into individual words or phrases for a more comprehensive analysis.

Following the data cleaning, we count the number of tweets that meet the search criteria for each month. To control for changes in the volume of total tweets over time and the possibility of some tweets covering more news about monetary policy than others, we follow the methodology of Husted, Rogers and Sun (2017) and normalize the monthly number of cleaned tweets by the total number of tweets containing the word ”SARB.” This calculation is performed for each month as follows:

$$n_t = \frac{\text{number of monthly tweets satisfying the search criteria}}{\text{number of monthly tweets containing the word 'SARB'}} \quad (2.1)$$

Finally, we rescale this series by a mean of 100 and a standard deviation of 1 to obtain the Monetary Policy Uncertainty Index. This normalization allows for easier comparisons over time. The resulting MPU index provides a quantifiable measure of monetary policy uncertainty. A higher index value indicates increased uncertainty, while a lower value suggests a more stable policy environment. Figure 2.1 shows the evolution of the newly constructed monetary policy uncertainty index throughout the study period.

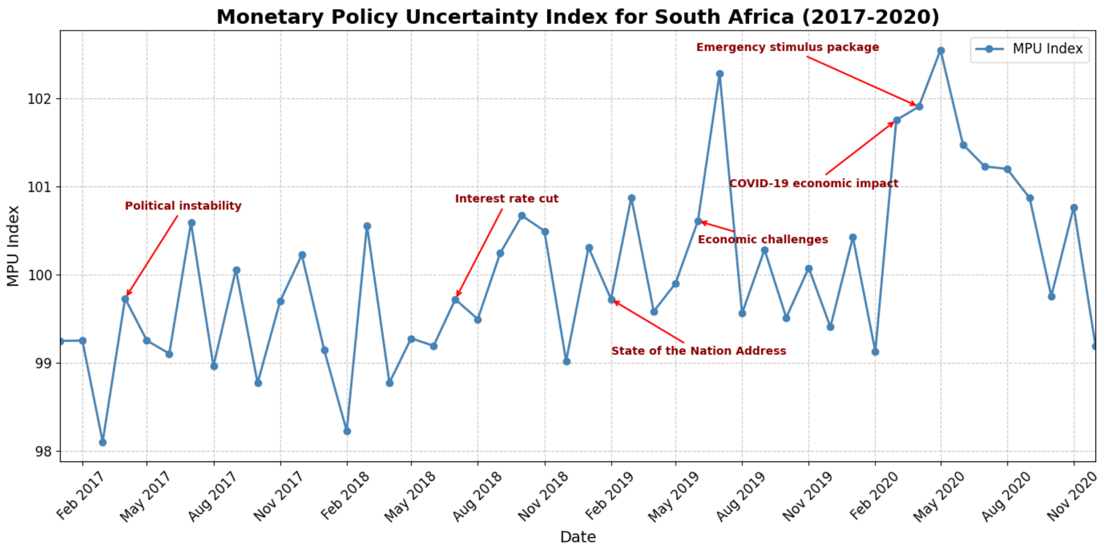


FIGURE 2.1: Monetary Policy Uncertainty Index
Notes: The figure plots the monthly monetary policy uncertainty (MPU) index constructed from Twitter data. The series is standardised to show fluctuations in uncertainty over time.

A rise in the number of tweets searched using the key terms in Table 1, indicate that there is more uncertainty about the South African Reserve Bank's actions as perceived by the public. From the graph, we can see a notable peak around April 2020. This was a period when monetary policy uncertainty was high in South Africa due to the outbreak and spread of the Covid-19 virus. The public was unsure about the path that the South African Reserve Bank was willing to take in order to combat inflation following the unexpected outbreak of Covid-19. Furthermore, this was also the month where the SARB committee met to decide on the policy rate hence the public was unclear on what direction the committee will take. Another notable peak can be seen around July 2019. This was a time when Moody's had realized a report indicating low confidence in South Africa's economic growth rate, which further depreciated the South African currency against other major currencies such as the US dollar. As such, the Moody's report may have caused the public to be unsure about the path South Africa's monetary policy would take.

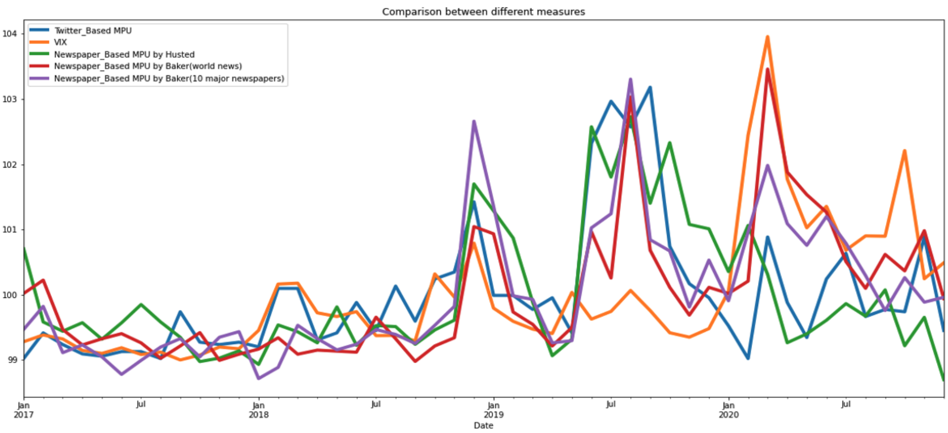


FIGURE 2.2: Comparison of different Monetary Policy Uncertainty Index Measures

Notes: The figure compares alternative measures of monetary policy uncertainty, including the Twitter-based index and benchmark indices from the literature. All series are normalised for visual comparison.

Figure 2.2 shows a graph that compares different measures of monetary policy uncertainty with the twitter based monetary policy uncertainty. For comparison purposes, using the same methodology, we create a monthly Twitter-based monetary policy uncertainty (MPU) index for the United States of America and compare it with the readily available monthly newspaper-based measures developed for the United States as well as a financial uncertainty measure (the VIX). This is because there are no such measures in South Africa, thus making comparison more difficult. From the graph, we can see that the Twitter-based index tracks and moves with the newspaper-based measures developed by Husted et al. (2017) and Baker et al. (2016). This is also further evidenced by the correlation between the different measures, as shown in Table 2.2. There is a positive correlation between the newly constructed Twitter MPU index and the newspaper monetary policy uncertainty index by (Baker et al., 2016) created from 10 major newspapers. Similarly, the Twitter MPU index is also positively correlated with the newspaper-based uncertainty index created by Husted et al. (2017). The similarity between the South African and United States indices reflects the transmission of global monetary and financial shocks to a small open economy. South Africa's flexible exchange rate and its reliance on portfolio flows mean that episodes of elevated uncertainty in the United States can quickly influence domestic sentiment through expectations about interest rate differentials, capital flow pressures, and exchange rate volatility. Domestic factors such as policy announcements and communication by the South African Reserve Bank still generate independent fluctuations when global conditions are stable, indicating that both external and local forces shape the pattern of uncertainty.

TABLE 2.2: Correlation Between Different Measures of Uncertainty

	VIX	Twitter MPU	Husted MPU	Baker MPU (World News)	Baker MPU (10 Major Newspapers)
VIX	1.000				
	(0.000)				
Twitter MPU	0.157	1.000			
	(0.285)	(0.000)			
Husted MPU	0.056	0.698***	1.000		
	(0.707)	(0.000)	(0.000)		
Baker MPU (World News)	0.674***	0.528***	0.495***	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	
Baker MPU (10 Major Newspapers)	0.555***	0.675***	0.697***	0.861***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: The table reports pairwise correlations between alternative uncertainty measures, with p-values in parentheses. Significance levels are denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

2.4 Methodology and Data

2.4.1 Econometric Framework

A shock-restricted structural vector autoregressive (SVAR) model is used to study the relationship between stock market volatility and monetary policy uncertainty in South Africa and to determine the causal relationship between these variables.

2.4.1.1 Overview of the SVAR Model

An SVAR model extends the vector autoregression (VAR) model, which is used to model the interrelationship between a set of variables by estimating a set of linear equations. The VAR model assumes that each variable is influenced not only by its own lagged values but also by the lagged values of all other variables in the system. This multivariate time series approach captures the dynamic interactions among the variables.

However, to effectively estimate causal relationships, VAR models often rely on exclusion restrictions. These restrictions assume that certain variables do not respond to specific shocks, implying that their response is negligible or zero. Although such assumptions can simplify model estimation, they may lack robustness and justification based on economic theory. This limitation motivates the use of a shock-restricted SVAR model, which is more data-driven and minimizes strong theoretical assumptions.

2.4.1.2 Identification Strategy

To identify structural shocks, we focus on a shock-restricted approach by Ludvigson et al. (2021). This method avoids the pitfalls of sign restrictions, which impose specific constraints on the direction of shocks. Given the ambiguity in existing literature regarding the relationship between uncertainty and other macroeconomic variables, using sign restrictions could lead to unreliable impulse response functions.
Furthermore, incorporating external instrumental variables for identification can be problematic, as credible exogenous instruments are often difficult to find. Therefore, a shock-based SVAR model is employed to identify structural shocks without relying heavily on restrictive assumptions.

2.4.1.3 Baseline model

The reduced form VAR is estimated as follows:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + u_t \tag{2.2}$$

where $u_t \sim N(0, \Sigma_u)$.
Here, Y_t is a vector defined as:

$$Y_t = [MPU_t, IP_t, SMV_t]'$$

with MPU_t representing monetary policy uncertainty, IP_t denoting industrial production, and SMV_t indicating stock market volatility at time t. The model uses a three variable structure to identify how monetary policy uncertainty affects financial markets and real activity. This follows the approach of Ludvigson et al. (2021), who argue that small and well-defined systems help to separate the effects of uncertainty from other macroeconomic influences. Inflation and the policy rate are excluded since the model focuses on uncertainty transmission, not on policy implementation. The interest of the analysis is not in how the central bank sets policy but in how changes in uncertainty about that policy influence economic outcomes. Including inflation or the policy rate in the same short sample system would make it difficult to disentangle an uncertainty shock from a conventional policy or price shock because these variables are jointly determined. For example, a rise in uncertainty can cause the central bank to adjust the policy rate, while policy moves can in turn alter perceptions of uncertainty. Treating them as separate structural shocks within such a small sample would risk confounding these effects and make interpretation of the impulse responses ambiguous. From an empirical point of view the sample contains few monthly observations, which restricts the number of parameters that can be estimated reliably. Each additional variable would multiply the number of coefficients and increase estimation error, weakening the precision of the responses. A parsimonious system therefore provides more stable estimates of the transmission of uncertainty. The two remaining variables already capture the key channels through which monetary policy uncertainty influences the economy. Stock market volatility reacts immediately to new information about the policy environment and reflects changes in investor risk perceptions, while industrial production summarizes the response of real activity to those financial conditions. Hence, together they provide a concise representation of the financial and real sectors without overstretching the available data. This design gives a transparent view of how an uncertainty shock propagates through the economy while keeping the identification of that shock conceptually and statistically clear. This specification is thus consistent with the benchmarking choices used in the main uncertainty literature, including Ludvigson et al. (2021), who employ small and tightly defined VARs to isolate uncertainty shocks, and Bloom (2009), where uncertainty is identified separately from standard policy and demand disturbances. These studies provide the methodological basis for using a limited variable system to distinguish uncertainty shocks within a short sample.

The matrix Σ_u represents the variance-covariance matrix of the reduced form innovations u_t. Additionally, we have:

$$\Sigma_u = PP'$$

where P is the unique lower triangular Cholesky factor with non-negative diagonal elements.

The reduced form innovations u_t are related to the structural shocks e_t by the equation:

$$u_t = Be_t \tag{2.3}$$

The structural shocks e_t are assumed to be mutually and serially uncorrelated, with mean zero and unit variance. In contrast, the reduced form innovations are correlated, and therefore, they do not provide clear econometric meaning. This correlation hinders the ability to identify and interpret the distinct effects of the underlying shocks on the endogenous variables. The main aim is therefore to study the structural shocks affecting these variables.

By construction, structural shocks are orthogonal, hence we can trace the effect of each individual shock on the endogenous variables at the time the shock occurs and in subsequent periods. To identify the structural shocks, we run a reduced form SVAR and obtain the residuals and coefficients. Since, under regularity conditions, we can consistently estimate coefficients from an auto regressive model, the sample residuals estimated from the SVAR model serve as consistent estimates of the reduced form innovations.

Orthogonality ensures that both MPU and SMV shocks are uncorrelated with contemporaneous innovations in industrial production (IP) and with each other. This allows us to treat them as exogenous disturbances to the system. To reduce concerns about reverse causality, where movements in IP could themselves generate higher uncertainty or volatility, we impose additional restrictions. These require shocks to align with historically recognised episodes of heightened uncertainty or volatility and to be consistent with external financial indicators, such as negative stock market returns. These conditions support the interpretation of both MPU and SMV shocks as exogenous drivers rather than mechanical responses to changes in IP or to each other.

Next, we identify the matrix B in equation 2.3 using the following covariance restrictions deduced from the reduced form VAR relationship:

$$\Sigma_u = BB'$$

However, there are $n^2 = 9$ unknown elements in B and only $n^2 - n = 6$ equations. This discrepancy arises from the symmetric properties of the variance-covariance matrix. Only six restrictions in the form of:

$$\bar{g}_z(B) = vec(\Sigma_u) - vec(BB') = 0$$

are provided by the covariance structure of the reduced form innovations, indicating that the model is under-identified. As a result, there can exist many solutions that satisfy the covariance restrictions, which we collect into the unconstrained set $\hat{\mathrm{B}} = \{B = \hat{P}Q : Q \in O_n,$ diag$(B) \geq 0;\ \bar{g}_z(B) = 0\}$, where O_n denotes the set of $n \times n$ orthonormal matrices. This under-identification implies that we will need to explore additional methods to narrow down this set in our analysis.

The methodology of constructing the set of unconstrained solutions, $\hat{\mathrm{B}}$, follows that of Ludvigson et al. (2021). First, B is defined as the unique lower-triangular Cholesky factor of Σ_u with diagonal elements greater than or equal to zero. The matrix B is then rotated by 1.5 million random orthogonal matrices, with each rotation initiated by drawing an $n \times n$ matrix of NID(0,1) random variables. The orthonormal matrix is then obtained through the QR decomposition of this matrix, ensuring that $B = PQ$ imposes the covariance restrictions by construction.

From this procedure, 1.5 million matrices are generated, resulting in 1.5 million values of unconstrained structural shocks (e_t) for $t = 1, ..., T$. Shock-based restrictions are then applied to determine which potential solutions to retain from the unconstrained set. Specifically, two types of shock-based restrictions are employed, the event restrictions and external variable constraints, which narrow down the unconstrained set into a set of admissible solutions, referred to as the constrained set. These restrictions focus on specific characteristics of the shocks, allowing for a more informed selection process. Although we do not reach point identification, the set-identified matrices allow us to find the direction of causality. Therefore, identification of shocks in the SVAR model is achieved through imposing both event restrictions and external variable constraints.

2.4.1.4 Event Restrictions

Event restrictions are uncommon episodes in history such as the Lehman event and the great depression, where a broad-based statistical and historical reading of the times suggests a specific characteristic of structural shocks. Event restrictions impose constraints on the size and sign of structural shocks rather than placing constraints on the signs of impulse response functions, as in the sign-restricted SVAR literature. During periods of interest, shocks from a credible identification scheme should not be different from our historical understanding of events. By requiring the properties of the identified shocks to agree with the major economic events that have been realized, researchers can obtain more informative results. This approach considers the historical context and aligns the shocks with known economic conditions.

As such, to help narrow down the unconstrained set of solutions, $\hat{\mathrm{B}}$, we first identify the major economic events in South Africa between 2017 and 2020 where uncertainty is heightened. We call these major economic events 'big shock events'. Structural shocks at these dates should be high and consistent with our current understanding of historical events to ensure the credibility of identification constraints. But what constitutes a ”big shock event” in our sample? In the sample studied, we identify the largest monetary policy uncertainty episode to be during the COVID-19 pandemic, in April 2020. This month marked the global spread of COVID-19, leading to widespread uncertainty about how central banks will react. It also coincided with the South African Government’s announcement of a lockdown that had minimal guidance, further heightening uncertainty about the future. Lastly, this date also coincides with the month that the South African Reserve Bank monetary policy committee met to decide on the policy rates. In a surprise move, they cut the repurchase rate by a further 100 basis points. This contributed to increased monetary policy uncertainty in an already uncertain world. In terms of stock market volatility, we identify the largest volatility episode to be in the month of April 2017. This was the month where former President Jacob Zuma fired the then Finance Minister Pravin Gordhan, and South Africa’s credit rating was cut to junk status, causing uncertainty and instability in financial markets.

Before imposing any identifying restrictions, we study the structural shocks in our sample period and identify when big shocks have occurred by searching across the unconstrained set of solutions, $\hat{\mathrm{B}}$, for the date in which the monetary policy uncertainty shocks, $e_{MPUt}(B)$ and stock market volatility shocks $e_{SMVt}(B)$, appear to be the largest. We let the data speak and are informed by the data, especially by the covariance of reduced form residuals. From the 1.5 million values of unconstrained structural shocks we constructed above, we search for month across the 1.5 million rotations in which the monetary policy uncertainty shocks appeared the highest most frequently. The date with the most maxima in monetary policy structural shocks (45% of them) is found to be April 2020[2]. Studying the structural shocks at this date further, we find that most of the shocks take a standard deviation of 3 or larger and are positively skewed with few negative values. Therefore, the covariance structure of the data alone provides evidence of large positive monetary policy uncertainty shock in the month of April. This date thus aligns with our understanding of historical economic events.

We repeat the same procedure for stock market volatility shocks and identify the date where stock market volatility structural shocks appeared the highest, which is April 2017 (48% of them). The distribution of the volatility shocks at this date

[2]This is the date in which the monetary policy uncertainty structural shock reaches its maximum most often. This follows Ludvigson et al. (2021)’s methodology. For robustness, this date is still identified when using 5000, 1.5 million, 2.5 million, 3.5 million, 4.5 million, and 5 million rotations.

is negatively skewed and take a value of 2 or higher, and hence the covariance structure of the data shows evidence of a large positive volatility shock at this date.

These events represent the major shock events considered between 2017 and 2020 used to narrow down the unconstrained set. Additionally, following Ludvigson et al. (2021), we identify other significant economic events during this period that while not major shocks, justify the use of weaker restrictions on the sign of structural shocks. We call these 'non-negative constraints'.

- In October 2018, South Africa, faced severe food insecurity due to drought and the potential onset of an El Nino phenomenon, influencing economic stability and policy decisions, thus affecting both stock market volatility and monetary policy uncertainty.
- FRED[3] indicates that South Africa entered a technical recession between February and April 2020, suggesting a negative sum of structural shocks during this period, indicating decreased industrial production.

The use of shock-based restrictions thereby helps us decide whether to keep a potential solution in the unconstrained set by making use of the features of shocks. Specifically, we require that any structural shocks $e_t(B)$ formed from the B matrix satisfy the following inequality constraints:

- $g_{\mathcal{E}_1} : e_{mpu,\tau_1} \geq \bar{k}_1$ at $\tau_1 =$ April 2020
- $g_{\mathcal{E}_2} : e_{smv,\tau_2} \geq \bar{k}_2$ at $\tau_2 =$ April 2017
- $g_{\mathcal{E}_3} : e_{smv,\tau_3} \geq 0$ at $\tau_3 =$ October 2018.
- $g_{\mathcal{E}_4} : e_{mpu,\tau_4} \geq 0$ at $\tau_4 =$ October 2018.
- $g_{\mathcal{E}_5} : 0 \geq \sum e_{ip,\tau_5}$ for $t = \tau_5 \in [\text{February 2020}, \text{April 2020}]$

Where $\bar{k}$ are parameters and τ are event dates. The above restrictions pertain to significant shock events as discussed above. $g_{\mathcal{E}_1}$ and $g_{\mathcal{E}_2}$ are the big shock events whilst $g_{\mathcal{E}_3}$ to $g_{\mathcal{E}_5}$ are the non-negative constraints. For example, the first restriction implies that the monetary policy shock found in April 2020 should be large, exceeding $\bar{k}_1$ standard deviations above the mean. Similarly, the second restriction implies that the stock market volatility structural shock found in April 2017 should be greater than $\bar{k}_2$ standard deviations above the mean.

[3] https://fred.stlouisfed.org/series/PRMNTO01ZAQ661N

$\bar{k}$ is calculated as the 75th percentile of stock market volatility and the 75th percentile of monetary policy uncertainty structural shocks in the unconstrained set $\hat{\mathrm{B}}$. These parameters stipulate how big a shock should be at specified dates. That is, a monetary policy uncertainty or stock market volatility structural shock is a big shock if it is within the top 25% of all observed shocks at a specified event date τ.

2.4.1.5 External Variable Constraints

In addition to event restrictions, we use external variables that contain information about shocks of interest to aid in identification. Ludvigson et al. (2021) explains that these variables need not be pure external variables, as in the Instrumental Variable literature (Piffer and Podstawski, 2018)), but should carry some information about the shocks of interest. They follow the relevance condition but need not be exogenous, thus not qualifying as valid instruments. While theory and economic reasoning suggests that external variables are informative about the shocks of interest, these variables can assist in identification. We follow the same reasoning and use the absolute change in the price of JIBAR Futures[4] and the log difference in the real price of Gold as external variables. The price change in JIBAR Futures likely contains information about monetary policy uncertainty, such as information on interest rates and asset purchases. An increase in monetary policy uncertainty can lead to greater fluctuations in interest rates as investors demand higher risk premiums, causing more significant changes in JIBAR rates. Therefore, absolute changes in JIBAR rates are likely to be positively correlated with monetary policy uncertainty shocks. Similarly, changes in JIBAR rates are also positively correlated with stock market volatility shocks. This is because during periods of increased stock market volatility, investors may seek safer investments, leading to more pronounced changes in short-term interest rates like the JIBAR. Furthermore, during periods of high uncertainty, investors are more likely to become risk-averse and invest in safe-haven assets like Gold. Thus, we expect Gold prices to be positively correlated with both stock market volatility and monetary policy uncertainty structural shocks.

[4]Three-month reference rate in the domestic financial markets. The Johannesburg Interbank Average Rate (JIBAR) is a daily calculated benchmark interest rate composed of an average of the negotiable certificate of deposit (NCD) mid-rates of a number of the leading South African banks. The 3-month rate provides the settlement index for most South African interest rate derivatives.

Correlations between the external variables and uncertainty shocks are therefore employed to impose additional inequality restrictions, further narrowing the unconstrained set. Motivated by the facts above, we require that structural shocks in the identified set follow the following constraints:

- $\bar{g}_{C1}$: corr$(e_{jt}(B), S_{1t}) \geq 0, \quad j = MPU, SMV$
- $\bar{g}_{C2}$: corr$(e_{jt}(B), S_{2t}) \geq 0, \quad j = MPU, SMV$

The first restriction requires that both stock market volatility shock and monetary policy uncertainty shocks should be positively correlated with the absolute change in the price of JIBAR futures. The second inequality restriction requires that the shocks should be positively correlated with the log difference in the price of Gold.

2.4.2 Data and Implementation

This section describes the data used to analyse this causal relationship between stock market volatility and monetary policy uncertainty in South Africa. The data used includes stock market return prices from the Johannesburg Stock Exchange, industrial production, JIBAR Futures, Gold, and a monetary policy uncertainty index. The sample period is on a monthly frequency and runs from January 2017 to December 2020. The data on stock market prices is obtained from the Bloomberg terminal. The table below details the source and description of the economic variables used in this paper.

TABLE 2.3: Source of variables

Variable	Source	Description
Monetary Policy Uncertainty	Computed from tweets obtained from X-formerly Twitter	Monthly frequency
Industrial Production	Passport	Monthly frequency.
Stock Market Volatility	Bloomberg	Computed from Stock Market returns. Monthly frequency
Gold	Bloomberg	Monthly frequency
JIBAR Futures	Bloomberg	Monthly frequency

Notes: The table summarises the sources and construction of the key variables used in the analysis. All variables are collected at monthly frequency, with stock market volatility computed from equity returns and monetary policy uncertainty obtained from processed Twitter data.

2.4.2.1 Descriptive Statistics

Table 2.4 presents summary statistics for the 46 monthly observations. The estimation sample runs from January 2017 to December 2020, providing forty-eight monthly observations, of which forty-six are used in estimation

TABLE 2.4: Summary Statistics of Key Variables

	MPU	LOGIND	VOL
Mean	99.98	4.64	0.037
Median	99.61	4.68	0.031
Minimum	99.25	3.97	0.002
Maximum	104.15	4.81	0.184
Std. Dev.	0.99	0.14	0.032
Observations	46	46	46

Notes: The table reports summary statistics for monetary policy uncertainty (MPU), log industrial production (LOGIND), and stock market volatility (VOL). All variables are measured at monthly frequency.

after accounting for the two lags in the VAR. The sample length reflects data availability. Consistent Twitter data on monetary policy uncertainty are not available before 2017, and the series ends in 2020 because the data were no longer accessible through the free research API used for this study. The short span therefore limits the number of parameters that can be estimated reliably. While the small sample reduces statistical power and widens confidence bands, the use of monthly data allows the model to capture short-term responses that would be obscured at lower frequency. The monetary policy uncertainty index (MPU) averages 100, industrial production in logs (LOGIND) averages 4.64, and stock market volatility (VOL) averages 0.04. MPU shows the smallest dispersion, while LOGIND and VOL display larger variation relative to their means. To ensure the time series data is stationary, we run the augmented Dickey-Fuller test. Stationarity ensures against spurious regressions which may lead to misleading results. Our hypothesis is as follows:

$$H_0 : \text{Contains a unit root}$$
$$H_1 : \text{Does not contain a unit root}$$

The results in the table below show that all our data series have a p-value less than 5% and therefore we reject the null hypothesis that they contain a unit root. As such, they are all stationary.

TABLE 2.5: Augmented Dickey-Fuller Test Results

Variable	Stock Volatility	MPU	Log(Industrial Production)
P-value	0.0001	0.0000	0.0030

Notes: The table reports Augmented Dickey-Fuller test statistics. The null of a unit root is rejected for all variables at conventional significance levels, indicating that stock volatility, MPU, and log industrial production are stationary.

Lastly, Figure 2.3 plots a graph of the uncertainty of standardized monetary policy and the volatility of the stock market over the sample period. Both MPU and SMV have high spikes during the COVID-19 pandemic, a period where there was heightened uncertainty about the economy as well as the path that the future interest rate will take. Although, the market gradually recovered towards the end of the month as the government announced measures to support the economy and businesses. Despite this, the market remained volatile and uncertain, with investors closely monitoring the situation and adjusting their investment strategies accordingly. SMV often displays spikes when MPU is high showing that there exists a relationship between the two. We use a VAR to capture the predictable variations and use event and external variable constraints to identify the unpredictable shocks for the VAR residuals.

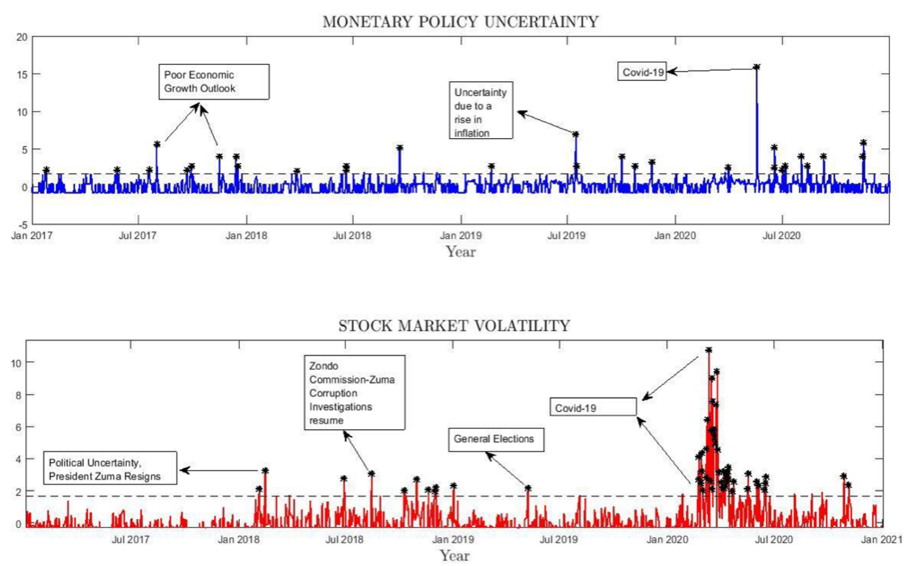


FIGURE 2.3: Monetary Policy Uncertainty Index and Stock Market Volatility
Notes: The figure plots standardised monetary policy uncertainty (MPU) and stock market volatility (SMV) over time.

We use the restrictions above to narrow the unconstrained set in order to obtain the identified set. The structural shocks should satisfy all the restrictions for them to be admitted into the identified set. We ensure careful consideration when choosing the value of the big shock parameters $\bar{k}$. It should be noted that if $\bar{k}$ is too restrictive, the identified solution set will be empty. If it is less restrictive, then the restrictions will have little identifying power. Therefore, a set of restrictions for one set of data could be too restrictive if there is a change to the data. $\bar{k}$ is therefore set using a data dependent procedure consistent with economic reasoning and then as a robustness test, we examine the sensitivity of the results to changes in this parameterization.

2.5 Results and Discussion

2.5.1 Impulse Response Function

Using a lag[5] of 2, we run a shock-restricted SVAR model and produce impulse response functions. To check for the sensitivity of the results, different alternative combinations of event restrictions as well as alternative specifications of the big shock parameter $\bar{k}$ are examined. The impulse response functions are normalized to a one standard deviation shock.
Our analysis starts with Figure 2.4, which displays a simple case where only minimal restrictions are imposed. MPU refers to monetary policy uncertainty, Y refers to industrial production and SMV is the stock market volatility. The blue shaded region shows the impulse response if no restrictions are imposed, that is, where only the reduced form covariance restrictions $\bar{g}_z(B) = 0$ are imposed. Due to a large solution set, the impulse response functions formed from this set provide inconclusive results. We therefore need to narrow down this set by adding on additional restrictions. The black dotted lines show the solution set after adding external variable constraints. Although the impulse response functions are still inconclusive, there are some clear results starting to form. The red dotted lines represent the constrained solution set if the reduced form covariance restrictions, the external variable constraints, and the event constraints are imposed.
Figure 2.5 uses the non-negative event, $g_{\mathcal{E}_5}$, external variable constraints, and big shock events to narrow down the solution set. We then test the sensitivity of impulse responses to changes in the big shock parameter $\bar{k}$. The first case,

[5] calculated using the Akaike information criterion (AIC)

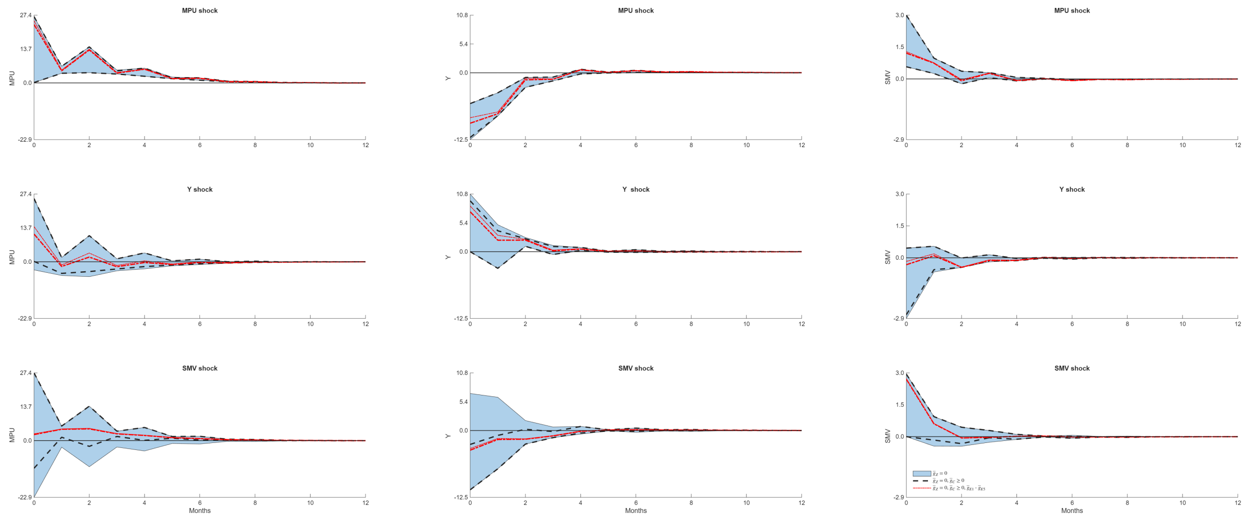


FIGURE 2.4: Impulse Response Functions Under Minimal Restrictions

Notes: The figure reports identified sets of impulse responses to positive, one-standard-deviation shocks for system $\mathbf{X} = (MPU, Y, SMV)'$ *under different restrictions.* $g_Z(\mathbf{B}) = 0$ *denotes covariance restrictions;* $g_C(\mathbf{e}(\mathbf{B}); \mathbf{S}) \geq 0$ *denotes external variable restrictions;* g_{E3}–g_{E5} *denotes all nonnegative event constraints and* g_{E1}, *and* g_{E2} *represents big shock events. The sample spans the period 2017:03 to 2020:12.*

shown by the grey shaded region, sets $\bar{k}$ to be the 75 percentile of all MPU structural shocks and all SMV structural shocks whilst the second case (red dotted lines) sets $\bar{k}$ to be the 65 percentile of all MPU structural shocks and all SMV structural shocks. The last case (black dotted lines), sets $\bar{k}$ to be the median.

That is, we want the MPU structural shocks to either above the median, in the top 25% or in the top 35%. Similarly, we also set the SMV structural shocks to either be above the median, in the top 25% or in the top 35%. We find that under these different parameterizations, the impulse response functions are more defined and conclusive, with case 1 being more conclusive than case 2 or using the median.

Main Results Figure 2.6 reports the main results. It adopts case 1 and sets $\bar{k}$ to be the 75th percentile of all monetary policy uncertainty structural shocks and all stock market volatility structural shocks. Using all non-negative constraints, big-shock events and external-variable restrictions, Figure 2.6 plots impulse response functions. The dashed lines show the 95% bootstrapped error bands based on 1,000 replications.

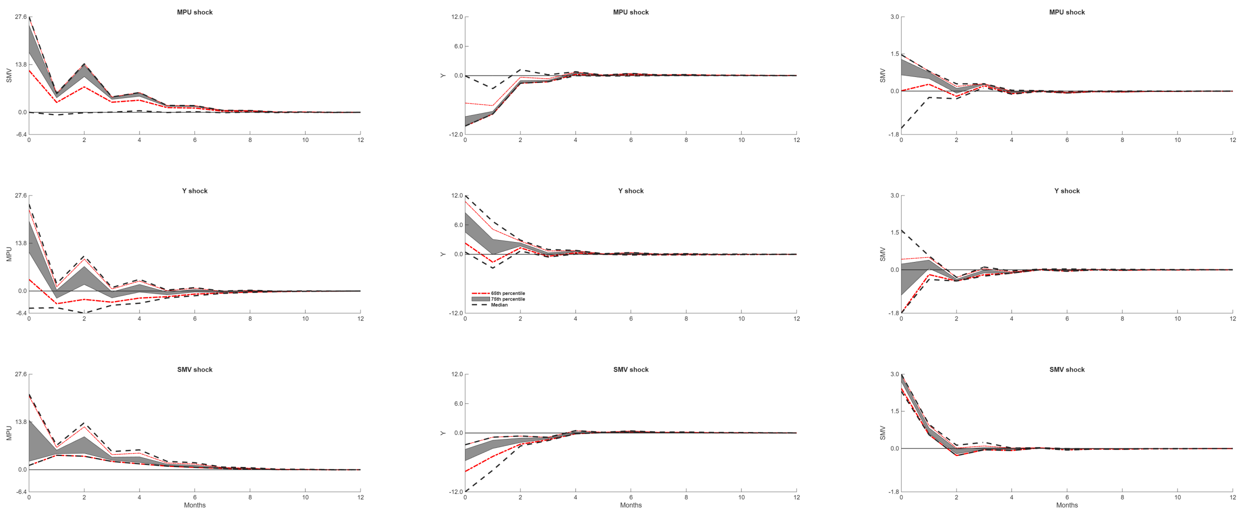


FIGURE 2.5: Impulse Response Functions Under Different Big Shock Parameters

Notes: The figure reports identified sets of impulse responses to positive one–standard-deviation shocks in the system $X = (MPU, Y, SMV)'$. The black dotted lines show the identified set obtained when k is set to the median of the unconstrained shock distribution. The red dotted lines correspond to the identified set when k is fixed at the sixty-fifth percentile. The grey shaded region shows the identified set generated when k is set to the seventy-fifth percentile. All specifications impose the external variable constraints g_C and the nonnegative event constraints g_{E3}–g_{E5}. The sample runs from 2017 to 2020.

The impulse responses are expressed as percentage-point deviations from steady state. In addition to the IRF plots, several summary measures are reported to describe the size and persistence of each response. These include the peak effect, the cumulative impact over the full horizon, the timing of the maximum response, and the half-life, defined as the number of months required for the response to fall to half its peak. The uncertainty around these measures is summarised using confidence bands constructed from the lower and upper 95% IRF envelopes.

Subplot (1,2) shows that a positive one standard deviation shock to monetary policy uncertainty results in an instantaneous decrease in industrial production[6]. The peak effect is a decline of about 13 percentage points on impact. Based on the confidence intervals, the true effect is likely somewhere between a fall of roughly 15 percentage points and a more moderate reduction of about 2.5 percentage points. The response stays negative for several months, and about half of the initial drop unwinds after around two months. Over the full

[6]South African Industrial Production as measured by Passport only includes the manufacturing sector.

horizon, the total effect remains negative, consistent with the overall contraction shown in the IRF. This is not a surprising result because monetary policy uncertainty affects the behaviour of consumers, firms, and financial markets. When economic agents become more uncertain about the future path of policy rates, they tend to invest and consume less, thus leading to a decrease in industrial production. Moreover, due to an increase in borrowing costs, firms might invest less and thus produce less output, hence leading to a decline in industrial production. This is in line with the findings in economic literature that investigates the effects of uncertainty on the economy (Disney et al., 2003; Bloom, 2009). Furthermore, subplot (**2,1**) illustrates that a one standard deviation positive shock to industrial production led to an increase in monetary policy uncertainty. The peak rise is about 27.5 percentage points, and the confidence interval indicates that the true effect is likely between just under 20 percentage points and around 30 percentage points. The adjustment is short-lived, with a half-life of roughly one month. The cumulative effect over the horizon is modest, at around 8.2 percentage points, although the confidence range is wide, that is, from a decline of about 19 percentage points to an increase of roughly 35 percentage points. This can happen because an increase in industrial production could signal higher economic growth, which may prompt the central bank to adjust its monetary policy. The uncertainty arises from the market's speculation on how the central bank will respond to the improved economic conditions. Traders and investors may be uncertain about the timing and magnitude of potential monetary policy changes.

Subplot (1,3) shows that a positive MPU shock initially raises stock market volatility, though the effect is short-lived and subsides after a few months. A shock to monetary policy uncertainty raises financial market volatility immediately. In particular, the peak increase is around 2.7 percentage points, and the confidence interval indicates that the true effect lies between about 2.35 and 3.05 percentage points. As the shock dissipates, the response fades quickly, with a half-life of approximately one month. Over the full horizon, the cumulative impact is modest at roughly 3.3 percentage points, with a confidence range from about 0.8 to around 5.7 percentage points. This could be due to initial investor uncertainty regarding future interest rate paths, leading to portfolio adjustments and heightened trading activity, thus increasing volatility. However, as the central bank clarifies its stance or market participants gain more information, volatility decreases, reflecting a return to stability once expectations are adjusted. This aligns with theories on policy communication, where increased transparency can help mitigate the market's sensitivity to uncertainty (Blinder et al., 2008;

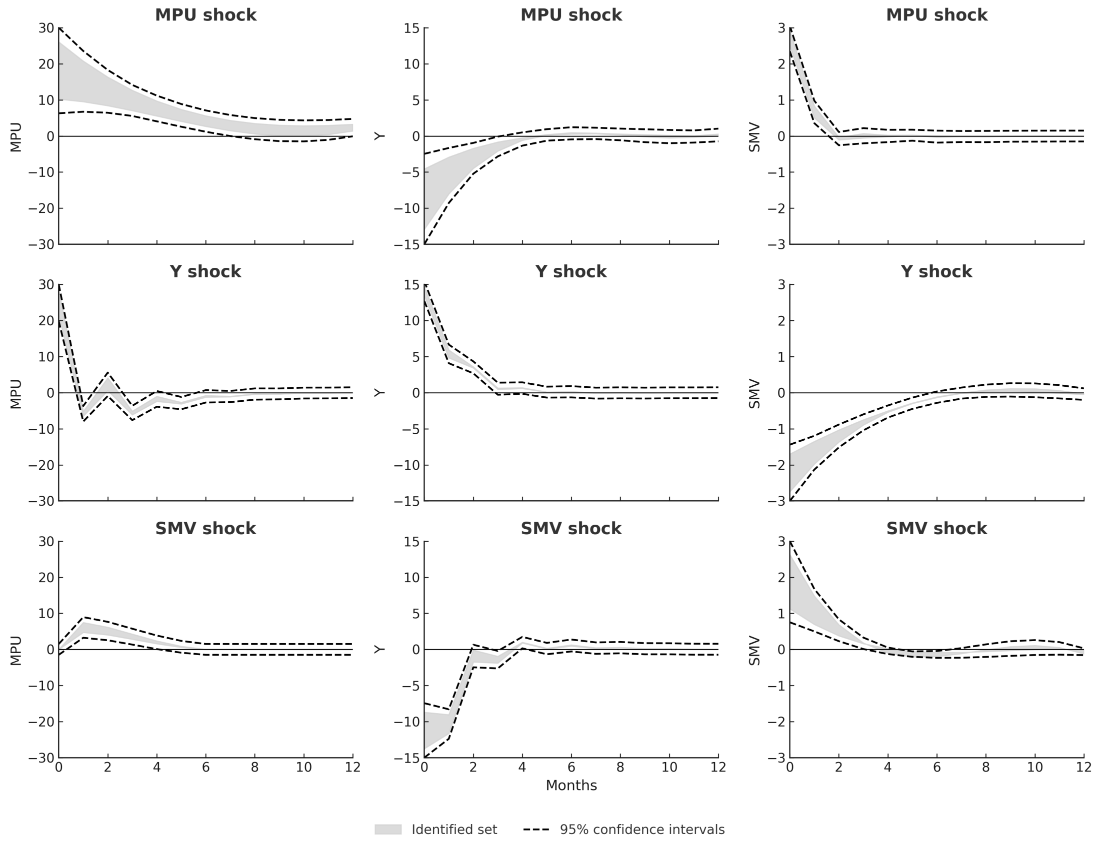


FIGURE 2.6: Impulse Response Functions Using All Restrictions

Notes: The figure reports impulse response functions from the VAR system including monetary policy uncertainty (MPU), industrial production (Y), and stock market volatility (SMV), estimated under the full set of identifying restrictions. Solid lines show median responses and dashed lines denote 95% bootstrapped confidence intervals based on 1,000 replications. Each row corresponds to the variable receiving the shock (MPU, Y, SMV), and each column shows the response of MPU, Y, or SMV. The sample covers 2017–2020.

Morris and Shin, 2002).

Similarly, subplot (3,1) shows that a positive shock to volatility results in little to no effect on monetary policy uncertainty on impact, but then MPU rises after a month and dies off after the sixth month. An increase in stock market volatility subsequently leads to a rise in monetary policy uncertainty. The response reaches its maximum after one month at roughly 6.1 percentage points, and the confidence interval suggests a plausible range between about 4.1 and 8.0 percentage points. Once the peak has passed, the effect diminishes rapidly, and the half-life is effectively immediate. Over the full horizon, the cumulative impact amounts to around 17.4 percentage points, with a confidence interval running from approximately 6 to almost 29 percentage points. In the short term, the positive shock to stock market volatility may have led to increased monetary policy uncertainty as investors and market participants try to assess the implications of the shock on policy decisions. However, as the shock and its effects are better understood, certainty may increase as market participants adjust their expectations accordingly.

Lastly, we also find that a one standard deviation positive shock to industrial production leads to a decrease in stock market volatility. The peak decline is about 2.2 percentage points, and the confidence interval implies that the true reduction lies between roughly 3.0 and 1.44 percentage points. Beyond the initial response, the effect displays moderate persistence, with a half-life of around three months. Over the full horizon, the cumulative decline is close to 6.7 percentage points, and the confidence interval indicates that the total reduction is likely to fall between about 10 percentage points and 3.4 percentage points in absolute magnitude. This might be because an increase in output can signal greater macroeconomic stability, thereby boosting investor confidence and leading to reduced volatility.

Our results are in line with existing literature on macroeconomic uncertainty and emphasise the importance of central bank communication in mitigating the adverse effects of uncertainty. By stabilising expectations, policymakers can reduce the negative spillovers of uncertainty shocks on industrial production and market stability, contributing to a more resilient economic environment.

In the South African case, these dynamics are particularly informative for an emerging-market setting. Financial markets are relatively shallow and more sensitive to shifts in external risk sentiment, which means that uncertainty shocks transmit more abruptly through financial channels. The response of stock market volatility to monetary policy uncertainty is therefore sharper but short-lived, consistent with uncertainty feeding quickly into asset prices and dissipating once policy signals become clearer. In contrast, evidence from advanced economies suggests that deeper markets and more established policy frameworks tend to dampen the immediate impact of such shocks.

The Twitter-based measure is also well suited to this context. It provides high-frequency information that captures rapid shifts in sentiment around monetary policy decisions, something that is difficult to obtain from newspaper-based or survey-based indices. For instance, the Policy Uncertainty Index (PUI) developed by Raymond Parsons (Parsons and School, 2016) relies on lower-frequency newspaper coverage and business surveys. The higher frequency of the Twitter data allows the index to reflect fast-moving uncertainty episodes that conventional measures may miss, making it a useful complement to existing approaches in the South African environment.

Further to this, we carry out Granger causality tests to complement the impulse response analysis. The IRFs indicate that MPU shocks raise SMV and that

SMV shocks raise MPU, showing short run interactions in both directions. The Granger tests on Table 2.6 provide evidence on predictive content. The null that MPU does not Granger cause SMV cannot be rejected, whereas the null that SMV does not Granger cause MPU is rejected at the one percent level. Hence stock market volatility forecasts monetary policy uncertainty, while monetary policy uncertainty does not forecast stock market volatility. This clarifies that MPU shocks can generate immediate movements in volatility, but volatility is the driver of predictable future changes in MPU.

TABLE 2.6: Granger Causality Tests between MPU and SMV

Null Hypothesis	Test Statistic	Distribution	Critical Value (5%)	p-value
MPU does not Granger cause SMV	1.564	$\chi^2(2)$	5.991	0.457
SMV does not Granger cause MPU	9.257	$\chi^2(2)$	5.991	0.010

Notes: The table reports Granger causality tests from the three variable VAR with two lags chosen by the Akaike Information Criterion.

2.5.2 Discussion

This paper studies the relationship between monetary policy uncertainty (MPU) and stock market volatility (SMV) in South Africa using a novel Twitter-based MPU index and a Structural Vector Autoregressive (SVAR) model. We find a bidirectional relationship between MPU and SMV, allowing us to investigate the dynamics of monetary policy uncertainty and market behaviour. The impulse response results indicate short run interactions in both directions, with MPU shocks raising SMV and SMV shocks raising MPU. However, the Granger causality tests show an asymmetric pattern, as only SMV has predictive power for MPU. Interestingly, when we study the impulse response functions, MPU shocks also generate a pronounced response in SMV, despite the lack of Granger causality in that direction. This apparent contradiction is resolved by recognising that Granger causality tests predictive power, whereas IRFs capture contemporaneous and dynamic responses. Thus, MPU may not forecast SMV, but it can still exert immediate effects on market volatility when uncertainty spikes.

Our findings are consistent with prior research by Baker et al. (2016) and Ludvigson et al. (2021), which illustrate the negative effects of policy uncertainty on economic activity. However, this paper extends the literature by emphasizing the complementary relationship between monetary policy uncertainty and stock market volatility. As investors react to potential policy changes, a positive shock to monetary policy uncertainty leads to higher stock market volatility. Conversely, heightened stock market volatility also increases monetary policy uncertainty as economic agents face greater uncertainty about economic conditions and the potential actions that the central bank will take.

This observed relationship between MPU and SMV can be interpreted through the lens of the real options theory, which states that uncertainty leads to delayed investment and consumption decisions (Bloom, 2009). In this context, heightened stock market volatility increases policy uncertainty by making future economic conditions harder to predict, creating a feedback loop that destabilizes both financial markets and the broader economy.

Additionally, the asset price channel theory (Bernanke, 1983; Cecchetti, 2000) can also be used to explain this relationship. It suggests that fluctuations in stock prices, influenced by central bank policies, can affect investment decisions and economic output. This theory supports our findings that monetary policy uncertainty can lead to stock market volatility, which in turn impacts economic activity. Empirical evidence from recent literature corroborates our findings. For example, Caggiano et al. (2020) show that uncertainty shocks negatively affect industrial output, consistent with the decline in economic activity observed in our results. Furthermore, studies on emerging markets indicate that central banks operating in uncertain environments face greater policy setting challenges (Cevik and Erduman, 2020).

There is therefore need for central banks to adopt transparent communication strategies and proactive policy frameworks. Addressing financial market instability requires a more comprehensive approach that integrates financial stability targets alongside the objective of price stability.

Whilst our research provides valuable results for policymakers, several limitations should be acknowledged. The reliance on Twitter data may introduce biases, as social media activity does not fully represent the population's economic expectations. Additionally, the SVAR model assumes linear dynamics, which may oversimplify the complex relationship between MPU and SMV. Future research could explore non-linear effects, cross-country comparisons, and broader sentiment analysis using more advanced machine learning techniques (Athey and Imbens, 2019; Chernozhukov et al., 2018). Lastly, as we live in a data-abundant world, further research could also use other advanced machine learning techniques to create a monetary policy uncertainty index for other emerging market economies.

All in all, by studying the relationship between policy uncertainty and stock market volatility, this paper adds to the discussion on the impact of policy uncertainty in developing countries and the importance of coordinated policy frameworks that ensure financial stability and economic resilience.

2.5.3 Policy Implications

Our findings indicate significant implications for monetary policy, particularly for the South African Reserve Bank (SARB). Policymakers could therefore make use of our results to enhance policy effectiveness and mitigate systemic risks. Firstly, the results suggest that heightened monetary policy uncertainty leads to increased stock market volatility, emphasizing the critical role of clear and consistent communication by central banks. SARB could therefore enhance its transparency by issuing forward guidance and policy outlooks, thus reducing speculative market behaviour and stabilizing investor expectations. Secondly, the Granger results show that stock market volatility helps predict monetary policy uncertainty, while uncertainty does not forecast volatility. This asymmetry indicates that financial market conditions should be monitored and integrated into the monetary policy framework. Therefore, SARB should consider incorporating financial stability targets into its inflation-targeting regime to reduce the volatility spillovers. Thirdly, since Twitter-based indices provide real-time feedback on economic agents' views, SARB could adopt sentiment monitoring tools to gauge market reactions and adjust policy communication strategies accordingly. As a result, this approach could enable more adaptive policy responses and reduce monetary policy uncertainty in real time.

Furthermore, our findings indicate that the debate on central bank intervention remains relevant. Cecchetti (2000) advocated for pre-emptive action to prevent asset bubbles, while Greenspan (1997) and Bernanke (2002, 2009) preferred minimal intervention and argued that the focus should be on low inflation and stable growth. In light of these perspectives, our results place South Africa closer to Cecchetti's position, since ignoring volatility risks could allow shocks to spill into higher policy uncertainty and weaker output. This suggests that the SARB's policy framework could be recalibrated to balance proactive market stabilization with its core inflation-targeting mandate. Thus, in the long run, a proactive approach could improve financial resilience, reduce economic volatility, and support sustained growth. Our results therefore indicate that SARB might benefit from incorporating financial stability into its decision-making framework. Lastly, given the unique structural characteristics of emerging economies such as South Africa, international monetary organizations and policymakers in similar contexts could adopt this model. A tailored policy approach that takes into account market sentiment and real-time data could improve resilience against external shocks and domestic economic instability.

Therefore, by acknowledging the role played by enhanced transparency and adaptive policy tools, policymakers can mitigate the adverse effects of monetary policy uncertainty, thus enhancing economic stability and strengthening market confidence.

2.6 Conclusion

This paper addressed the research problem of measuring monetary policy uncertainty in South Africa and its interaction with stock market volatility. The lack of existing measures of monetary policy uncertainty for emerging economies motivated the creation of a novel Twitter-based index, which allows us to study how uncertainty and financial markets interact in real time.

Our findings indicate that an increase in stock market volatility produces little to no immediate effect, but subsequently raises monetary policy uncertainty before the effect fades. Conversely, a positive shock to monetary policy uncertainty initially increases stock market volatility, though the impact dissipates over time. We also document that higher monetary policy uncertainty is associated with a decline in industrial production, consistent with evidence that uncertainty depresses real economic activity.

The implications of these results are significant for policymakers. Clearer and more transparent communication could reduce monetary policy uncertainty, support economic stability, and strengthen resilience in financial markets. For the South African Reserve Bank, this means considering financial stability alongside its inflation-targeting mandate and making greater use of forward guidance and policy outlooks to anchor expectations.

This study is not without limitations. The reliance on Twitter data introduces potential bias, as social media participation may not fully reflect the broader population. In addition, the SVAR framework assumes linear dynamics, which may not capture the full complexity of interactions between uncertainty, financial markets, and the real economy.

Future work could extend the analysis in several directions. First, examining nonlinearities in the relationship between uncertainty and volatility may reveal asymmetries not captured here. Second, constructing similar indices for other developing economies would allow cross-country comparisons and highlight the role of institutional differences. Finally, integrating more advanced machine learning techniques and alternative data sources could improve the precision and representativeness of uncertainty measures.

In conclusion, this paper contributes to the literature by developing a novel measure of monetary policy uncertainty for South Africa and showing that uncertainty and stock market volatility interact dynamically. The impulse responses indicate short run effects in both directions, while the Granger tests show that only volatility has predictive power for uncertainty. These results suggest that reducing uncertainty through enhanced transparency and adaptive communication strategies could help to stabilise markets, support price stability, and strengthen long-term economic resilience.

Chapter 3

The relationship between monetary policy uncertainty and stock market volatility: Evidence from French Households

3.1 Introduction

Since the global financial crisis of 2008, monetary policy uncertainty has become a key subject of interest for policymakers and economic agents alike. Research[1] has shown that monetary policy uncertainty can have dire effects on the economy, including financial markets. This is because monetary policy uncertainty reduces the effectiveness of monetary policy tools as set by central banks. One transmission mechanism for monetary policy is through the financial markets. As such, because volatility in the stock markets is used to price financial assets, it thus plays a crucial role in financial markets. Credible monetary policy, by contrast, is important for central banks as it helps them achieve their objectives of price stability while maintaining sustainable economic growth. As such, when uncertainty is elevated or persistent, it can erode the credibility of central banks and weaken their ability to achieve those objectives. It is therefore important to consider whether monetary policy uncertainty influences financial markets or vice versa.
The literature on monetary policy uncertainty has grown rapidly in recent years.

[1]Various theoretical and empirical papers emphasize the effects of policy uncertainty. See, for example:(Al-Thaqeb et al., 2022; Bernanke, 1983; Bloom, 2009).

However, it has mostly examined policy uncertainty at a macro level.[2] Although macro level data can provide a broad overview of the economy and society, household surveys are essential for understanding the complexities of individual households and their experiences. They are more effective in capturing the heterogeneity and diversity of the population, thus better informing policies that address specific challenges and opportunities. Against this background, we move beyond the macro perspective of Chapter 2 and focus on household level perceptions and expectations. Empirical work using household surveys to study monetary policy uncertainty remains scarce, which motivates our contribution.

Our motivation builds on these gaps by following Greenspan's policy view that monetary policy should not react automatically to market swings (Greenspan, 2004). This view implies a null hypothesis of no direct relationship between stock market volatility and monetary policy uncertainty. We also adopt the perspective of Veldkamp (2011) that uncertainty is inherently forward looking and, under the assumption of normality, can be summarised by the standard deviation of subjective expectations. This framing allows us to test whether monetary policy uncertainty affects stock market volatility, whether volatility feeds back into uncertainty, or whether the two remain unrelated, as implied by the null hypothesis.

This paper exploits novel survey data from French households to shed more light on household perceptions and expectations about monetary policy rates. The dataset provides rare information on how individuals perceive monetary policy and stock market volatility, yet response quality is limited. Only about half of respondents completed the main expectation questions, and several did not allocate probabilities correctly across forecast bins. This low response rate means that some of the variation may reflect noise rather than informed beliefs. At the same time, weak responses are informative about how little households understand monetary policy, which is itself an important feature of the data. The analysis treats this limitation as part of the phenomenon rather than as a measurement error and interprets results cautiously, focusing on patterns that remain consistent across specifications. Despite these limitations, the data remain valuable for understanding how households perceive and process information about monetary policy and financial markets.

Furthermore, this paper examines the relationship between monetary policy uncertainty and stock market volatility through the lens of French households.

[2] In the previous chapter, we did exactly this but using twitter-based monetary policy uncertainty and aggregate stock market volatility. Other authors also discuss policy uncertainty at a macro-level. See (Baker et al., 2016; Husted et al., 2017; Bauer et al., 2019; Lastauskas and Nguyen, 2023).

To do so, we use forward looking subjective measures of monetary policy uncertainty at the household level and assess their relationship with forward looking subjective measures of stock market volatility, adopting the perspective of 'what is top of mind' (Haaland et al., 2024). Specifically, we ask three questions. Firstly, do households who are less informed about the current level of interest rates produce less accurate forecasts of the distribution of future interest rates? Secondly, are households with higher debt burdens more attentive to current policy rates and do they make more precise forecasts of future rates? Finally, using causal machine learning techniques, we analyse the relationship between monetary policy uncertainty and stock market volatility across households as measured by subjective probabilities, considering both directions of influence. These questions allow us to evaluate the null hypothesis that there is no direct link between stock market volatility and monetary policy uncertainty. They also enable us to assess how household expectations deviate from this benchmark, providing a micro level perspective that complements the macro level analysis in Chapter 2 and sets the stage for the behavioural analysis in Chapter 4. Lastly, our findings have implications for monetary-policy communication since household misperceptions of policy rates or market signals may weaken the effectiveness of transmission.

Relation to the Literature. This paper contributes to the literature in several ways. First, we contribute to the broad empirical literature that uses household survey data (Gospodinov and Jamali, 2015; Beer et al., 2015; McFadden et al., 2004; Christensen et al., 2006; Dominitz and Manski, 1996; D'Acunto and Weber, 2024). Survey data has long been used in economics to study and evaluate consumer behaviour and decision making, providing a direct measure of individuals' beliefs about future economic variables. This data is typically collected from households, firms, and financial market participants through various surveys. The most widely used examples include the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE) and the European Central Bank's Survey of Professional Forecasters (SPF).[3]The use of survey data offers several advantages. One important benefit is that surveys provide a direct measure of expectations, which may differ substantially from market-based indicators. In addition, survey data allow researchers to analyse the heterogeneity of expectations across groups such as age, income, and education. A further advantage is that they make it possible to study

[3]See the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE) and the European Central Bank's Survey of Professional Forecasters (SPF) for widely used applications.

how expectations are formed, including the influence of past experience and information sources.

However, there is limited research on subjective monetary policy. Much of the literature remains focused on inflation expectations, perceptions, and uncertainty (Weber et al., 2022; Baumann et al., 2021; Rumler and Valderrama, 2020; De Bruin et al., 2011). We extend this work by shifting the focus to monetary policy uncertainty and its link with stock market volatility at the household level. To situate our contribution, it is useful to note that a number of studies have already examined related aspects of expectations. Various authors such as Weber et al. (2022) and Calvo-Pardo et al. (2021) have documented several aspects of inflation and stock market expectations, including the uncertainty across individuals, changes over time, and their relationship with household characteristics. A growing strand of this research also provides evidence that expectation formation varies significantly across socioeconomic groups (D'Acunto and Weber, 2024; Easaw et al., 2013). These studies find that higher-earning and more financially literate households tend to form more accurate expectations, while lower-income households rely more on rule-of-thumb heuristics, leading to systematic biases in their forecasts. These disparities in expectation accuracy have important implications for the transmission of monetary policy and financial decision making. We add to this literature by documenting novel facts about monetary policy rates. While previous studies have documented that households in the euro area are generally uninformed about policy rates, they do not link households' knowledge of monetary policy to their perceptions of stock market volatility, nor do they combine probabilistic measures of policy rate awareness with subjective assessments of financial uncertainty. In addition, evidence from Ehrmann et al. (2023) shows that communication can influence how households interpret monetary policy, yet these results are presented at the euro area level and therefore do not reveal country specific patterns or micro-level links between policy rate knowledge and perceived financial conditions. As such, these gaps motivate our contribution. By combining probabilistic perceptions of policy rates with subjective evaluations of stock market volatility, this chapter provides a microeconomic mechanism that complements the macro level relationship documented in Chapter 2. Moreover, the survey data exhibit substantial item non-response and low completion rates (features common to long-running household surveys such as the Michigan Survey of Consumers and the New York Fed's Survey of Consumer Expectations) and this pattern is itself informative about how little households understand monetary policy.

Using the French household survey thus offers country-specific evidence that is absent from broader euro-area surveys and links households' awareness of policy rates to their perceived volatility in a way that the existing literature has not addressed.

Secondly, we contribute to the literature that uses subjective probabilities. The use of subjective probabilities in household surveys dates to the 1990s, with early examples including the Survey of Economic Expectations (Dominitz and Manski, 1996, 1997) and the Health and Retirement Study (HRS).[4] Before the 1990s, the main application of survey data in economics was to analyse how agents should form expectations, with strong assumptions about expectation formation. Since then, research has increasingly turned to how agents actually form expectations, relying on micro-level survey data rather than abstract modelling assumptions. The use of subjective probabilities has therefore been instrumental in understanding how expectations are formed and how uncertainty is perceived at the household level. More recently, studies have indicated that expectation formation does not solely depend on available economic data but is also shaped by cognitive biases and heuristics (Alkhars et al., 2019; Weber et al., 2022; D'acunto et al., 2023). Agents tend to form beliefs based on simplified decision-making processes rather than fully optimising their choices, challenging traditional rational expectations models. We build on this literature and extend it by using subjective probabilities to examine how households perceive both monetary policy and stock market volatility.

Although the literature on interest rate expectations using survey data has produced several empirical findings, there remain important gaps in understanding. Available data on perceptions of prevailing interest rates is often embedded within specific financial products, such as household loans or investment accounts. For example, the US Survey of Consumer Finances (SCF) and the Euro System Household Finance and Consumption Survey (HFCS) collect interest rate expectations only from respondents with relevant financial products, limiting the scope for generalisation. Furthermore, even though interest rate information is widely available, survey responses suggest that many households do not fully process or utilise this information when forming expectations (Beer et al., 2015). This aligns with studies such as Mankiw and Reis (2002) that argue households do not actively update their expectations unless economic conditions change substantially, suggesting that many individuals may not

[4] The Survey of Economic Expectations collects subjective probabilities regarding future economic conditions, while the Health and Retirement Study is a longitudinal survey on the health and economic well-being of Americans over the age of 50.

continuously monitor economic indicators, leading to infrequent adjustments in their expectations. This inattention to monetary policy shifts can contribute to persistent forecasting errors and slow adjustments in consumer and investment behaviour. Building on this literature, we examine whether households systematically overestimate both current and expected monetary policy rates. This allows us to assess how limited attention and persistent misconceptions may distort the transmission of monetary policy by dampening or delaying its intended effects on economic behaviour.

Lastly, this paper employs instrumental variable lasso (IV- LASSO), a machine learning-based regression approach, to examine the relationship between monetary policy uncertainty and stock market volatility. We use machine learning because traditional regression models often face challenges in handling high-dimensional data and selecting the most relevant predictors when estimating economic relationships. By applying IV-LASSO, we improve variable selection while reducing the risk of omitted variable bias, ensuring that our empirical analysis captures the most significant drivers of stock market volatility in response to monetary policy uncertainty. Building on recent advancements in computational economics,[5] our approach enhances the robustness of regression-based inference, particularly in settings where traditional econometric techniques may struggle with overfitting or endogeneity concerns.

The rest of the paper is structured as follows. Section 3.2 describes the data. Section 3.3 presents measures household perceptions and expectations. Section 3.4 reports the results. Section 3.5 concludes.

3.2 Data

This section describes the survey data and provides descriptive statistics on household perceptions and expectations of stock market volatility and monetary policy uncertainty.

3.2.1 Survey Design

We use survey data collected from French households by Taylor-Nelson-Sofres (TNS) in two waves[6]. The first wave, conducted in December 2014, did not

[5] See for example Cameron (2019), Chernozhukov et al. (2018), Gogas and Papadimitriou (2021), Adam et al. (2024), Angrist and Frandsen (2022), and Athey and Imbens (2019).

[6] The original TNS panel consisted of approximately 4,000 volunteers, recruited to be broadly representative of the French population. The first wave achieved a response rate of about

include questions related to interest rates or monetary policy, but recorded information on sociodemographic and expectations about stock market returns. The second wave, conducted in May 2015, re-interviewed 2,587 respondents and extended the questionnaire to cover households' knowledge of the current policy rate set by the European Central Bank and their expectations of the policy rate five years ahead. For this reason, we, therefore, base our analysis on the second wave.

Furthermore, the survey was administered by post, and participants completed a paper questionnaire. Questions on perceptions and expectations were framed in terms of subjective probabilities, with responses recorded on a seven-point probability scale. This format allows the construction of both mean expectations and subjective distributions, from which we compute household level measures of uncertainty. Probability-based elicitation has become increasingly common in recent literature, as it provides richer information on expectations and has been shown to be useful in modelling how economic agents form beliefs (Manski, 2018). In this study, we use the reported probabilities to measure household-level uncertainty about both monetary policy and stock market returns, and to examine whether perceptions, expectations, and outcomes are systematically related.

3.2.2 Eliciting Perceptions and Expectations

The probabilistic format was applied to both stock market returns and policy rates. For stock market returns, households were asked about their perceptions of past performance and their expectations for the next 12 months. For policy rates, households reported their knowledge of the current ECB policy rate as well as their expected level five years ahead. The 5-year horizon was chosen to capture long-term expectations while limiting the influence of short-term business cycle variation. This design follows existing surveys on inflation expectations, where longer horizons are often used to separate cyclical noise from structural beliefs. Using a 5-year horizon implies that the measure of monetary policy uncertainty captures broader macroeconomic uncertainty such as expectations about growth, inflation regimes or structural shifts rather than short-term policy decisions alone. This choice reflects the context of May 2015, when euro area policy rates had been exceptionally stable for a

92 percent, while the follow up wave retained around 70 percent of the initial sample. To encourage participation, households received a €25 voucher as compensation. We use the survey-provided sampling weights to account for any differences in representativeness between waves.

prolonged period. At shorter horizons, households' expectations would have shown very little meaningful variation, which would have resulted in a weak and uninformative measure. Extending the horizon was therefore necessary to generate enough movement in expectations for empirical analysis, even though it increases the likelihood that the measure reflects broader, longer-run uncertainties alongside more immediate policy-related risks. In this sense, the indicator should be interpreted as perceived medium to long-term monetary policy uncertainty that reflects households' broader views about long-run monetary stability rather than uncertainty about immediate rate adjustments. Lastly, the use of a seven-point probability scale makes it possible to recover both the mean expectation and the subjective standard deviation for each respondent. We treat the latter as a measure of household-level uncertainty. Following Veldkamp (2011), we interpret uncertainty as the uncertainty of subjective expectations.

3.2.3 Other Variables

In addition to perceptions and expectations, the survey collected information on a range of socioeconomic characteristics, including income, wealth, debt, employment status, and education. We also observe households' balance sheet positions, such as asset holdings and liabilities, as well as risk preferences and borrowing constraints. These variables are used as controls in empirical analysis and allow us to examine how perceptions and expectations vary systematically across households.

3.2.4 Descriptive Statistics

Table 3.1 presents descriptive statistics for the key economic and demographic characteristics of the French household survey. The full sample consists of 2,587 households, although effective sample sizes vary across variables depending on item response. Specifically, the survey captured expectations of stock market returns for 945 households, perceptions of past returns for 825 households, current perceptions of the policy rate for 846 households, and expectations of the policy rate five years ahead for 681 households. The lower number of usable observations for E6a and E6b compared to the full survey reflects both item nonresponse and the relatively high number of "Don't know" answers. We retain these cases in our regressions by including dummy variables for non-response and "Don't know" answers. This approach preserves the sample size and ensures that patterns of nonresponse do not bias the estimates. For brevity, we do not report the coefficients on these NR and DK dummies in the main tables, but they are included in all specifications.

TABLE 3.1: Descriptive Statistics: Expectations and Household Characteristics

Variable	Mean	SD	p25	Median	p75	N
Perceptions and Expectations						
Perceived stock returns (B1a, %)	5.08	11.71	0.00	2.88	8.85	945
Expected stock returns (B2a, %)	10.07	14.72	0.00	5.50	17.50	825
Perceived policy rate (E6a, %)	1.56	1.02	0.76	1.30	2.20	846
Expected policy rate in 5y (E6b, %)	1.83	1.03	1.00	1.75	2.50	681
Demographics						
Male	0.47	0.50	0	0	1	2,587
Income group	2.25	1.04	1	2	3	2,543
Assets category	2.27	1.00	1	2	3	2,182
Employment status	3.09	0.98	2	3	4	2,587
Education level	3.13	0.84	3	3	4	2,587
Age group	2.81	1.06	2	3	4	2,587
Financials						
Debt	0.40	0.49	0	0	1	2,548
Debt repayments (% gross monthly income)	23.37	15.77	10	25	30	1,067

Notes: Stock return measures and policy rate expectations are expressed in percentage points. Binary variables (Male, Debt) report population shares. Ordered categorical variables are coded as follows: Income (1 = €0–11,999; 2 = €12,000–19,999; 3 = €20,000–29,999; 4 = €30,000 or more); Assets (1 = €0–74,999; 2 = €75,000–224,999; 3 = €225,000–449,999; 4 = €450,000 or more); Employment (1 = Self-employed; 2 = Retired; 3 = Unemployed; 4 = Employed); Education (1 = Less than High School; 2 = High School; 3 = Technical/Professional; 4 = College or more); Age (1 = under 35; 2 = 35–44; 3 = 45–65; 4 = 65 or older). The variable on debt repayments (E4) reports monthly repayments as a percentage of gross income. Sample sizes vary across rows due to item nonresponse.

Turning to *Demographics*, the sample contains slightly more females (53%) than males (47%). The mean income group is 2.25, which corresponds to households in the €12,000–19,999 bracket, although the full distribution ranges from up to €11,999 to €30,000 or more. The mean assets category is 2.27, placing the typical household in the €75,000–224,999 range, with values spanning from up to €74,999 to €450,000 or more. Employment status averages 3.09 on the four-point scale, which indicates that most respondents are in the employed category, with smaller shares that are unemployed, retired, or self-employed. The mean education level is 3.13, consistent with respondents on average having either technical/professional training or a college degree. The average age group is 2.81, placing the typical respondent in the 45–65 bracket, though the data include younger households under 35 and older households aged 65 or above.

In the *Perceptions and Expectations* block, households report an average perceived stock return of 5.1%. The distribution is wide: the 25th percentile is at zero, the median is 2.9%, and the 75th percentile is 8.9%, with some households reporting large negative or very high positive values. Expected stock returns are higher on average at 10.1%, with the interquartile range spanning from 0 to 17.5%, suggesting households are more optimistic about future returns than past performance. For monetary policy, the mean perceived policy rate (E6a) is 1.6%, while the expected rate five years ahead (E6b) is 1.8%. In both cases, the median is below the mean, reflecting right-skewed distributions in which a small share of households expects much higher values than most respondents.

In terms of *Financials*, 40% of households report holding debt. Debt repayments account for an average of 23.4% of gross monthly income, with an interquartile range of 10–30%. This shows that while many households face moderate repayment burdens, a share allocate more than 30% of their income to debt service.

3.3 How do French households perceive and forecast stock market returns and policy rates?

In this section we analyse French households' perceptions and expectations. We ask two related questions. First, do households who are less informed about current interest rates also make less accurate forecasts of future rates? Second, are households with higher debt burdens more attentive to current policy rates and do they make more precise forecasts of future rates? To answer these questions, we examine survey evidence on French households' perceptions and expectations about the stock market and the monetary policy rate.

3.3.1 Stock Market Returns

To measure households' perceptions about the current stock market returns, a series of questions were asked. Respondents were asked to award a probability to each bin. They were also asked to ensure that the sum of the bins was equal to a hundred. This followed the recent literature that used probability distributions in lieu of point estimates (Manski, 2004). Probability distributions have the advantage of providing a more complete picture of individuals' beliefs about future events. Point estimates, such as asking individuals to provide a single number for their expected future value, can be subject to biases and may not capture the full range of possible outcomes. Probability questions, on the other hand, ask individuals to assign probabilities to different outcomes, which can provide a more comprehensive understanding of their beliefs. Probability questions also allow for the calculation of more sophisticated statistical measures, such as variance and the standard deviation, which can help us understand the distribution of beliefs among survey respondents. This information can be particularly useful for policymakers and researchers who are interested in understanding the heterogeneity of beliefs across different groups. Question B2a asked respondents about their perception on the historical evolution of the French stock market. The following question was presented.

B2a) Over the past three years, would you say that the stock market (CAC 40) has...

The sum of the responses in the column must total 100%. Each respondent could select only one option per line.

- *Risen by more than 25%*
- *Risen by 10% to 25%*
- *Risen less than 10%*
- *Remained at the same level*
- *Fallen less than 10%*
- *Fallen 10% to 25%*
- *Fallen more than 25%*

There were 2,587 respondents of which 1,247 (52%) failed to answer the question. Out of the remaining 1,340 (48%) that answered the question, only 825 (34%) answered the question meaningfully and correctly by allocating a total of 100 points across all bins. We also accepted responses where the total fell between 95 and 105 points to allow for small reporting errors, thereby increasing the valid sample. This adjustment is common in survey-based probability elicitation. Figure 3.1 shows the histogram which provides the average frequency of those that answered question B2a meaningfully and correctly.

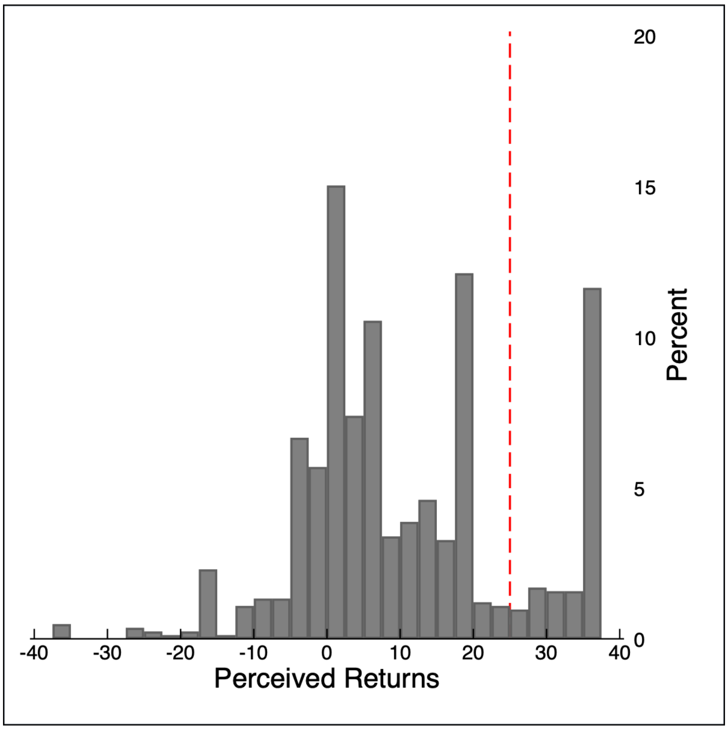


FIGURE 3.1: Histogram of Stock Market Return Perceptions

Notes: The figure plots the distribution of respondents' perceptions of stock market returns over the previous three years. The vertical dashed line marks the correct response bin, corresponding to actual gains of more than 25%. Only about 17% of respondents selected this bin, indicating limited awareness of recent stock market performance.

Of the 825 respondents, only 17% correctly responded that the French stock market had risen by more than 25%. This is illustrated in Figure 3.1 by the vertical dashed line, which marks the threshold for the ">25%" response category. Since information on the French stock market is publicly available, we might expect most respondents to answer this question correctly. The fact that only a minority did so suggests that households were poorly informed about recent market performance, despite the information being accessible. Possible explanations include limited attention to financial markets or difficulty processing stock market data. These remain hypotheses rather than causal explanations. This evidence highlights heterogeneity in how information about the historical performance of the CAC 40 is processed and retained, which is relevant for understanding the formation of expectations.

Respondents were also asked about their expectations regarding the French stock market five years ahead. Respondents were asked to follow similar rules as in question B2a. The following question was asked:

B1a) In five years from now, do you think the stock market (CAC-40) will have...
The sum of the answers in the column must be 100. One answer per line.

- *Risen more than 25%*
- *Risen 10% to 25%*
- *Risen less than 10%*
- *Remained at the same level*
- *Fallen less than 10%*
- *Fallen 10% to 25%*
- *Fallen more than 25%*

There were 2,587 respondents, of which 945 (37%) answered the question meaningfully and correctly by allocating a total of 100 points across all bins. As with B2a, we allowed responses between 95 and 105 points. Figure 3.2 depicts a histogram showing the average frequency of those that answered question B1a meaningfully and correctly.

By May 2020, the French stock market had fallen by approximately 6% compared to May 2015. Of the 945 respondents, only 154 (16%) correctly predicted that the French stock market would fall by less than 10%. This indicates that most households expected more favourable outcomes than were realised, with many anticipating gains rather than a moderate decline. Furthermore, Figure 3.2 shows that respondents were generally more optimistic, expecting the stock market to rise over the following five years.

Out of the 154 respondents that correctly predicted the direction of the stock market, only 36% had previously answered B2a correctly regarding the past three years. This suggests that accurate knowledge of past market performance did not necessarily translate into more accurate forecasts of future outcomes. One explanation is that households view forecasting the future as qualitatively different from recalling the past: while past outcomes can be verified, expectations about the future remain uncertain. Another explanation is that respondents may rely on heuristics or general sentiment when forming forward-looking expectations, which need not be linked to knowledge of recent history.

These descriptive patterns shows that many French households often misjudged past stock market performance and were generally too optimistic about the future. As such, this provides us with a useful comparison point for policy rates, where we ask whether similar patterns hold and whether households differ in attentiveness and forecasting accuracy.

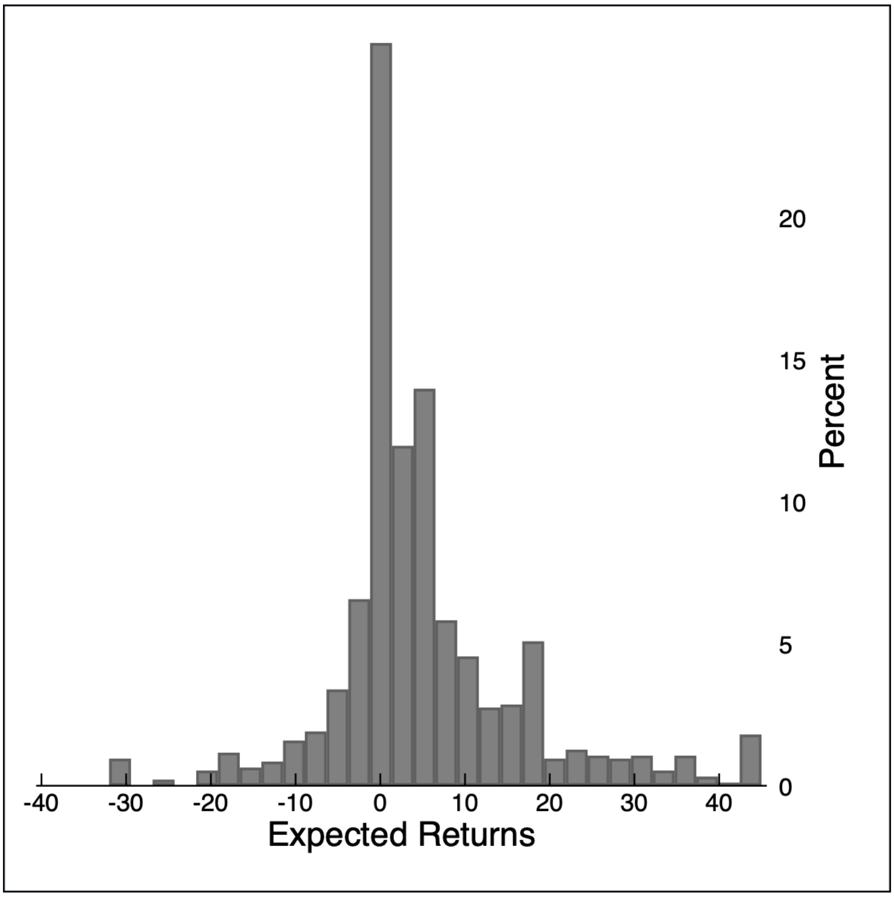


FIGURE 3.2: Histogram of Stock Market Return Expectations
Notes: The figure displays the distribution of respondents' expectations for stock market returns over the year ahead. Values are based on individual survey responses to the question on expected stock market performance.

3.3.2 Policy Rates

Respondents were also asked questions about their perceptions and expectations regarding the monetary policy rate as set by the European Central Bank and the Bank of France. The following questions were asked:
E6a) Would you say that the interest rate of the Bank of France (or ECB) is today… For each item, please clearly write the probability from 0 to 100. The sum of the answers in the column must be 100. One answer per line.

- *Less than 0.5%*
- *Between 0.5% and 1.5%*
- *Between 1.5% and 2.5%*
- *Between 2.5% and 3.5%*
- *Between 3.5% and 4.5%*

- *More than 4.5%*
- *I do not know*

E6b) In five years from now, do you think the European Central Bank interest rate will be... For each item, please clearly write the probability from 0 to 100. The sum of the answers in the column must be 100.

- *Less than 0.5%*
- *Between 0.5% and 1.5%*
- *Between 1.5% and 2.5%*
- *Between 2.5% and 3.5%*
- *Between 3.5% and 4.5%*
- *More than 4.5%*
- *I do not know*

Question E6a asked respondents about their current knowledge of interest rates set by the European Central Bank. Out of 2,587 respondents, 2,359 chose to answer the question. Among these, only 846 answered meaningfully and correctly by ensuring that the total across all bins summed to 100. In contrast, 1,466 respondents indicated that they did not know the current policy rate. To preserve sample size, “don’t know” responses were retained in regressions by including a dummy variable for DK answers. We also accepted responses whose totals fell between 95 and 105, thereby accounting for small reporting errors. This approach allowed us to construct a more robust measure of subjective expectations regarding the current policy rate.
During this period, the ECB policy rate was 0.3% as of May 2015. We expected most respondents to indicate that the rate was less than 0.5%. However, only 163 respondents did so. This shows that most households misperceived the prevailing rate, despite it being publicly observable. A plausible explanation is that households rely on borrowing rates offered by commercial banks, which are considerably higher than the ECB policy rate (e.g. Coibion et al., 2018). Another explanation is that limited financial literacy and information overload reduce households’ ability to filter out central bank announcements.
On average, households perceived the policy rate to be higher than its actual level. Only a small proportion correctly answered that it was less than 0.5%.

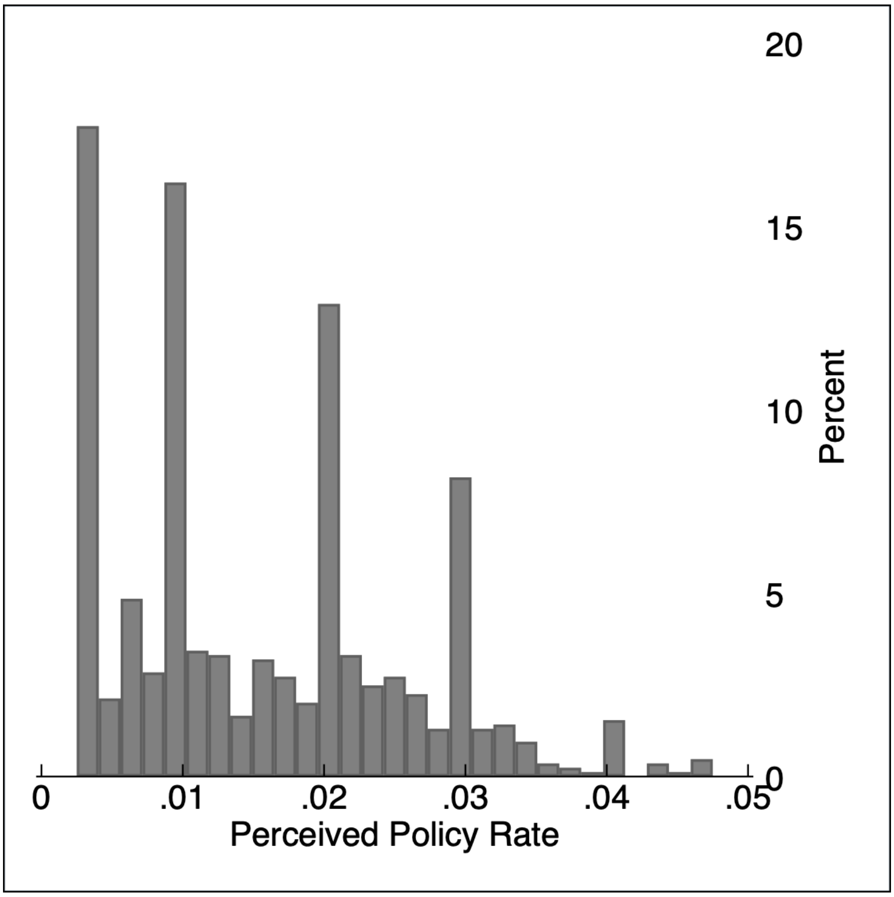


FIGURE 3.3: Distribution of respondents' perceived policy rate.
Notes: The figure presents the distribution of respondents' perceptions of the current ECB policy rate. Values reflect individual answers to the survey question on the prevailing policy rate at the time of the interview.

This indicates that most households misperceived the stance of monetary policy. Possible reasons include low salience of central bank actions and reliance on heuristics when thinking about interest rates.
Respondents were also asked what they expected the policy rate to be five years later in question E6b. Out of 2,587 respondents, 2,320 provided an answer, but only 681 did so meaningfully and correctly by ensuring that the sum of their allocations equalled 100. A total of 1,639 respondents said they did not know. The official ECB policy rate as of May 2020 was 0.25%, so the correct answer was that rates would be less than 0.5%. Only 54 respondents accurately predicted this. This low proportion is not surprising given the difficulty of forecasting monetary policy over a five-year horizon. Even among those who correctly identified the current rate in E6a, few correctly predicted its future value. This indicates that knowledge of the present does not automatically translate into better forecasting ability, consistent with research on expectation formation under uncertainty (Armantier et al., 2015).

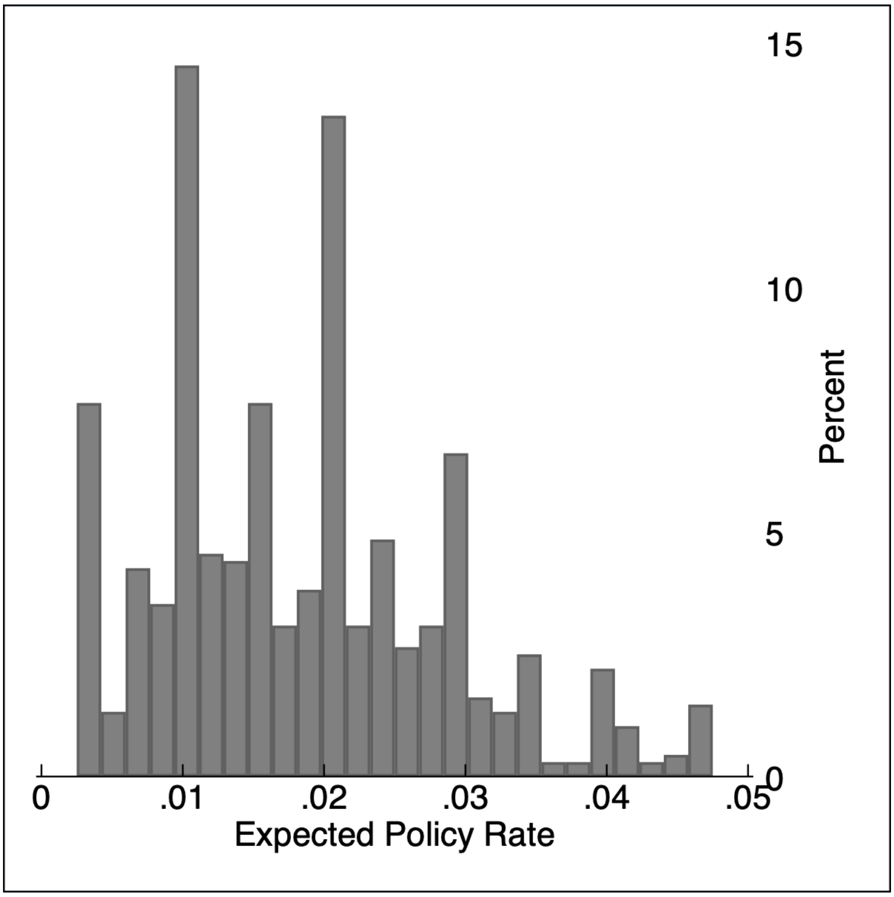


FIGURE 3.4: Distribution of respondents' expected policy rate five years ahead. *Notes:* The figure shows the distribution of respondents' expectations for the ECB policy rate five years ahead. Values are based on individual survey responses to the forward-looking policy rate question.

The distribution of expectations is right-skewed, with most respondents placing positive probability on bins above the realised outcome of less than 0.5%. This indicates that many households anticipated a tightening of monetary policy, even though official rates remained close to zero over the period. Such upward bias is consistent with survey evidence showing that households often expect stable interest rate environments to be followed by increases.

Next, we explore whether income plays a role in shaping awareness of monetary policy. Figure 3.5 examines whether monetary policy knowledge varies systematically across the income distribution. Respondents were divided into four income groups. Among those earning less than €12,000 annually, only 157 out of 785 (20.0%) correctly identified the current ECB policy rate as below 0.5%. The proportion rises modestly to 24.5% in the €12,000–19,999 group (173 out of 707) and more sharply to 41.3% in the €20,000–29,999 group (286 out of 693). The highest income group, earning €30,000 or more, shows the strongest awareness of the current policy rate, with 225 out of 358 respondents (62.8%)

reporting the correct rate. These results show a clear income gradient, with higher income households more likely to report the correct policy rate. This pattern suggests that income is positively associated with monetary policy knowledge, possibly because higher income individuals have greater exposure to financial information or stronger incentives to monitor policy decisions.

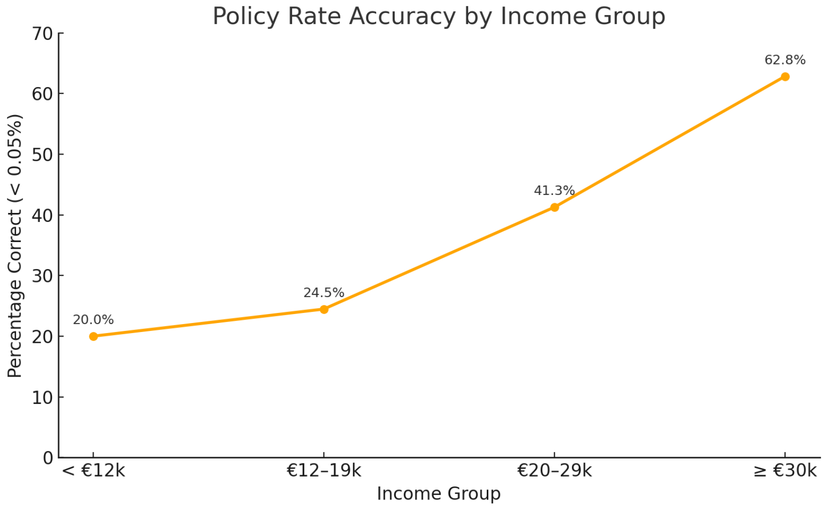


FIGURE 3.5: Percentage of Respondents Accurately Identifying the ECB Policy Rate, by Income Group

Notes: The figure reports the share of respondents who correctly identified the current ECB policy rate, grouped by income category. Accuracy is defined as the percentage of individuals whose reported policy rate falls within the ECB's actual rate range in the corresponding survey wave. Income groups are based on self-reported annual household income brackets.

We also analyse whether households that allocate a larger share of their gross income to debt repayments are more likely to correctly identify the current monetary policy rate compared to those with lower repayment burdens. Figure 3.6 plots the percentage of respondents in each debt-to-income quartile who correctly reported the ECB's policy rate as below 0.5%. These quartiles are based on the share of monthly gross income used to repay debt.

The results show that respondents in the middle of the distribution, those in the second and third quartiles (25–50% and 50–75%), are most likely to report the correct rate, with 45.8% and 49.5% of households respectively giving the correct response. Respondents in the lowest quartile, who spend the smallest share of income on debt, perform slightly worse, with 40.7% reporting the correct policy rate. Those in the highest quartile (75–100%) are the least accurate, with only 36.5% reporting the correct rate. This pattern suggests that moderate debt exposure may be associated with greater monetary policy awareness, possibly because these households are more regularly engaged with interest-sensitive financial decisions. By contrast, households at the extremes (those with little or no debt and those with high repayment burdens) are less likely to be informed about policy rates.

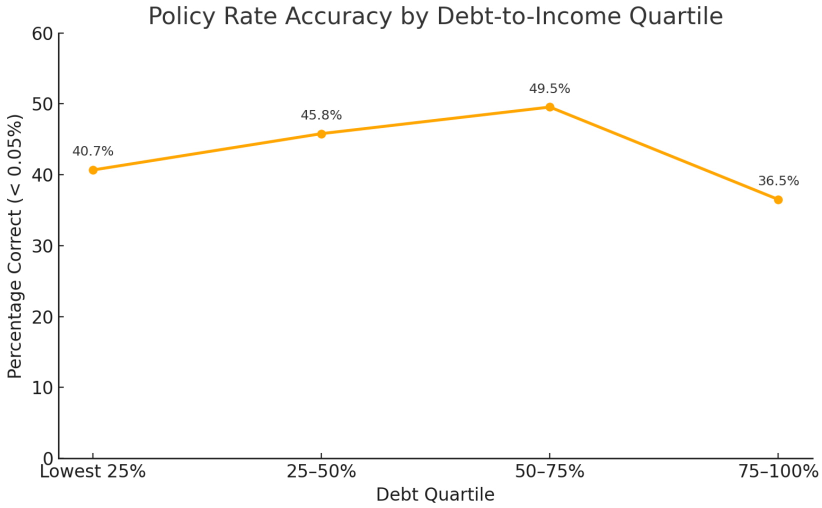


FIGURE 3.6: Percentage of Respondents Accurately Identifying the ECB Policy Rate, by Debt-to-Income Quartile

Notes: The figure shows the share of respondents who correctly identified the current ECB policy rate, grouped by debt-to-income quartile. Accuracy is computed as the percentage of individuals whose reported policy rate falls within the ECB's actual rate range at the time of the survey. Quartiles are defined using the distribution of households' debt-to-income ratios.

We next turn to regression analysis to test these patterns more formally and to examine how perceptions and expectations of policy rates vary with demographic and financial characteristics. Table 3.2 presents the average perceived (μ_{E6a}) and expected (μ_{E6b}) policy rates across different demographic groups. We find systematic variation across gender, age, education, employment, income, and debt.

For gender, women report higher average perceived and expected rates than men (1.77% vs. 1.40% for perceptions and 1.95% vs. 1.75% for expectations). This gender gap is consistent with survey evidence that women tend to report greater uncertainty and lower financial confidence

Across age groups, we see that differences are modest. Respondents aged 65 and above report slightly higher expected rates (2.05%) than younger cohorts, whose averages lie closer to 1.65 - 1.81%. This may reflect weaker exposure of older households to interest-sensitive products such as mortgages, leading them to rely on general sentiment rather than direct financial experience when forming expectations.

Next, in terms of education, French households with less than high school education perceive an average rate of 1.76% and expect 2.42%, while those with a college degree or more perceive 1.31% and expect 1.68%. These differences suggest that education is linked to monetary policy awareness, with more educated respondents reporting lower and more accurate values. This is consistent with research showing that education improves financial literacy and the ability to interpret macroeconomic information.

Employment status also matters. Retired and unemployed respondents report higher averages than those who are employed. For example, unemployed respondents report perceived and expected rates of 1.70% and 1.97% respectively, compared to 1.57% and 1.75% among employed respondents. One explanation is that individuals outside the labour force are less engaged with borrowing and lending markets, which reduces their exposure to monetary policy communication.

Income is a key differentiator. The lowest income group, earning less than €12,000, perceives an average policy rate of 1.73% and expects 1.85%, while the highest income group, earning above €30,000, reports significantly lower averages of 1.11% and 1.68%. This pattern suggests that higher income households have greater awareness of policy conditions, potentially due to stronger incentives to track interest rate developments or better access to financial information.

Debt quartiles show less systematic differences, but some patterns emerge. Respondents in the top quartile, devoting the largest share of income to debt repayments, perceive higher average rates (1.72%) compared to those in the middle quartiles (1.47–1.52%). This suggests that heavy debt burdens may be associated with upward-biased perceptions of current policy rates. In contrast, households with moderate debt levels provide more accurate responses, consistent with greater attentiveness to interest-sensitive conditions.

These results show that perceptions and expectations of policy rates are strongly influenced by demographic and financial characteristics, particularly income and education. This sets the stage for the econometric analysis in the next section, where we test how these misperceptions correlate with household behaviour.

TABLE 3.2: Average Perceived and Expected Policy Rates by Demographic Groups

Group	Perceived Rate (μ_{E6a})	Expected Rate (μ_{E6b})
Gender		
Female	1.77	1.95
Male	1.40	1.75
Age Group		
Under 35	1.60	1.65
35–44	1.59	1.81
45–65	1.58	1.75
65 and above	1.47	2.05
Education Level		
Less than High School	1.76	2.42
High School	2.02	2.30
Technical/Professional	1.82	1.96
College or More	1.31	1.68
Employment Status		
Self-employed	1.69	1.74
Retired	1.45	1.98
Unemployed	1.70	1.97
Employed	1.57	1.75
Income Group (Euro)		
$<$12,000	1.73	1.85
12,000–19,999	1.82	1.88
20,000–29,999	1.65	1.89
30,000+	1.11	1.68
Debt Quartiles		
Lowest 25%	1.34	1.81
25–50%	1.47	1.66
50–75%	1.52	1.75
Top 25%	1.72	1.71

Notes: The table reports average perceived and expected policy rates (in percent) across demographic groups. μ_{E6a} denotes perceived current policy rates, and μ_{E6b} denotes expected rates five years ahead. Sample sizes vary due to item nonresponse. “Don’t know” responses were retained in regressions using DK dummies but are excluded from these descriptive averages.

Building on the descriptive patterns, Table 3.3 reports OLS estimates of the demographic and financial correlates of perceived and expected policy rates. These regressions address our second research question by testing whether differences across groups such as education, income, and debt repayment burdens (measured as a share of gross income) remain significant after controlling for other characteristics. In addition, Model (3) links expectations to current perceptions, which provides initial evidence relevant to our first research question on whether less informed households also make less accurate forecasts. Model (1) focuses on perceived rates (μ_{E6a}). Male respondents report significantly lower perceived rates ($p<0.01$), as do households with college education (p<0.05) and those with incomes above €30,000 (p<0.05). Debt repayment quartiles are not significant once controls are included. These results are consistent with the descriptive evidence that men, higher-income, and more educated households are closer to the prevailing policy rate.

Furthermore, Model (2) examines expected policy rates five years ahead (μ_{E6b}). Male respondents continue to expect lower rates, with the coefficient marginally significant at the 10% level. By contrast, education, income, and debt quartiles are not statistically significant. This suggests that forward-looking expectations are less closely tied to socioeconomic characteristics once other controls are in place.

Lastly, Model (3) introduces perceived rates as a predictor of expectations. The coefficient on μ_{E6a} is large (0.468) and highly significant (p<0.01), showing that expectations are strongly anchored in perceptions of the current policy stance. Once this channel is included, the coefficients on gender, education, income, and debt repayment quartiles are no longer significant, indicating that these differences influence expectations mainly through their effect on perceptions.

TABLE 3.3: Determinants of Perceived and Expected Policy Rates

	(1) Perceived Rate (μ_{E6a})	(2) Expected Rate (μ_{E6b})	(3) Expected Rate w/ Perceptions
Male	-0.165***	-0.082*	-0.009
	(0.048)	(0.042)	(0.033)
College or More	-0.341**	-0.169	-0.033
	(0.166)	(0.141)	(0.134)
Income >30k	-0.190**	-0.071	0.013
	(0.093)	(0.079)	(0.065)
Perceived Policy Rate	—	—	0.468***
			(0.050)
Controls (age, other ed/income, employment, debt)	Yes	Yes	Yes
Observations	963	963	963
R-squared	0.564	0.667	0.762

Notes: Ordinary least squares estimates. Robust standard errors in parentheses. Model (1) regresses perceived current policy rates (μ_{E6a}) on demographic and financial characteristics. Model (2) regresses expected future policy rates (μ_{E6b}) on the same set of covariates. Model (3) adds perceived rates as an explanatory variable for expected rates. All specifications include controls for age, education, income, employment status, and debt quartiles. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.3.3 Subjective Monetary Policy Uncertainty and Stock Market Volatility

We use expectations data to compute stock market volatility and monetary policy uncertainty. This is measured as the standard deviation of the expected stock market returns five years ahead and the standard deviation of the expected monetary policy rate, respectively. We follow the midpoint probability-mass methodology of Giordani and Söderlind (2003), which is also applied in recent work on subjective expectations, and calculate the mean and standard deviation as follows:

$$E(X) = \sum_{k=1}^{K} \alpha(k) \cdot Pr(k) \tag{3.1}$$

$$\text{Var}(X) = \sum_{k=1}^{K} [\alpha(k) - E(X)]^2 \cdot Pr(k) \tag{3.2}$$

where $\alpha(k)$ is the midpoint of the intervals, $Pr(k)$ is the subjective probability of the interval k, and X refers to our variable of interest. We assume that all the probability mass is located at the midpoint of each interval.

Figure 3.7 illustrates the distribution of household expectations regarding stock market volatility and monetary policy uncertainty in France. The summary statistics for both variables are presented in Table 3.4, providing additional context for the observed distributions.

The histogram of expectations for stock market volatility (Panel a) is right-skewed, indicating that while most households expect moderate levels of volatility, a subset anticipates extreme fluctuations. The distribution broadly resembles a log-normal shape, consistent with empirical work on stock market return volatility. The shape resembles log-normal patterns noted in the finance literature, indicating that households account for the chance of rare but large market swings.

In contrast, monetary policy uncertainty (Panel b) is more tightly concentrated near zero and displays a thinner right tail, suggesting that expectations about future interest rates, five years ahead, are less dispersed than those about stock market volatility. The distribution of policy uncertainty is concentrated close to zero, with few households assigning very high values.

This difference shows that while French households have different views about equity market fluctuations, their expectations about monetary policy tend to be more clustered. The lower spread in policy expectations likely reflects the anchoring role of central bank communication, which offers a common reference point even if households still differ in their precise forecasts.

Table 3.4 further disaggregates the dispersion of household expectations by key demographic groups, showing how disagreement varies across gender, age, education, income, and debt levels.

In most demographic groups, the dispersion of stock market expectations ($\sigma_{\text{SMV}} = 9.30$) is higher than that of monetary policy expectations ($\sigma_{\text{MPU}} =$

0.45), which matches the pattern seen in the full sample. This gap appears consistently across gender, age, education, income, and debt categories.

First, with respect to gender, males exhibit higher dispersion in stock market expectations (9.81) compared to females (8.63), whereas monetary policy dispersion is slightly lower for males (0.4540) than for females (0.4488). This suggests that men express a wider range of opinions on financial market outcomes, while women are somewhat more heterogeneous when it comes to policy expectations.

Turning to age, an inverted U pattern is visible across age groups for stock market volatility. Younger respondents under age 35 exhibit the highest dispersion (10.07), which declines in middle-aged groups (9.09–9.10), and rises slightly among older respondents (9.29 among those aged 80+). Monetary policy dispersion, by contrast, varies less systematically with age but is slightly higher among the youngest and oldest respondents. For monetary policy uncertainty, there is no clear age gradient, though dispersion is marginally higher at the tails of the age distribution.

Looking across education, the results show mixed effects. Respondents with college education or more exhibit slightly higher dispersion in stock market expectations (9.46) and notably lower dispersion in monetary policy expectations (0.4514) relative to less educated groups. This pattern is consistent with the idea that higher education broadens the range of financial opinions but provides a more common anchor for interpreting monetary policy.

Income also matters. Higher income households (income $\geq$ €30k) report markedly higher dispersion in stock market expectations (10.25) and somewhat higher dispersion in monetary policy expectations (0.4715) relative to lower income groups. This suggests that wealthier households are more exposed to and engaged with equity markets, generating greater diversity in their views about returns, while at the same time holding slightly more varied expectations about policy settings.

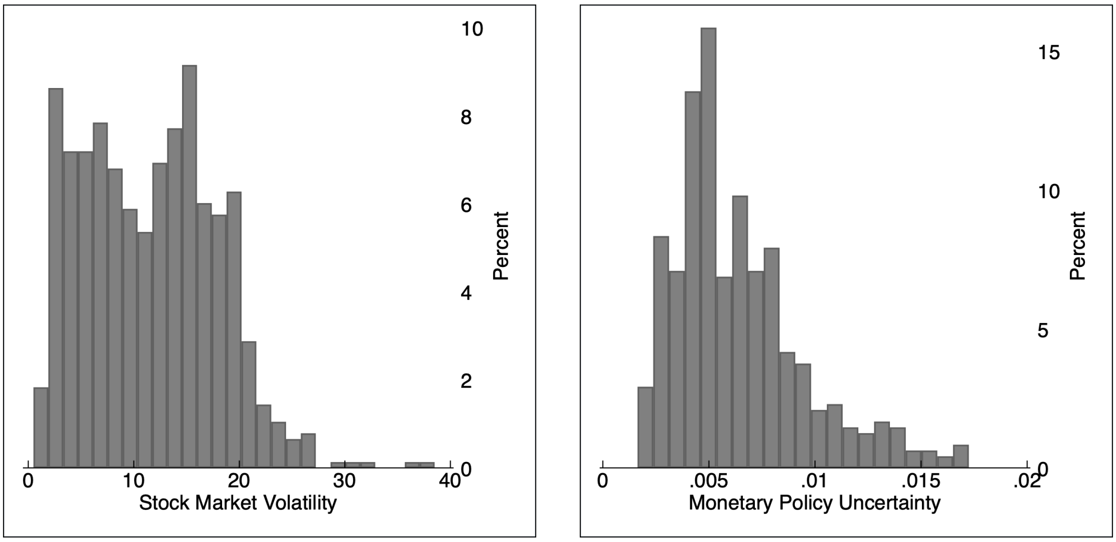
Finally, debt exposure shows a different pattern. Dispersion by debt quartile (the percentage of gross income that goes towards debt payments) suggests that households in the lowest debt group (lowest 25%) exhibit the highest dispersion in stock market expectations (10.36), whereas dispersion declines in the middle quartiles and rebounds slightly in the highest quartile. Monetary policy dispersion remains relatively stable across debt groups. By contrast, dispersion in policy expectations shows little variation across debt quartiles, suggesting that indebtedness plays a limited role in shaping perceptions of monetary policy.

These demographic breakdowns show that heterogeneity in expectations is not uniform. the evidence suggests that heterogeneity in expectations is shaped by demographic and financial characteristics. Gender, age, education, income, and debt are all associated with distinct patterns of disagreement, which will be examined further in the regression analysis of the next subsection.

TABLE 3.4: Average Subjective Uncertainty by Demographic Group

Group	Stock Market Dispersion (σ_{SMV}) (Mean Std. Dev.)	Monetary Policy Dispersion (σ_{MPU}) (Mean Std. Dev.)
Full sample	9.30	0.4519
Panel A: Gender		
Female	8.63	0.4488
Male	9.81	0.4540
Panel B: Age Group		
$<$35	10.07	0.4645
35–44	9.09	0.4516
45–65	9.10	0.4444
80+	9.29	0.4535
Panel C: Education Level		
Less than High School	9.09	0.5049
High School	9.14	0.3026
Technical/Professional	9.12	0.4617
College or More	9.46	0.4514
Panel D: Income Group		
Income $<$12k	9.60	0.3914
12k–19k	8.22	0.5021
20k–29k	9.27	0.4367
Income $\geq$30k	10.25	0.4715
Panel E: Debt Quartile		
Lowest 25%	10.36	0.4324
25–50%	9.52	0.4791
50–75%	7.87	0.4874
75–100%	9.30	0.4233

Notes: This table reports the average subjective uncertainty in household expectations. σ_{SMV} denotes the standard deviation of expectations regarding future stock market returns; σ_{MPU} denotes the standard deviation of expectations regarding future monetary policy rates. Full sample observations: $N = 945$ (SMV) and $N = 681$ (MPU). Higher values indicate greater disagreement or uncertainty among respondents.



(A) Stock Market Volatility

(B) Monetary Policy Uncertainty

FIGURE 3.7: Comparison of Monetary Policy Uncertainty and Stock Market Volatility

Notes: Each panel plots the time series of subjective stock market volatility (SMV) and monetary policy uncertainty (MPU) constructed from household survey responses. Values represent wave-level averages for each variable.

After presenting group level averages in Table 3.4, Figure 3.7 shows the full distribution of responses. The right-skewed distribution of stock market volatility (Panel a) indicates that while most households cluster around moderate expectations, a smaller share anticipate very large swings.
Panel b shows that monetary policy uncertainty is concentrated near zero with a relatively thin right tail. This aligns with the descriptive statistics, indicating that households disagree more about stock market volatility than about policy rates. These descriptive results motivate the next section, where we examine more formally whether French households who report higher monetary policy uncertainty also tend to expect greater stock market volatility. We also ask whether those who perceive higher stock market volatility tend to forecast higher policy rates in the future.

3.4 The Relationship Between Subjective Monetary Policy Uncertainty and Subjective Stock Market Volatility

Monetary policy uncertainty (σ_{mpu}) and stock market volatility (σ_{smv}) play an important role in shaping household expectations and financial behaviour

(Bloom, 2009; Baker et al., 2021; Husted et al., 2017; Ludvigson et al., 2017). This chapter extends the analysis from Chapter 1 by moving from aggregate measures to a micro-level perspective.
We use French household survey data to examine whether households that perceive greater stock market volatility (SMV) also report higher monetary policy uncertainty (MPU). The null hypothesis is that there is no relationship between SMV and MPU. This is consistent with the central bank perspective, expressed by Greenspan, that policy should not respond automatically to financial market swings. Rejecting the null would imply that households link financial and monetary domains when forming expectations, with implications for how uncertainty propagates through the economy.

3.4.1 Econometric Framework

Our empirical strategy combines instrumental variables (IV) with machine learning methods to address endogeneity and high dimensionality in the data. The estimation problem is that SMV may be correlated with unobserved traits such as financial literacy, macroeconomic knowledge, or pessimism, which also shape MPU. In addition, we have 237 demographic, behavioural and survey design variables as potential controls. Traditional IV or OLS approaches would risk either omitted variable bias or overfitting.
We estimate the following system:

$$mpu_i = \alpha smv_i + x_i'\beta + \epsilon_i \tag{3.3}$$

$$smv_i = x_i\gamma + \bar{z}_i'\delta + u_i \tag{3.4}$$

where mpu_i is forward-looking monetary policy uncertainty (MPU) reported by household i, smv_i is subjective stock market volatility (SMV), x_i is a high-dimensional vector of controls, and $\bar{z}_i$ is a vector of excluded instruments.
We use three related IV-Lasso approaches from Chernozhukov et al. (2015). First, post-regularization Lasso partials out controls from both the outcome and the endogenous regressor before estimation. Second, post-Lasso refits OLS on selected controls to remove shrinkage bias. Third, post-double selection (PDS) runs separate Lasso regressions of the outcome and treatment on the full set of controls, and uses the union of selected variables in the final specification. PDS provides strong guarantees against omitted variable bias when the number of controls is large. Our preferred specification follows the CHS post-Lasso method, which orthogonalizes the moment condition and is robust to weak

instruments, but we also report results using PDS and post-regularization as robustness checks.

3.4.2 Identification Strategy

The main empirical challenge is potential endogeneity of SMV. Households who believe markets are volatile may also feel that monetary policy is unpredictable because of unobserved traits such as risk aversion. To address this, we construct instruments based on cross-sectional dispersion in expectations. These dispersion measures vary across survey waves but are common to all households within a wave, making them unlikely to correlate with individual unobservables once controls are included.

Endogeneity arises because households who believe that markets are volatile may also view monetary policy as uncertain for reasons that are unrelated to actual policy signals, such as differences in financial literacy or individual risk preferences. If these unobserved traits influence both perceptions, the estimated relationship between SMV and MPU would be biased. To address this, the wave-level instruments used in the empirical specification are defined explicitly. For each survey wave, we construct measures of disagreement by computing the standard deviation of households' expectations about stock market returns and, separately, the standard deviation of their expectations about future policy rates. These measures capture how much views differ across respondents within a given wave and vary over time as public information and macroeconomic conditions change. Importantly, they take the same value for all households within a wave. This wave-level structure is central for identification. Because every household in the same wave receives the same measure of disagreement, the instrument cannot reflect individual traits such as pessimism, risk attitudes, or reporting errors once demographic controls are included, supporting the exogeneity condition. Theoretical models of information frictions and heterogeneous expectations show that greater variation in beliefs reflects noisier information environments, and when information is noisier, households tend to report higher perceived uncertainty about both financial markets and monetary policy. This provides the economic mechanism linking the instruments to SMV and MPU and establishes their relevance.

The instruments are (i) the cross-sectional standard deviation of expected stock market levels lagged by one wave, (ii) the cross-sectional standard deviation of expected stock market returns lagged by one wave, and (iii) the cross-sectional standard deviation of perceived monetary policy uncertainty measured contemporaneously. The lag structure ensures that stock market dispersion is predetermined with respect to current MPU, while the use of dispersion rather than levels supports the exclusion restriction. First stage results confirm instrument relevance with F-statistics above conventional thresholds. We also verified that lagged dispersion measures are not systematically correlated with household demographics, supporting their exogeneity.

3.4.3 Handling Missing Data

Nonresponse is common in survey data. To preserve sample size and control for potential bias, we include dummy indicators for item nonresponse in all specifications. This strategy flexibly accounts for differences between respondents with and without missing data. Full diagnostics are reported in the appendix.
This framework allows us to test the null hypothesis directly. If households who perceive higher SMV also report greater MPU, this would indicate that beliefs about monetary policy uncertainty and stock market volatility are interconnected. If no such relationship exists, it would be consistent with the central bank view that the two domains are independent.
Having established the empirical framework, we now turn to Section 3.4.4, where we estimate whether subjective household stock market volatility (SMV) "causes" forward looking monetary policy uncertainty (MPU) or vice versa.

3.4.4 Does subjective household stock market volatility influence subjective forward-looking monetary policy uncertainty

We estimate the causal relationship between forward-looking monetary policy uncertainty (MPU) and subjective stock market volatility (SMV) using the Post-Double Selection (PDS) Lasso framework outlined in equations 3.3 and 3.4. The IV-Lasso approach is well suited for our high-dimensional data because it selects only covariates and instruments with predictive relevance, thereby reducing the risk of overfitting while maintaining robustness in inference. In this setting, we are able to address the potential endogeneity of MPU and obtain consistent estimates of its effect on SMV. Our first specification focuses on the impact of forward-looking subjective MPU on reported SMV.
Table 3.5 reports the IV Lasso estimates of the effect of forward-looking monetary policy uncertainty on subjective stock market volatility. The estimated coefficient

TABLE 3.5: IV-Lasso Estimates of the Effect of Monetary Policy Uncertainty on Subjective Stock Market Volatility

	Dependent variable: Stock Market Volatility (SMV)		
	CHS (sqrt-lasso)	CHS (post-lasso)	PDS (full model)
MPU (endogenous regressor)	6.635***	6.797***	6.767***
	(1.067)	(1.037)	(1.022)
Selected controls			
Gender (male)	2.519***	2.519***	2.519***
	(0.538)	(0.538)	(0.538)
Asset category (top quartile, $>$450,000€)	3.319***	3.319***	3.319***
	(0.676)	(0.676)	(0.676)
Instruments and diagnostics			
Instrument(s)	σ_{E6a}	σ_{E6a}	σ_{E6a}
Robust F-stat	41.95	44.31	601.09
Sup-score test (5%)	Reject	Reject	–
Corr(resid., instrument)	-0.0007	-0.0007	-0.0007
Observations	626	626	626

Notes: This table reports IV–Lasso estimates of the effect of monetary policy uncertainty (MPU) on subjective forward-looking stock market volatility (SMV). Columns correspond to the CHS square-root Lasso estimator, the CHS post-Lasso estimator, and the Post-Double-Selection (PDS) estimator. The instrument for MPU is σ_{E6a}. Covariates are selected from 22 demographic and socio-economic variables, with only gender and the top asset quartile retained across all specifications. Robust standard errors are shown in parentheses. Significance levels: *** $p < 0.01$.

is around 6.7 across specifications, which means that a one percentage point increase in perceived monetary policy uncertainty is associated with an increase of nearly seven percentage points in reported stock market volatility. To interpret the magnitude of this effect, the coefficient can be viewed relative to the average level of reported stock market volatility in the sample, which is around 8.4 percentage points with a standard deviation of 5.2 percentage points. The estimated impact of one percentage point higher MPU therefore represents roughly 1.35 standard deviations of perceived SMV, indicating that the effect is economically meaningful but not implausibly large. Households generally report greater uncertainty about financial markets than about monetary policy, that is, the mean MPU is 2.7 percentage points with a standard deviation of 1.9 percentage points, and this is consistent with the higher frequency and visibility of market movements compared with policy-rate changes. The result is therefore not surprising but confirms that perceived financial volatility is closely tied to how uncertain households feel about future policy. This pattern supports the view that information about monetary policy and financial markets is processed jointly rather than independently. Robust standard errors are well below one percentage point, and the estimates remain stable across the CHS sqrt lasso, CHS post lasso, and PDS models. The instrument based on the cross-sectional uncertainty in perceived policy uncertainty denoted by σ_{E6a}, is strong with a robust F statistic well above conventional thresholds and sup score tests confirm that weak identification is not an issue. The residual instrument correlation is close to zero which supports the validity of the exclusion restriction. Lasso consistently selects male respondents and households in the top asset quartile as controls which shows that information differences and balance sheet exposure shape the way households translate monetary uncertainty into financial uncertainty.

The magnitude of the effect carries economic meaning. A one percentage point increase in forward looking uncertainty about policy rates leads households to perceive stock market volatility that is seven percentage points higher. This finding rejects the null hypothesis of no relationship between monetary and financial uncertainty. Therefore, if central banks communicate clearly, they can reduce household uncertainty and prevent it from adding to market volatility, which in turn helps policy to be more effective. From a policy perspective, this shows the importance of clear and credible communication.

TABLE 3.6: IV-Lasso Estimates of the Effect of Subjective Stock Market Volatility on Monetary Policy Uncertainty

	Dependent variable: Monetary Policy Uncertainty (MPU)		
	CHS (sqrt-lasso)	CHS (post-lasso)	PDS (full model)
SMV (endogenous regressor)	0.0192***	0.0164***	0.0166***
	(0.0053)	(0.0053)	(0.0053)
Selected controls			
Income group (4th quartile, $>$30,000€)	0.0878***	0.0878***	0.0878***
	(0.0321)	(0.0321)	(0.0321)
Asset category (top quartile, $>$450,000€)	0.0918***	0.0918***	0.0918***
	(0.0365)	(0.0365)	(0.0365)
Instruments and diagnostics			
Instrument(s)	σ_{sC39}	σ_{sC39}	σ_{sC39}
Robust F-stat	41.56	42.79	239.26
Sup-score test (5%)	Reject	Reject	–
Corr(resid., instrument)	-0.0036	-0.0036	-0.0036
Observations	800	800	800

Notes: This table reports IV–Lasso estimates of the effect of subjective forward-looking stock market volatility (SMV) on monetary policy uncertainty (MPU). Columns correspond to the CHS square-root Lasso estimator, CHS post-Lasso estimator, and Post-Double-Selection (PDS) estimator. The instrument for SMV is σ_{sC39}. Control variables are selected from 22 demographic and socio-economic characteristics, with only the top income quartile and top asset quartile retained across all specifications. Robust standard errors are shown in parentheses. Significance levels: *** $p < 0.01$.

Table 3.6 reports the IV Lasso estimates of the effect of subjective stock market volatility on forward looking monetary policy uncertainty for French Households. The estimated coefficient on SMV is between 0.016 and 0.019 across the three specifications. This means that a one percentage point increase in perceived stock market volatility is associated with an increase of about two percentage points in monetary policy uncertainty. The coefficients are statistically significant at the one percent level and are stable across the CHS sqrt lasso, CHS post lasso, and PDS specifications.

Furthermore, Lasso consistently selects the top income quartile and the top asset quartile as relevant controls. Both variables are positive and significant, which suggests that households with higher income and greater asset holdings report higher levels of monetary policy uncertainty. This finding points to heterogeneity in perceptions, where households with more financial exposure are more sensitive to changes in perceived stock market conditions.

The instrument used in all specifications is the uncertainty in expected stock market levels from the previous wave, denoted σ_{sC39}. The first stage is strong, with robust F statistics above 40 in the CHS specifications and above 200 in the PDS model. Sup score tests confirm that weak identification is not a concern in the CHS specifications, and the correlation between residuals and the instrument is essentially zero, which supports the exclusion restriction. The sample size is 800 observations in each specification.

The estimates provide both statistical and economic meaning. Statistically, the coefficients are precise and stable across methods, which increases confidence in the causal interpretation. Economically, the effect is smaller in magnitude than the reverse direction reported earlier, where monetary policy uncertainty strongly influenced stock market volatility. This asymmetry is consistent with our hypothesis that policy uncertainty plays a leading role in shaping household beliefs, while stock market volatility still matters but has more moderate feedback into policy expectations. The result also aligns with Greenspan's view that monetary policy should not react automatically to swings in financial markets, even though such uncertainty can still spill over into the wider economy. From a policy perspective, the finding suggests that sharp increases in perceived stock market volatility can spill into households' expectations of policy uncertainty, which makes monetary communication even more important in times of financial stress.

Why does subjective forward-looking stock market volatility affect subjective monetary policy uncertainty? The positive association between subjective stock market volatility and monetary policy uncertainty suggests that households treat financial market fluctuations as signals of greater instability. This perspective adds to the literature on volatility and macroeconomic uncertainty at the aggregate level (Baker et al., 2016; Bloom, 2009; Caggiano et al., 2020), while offering new evidence at the household level. It also connects back to Chapter 1, where the SVAR results left the direction of causality between financial instability and monetary policy uncertainty unresolved. At the household level, we find that higher expected stock market fluctuations are associated with greater perceived uncertainty about future monetary policy. This echoes the debate raised by Greenspan on whether central banks should respond to asset price volatility. There are several channels that may explain this link. Through the risk perception channel (Pflueger et al., 2020), households can see increased volatility in the stock market as a sign of weaker economic stability and adjust their views on the likelihood of policy changes. Financial friction and liquidity constraints can amplify this effect (Alfaro et al., 2024), while increasing volatility can also raise doubts about the credibility of central bank responses, increasing the uncertainty of beliefs. These mechanisms are plausible rather than definitive, and our data cannot distinguish between them. The effect we estimate is statistically significant, but modest in size. This indicates that households notice and interpret stock market fluctuations when assessing monetary policy uncertainty, but the strength of the response is limited. From a policy perspective, the results do not justify systematic interventions in asset markets, consistent with Greenspan's cautionary stance. Instead, the findings show the importance of clear and consistent central bank communication. By explaining how financial developments fit into their policy framework, central banks can reduce uncertainty and guide household expectations more effectively.

3.4.5 Robustness

We next assess whether the estimated relationships are stable across different household subgroups. Table 3.7 reports IV-LASSO estimates of the effect of subjective stock market volatility on monetary policy uncertainty. The coefficients remain positive and statistically significant across nearly all subgroups, although the economic magnitudes are modest, ranging between 0.01 and 0.04. This indicates that households in different demographic and financial categories interpret higher stock market volatility as a signal of greater policy uncertainty, but the strength of this link is limited. The results show that the effect is present in most groups, though weaker or insignificant in some subgroups, such as women and mid-age cohorts

Table 3.8 reports the reverse relationship, estimating the effect of subjective monetary policy uncertainty on perceptions of stock market volatility. The coefficients are larger in magnitude, ranging from about 5 to 9, and remain highly significant across most subgroups. This shows that households consistently view policy uncertainty as an important driver of expected financial market volatility. The pattern is stronger and more uniform than in the reverse direction. The robustness checks therefore support the main conclusions. Both directions of the relationship are statistically significant, but monetary policy uncertainty

TABLE 3.7: IV-LASSO: Effect of Stock Market Volatility on Monetary Policy Uncertainty Across Subgroups

	Gender		Age Group				Debt/Income Quartile	
	Female	Male	<35	35–44	45–65	80+	Low D/I	High D/I
SMV coefficient	0.0139	0.0248***	0.0343***	0.0122	0.0277***	0.0214**	0.0311***	0.0299**
	(0.0120)	(0.0056)	(0.0128)	(0.0099)	(0.0103)	(0.0098)	(0.0100)	(0.0148)
Constant	0.115	0.0499	-0.141	0.158*	0.0315	0.0889	-0.0482	0.0543
	(0.104)	(0.0525)	(0.125)	(0.0948)	(0.0872)	(0.0885)	(0.102)	(0.152)
Observations	342	485	125	245	239	218	104	198

Notes: Each column reports IV–Lasso estimates of the effect of subjective forward-looking stock market volatility (σ_{SMV}) on monetary policy uncertainty (MPU) for the indicated subgroup. The instrument is σ_{sC39}. Covariates are selected via the Lasso procedure from a set of 22 demographic and socio-economic variables, including gender, income, assets, employment status, education, and age categories. Robust standard errors are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

has a much stronger impact on stock market volatility than the reverse. This asymmetry is consistent with the view that policy uncertainty is a primary source of household risk perceptions, while stock market volatility plays a secondary role. The results highlight the importance of clear communication by central banks in anchoring expectations, since uncertainty around policy rates has broad effects on how households perceive financial market stability.

TABLE 3.8: IV-LASSO: Effect of Monetary Policy Uncertainty on Stock Market Volatility Across Subgroups

	Gender		Age Group				Debt/Income Quartile	
	Female	Male	<35	35–44	45–65	80+	Low D/I	High D/I
MPU coefficient	6.518***	6.384***	7.366*	6.561***	7.281***	5.727***	7.999*	4.720**
	(1.771)	(1.265)	(4.179)	(2.010)	(1.862)	(1.751)	(4.517)	(2.198)
Constant	2.454***	5.117***	3.237*	3.475***	3.890***	4.932***	4.738**	6.603***
	(0.792)	(0.632)	(1.838)	(0.936)	(0.883)	(0.921)	(1.891)	(1.160)
Observations	269	396	96	206	191	172	86	184

Notes: Each column reports IV–Lasso estimates of the effect of monetary policy uncertainty (MPU) on subjective stock market volatility (SMV) for the indicated subgroup. The instrument for perceived policy uncertainty is σ_{E6a}. The Lasso procedure selects covariates from a set of 22 demographic and socio-economic variables, including gender, income, assets, employment status, education, and age categories. Robust standard errors are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.6 Policy Implications

The results indicate that French households with heightened expectations of stock market volatility also report greater uncertainty regarding future monetary policy. This suggests that financial market fluctuations influence how households perceive macroeconomic stability, potentially distorting expectations about future interest rates. To mitigate these effects, central banks such as the European Central Bank (ECB) and the Bank of France should strengthen their

forward guidance policies. Improved communication about future monetary policy actions could help anchor expectations, reducing household uncertainty and thus enhancing the effectiveness of monetary transmission mechanisms.
Furthermore, the observed link between subjective monetary policy uncertainty and stock market volatility suggests that households adjust their financial behaviour in response to perceived instability. Higher MPU could lead to increased precautionary savings or reduced investment in financial markets, potentially dampening economic growth. Policymakers may need to address these behavioural responses by ensuring greater access to long-term financial instruments that help households hedge against uncertainty. Expanding financial literacy initiatives may also assist households in making informed financial decisions despite uncertain macroeconomic conditions.
An important consideration is that the relationship between stock market volatility and MPU may be stronger among households with lower financial literacy. If less-informed households misinterpret short-term stock market movements as indications of long-term instability, they may develop distorted expectations about monetary policy. This shows the importance of financial education programs that help households differentiate between transitory financial shocks and structural macroeconomic changes. By improving financial literacy, policymakers can contribute to more stable and rational expectations among the public.
A key challenge for policymakers is the tendency of households to extrapolate long-term stock market movements into long-term expectations about monetary policy, suggesting that uncertainty in financial markets translates into uncertainty about future interest rates, potentially leading to instability in consumption and investment decisions. To counteract this effect, central banks could provide explicit long-term guidance on inflation and interest rate expectations. By offering clearer communication about long-term monetary policy targets, policymakers can help households form more stable and well-anchored expectations.
Our findings have significant implications for financial stability and macroeconomic policy. If household uncertainty about future policy rates is linked to stock market volatility, monetary authorities should account for financial market fluctuations when designing policy interventions. Furthermore, addressing the information asymmetry between informed and uninformed households can also improve the overall effectiveness of monetary policy. Strengthening financial literacy initiatives and ensuring transparent central bank communication are key steps toward reducing uncertainty driven distortions in economic behaviour.

3.5 Conclusion

This chapter examined the relationship between subjective monetary policy uncertainty (MPU) and subjective stock market volatility (SMV) at the household level using novel French survey data. The analysis asked whether households that perceive greater financial market volatility also report greater monetary policy uncertainty, and whether this uncertainty in turn feeds back into how they view financial markets.

The key findings are fourfold. First, a large share of households is unaware of the current ECB policy rate, confirming earlier evidence that many people remain poorly informed about monetary conditions. Second, awareness of current rates does not guarantee more accurate forecasts of future policy. Even uninformed households were not systematically worse at predicting interest rates five years ahead, suggesting that long-term expectations are shaped by broader narratives rather than short-term information. Third, we find important heterogeneity, that is, higher income households are more likely to know the policy rate, and households with higher debt burdens are more attentive and forecast more precisely. Despite these differences, most respondents systematically overestimate both current and future policy rates, revealing a persistent upward bias. Fourth, our IV-Lasso results show a bidirectional link between SMV and MPU. Increases in perceived stock market volatility are associated with higher reported policy uncertainty, although the effect is modest. By contrast, increases in policy uncertainty have a large effect on perceived stock market volatility, with coefficients around seven, indicating a strong spillover from monetary to financial domains.

The implications are significant. If households are often misinformed or biased about monetary policy, the effectiveness of forward guidance is limited. The strong effect of MPU on SMV indicates that uncertainty around central bank actions is an important driver of financial risk perceptions. Clear and credible communication therefore becomes a central tool for policymakers. Improving outreach, tailoring messages to different household groups, and addressing biases could enhance the transmission of monetary policy. Financial literacy initiatives may also help households better interpret policy signals and distinguish between temporary financial shocks and long-term changes.

However, like any survey-based analysis, the results face limitations. Item non-response and do not know answers reduce sample size, although we addressed this with missingness dummies. The effects we estimate are statistically robust but economically modest in the SMV to MPU direction, which cautions against overinterpreting their magnitude. Our measures are also subjective, capturing perceptions rather than realised volatility or uncertainty.

Future research could extend this work in several directions. Linking household expectations to actual financial behaviour such as savings or portfolio choices would provide evidence on the transmission of uncertainty into real outcomes. Comparing across countries would show whether these patterns are unique to France or general across Europe. Methodologically, combining survey data with high-frequency financial market indicators could refine identification and improve external validity.

In conclusion, this chapter provides new micro-level evidence on how households perceive monetary and financial uncertainty. The results show that monetary policy uncertainty strongly influences perceived stock market volatility, while stock market volatility has a weaker but still significant effect on policy uncertainty. These findings show the importance of expectation formation for monetary policy effectiveness and point to communication and education as central tools for reducing uncertainty and supporting stable financial behaviour. Building on this evidence, the next chapter turns to the perception gap and tests whether French households form expectations in line with the rational expectations benchmark used by central banks.

Chapter 4

Perception VS Reality: Monetary Policy, Rational Expectations and Perception Gaps

4.1 Introduction

Subjective expectations are central to modern macroeconomics, serving as the cornerstone of many theoretical models and a key driver of household and firm behaviour. They also play a significant role in influencing and shaping the economic decisions of households and firms, such as their saving and spending decisions. Furthermore, other than consumption and spending decisions, subjective expectations, for example, on inflation, also influence economic decisions such as wage bargaining and investment decisions(Bernanke, 2007). As such it is crucial for central banks to control and manage these expectations in order to help inform and guide their monetary policy decisions and achieve their objectives. However, the effectiveness of monetary policy is dependent not only on subjective inflation expectations but also on subjective monetary policy rate expectations. If households and firms expect policy rates to increase in the future, they are likely to anticipate that inflation will also increase, and therefore affect their current economic decisions. This is also evidenced by Coibion et al. (2023), who shows that inflation expectations as well as interest expectations move together, that is, consumers update their interest rate and inflation rate expectations jointly. They save more to earn higher returns in the future, spend less to avoid paying back high interest on loans thus reducing borrowing costs, and firms might even retrench employees and reduce investment in anticipation of future inflation and possible monetary actions that the central bank might take. Lower expected policy rates might therefore lead to increased borrowing and investment, while higher expected rates might lead to reduced spending and investment. Therefore, by influencing policy expectations, central banks thereby shape economic behaviour by influencing borrowing costs, investment, employment, production levels, and price-setting.

Most of the research on subjective expectations has been based on inflation expectations with scarce research on policy rate expectations. However, policy rate expectations are important as they could help guide monetary policy in the form of forward guidance. Forward guidance[1] is a monetary policy tool that central banks use to control inflation and keep the economy stable by providing information about the likely path of future monetary policy rates. This helps reduce monetary policy uncertainty and lead to effective monetary policy by influencing the financial and economic decisions of firms and households through their policy rate expectations.

Historically, expectations were often treated as a theoretical construct rather than something observable in data. Early macroeconomic models relied on adaptive expectations, and even after Muth (1961) introduced the rational expectations hypothesis and Lucas Jr (1976) popularised it, many researchers dismissed survey data as unreliable or meaningless (Prescott, 1977). As a result, theory dominated and empirical tests of expectations were neglected for a long time. This changed with contributions such as Lovell (1986), who argued that subjective expectations can be measured and tested, opening the door for later survey-based research. Following this shift, a large body of empirical work has tested the rational expectations hypothesis using survey data, particularly in the context of inflation. For example, Carroll (2003) develops a sticky-information model showing that households adjust their inflation expectations gradually rather than instantaneously, leading to systematic deviations from rational expectations. Similarly, Coibion and Gorodnichenko (2015) find that household forecast errors for inflation are predictable, directly rejecting the FIRE assumption. More recent studies such as Bordalo et al. (2020) argue that households overreact to certain signals, while Weber et al. (2022) document substantial heterogeneity and bias across individuals in inflation expectations. As such, this body of research shows that subjective expectations are measurable and meaningful but often deviate from the rational expectations benchmark. Despite this growing evidence, most of the empirical focus remains on inflation expectations, with far less work on policy rate expectations. This literature gap matters because policy rate expectations are central to forward guidance. If

[1] See What is Forward Guidance and The importance of Forward Guidance

households misperceive the current or future path of policy rates, their saving, borrowing, and consumption decisions may diverge from the predictions of standard macroeconomic models that assume rational expectations, thus weakening the transmission of monetary policy. Therefore, whilst FIRE has been widely examined in the context of inflation expectations using survey data, subjective policy rate expectations remain relatively underexplored. There is therefore a gap in the literature on household policy rate expectations, and this chapter aims to address this gap.

As such, despite the central role of interest rate expectations in monetary transmission, very little is known about how households actually perceive and forecast policy rates. Understanding whether their expectations satisfy the rational expectations benchmark is crucial, since any systematic bias could weaken the effectiveness of forward guidance. Although central banks rely on policy rate expectations to transmit forward guidance, the household level evidence on whether these expectations satisfy FIRE remains scarce. Given that policy rates are the direct object of central bank forward guidance, addressing this gap is critical for both economic theory and the design of monetary policy communication. This paper therefore asks whether household policy rate expectations conform to the Full Information Rational Expectations (FIRE) assumption. Specifically, it investigates (i) whether systematic perception gaps and forecast errors exist, (ii) what household characteristics explain these deviations, and (iii) how such deviations shape saving and borrowing behaviour. To answer these questions, we focus on monetary policy rate expectations obtained from French households in 2015 and determine whether they conform to the FIRE assumption. Theoretically the FIRE assumption should hold. Therefore, if FIRE holds, then we assume that the policy rate perception gap should be non-existent as households use all the information available to them and keep updating their perception of current rates as they receive more information. As a result, well informed households are expected to have no perception gaps and their policy rate forecast errors should also be non-existent and equal to zero. To test this, we combine regression analysis of forecast errors on perception gaps with distributional tests of whether the perception gap equals zero and find evidence against the FIRE paradigm. The results indicate that French households misperceive current policy rates as set by the European Central Bank and make systematic forecast errors. This might be because households use limited information from their local environments rather than all the available aggregate information in the economy (D'Acunto and Weber, 2024) to form expectations thereby leading to an overestimation of future policy rates. This finding is in line with Andrade et al. (2023) who notes that French households overestimate future inflation when using survey data collected between 2004 and 2018. In the second part of this paper, we investigate the possible determinant for the policy rate perception gap amongst households in France and find that it is influenced by household socio economic factors such as income levels and literacy. The FIRE assumption postulates that households should make the same economic decisions when a similar policy is applied but, households in reality, tend to make varying economic decisions under a similar policy change. Since we have established that a perception gap exists and that forecast errors also exist, we further examine whether policy rate forecast errors can explain this puzzle of heterogeneous household economic decision making. We find that policy rate forecast errors influence consumption and saving decisions across French households. As such, this paper contributes to literature in three ways. First, it provides a micro level test of FIRE using household policy rate expectations, extending the literature beyond the dominant focus on inflation expectations. Second, it identifies the socioeconomic factors that explain systematic perception gaps across households. Third, it links these gaps to saving and consumption decisions, thereby linking what households believe about policy rates to the financial choices they make. By so doing, we therefore address an important gap in the expectations literature, which has largely focused on inflation, and contributes findings that can guide how we think about the communication and effectiveness of forward guidance. Lastly, we discuss the policy implications of this deviation from the FIRE assumption and conclude that policy makers using forward guidance should take into consideration subjective household policy rate expectations when using forward guidance as a monetary policy tool. If they assume that households are rational, make the same economic decisions and use all the information available to them then their monetary policy is likely to be ineffective. Therefore, clear, transparent, and targeted communication is necessary if forward guidance is to serve as an effective monetary policy tool. The rest of the paper is organised as follows: Section 4.2 illustrates the data and descriptive statistics, Section 4.3 details the empirical strategy. Section 4.4 tests whether FIRE holds by showing that policy rate perception gaps and forecast errors exist. Section 4.5 focuses on explaining this perception gap. Section 4.6 discusses whether the policy rate forecast error can help explain household economic decision making and Section 4.7 discusses the policy implications that policymakers face due to expected policy rates deviating from the FIRE assumption. Finally, Section 4.8 concludes.

4.2 Data and Descriptive Statistics

The data used in this chapter come from the French household survey conducted in 2015, which elicits households' perceptions of current interest rates as well as their expectations of future rates. The survey also contains information on household socio-economic characteristics, including income, education, and age, which are used later to study the determinants of perception gaps. The sample size contained 2587 respondents. As with most household surveys, we also faced the issue of item non-responsiveness as some respondents either did not answer all the survey questions or they filled the questionnaire incorrectly. For example, only 846 households answered the perceived policy rate (E6a) question in comparison to 681 French households who answered the question on the five-year-ahead expectations (E6b). Although some respondents were non-responsive, we still had a large sample size that responded to the questionnaire and hence the data was sufficient to support our empirical analysis.

As such, the results in this chapter should be interpreted with caution given the limitations of the survey data. As discussed in Chapter 3, some responses display low precision and partial completion rates, which can introduce measurement noise into the constructed variables. Our analysis therefore focuses on identifying consistent patterns across specifications rather than making strong causal claims and the estimated relationships should be interpreted as conditional correlations rather than structural effects. Despite these limitations, the correlations are informative about how households perceive and process policy information and how these perceptions relate to observable economic behaviours. The consistency of the results across OLS, median regression, and PDS Lasso estimators increases confidence that the patterns reflect genuine relationships rather than random variation.

The key variables used in our analysis are constructed as follows. Firstly, the *perception gap* (PG) is defined as the difference between household i's perceived current policy rate at time t and the actual policy rate set by the European Central Bank at the same time:

$$PG_{i,t} = \hat{r}_{i,t} - r_t.$$

Secondly, the *forecast error* (FE) is defined as the difference between the household's expected policy rate five years ahead and the realized policy rate at that horizon:

$$FE_{i,t+5} = E_{i,t}(r_{t+5}) - r_{t+5}.$$

By construction, under the FIRE assumption both the perception gap and forecast error should be zero. To visualise the extent of misperceptions, Figure 4.1 plots the distribution of the perception gap. Under the FIRE benchmark, all mass would be concentrated at zero, but instead, the distribution is shifted to the right with a median of 1pp, confirming that households systematically overestimate the policy rate. This visual evidence motivates our analysis by showing that households systematically misperceive the policy rate, a clear departure from the full information rational expectations benchmark. This pattern is consistent with existing empirical evidence. For example, Coibion and Gorodnichenko (2015) document similar positive perception gaps for inflation among New Zealand firms, indicating that upward-biased beliefs are a common feature of survey expectations rather than an anomaly of this dataset.

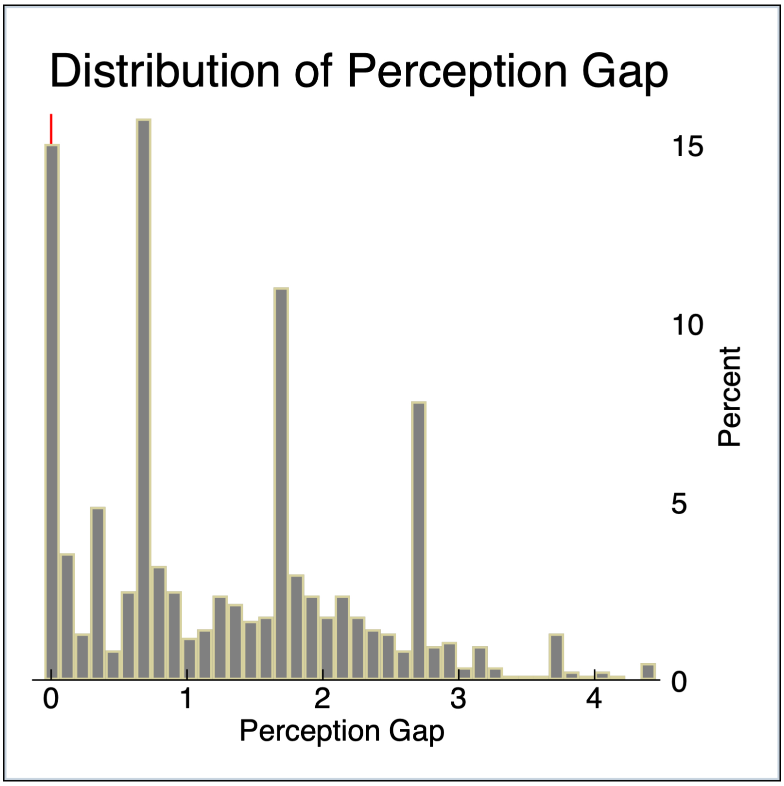


FIGURE 4.1: Distribution of the perception gap (PG). The dashed line indicates the FIRE benchmark of zero.

Notes: This figure plots the distribution of the perception gap (PG) across respondents. The dashed vertical line marks the full-information rational expectations (FIRE) benchmark of zero. The PG distribution is concentrated to the right of zero, with only a small number of observations taking slightly negative values (minimum PG = –0.05).

Table 4.1 reports descriptive statistics for the key variables. Both the perception gap (PG) and forecast error (FE) are positive on average and widely dispersed, inconsistent with the FIRE benchmark of zero. For example, the median PG is 1pp (IQR [0.46, 1.90]) and the median FE is 1.5pp (IQR [0.75, 2.25]). Although expectation formation under full information rational expectations assumes households are well informed about policy rates, this is not the case for French households on average. The table also indicates that the sample is balanced by gender, with an average age group between 45–65. The mean income group is 2.25 (equivalent to €12k–20k), and average assets correspond to the €75k–225k bracket. Furthermore, the table indicates that education is relatively high amongst French households, with the average household having completed "High School". Lastly, the table also shows that around 69% of households report having savings and 40% have debt, providing us with a basis for testing how policy rate misperceptions affect financial behaviour. Having established that perception gaps and forecast errors exist in the raw data, we now formally test whether French households' expectations conform to the Full Information Rational Expectations (FIRE) assumption.

TABLE 4.1: Descriptive Statistics: Core Outcomes and Household Characteristics

Variable	Mean	SD	p25	Median	p75	N
Core Outcomes						
Perception gap	1.26	1.02	0.46	1.00	1.90	846
Forecast error	1.58	1.03	0.75	1.50	2.25	681
Perceived policy rate (E6a)	1.56	1.02	0.76	1.30	2.20	846
Expected policy rate in 5y (E6b)	1.83	1.03	1.00	1.75	2.50	681
Has savings	0.69	0.46	0.00	1.00	1.00	2,477
Has debt	0.40	0.49	0.00	0.00	1.00	2,548
Demographics						
Male	0.47	0.50	0	0	1	2,587
Income group	2.25	1.04	1	2	3	2,543
Assets category	2.27	1.00	1	2	3	2,182
Employment status	3.09	0.98	2	3	4	2,587
Education level	3.13	0.84	3	3	4	2,587
Age group	2.81	1.06	2	3	4	2,587

Notes: Perception gaps (PG), forecast errors (FE), and policy rate variables (E6a, E6b) are expressed in percentage points. Binary variables (e.g. Male, Has savings, Has debt) are reported as population shares. Ordered categorical variables are coded as follows: Income (1 $\leq$12k; 2=12–20k; 3=20–30k; 4 $\geq$30k); Assets (1 $\leq$75k; 2=75–225k; 3=225–450k; 4 $\geq$450k); Employment (1=Unemployed; 2=Inactive/Other; 3=Employed; 4=Retired); Education (1=Primary or below; 2=High school; 3=Technical/Professional; 4=College or higher); Age (1 $<$35; 2=35–44; 3=45–65; 4=80+). Sample sizes vary across rows due to item nonresponse.

4.3 Empirical Strategy and Model

The central empirical question is whether French households form expectations consistent with the Full Information Rational Expectations (FIRE) benchmark.

As discussed in the previous section, FIRE implies that both the perception gap (PG) and the forecast error (FE) should be zero, and in particular that the perception of current policy rates should not systematically predict forecast errors.

To test this hypothesis, we estimate the following baseline regression:

$$FE_{i,t+5} = \alpha + \beta PG_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t}. \tag{4.1}$$

where $FE_{i,t+5}$ is household i's forecast error for the policy rate five years ahead, $PG_{i,t}$ is the perception gap at time t, and $X_{i,t}$ is a vector of household socio-economic controls such as income, assets, education, employment, and age.

Formally, the regression allows us to test the joint null hypothesis implied by FIRE:

$$H_0 : \alpha = 0 \text{ and } \beta = 0,$$

which states that households make no systematic forecast errors (intercept = 0) and that forecast errors are unrelated to perception gaps (slope = 0).

The alternative hypothesis is:

$$H_1 : \alpha \neq 0 \text{ or } \beta \neq 0,$$

which implies that households either exhibit a systematic bias in forecasts, or that misperceptions of current policy rates translate into biased forecasts of future rates, or both.

In our empirical analysis, we reject both restrictions, providing strong evidence against full-information rational expectations (FIRE). In addition to the regression-based test, we also perform distributional tests directly on the perception gap. The corresponding null hypotheses are that the mean of the perception gap equals zero, the median of the perception gap equals zero, and that the distribution of the perception gap is equal to zero. The alternative hypotheses are that the mean of the perception gap is not equal to zero, the median of the perception gap is not equal to zero, or that the distribution of the perception gap is not equal to zero.

These tests are implemented using a t-test (for the mean), a Wilcoxon sign-rank test (for the median), and a Kolmogorov–Smirnov test (for the distribution).

We begin with simple OLS estimates of α and β, which capture the average relationship between PG and FE. However, OLS estimates may be sensitive to

outliers in forecast errors, so we also estimate median regressions, which are robust to skewness and provide the conditional effect for the typical household.
A limitation of both OLS and median regressions is that they rely on a small, pre-specified set of controls. In reality, household survey data contain a large number of potentially relevant socio-economic variables, and omitting some of these may bias our estimates. To address this, we employ the Post-Double Selection (PDS) Lasso method of Belloni et al. (2014). This approach uses Lasso regressions in two stages: first, selecting variables that predict PG; second, selecting variables that predict FE. The union of selected variables forms the control set in the final regression of FE on PG.
The advantage of PDS-Lasso is that it allows us to control flexibly for a very high-dimensional set of household characteristics without overfitting, while maintaining valid inference on β. In this way, PDS-Lasso provides a robustness check that our results are not driven by omitted variable bias or arbitrary control selection.
These three approaches (OLS, median regression, and PDS-Lasso) therefore provide a comprehensive framework to test FIRE. If both α and β are significantly different from zero across specifications, we reject the null of FIRE and conclude that household policy rate expectations systematically deviate from the full information rational expectations benchmark. The analysis rejects the strict version of the Full Information Rational Expectations (FIRE) benchmark, but this result should be interpreted carefully. In this setting, rationality means that expectations are correct on average given the information available at the time, not that every forecast is exact. The positive perception gaps indicate that households tended to overestimate future policy rates, reflecting incomplete information and limited attention rather than behavioural irrationality. Forecast errors of this size are not unusual. Even professional forecasters miss policy outcomes when large unanticipated events occur, and the sample period ending in 2020 includes such shocks, making long horizon predictions particularly difficult. What this result shows is that many households form expectations with persistent information frictions that differ systematically across groups, rather than that people behave irrationally.

4.4 Does the Full Rational Expectations (FIRE) assumption hold?

Lucas Jr (1972) argued against the use of adaptive expectations in macroeconomic models and later advocated for models that assumed rational expectations in lieu of adaptive expectations. This assumption has now become the cornerstone of modern macroeconomic models. The FIRE assumption postulates that all household subjective expectations are homogeneous and that they make use of all available information.

More recently, models under FIRE have come under scepticism. Recent literature shows that micro-level expectations, more specifically, inflation expectations elicited from survey data, do not conform to the rational expectations hypothesis (Hori and Kawagoe, 2013; Coibion et al., 2018). However, this research is mainly based on inflation expectations and scarce research has tested whether this assumption holds in monetary policy rate expectations.

In the previous chapter, we documented descriptive evidence that French households deviate systematically from FIRE when forming their policy rate expectations. In this section, we therefore move from descriptive patterns to formal statistical tests of the FIRE assumption.

To investigate whether FIRE holds, we study whether policy rate perception gaps exist in French households. If households are fully informed about current policy rates, they should form accurate perceptions and expectations that are consistent with realized policy rates. That is, under FIRE, both forecast errors and perception gaps should be zero.

We therefore test whether forecast errors are related to perception gaps using Equation (4.1). Under FIRE, there should be no systematic bias when $PG = 0$ ($\alpha = 0$) and there should be no link between misperceptions today and forecast errors tomorrow ($\beta = 0$). Rejecting this condition implies that FIRE does not hold.

Table 4.2 presents estimates of the regression of forecast errors on perception gaps. The full regression outputs, including all control variables, are reported in Appendix C, Table C.1. Across OLS and median regression specifications, the coefficient on PG is positive and highly significant. This implies that households who overestimate the current policy rate also make proportionally larger forecast errors about future rates. The constant term is also significantly different from zero, indicating systematic bias even when $PG = 0$. The median regression further confirms that the rejection of FIRE is not driven by outliers. The effect of perception gaps on forecast errors remains strong and significant even at the median of the distribution, implying that the typical French household also misperceives policy rates and carries these misperceptions into their expectations of future rates. The constant term (α) is also significantly different from zero in both specifications, rejecting the hypothesis of unbiased forecasts.

In addition, the joint F-test of $\alpha = \beta = 0$ is strongly rejected, providing evidence against the FIRE assumption. For robustness, Column (3) reports estimates using the Post-Double Selection Lasso (PDS Lasso). This method accounts for the high dimensional set of controls in the survey and selects only the most relevant covariates in a data-driven way. The estimated coefficient on PG remains virtually unchanged (0.64) and highly significant, while the joint test of $\alpha = \beta = 0$ is again rejected. This robustness check confirms that the rejection of FIRE is not due to model specification or omitted variable bias.

TABLE 4.2: Regression of Forecast Errors on Perception Gaps

	(1) OLS	(2) Median Reg.	(3) PDS Lasso
Perception Gap (PG)	0.640***	0.733***	0.637***
	(0.041)	(0.036)	(0.035)
Constant (α)	0.700**	0.360	0.746***
	(0.314)	(0.292)	(0.075)
Controls	Yes	Yes	Lasso-selected
Observations	626	626	626
R^2 / Pseudo R^2	0.393	0.299	0.372
Joint test $\alpha = \beta = 0$	F=147.72	F=224.65	χ^2=1502.62
p-value	0.000	0.000	0.000

Notes: This table reports estimates from regressions of forecast errors on the perception gap. Column (1) presents OLS estimates with robust standard errors, column (2) reports median (quantile) regression estimates with bootstrap standard errors, and column (3) shows Post-Double-Selection Lasso estimates with valid standard errors. All specifications include the full set of controls, with Lasso selecting the relevant covariates in column (3). Significance levels are indicated by *** $p < 0.01$ and ** $p < 0.05$.

We also test whether the perception gap distribution is centred at zero. Table 4.3 reports results from the mean, median, and distributional tests. All three tests strongly reject the FIRE null at the 1% level. Households are therefore not fully informed about the policy rate, and these misperceptions carry through into their expectations of future rates. This pattern holds at the mean, the median, and across the full distribution. As such, we therefore reject the FIRE assumption for French households and conclude that French households are neither perfectly informed about the current policy rate nor able to form unbiased forecasts about its future path.

Since we have established that perception gaps exist for French households, in the next section we explore the determinants of these perception gaps in order to understand which household characteristics are linked to being more or less informed about the policy rate.

TABLE 4.3: Distributional Tests of Perception Gaps (PG)

Test	Statistic	p-value
t-test (mean = 0)	35.81	0.000
Sign-rank (median = 0)	24.12	0.000
Kolmogorov–Smirnov (distribution = 0)	1.000	0.000

Notes: This table reports distributional tests of the perception gap (PG). The t-test evaluates whether the mean PG equals zero, the Wilcoxon sign-rank test assesses whether the median equals zero, and the Kolmogorov–Smirnov test compares the empirical distribution of PG to a point mass at zero. In all cases, the null hypothesis of full information rational expectations is rejected at the 1% level.

4.5 What drives the perception gap

The previous sections documented, using both descriptive statistics and formal distributional tests, that French households systematically misperceive the policy rate, and thus rejecting the FIRE hypothesis. Whilst the FIRE paradigm implies homogenous expectations, the data reveals substantial heterogeneity in perception gaps across households. This is in line with literature, for example, D'Acunto et al. (2023), who argues that most households in advanced economies rarely pay attention to economic indicators such as inflation and policy rates and are such, this limited attention could lead to systematic perception gaps. The evidence from the previous section shows that this also holds true for French households, on average, they are not well informed about the current policy rate and therefore form inaccurate expectations of future rates. This motivates an analysis of what drives this gap and which household characteristics are associated with larger or smaller perception gaps.

To investigate this, we estimate regressions of PG on a set of socio-economic variables, including income, assets, education, employment status, age, and gender. The general specification is:

$$PG_{i,t} = \alpha + \delta' Z_{i,t} + \varepsilon_{i,t}, \tag{4.2}$$

where $Z_{i,t}$ is a vector of household characteristics. We report results from both OLS and median regressions to capture average and median effects. Median regression is less sensitive to outliers and therefore useful given the skew in PG.

This analysis helps us to understand which households are most likely to misperceive policy rates. Therefore, identifying these groups provides evidence on the sources of deviation from FIRE and lays the groundwork for discussing the role of communication in reducing such gaps.

TABLE 4.4: Determinants of the Perception Gap

	(1) OLS	(2) Median	(3) PDS-Lasso
Male (Gender)	-0.285***	-0.431***	-0.275***
	(0.074)	(0.113)	(0.071)
Income 12–19k	0.142	0.331*	
	(0.130)	(0.194)	
Income 20–29k	0.087	0.031	
	(0.128)	(0.182)	
Income $\geq$30k	-0.294**	-0.350*	-0.369***
	(0.125)	(0.196)	(0.080)
Assets 75–224k	-0.198*	-0.025	
	(0.117)	(0.169)	
Assets 225–449k	-0.185	0.056	
	(0.120)	(0.172)	
Assets $\geq$450k	-0.410***	-0.300	-0.258***
	(0.123)	(0.191)	(0.084)
Retired	-0.265	0.150	
	(0.235)	(0.341)	
Unemployed	-0.277	0.056	-0.159
	(0.210)	(0.326)	(0.122)
Employed	-0.086	0.169	
	(0.201)	(0.276)	
High School	0.287	0.481	
	(0.269)	(0.393)	
Technical/Professional	-0.083	0.100	
	(0.211)	(0.308)	
College or more	-0.482**	-0.319	-0.353***
	(0.216)	(0.315)	(0.070)
Age 35–44	0.162	0.281	
	(0.125)	(0.188)	
Age 45–65	0.092	0.200	
	(0.127)	(0.191)	
Age 80+	0.047	0.000	
	(0.171)	(0.279)	
Specialist media (N/A)			0.299***
			(0.088)
Constant	1.972***	1.275**	1.705***
	(0.305)	(0.448)	(0.074)
Observations	793	793	793
R^2 / Pseudo R^2	0.151	0.111	–

Notes: This table reports regressions of the perception gap on demographic and socio-economic characteristics. Column (1) presents OLS estimates with robust standard errors, column (2) reports median regression estimates with bootstrap standard errors, and column (3) shows Post-Double-Selection Lasso estimates with valid standard errors. Income, assets, education, employment status, and age groups are included as categorical indicators, with omitted categories serving as reference groups. The Lasso specification selects the covariates retained in column (3). Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4.4 reports estimates of Equation (4.2) using OLS, median regression, and PDS-Lasso. Across specifications, several socio-economic characteristics are strongly correlated with the perception gap. Men consistently report lower perception gaps than women. Higher income and wealth are also associated with smaller gaps, with households earning over €30,000 or holding more than €450,000 in assets showing significantly lower misperceptions. Education plays a similar role, households with a college degree or more have smaller perception gaps than those with only primary education.

By contrast, employment status and age show no systematic association with the perception gap.

The robustness check using PDS Lasso confirms these patterns. Gender, income, assets, and education remain significant predictors when controlling for a high dimensional set of survey covariates. In addition, households who reported not consulting specialist media have significantly larger perception gaps. This suggests that limited exposure to financial information sources contributes to systematic misperceptions. Our results, therefore show that misperceptions of the policy rate are concentrated amongst women, lower income, less wealthy, and less educated households, as well as those with limited use of specialist financial media.

Overall, the magnitude of these effects is meaningful. For instance, the coefficient on college education implies a reduction in PG of about 0.35 percentage points (pp), which is sizable relative to the mean gap. Likewise, the income and asset coefficients suggest that financially better-off households are substantially more informed. These results fit well with theories of limited attention and financial literacy: households with more resources and education have both stronger incentives and better capacity to track monetary policy. In contrast, those who report not consulting specialist media appear more detached from financial information flows, which explains their larger gaps. The determinants section therefore highlights that systematic misperceptions are concentrated among specific groups, providing a natural link to our later discussion of behavioural consequences and policy communication.

In terms of economic magnitude, we can see that these effects are meaningful. For example, the coefficient on college education reduces the perception gap by around 0.35pp, which amounts to roughly one quarter of the mean gap of 1.2pp. Likewise, the effect of high income (-0.37pp) and high assets (-0.26 pp) suggests that financially better-off households are substantially more informed. These results fit well with theories of limited attention and financial literacy, that is, households with more resources and education have both stronger incentives and better capacity to track monetary policy. The absence of significant effects for age and employment status also merits discussion. It suggests that once income, wealth, and education are accounted for, differences in age or employment do independently affect how French households perceive the policy rate and therefore do not independently shape the perceptions of monetary policy rates in France. This finding is consistent with rational inattention models, which emphasize resources and cognitive capacity rather than demographic characteristics as the main drivers of expectation heterogeneity (Sims, 2003)[2]. Recent household level evidence also supports this view, showing that limited attention and financial literacy, rather than age or employment status, explain systematic gaps in expectations (D'Acunto et al., 2023)[3]

We also find that French households that report not consulting specialist media appear more detached from financial information flows, which helps explain their larger gaps. The positive association with not consulting specialist media is related to the limited attention interpretation. Rather than specialist media improving knowledge, those who mark "N/A" (do not consult) are particularly disengaged and do not follow specialised media that discuss monetary policy, which as a result, might lead to larger misperceptions. This result is consistent with evidence that selective exposure to information sources plays a critical role in expectation formation (D'Acunto et al., 2023; Carroll, 2003; Coibion and Gorodnichenko, 2015).

In conclusion, our results are not only statistically significant but also economically meaningful. They indicate that misperceptions of the policy rate for French households are concentrated among women, lower income, less wealthy, and less educated households, as well as within those that do not consult specialist financial media. On the other hand, having higher income, greater wealth, or a college education reduces the perception gap by around 0.3 to 0.4pp, which corresponds to roughly 20–30% of the average perception gap. This heterogeneity thereby provides a foundation for the next section, where we examine the behavioural consequences of these perception gaps for French households on their saving and borrowing decisions.

4.6 Does the policy rate forecast error influence household making decisions?

In the previous section we showed that perception gaps are systematically related to household characteristics, with larger gaps concentrated among women, lower income, less wealthy, and less educated households. We now turn to the behavioural consequences of these gaps. This step links back to

[2](Sims, 2003) develop the concept of rational inattention, where economic agents optimally allocate limited attention across information sources. Because processing information is costly, households choose to focus selectively, which generates systematic expectation errors.

[3](D'Acunto et al., 2023) provide household-level survey evidence showing that most households devote little attention to macroeconomic indicators such as inflation and policy rates. This limited attention explains why socioeconomic resources and financial literacy, rather than age or employment status, drive heterogeneity in expectations.

Chapter 4.4 and Chapter 4.5, and connects our evidence to the wider literature on how monetary policy expectations shape household financial behaviour (Carroll, 2003; Coibion et al., 2018; D'Acunto et al., 2023).

The theory of full rational expectations assumes that economic agents use all the information that is available to them to make important economic decisions. Lucas Jr (1972) advocated for this model where he argued for the use of equilibrium models that assumes economic agents have rational expectations in lieu of economic models that used adaptive expectations. Most central banks have even adopted the use of FIRE based models.[4] In terms of monetary policy rates, FIRE assumes economic agents have subjective homogenous expectations of future monetary policy rates. Therefore, under FIRE, we cannot explain household saving, investment and debt decisions as it is assumed that all households have the same expectations of monetary policy rates five years ahead in time and therefore make the same economic decisions. However, the French household survey data has indicated that the FIRE assumption does not hold. Households may not have access to full information about monetary policy rates or make household decisions such as saving, and investment based on rationality. Since monetary policy expectations five years ahead are heterogenous and the FIRE assumption does not hold, a forecast error must therefore exist. Since Forecast errors are non-zero, households' expectations about monetary policy rates could explain why some households save, invest or have more debt than others at a point in time.

Savings

In this section, we investigate whether monetary policy rate absolute forecast error and perception gaps influence household decision making, particularly French households' saving behaviour. This analysis follows from the previous section, having established that many households misperceive the policy rate, we now ask whether these misperceptions translate into observable financial behaviour.

We begin with savings. Question E11 of the TNS survey asked respondents whether they had saved money in the last 12 months, and if so, how much (in seven ordered categories ranging from "none" to "more than €10,000"). To study

[4]Most central banks use FIRE-based models such as Fischer (1977), Taylor (1977), Calvo (1983), and Lucas Jr (1972, 1976) instead of Keynesian economic models such as Phillips (1958) and Samuelson and Solow (1960).

the effect of perception gaps (PG) and forecast errors (FE) on these outcomes, we estimate ordered logit models of the form:

$$y_i^{S*} = \beta D_i + \gamma' X_i + \varepsilon_i, \qquad \varepsilon_i \sim \text{logistic}(0,1), \tag{4.3}$$

where y_i^S is the observed savings band, $D_i \in \{PG_i, FE_i\}$, and X_i is the set of household controls. The observed categories are defined by cut points κ_k such that

$$y_i^S = k \quad \Longleftrightarrow \quad \kappa_k < y_i^{S*} \leq \kappa_{k+1}.$$

The probability of being in savings band k is

$$\text{Pr}(y_i^S = k \mid X_i, D_i) = \Lambda(\kappa_{k+1} - \eta_i) - \Lambda(\kappa_k - \eta_i), \tag{4.4}$$

where $\eta_i = \beta D_i + \gamma' X_i$ and $\Lambda(\cdot)$ is the logistic cdf. Average marginal effects (AMEs) are then calculated as

$$AME_k(D) = \frac{1}{N} \sum_{i=1}^{N} \beta \{\lambda(\kappa_k - \eta_i) - \lambda(\kappa_{k+1} - \eta_i)\}, \tag{4.5}$$

with $\lambda(\cdot)$ the logistic pdf.

This setup allows us to interpret the coefficients as shifts in the underlying savings index, while the AMEs translate these shifts into economically meaningful changes in the probability of being in a particular savings band. In other words, the AMEs show how much more (or less) likely a household is to be in “low” versus “high” savings categories when PG or FE increases by one percentage point.

Table 4.5 shows that perception gaps are strongly and negatively associated with household saving. A one percentage point increase in PG reduces the probability of being in higher savings bands by around 2.5 percentage points, with a corresponding increase in the probability of being in lower bands. By contrast, FE is not significantly related to saving behaviour.

The marginal effects reported in Table 4.6 provide further detail. Households with larger misperceptions (higher PG) are more likely to report no or very low savings (bands 1–3) and less likely to report high savings (bands 5–7). For example, moving PG up by one percentage point raises the probability of being in the lowest savings band (“none”) by about 1.7 percentage points and reduces the probability of being in the highest band (“more than €10,000”) by around 0.8–0.9 percentage points. These shifts are non-trivial given the mean PG of about 1.2pp.

TABLE 4.5: Perception Gaps, Forecast Errors, and Household Savings (Ordered Logit)

	Perception Gap (PG)		Forecast Error (FE)	
	All HHs	Excl. Voluntary Zeros	All HHs	Excl. Voluntary Zeros
Perception Gap (PG)	-0.122*	-0.138**		
	(0.070)	(0.071)		
Forecast Error (FE)			0.016	0.011
			(0.068)	(0.069)
Income: €12k–19,999	0.156	0.143	0.168	0.130
	(0.226)	(0.233)	(0.265)	(0.271)
Income: €20k–29,999	0.486**	0.513**	0.367	0.342
	(0.230)	(0.236)	(0.268)	(0.273)
Income $>$ €30k	0.949***	0.997***	0.846***	0.865***
	(0.245)	(0.250)	(0.274)	(0.276)
Assets €75k–224k	0.459**	0.440**	0.286	0.298
	(0.184)	(0.189)	(0.202)	(0.207)
Assets €225k–449k	0.943***	1.005***	0.962***	1.062***
	(0.195)	(0.201)	(0.215)	(0.221)
Assets $>$ €450k	1.795***	1.970***	1.812***	1.965***
	(0.260)	(0.264)	(0.287)	(0.291)
Employment: Retired	-0.689	-0.783*	-0.750	-0.786
	(0.440)	(0.453)	(0.498)	(0.508)
Employment: Unemployed	-0.297	-0.191	-0.459	-0.321
	(0.426)	(0.433)	(0.473)	(0.478)
Employment: Employed	0.070	0.089	-0.026	0.013
	(0.379)	(0.391)	(0.411)	(0.420)
Education: High School	-0.416	-0.025	-0.036	0.221
	(0.527)	(0.508)	(0.592)	(0.601)
Education: Tech/Prof	0.346	0.433	0.300	0.384
	(0.421)	(0.443)	(0.521)	(0.552)
Education: College+	0.683	0.746	0.788	0.864
	(0.434)	(0.456)	(0.534)	(0.565)
Age 35–44	-0.364*	-0.384*	-0.174	-0.193
	(0.204)	(0.208)	(0.227)	(0.230)
Age 45–65	-0.346	-0.395*	-0.173	-0.204
	(0.223)	(0.228)	(0.252)	(0.256)
Age 80+	-0.042	0.142	-0.106	0.033
	(0.339)	(0.339)	(0.381)	(0.380)
Observations	793	771	642	625
Pseudo R^2	0.063	0.069	0.064	0.068

Notes: Ordered logit estimates of household savings on absolute perception gaps (PG) and forecast errors (FE). Columns 2 and 4 exclude households who reported "chose not to save" (E12=2). All regressions include income, assets, employment, education, and age group dummies. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Importantly, the effect is heterogeneous across income groups. Among households earning under €12,000, the AME implies that a one percentage point increase in PG raises the likelihood of being in the lowest savings band by roughly 6.6 percentage points, showing that misperceptions matter most for already vulnerable households.

These findings are consistent with work showing that limited attention and misperceptions of policy rates can weaken the transmission of monetary policy through household saving decisions (Coibion et al., 2018; D'Acunto et al., 2023). These results are also consistent with evidence that households with lower

TABLE 4.6: Marginal Effects of Perception Gaps and Forecast Errors on Savings Bands

	Perception Gap (PG)		Forecast Error (FE)	
	All HHs	Excl. Voluntary Zeros	All HHs	Excl. Voluntary Zeros
Pr(Savings band = 1)	0.0169*	0.0176**	-0.0021	-0.0013
	(0.0097)	(0.0091)	(0.0091)	(0.0083)
Pr(Savings band = 2)	0.0038*	0.0048*	-0.0005	-0.0004
	(0.0022)	(0.0025)	(0.0023)	(0.0026)
Pr(Savings band = 3)	0.0037*	0.0046*	-0.0005	-0.0004
	(0.0022)	(0.0024)	(0.0022)	(0.0024)
Pr(Savings band = 4)	0.0008	0.0012	-0.0001	-0.0001
	(0.0006)	(0.0008)	(0.0006)	(0.0007)
Pr(Savings band = 5)	-0.0066*	-0.0071*	0.0008	0.0005
	(0.0038)	(0.0037)	(0.0034)	(0.0032)
Pr(Savings band = 6)	-0.0105*	-0.0118*	0.0013	0.0009
	(0.0061)	(0.0061)	(0.0058)	(0.0058)
Pr(Savings band = 7)	-0.0081*	-0.0093*	0.0011	0.0008
	(0.0047)	(0.0048)	(0.0049)	(0.0050)
Effect on Pr(Low savings, bands 1–3)	+0.025*	+0.027**	-0.003	-0.002
	(0.013)	(0.012)	(0.013)	(0.012)
Effect on Pr(High savings, bands 5–7)	-0.025*	-0.028**	+0.003	+0.002
	(0.013)	(0.012)	(0.013)	(0.012)
Observations	793	771	642	625

Notes: Table reports average marginal effects from ordered logit regressions of household savings bands . Columns 2 and 4 exclude households who reported "chose not to save" (E12=2). Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$. Positive (negative) values indicate that a higher PG or FE increases (decreases) the probability of being in that savings band. Summary rows group effects on lower savings (bands 1–3) and higher savings (bands 5–7).

income and less education are more likely to hold misperceptions and that their saving decisions are more sensitive to those misperceptions (Campbell, 2006; Lusardi and Mitchell, 2014).

Debt

We next consider household debt. Question E1 of the TNS survey asked whether respondents currently had any outstanding debt (yes/no). To test the effect of the absolute perception gap (PG) and the absolute forecast error (FE) on debt participation we estimate probit models of the form:

$$y_i^{D*} = \alpha + \beta D_i + \gamma' X_i + u_i, \qquad u_i \sim \mathcal{N}(0,1), \tag{4.6}$$

where $y_i^D = 1$ if the household has outstanding debt and 0 otherwise. The probability of debt is

$$\Pr(y_i^D = 1 \mid X_i, D_i) = \Phi(\alpha + \beta D_i + \gamma' X_i), \tag{4.7}$$

with $\Phi(\cdot)$ the standard normal cdf. The average marginal effect is

$$AME(D) = \frac{1}{N}\sum_{i=1}^{N} \beta\,\phi(\alpha + \beta D_i + \gamma' X_i), \tag{4.8}$$

where $\phi(\cdot)$ is the standard normal pdf.

This setup is directly comparable to the savings models, but with a binary outcome instead of ordered categories. The coefficient on PG or FE captures how misperceptions shift the latent probability of holding debt, while the AME translates this into the effect on the observed probability that a household has any outstanding debt.

Table 4.7 reports the results. We find that neither PG nor FE significantly predicts whether households hold debt. In fact, the average marginal effects are close to zero (–0.006 for PG and –0.013 for FE). However, this null effect is economically important. It suggests that while misperceptions of the policy rate are linked to savings behaviour, they do not meaningfully alter whether households participate in debt markets. The decision to hold debt appears instead to be dominated by structural balance sheet factors such as wealth and age. For example, households with higher assets are more likely to borrow, while older households are less likely to do so. This pattern is consistent with earlier findings in literature showing that borrowing behaviour is primarily shaped by income, wealth, and age (Carroll, 1996; Campbell, 2006).

The strong positive coefficients on higher asset groups in Table 4.7 further confirm that credit access and collateral matter much more for debt uptake than monetary policy perceptions. Conversely, the large negative coefficients for the 45–65 and 80+ age groups reflect life-cycle deleveraging, as older households are less likely to take on new debt, which is consistent with standard consumption–saving models. As such, the debt regressions show a key asymmetry, that perception gaps matter for savings but not for current debt. This finding fits with household finance models in which precautionary saving responds to beliefs about interest rates, while debt participation is governed by liquidity constraints, collateral, and life-cycle effects (Campbell, 2006; Lusardi and Mitchell, 2014; Carroll, 1996).

Lastly, Table 4.8 reports the average marginal effects from the logit models. The results show that a one-unit increase in either the perception gap or the forecast error changes the probability of holding debt by less than two percentage points, and the effects are statistically insignificant. In other words, misperceptions of monetary policy rates by French households does not

TABLE 4.7: Perception Gaps, Forecast Errors, and Household Debt (Logit)

	Perception Gap (PG)	Forecast Error (FE)
Perception Gap (PG)	-0.028	
	(0.083)	
Forecast Error (FE)		-0.064
		(0.096)
Income: €12k–19,999	-0.332	-0.268
	(0.287)	(0.335)
Income: €20k–29,999	-0.163	0.178
	(0.261)	(0.308)
Income $>$ €30k	0.309	0.434
	(0.283)	(0.318)
Assets €75k–224k	0.991***	1.176***
	(0.274)	(0.312)
Assets €225k–449k	1.134***	1.339***
	(0.284)	(0.325)
Assets $>$ €450k	1.298***	1.400***
	(0.328)	(0.365)
Employment: Retired	-0.238	-0.720
	(0.511)	(0.620)
Employment: Unemployed	-0.628	-0.876
	(0.494)	(0.606)
Employment: Employed	0.560	-0.055
	(0.409)	(0.519)
Education: High School	-1.087	-0.536
	(0.680)	(0.839)
Education: Tech/Prof	-0.534	0.357
	(0.492)	(0.627)
Education: College+	-0.575	0.269
	(0.501)	(0.633)
Age 35–44	-0.088	-0.165
	(0.268)	(0.302)
Age 45–65	-1.001***	-1.099***
	(0.277)	(0.314)
Age 80+	-1.606***	-1.620***
	(0.442)	(0.516)
Observations	793	642
Pseudo R^2	0.155	0.162

Notes: Logit estimates of household debt participation on absolute perception gaps (PG) and forecast errors (FE). Dependent variable is a binary indicator of whether the household reported current debt (yes/no). Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 4.8: Marginal Effects of Perception Gaps and Forecast Errors on Household Debt

	Perception Gap (PG)	Forecast Error (FE)
AME on Pr(Debt=1)	-0.0056	-0.0126
	(0.0165)	(0.0190)
Observations	793	642

Notes: Average marginal effects from logit regressions of debt incidence (E1: do you currently have debt = 1). All models include controls for income, assets, employment, education, and age group. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

meaningfully change the French households' likelihood of participating in debt markets once demographic and financial controls are taken into account.

4.7 Discussion

This chapter set out to test whether French households form expectations consistent with the Full Information Rational Expectations hypothesis. The evidence rejects this view. We find that French households misperceive the policy rate by about one percentage point on average, and these misperceptions predict forecast errors. In addition, distributional tests show that such biases are widespread across the population. In this way, the analysis extends recent work on expectation formation and household level perceptions (Candia et al., 2023; Bauer et al., 2024; D'Acunto et al., 2024). Against this background, it is also important to distinguish between misperceptions of the current policy rate and errors in expectations of future policy decisions. The current ECB rate is publicly observable at no cost, so misperceptions cannot be attributed to imperfect information in the usual sense. Instead, they likely arise from limited attention or imperfect recall, consistent with the framework of Azeredo da Silveira et al. (2024). These mechanisms complement, rather than replace, expectation-formation models such as sticky or noisy information, which relate to forecasts of future policy rates rather than perceptions of the current rate.

Turning to the determinants analysis, the results show clear social and economic patterns behind these misperceptions. Men, higher-income, wealthier, and more educated households report smaller gaps. By contrast, employment status and age play little role once resources and education are taken into account. This suggests that financial literacy and socioeconomic position are more important than employment status or age for accurate perceptions. These findings are consistent with Carroll (2003) and Lusardi and Mitchell (2014), who emphasise heterogeneity in information processing and financial literacy.

With respect to behavioural outcomes, the evidence is asymmetric. Perception gaps reduce the probability of being in higher savings bands. A one-percentage-point larger gap increases the likelihood of being in the lowest savings band by two to three percentage points, with stronger effects for low-income households. These effects are meaningful given that the average perception gap is around 1.2 percentage points. By contrast, forecast errors show no link with saving, and neither gaps nor errors are related to debt participation. In this case, average marginal effects for debt are close to zero, while income, assets, and age explain most of the variation in borrowing. These results are in line with life-cycle models of saving and borrowing (Carroll, 1996; Campbell, 2006) and with evidence that monetary policy communication shapes expectations more than behaviour (Coibion et al., 2018, 2022).

The asymmetric response between saving and debt behaviour can be interpreted through standard models of precautionary saving and liquidity constraints. When households perceive greater uncertainty about policy or future interest rates, they may increase savings as a buffer against possible income or rate shocks, a reaction consistent with precautionary-motive theory. Debt behaviour, however, tends to be more constrained by access to credit, collateral requirements, and existing loan contracts, which limits short-term adjustment to perceived policy uncertainty. This difference implies that saving is the more flexible margin through which households respond to uncertainty, while debt positions are slower to change. The pattern therefore fits with theories of liquidity frictions and heterogeneous financial flexibility across households (Vihriala, 2023; Cloyne et al., 2020; Fagereng et al., 2019).

All in all, the findings support a rational-inattention interpretation in that French households may ignore small errors in their perception of policy rates because these signals matter little for their immediate financial position. For lower income households, however, misperceptions can reduce saving in a way that is economically important. As such, the analysis shows the uneven transmission of policy information across French households. In the next section, we turn to the policy implications that follow from these findings.

4.8 Monetary Policy Implications

Central banks rely on monetary policy to stabilise inflation, employment, and output. They use a range of instruments including open market operations, quantitative easing, and forward guidance. In recent years forward guidance has become more prominent as a way of reducing uncertainty by signalling the likely path of policy rates. Its effectiveness depends on households and firms forming expectations that are close to realised outcomes, so that communication anchors behaviour. The Full Information Rational Expectations paradigm assumes this is the case, with households making use of all available information and holding unbiased beliefs. However, our evidence shows that this assumption does not hold. Households systematically misperceive the policy rate, and their expectations deviate from realised values. Consequently, this calls into question the effectiveness of forward guidance when it is designed under the assumption of FIRE. In line with D'Acunto and Weber (2024), households often rely on local sources of information such as family, peers, and social media, rather than central bank publications or traditional media. Policymakers therefore need to take subjective household expectations into account and adapt the channels through which guidance is delivered.

Our findings carry three main implications for monetary policy and household finance. First, they illustrate the limits of FIRE-based models in policy design. Models that assume homogeneous and unbiased expectations overstate the effectiveness of forward guidance. In practice, households hold biased beliefs, and these biases translate into weaker behavioural responses, particularly for borrowing.

Second, while perception gaps matter for expectations, their real consequences are concentrated in saving behaviour. Central banks aiming to strengthen the transmission of policy through households may therefore need to focus less on stimulating borrowing via communication and more on anchoring expectations in ways that support precautionary saving. This is in line with Coibion et al. (2018), who find that expectation management is effective in shifting beliefs but has muted effects on household finance.

Third, differences in perception accuracy across socioeconomic groups suggest the need for complementary tools. As such, financial literacy initiatives (Lusardi and Mitchell, 2014) and targeted communication strategies could help close gaps among women, lower-income, and less-educated households in France. At the same time, access to savings vehicles and credit remains central, as Campbell (2006) emphasise. Communication alone cannot substitute for institutional features that shape financial capacity.

The asymmetry identified in this chapter also points to the importance of designing communication that accounts for rational inattention. Since households adjust savings more readily than debt in response to perceived policy uncertainty, effective guidance must recognise that attention is selective and uneven across groups. Evidence from this chapter shows that lower income and less educated households devote less attention to monetary news, which amplifies perception gaps and dampens transmission. By combining clear forward guidance with accessible communication formats and sustained engagement through national media, central banks can reduce perception gaps and improve policy reach.

In this sense, communication is not just a complement to policy but a channel through which monetary policy operates.

In conclusion, this chapter shows that perception gaps are real and consequential, yet their impact is uneven. For policy, this means forward guidance should be complemented by broader measures such as financial education, inclusive credit access, and clearer communication to improve the reach of monetary policy across the household sector.

4.9 Conclusion

Policy rate expectations are important for both policymakers and economic agents. They help determine spending, investment, borrowing and consumption decisions. Policy makers make use of policy rate expectations to control inflation through forward guidance. Central banks assume economic agents form their policy rate expectations through the FIRE paradigm and hence assume households' expectations are model implied and homogeneous. However, recent literature on inflation expectations has proved that this is not the case as households do not conform to the FIRE paradigm. We add onto this literature but focus on policy rate expectations.

Our results show that subjective French household policy rate expectations deviate systematically from the FIRE benchmark. Households misperceive the current policy rate, generating a perception gap that is both statistically and economically meaningful. These gaps can be partly explained by socioeconomic factors. For example, we find that men, wealthier, higher-income, and more educated households are better informed, while gaps are larger among women, lower-income, and less-educated groups. This heterogeneity challenges the assumption of homogeneous expectations and shows the need to account for demographic structure when modelling expectation formation. We also study the behavioural consequences of these gaps. We find that savings decisions are sensitive to perception gaps. That is, French households with larger gaps in their knowledge about policy rates are less likely to be in higher savings bands, with especially strong effects among low-income households. By contrast, borrowing behaviour is unaffected by policy rate misperceptions and remains dominated by income, wealth, and age. This asymmetry suggests that misperceptions constrain the savings channel of monetary policy transmission, but not the borrowing margin. From a policy perspective, these findings imply that central bank communication strategies cannot assume homogeneous FIRE-consistent beliefs. Instead, communication must be not only clear and transparent but also tailored to reach groups most prone to misperceptions.

Otherwise, forward guidance may have muted effects on household financial behaviour.

Nonetheless, this paper is not without its limitations. Since it is based on French households, collected in a single survey wave (2015), this limits generalisability across time and countries. Moreover, while we document strong links between perception gaps and savings, we cannot fully identify causal mechanisms, as other unobserved household traits (such as risk preferences or financial literacy) may also play a role. Future research should extend the analysis to panel data or cross-country settings, explore how perception gaps evolve with macroeconomic shocks, and investigate the role of targeted communication interventions in closing these gaps. Linking household-level misperceptions to aggregate consumption and saving dynamics would also help bridge micro evidence with macroeconomic policy models.

This chapter has therefore provided novel household-level evidence that expectations of policy rates deviate systematically from the Full Information Rational Expectations benchmark and that these misperceptions carry behavioural consequences, particularly for saving. In the next chapter the focus shifts from households to central banks themselves. Chapter 5 studies how policy decisions are communicated in official statements, considering both the language and the sentiment they convey. The analysis then examines how financial markets, and exchange rates in particular, respond to these communications. This broader perspective shifts attention from the receivers of information, namely households, to the senders of information, central banks.

Chapter 5

What are Central Banks Talking About? An Application of Large Language Models to Central Bank Communication

5.1 Introduction

How does central bank policy attention affect exchange rate dynamics? Central banks have increasingly used public communication to support their policy objectives. Transparent and clear communication is now viewed as a crucial mechanism for shaping market expectations, thereby enhancing the effectiveness of central bank monetary policy framework. By openly articulating their policy goals and the rationale behind their policy decisions, central banks aim to guide market behaviour in a way that supports their objectives, such as achieving price stability and maintaining financial stability. This proactive approach helps to manage expectations regarding interest rates, asset prices, and the broader economic environment, thereby influencing economic outcomes in line with their policy targets. While existing literature on the macroeconomic impact of central bank communications has primarily focused on their influence on domestic policy objectives, less is known about their effects on external policy objectives, such as exchange rates.

Recent advancements in Natural Language Processing (NLP) have led to the introduction of Large Language Models (LLMs) in analysing textual data. Although traditional text analysis methods (e.g., bag of words) are more common, they are less effective than advanced techniques like LLMs that capture the syntax and semantics of textual data. LLMs are therefore important because they can process and analyse complex sequences of text, including sentences and paragraphs, with a deep understanding of linguistic structures, idiomatic expressions, and nuanced phrases. This capability enables more precise analysis of central bank communications, enhancing our ability to interpret their impact on market dynamics. To achieve this, our study employs three complementary NLP techniques, that is, Latent Dirichlet Allocation (LDA) for uncovering broad topics in our data, few-shot learning approach with SetFit for classifying sentences according to specific keywords, and FinBERT, which is fine-tuned for sentiment analysis. While classification tasks could theoretically rely on LDA topics, SetFit's ability to independently handle classification ensures that syntax and semantics of textual data are preserved. This paper, therefore, aims to contribute to the existing literature by employing textual analysis in three key ways. Firstly, it constructs a new international database of central bank communications, focusing on Monetary Policy Committee press releases in addition to governors' speeches which are commonly used in literature. Most existing research on central bank communication mainly focuses on a few advanced economies and does not fully capture the breadth of central bank communication across countries and over time. Secondly, it analyses how policy decisions are articulated in central bank communications using a novel approach that pre-trains and fine-tunes an LLM to identify, collect, and extract sentiments related to inflation and exchange rates from policy language. Unlike traditional word-based methods like bag-of-words (BoW) or word vectors, the contextualized representation of LLMs captures both syntax and semantics, offering a more comprehensive understanding of the text's meaning. This is particularly advantageous as traditional methods are more prone to errors, especially in the presence of negation words in central bank communications. Finally, this paper examines the impact of central bank communication on exchange rate dynamics through sentiment analysis. This analysis explores how sentiment expressed in policy communications influences foreign exchange interventions. Additionally, we will evaluate the impact of policy language sentiment on Foreign Exchange market volatility and Foreign Exchange interventions.

We study official central bank communications from 80 countries to understand the impact of central bank communication on exchange rates. Countries included in the analysis were selected based on the availability of comprehensive and accessible data on official websites. To maintain uniformity, only English language communications were analysed. Using NLP machine learning techniques, we find that in terms of content discussed, press releases are more focused than speeches. Furthermore, using LLMs for sentence classification, we find that from the governor's speeches, 28.72 percent of the total sentences communicate about inflation whilst 2.93 percent communicate about exchange rates. Furthermore, from the press release data, we find that 55.32 percent relate to communication about inflation whilst 5.04 percent communicate about exchange rates. This disparity suggests that exchange rates may not be as frequently addressed in official communications as compared to inflation. Our findings reveal that an increase in positive sentiment about inflation in speeches significantly impacts exchange rate returns, leading to increased FX returns and decreased real effective exchange rate (REER) returns, though it does not affect volatility. Conversely, an increase in positive inflation sentiment in press releases does not significantly influence returns or volatility. Positive sentiment regarding exchange rates increases FX returns and REER volatility, reflecting its broader effect on market fluctuations. Lastly, our panel regression analysis shows that an increase in positive inflation sentiment generally reduces FXI as a percentage of GDP, reflecting increased market confidence and reduced hedging demand. An increase in positive exchange rate sentiment leads to decreased FXI-forward positions in favourable conditions but can increase total FXI in flexible exchange rate regimes. These results highlight the important role of central bank communication in shaping FX market dynamics and emphasize the need for central banks to enhance their communication strategies to maintain price and financial stability and achieve economic objectives. The rest of this paper is structured as follows: Section 5.2 provides a literature review. Section 5.3 explains the methodology and data. Section 5.4 presents the results and Section 5.5 concludes.

5.2 Literature Review

In recent years, central bank communication has become pivotal in monetary policy analysis, influencing market expectations, and achieving policy goals such as price stability and financial stability. Traditionally reliant on formal statements and speeches, central banks have increasingly adopted transparency as a cornerstone of effective policy implementation, particularly following the use of unconventional monetary tools post the 2008 Global Financial Crisis (GFC) such as forward guidance and quantitative easing. Despite this evolution, significant global variation in communication strategies suggests ongoing debate on optimal practices (Blinder et al., 2008).

The integration of advanced computational methods into economic research has gained significant momentum, particularly with the utilization of textual data and deep learning techniques. Gentzkow et al. (2019) provide a comprehensive introduction to the use of text as data in economic research. They discuss the unique features of textual data, such as its high dimensionality and unstructured nature, which distinguish it from traditional quantitative data. The authors offer a practical overview of statistical methods relevant to text analysis, including natural language processing and machine learning techniques, and survey a variety of applications where text data has been effectively employed to study and analyse economic phenomena. Building upon the foundation of text analysis, Dell (2025) explores the application of deep learning methods to large-scale, unstructured text and image datasets in economic research. She introduces deep neural networks and covers methods such as classifiers, regression models, generative AI, and embedding models. Dell discusses applications including classification, document digitization, record linkage, and data exploration in massive text and image corpora. She emphasizes that, when appropriately applied, deep learning models can be efficiently tuned and scaled to handle problems involving millions or billions of data points, making them valuable tools for economists.

The introduction of Large Language Models (LLMs) thus represents a paradigm shift in studying central bank communication by employing computational text analysis and machine learning to analyse a variety of communication channels, including central bank reports, press releases and social media content. Research in this area shows the influence of transparent communication on market sentiment, expectation formation surrounding monetary policy events, and also examines the effectiveness of different communication strategies in achieving policy objectives. There is ongoing debate on what constitutes an optimal communication strategy, considering factors such as content, procedures, timing, and audience. The importance of communication content is illustrated by the adoption of forward guidance as a monetary policy tool. While intended to reduce uncertainty about future interest rate paths, studies such as those of Coenen et al. (2017) and Ehrmann et al. (2019) argue that the effectiveness of forward guidance depends on the specific form adopted. They find that short-horizon forward guidance can potentially increase uncertainty, whereas the long-horizon forward guidance tends to stabilize markets and decrease uncertainty regarding future policy rates.

However, although effective central bank communication methods, such as annual reports, social media updates, public interviews, and speeches, play a crucial role in shaping market expectations and policy outcomes, excessive transparency can lead to forecast inaccuracies. This is highlighted by Do Hwang et al. (2022), who find that too much transparency coupled with frequent communication can lead to inaccuracies in financial and macroeconomic forecasts. To mitigate these effects, Ehrmann and Fratzscher (2009) advocate for quiet periods before key monetary policy decisions. Similarly, Cieslak et al. (2019) find that media leaks, a form of systematic informal communication, correlate with stock market reactions beyond official Federal Open Market Committee (FOMC) announcements, emphasizing the influential role of central bank communications in financial markets. Effective central bank communication also hinges on timing, as noted in studies by Al Guindy and Riordan (2017), Ehrmann and Fratzscher (2007), and Hu et al. (2015). Research on the timeliness of minutes further influences market expectations and policy outcomes (Reinhart and Sack, 2006; Reeves and Sawicki, 2007). Moreover, scholars have analysed the language used in central bank communications, emphasizing its role in shaping policy effectiveness and market reactions (Gerlach, 2004; Boukus and Rosenberg, 2006; Heinemann and Ullrich, 2007; Rosa and Verga, 2007; Berger and Schwartz, 2011). These findings collectively highlight the nuanced strategies central banks employ to communicate effectively and manage market expectations.

Recent applications of LLMs have revolutionized the analysis of central bank communication by enabling precise extraction and interpretation of policy language from diverse textual sources. By leveraging machine learning algorithms, researchers can develop LLM embeddings tailored to identify and extract policy language from central bank statements, speeches, and press releases, facilitating a more comprehensive analysis of how central banks communicate their policy decisions, including references to inflation targets, exchange rate interventions, and other economic variables. The consistency and replicability of the results obtained using these techniques have proven to be less subjective compared to traditional methods (Hansen and McMahon, 2016; Picault and Renault, 2017; Hubert and Labondance, 2021).

LLMs have proven effective in evaluating communication impacts, notably discerning inflation expectations from central bank Tweets. For instance, Gorodnichenko et al. (2021) use Twitter data to differentiate the content communicated by the Federal Reserve (FED), its intended recipients, and corresponding reactions. Leveraging natural language programming techniques, they analyse a spectrum of tweet topics including monetary policy, economic growth, unemployment, inflation, fiscal policy, financial risk, and community perspectives. Through few-shot learning classification, they extract signals pertaining to inflation expectations, revealing active engagement by media and economists with FED communications, thereby amplifying central bank discourse among Twitter users.[1]

Moreover, LLMs enable detailed analysis of central bank communications, revealing patterns in policy discussions, exchange rate dynamics, and the influence of transparency on communication effectiveness and resilience to political pressures. Bertsch et al. (2022) investigated the Federal Reserve's stance on price stability and explored the feasibility of adopting a secondary mandate using LLMs such as the transformer model by Vaswani et al. (2017) and the zero-shot learning classification.[2] Their findings reveal that discussions on financial stability and the impact on financial crisis influence FED monetary policy decisions and financial markets. In a subsequent study, Bertsch et al. (2024) introduced a novel database using NLP methods to extract text features from speeches delivered by 53 central banks between 1996 and 2023. Their research identifies distinct communication patterns of central banks with floating and pegged exchange rates, particularly in discussions involving exchange rates and the dollar. They also note significant communication spillovers from the FED, influencing exchange rate topics and dollar-pegged currencies and evoking hawkish sentiments in other contexts. Moreover, their analysis highlights central banks' engagement in foreign exchange intervention guidance and suggests that more transparent institutions are less susceptible to political pressures in their communication practices, using zero-shot learning methods.

The use of LLMs offers significant advantages by capturing complex patterns and semantic meanings, facilitating comprehensive analyses of central bank communications to identify key policy signals and shifts in tone or sentiment. Moreover, LLMs excel in processing large volumes of text data across multiple central banks and communication channels, leveraging zero-shot and few-shot learning techniques to generalize and adapt to new communication contexts with minimal labelled data, thereby enhancing scalability and versatility.

While existing literature on central bank communications' macroeconomic impacts often focuses on domestic policy objectives (Blinder et al., 2008;

[1]Few-shot learning classification is a form of machine learning where a model is designed to learn to classify objects or entities with a very limited amount of training data.

[2]A transformer is a type of artificial intelligence model designed to understand, interpret, and generate human language. Transformers are used in various applications, such as translating languages, summarizing texts, and creating chatbots.

Ehrmann et al., 2019), our project aims to extend this analysis to external objectives like exchange rates. Using LLMs, we contextualize policy decisions, pre-training embeddings to extract sentiments on inflation and exchange rates, thus offering a more comprehensive understanding compared to traditional methods (Gorodnichenko et al., 2021; Vaswani et al., 2017; Tunstall et al., 2022). Our empirical analysis assesses how central bank communication influences foreign exchange interventions, building on findings that central bank communication interacts with exchange rate policy and intervention effectiveness (Fratzscher et al., 2019; Bertsch et al., 2024).

5.3 Methodology

5.3.1 LLM: Few Shot-learning Approach

We utilize a Large Language Model (LLM) to measure central banks' policy message attention. The policy message attention is measured as the share of sentences related to inflation and exchange rate in policy rate decision communications. We classify policy messages using a few-shot learning approach with SetFit that focuses on classifying text into any number of categories with very few labelled examples. Traditional machine learning algorithms typically require large datasets to learn effectively. However, in many real-world scenarios, such a wealth of data is not available. Few-shot learning algorithms are designed to overcome this limitation. Figure[3] 5.1 explains how the few-shot learning approach with SetFit works.
SetFit[4] combines a pretrained body from sentence transformers and uses a two-stage training approach. In the first stage, a Sentence Transformer[5] (ST) is fine-tuned on the input data (very few labelled examples).

- During this stage, we use a pretrained `all-mpnet-base-v2` sentence transformer model which maps sentences and paragraphs to a 768-dimensional dense vector space and can be used for tasks like clustering or semantic search.

[3]This figure was sourced from Tunstall et al. (2022).
[4]SetFit is an efficient and prompt-free framework for few-shot fine-tuning of Sentence Transformers (ST). SetFit is based on Sentence Transformers, which are modifications of pretrained transformer models that use Siamese and triplet network structures to derive semantically meaningful sentence embeddings.
[5]All-mpnet-base-v2 from hugging face is used as a pre-trained model.

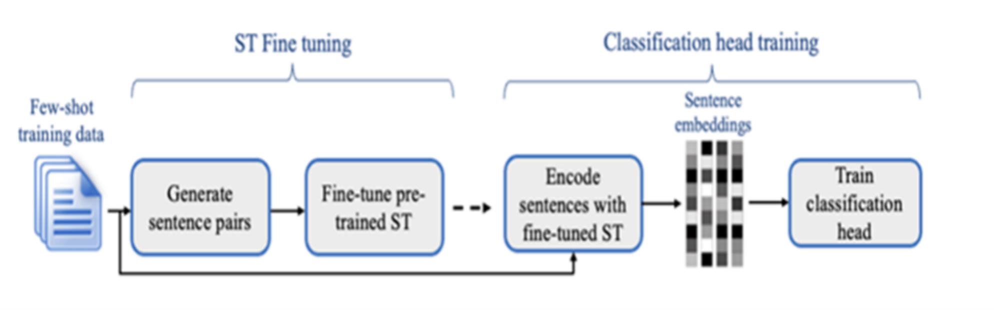


FIGURE 5.1: Few-shot Learning: Fine-tuning and Training Block Diagram.
Notes: The figure illustrates the two-stage few-shot learning procedure used in the SetFit framework. In the first stage, a pretrained Sentence Transformer model is fine-tuned on a small number of labelled examples. In the second stage, a classification head is trained on the resulting sentence embeddings to assign texts to the inflation and exchange-rate classes. The diagram summarises the flow of information across these steps.

- In the second stage, a text classification head is trained using the rich embeddings (or sentence representations) obtained from the first stage.

One of the primary mandates of a central bank is price stability. With this objective in mind, they either target inflation directly or via an intermediate target, the most popular of which being the exchange rate. Therefore, we set two classes of policy messages: inflation and exchange rate. The assumption is that communication should focus on inflation but reference to exchange rate could emerge because of its role in price formation (and for final stability in some cases). We manually label over 4000 sentences classified into inflation and exchange rate collected from 118 central banks' monetary policy communications. From the manually labelled sentences, we select 12 sentences per class as our training data. The rest of the manually labelled data is then split into 60 percent validation and 40 percent test dataset. During fine-tuning, the model's parameters, which were learned during pre-training, are updated to optimize the model's performance on the specific task using our labelled dataset. This process is usually faster and requires less data than pre-training because the model has already learned a lot of the necessary language understanding during pre-training.
For the fine-tuning objective, we use the "Cosine Similarity Loss" function which tries to minimize the distance between two sentences. This function helps in teaching the model how to understand and measure contextual similarity between sentence pairs.
After fine-tuning, we evaluate the performance of the model on a separate test set to assess how well it has learned to embed and classify unseen sentences.

	Cosine Similarity Score	
Sentence Pair	Word Count Approach	SETFIT/ Approach (LLM)
(How old are you, What is your age)	0.00	0.91
(How old are you, How are you)	0.78	0.28

FIGURE 5.2: Example of Contextual Similarity Embedding

Notes: As illustrated in the example above, the goal of the SetFit approach is to minimize the distance between pairs of semantically similar sentences and maximize the distance between sentence pairs that are semantically distant. The cosine similarity loss function plays a critical role when fine-tuning the model. It determines how well our embedding model will work for the specific downstream task, which in our case is semantic search.

Based on these results, one can further refine the model by adjusting hyperparameters or increasing the amount of labelled data for fine-tuning.
Lastly, the performance of the model is evaluated against other LLMs that use a zero-shot learning and other transformer approach. Performance is assessed using key metrics such as accuracy, precision, recall, and F1 score.[6] This comparative analysis aims to determine how well the few-shot learning approach with SetFit performs relative to zero-shot learning with SetFit and other transformer models.

5.3.2 Sentiment Analysis

FinBERT, a specialized language model developed by Araci (2019), is employed to analyse sentiment in central bank communications. Unlike traditional dictionary-based methods, which often misclassify financial terms due to their general nature, FinBERT[7] is tailored for the financial domain. It surpasses traditional methods by accurately handling financial jargon and context, making it highly effective for sentiment classification in this specialized field. The methodology for using FinBERT involves pre-training and fine-tuning. Initially, FinBERT is pre-trained on a large corpus of financial texts, such as news articles and SEC filings, to learn domain-specific linguistic patterns. It is then fine-tuned on a labelled dataset of financial news headlines categorized into positive, negative, or

[6]The F1 score is a statistical measure used in the evaluation of binary classification systems, a task common in natural language processing (NLP) and other areas of machine learning. It considers both the precision and the recall of the test to compute the score. Precision is the number of true positive results divided by the number of all positive results, including those not identified correctly, while recall (also known as sensitivity) is the number of true positive results divided by the number of all samples that should have been identified as positive.

[7]For a more detailed description, please see FinBERT: Financial Sentiment Analysis with Pre-trained Language Models.

neutral sentiments. This fine-tuning adapts the model to capture sentiment in financial contexts more precisely.

5.4 Data

5.4.1 Press Release and Governor Speech Communications

Central banks employ a range of tools beyond traditional statements and speeches, including regular press conferences, detailed economic reports, and real-time updates through digital platforms and social media. This multi-channel approach not only enhances the accessibility of information but also helps in managing market expectations and stabilizing economic fluctuations. By providing more frequent and comprehensive analysis about policy intentions and economic conditions, central banks aim to build greater trust and credibility with both the public and financial markets.

This paper introduces a novel dataset, that is, press releases that have not been previously utilized in central bank communication analyses. Specifically, we scraped central bank websites to collect press releases on policy decisions. These documents are particularly valuable as they provide detailed explanation about policy rates and the broader economic context. For the analysis, we minimize pre-processing to maintain the integrity of the raw data. Unlike many NLP models that require extensive text pre-processing, such as removing stop words, lemmatization, or punctuation removal, LLMs allows for minimal text data cleaning, hence we use the raw text.[8] All documents were standardised by removing headers, footers, legal notices, and repeated boilerplate. Speeches and press releases were tokenised at the sentence level using a consistent rule-based parser, and non-English material was excluded based on explicit language tags rather than keyword filters. Duplicate communications were removed, and country-year identifiers were checked against the release dates of the original sources. We complemented the press release data with central bankers' speeches obtained from the BIS website.

In total, our data consists of 16,979 speech documents from 118 central banks, spanning the period between 1997–2022. We split the documents into sentences and obtained 2,066,036 sentences from governor speeches. Figure 5.3 below plots the distributions of central bank communication speeches in our dataset and the distribution of the total number of sentences and words.

[8] Lemmatization is a linguistic process used in natural language processing (NLP) that involves reducing a word to its base or root form, which is called a "lemma."

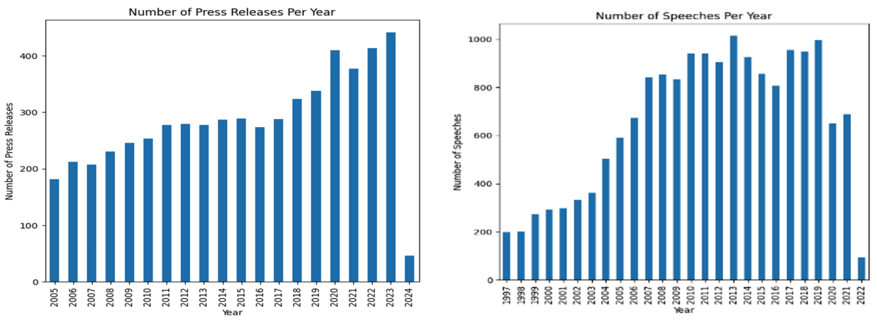
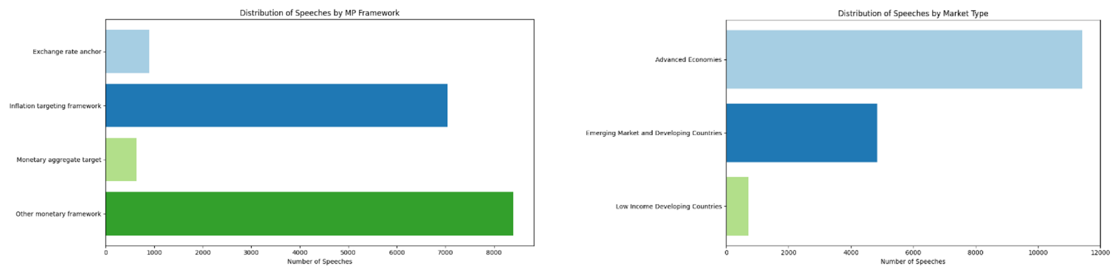


FIGURE 5.3: Temporal Distribution of Press Releases and Governors' Speeches

Notes: This figure shows the yearly distribution of central bank press releases and speeches in the dataset. The series reflect the total number of documents collected per year after standard cleaning, including removal of duplicates and exclusion of non-English material. Counts represent the number of documents available in each year and illustrate how the volume of communication changes over time.

On average our speech data has 122 sentences and 2825 words. Furthermore, Figure 5.4 reports the number of governors' speeches across different market types and by monetary policy framework. The charts show that most communications come from advanced economies, with fewer documents from emerging markets and low-income developing countries. This pattern reflects differences in publication practices and in the frequency with which central banks issue formal statements, as advanced economies tend to release more regular and structured communication, while many emerging and low-income central banks publish less often. In terms of monetary policy frameworks, the distribution is similarly uneven. Inflation-targeting central banks account for the largest share of speeches in the corpus, consistent with the emphasis these regimes place on forward guidance, transparency, and regular communication. Frameworks such as exchange rate targeting or monetary aggregate targeting contribute fewer speeches, which aligns with their more limited use of scheduled communication and, in some cases, more constrained institutional capacity.



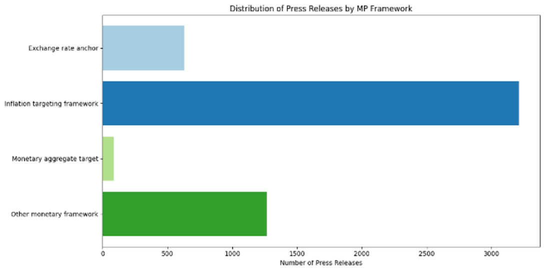
(A) Monetary Policy Framework

(B) Market Type

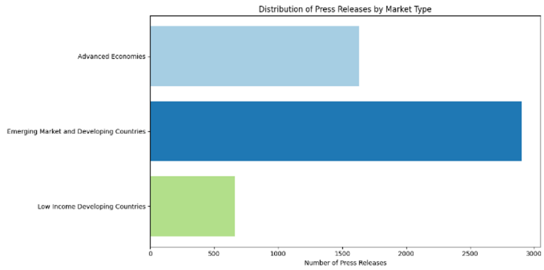
FIGURE 5.4: Distribution of Governors' Speeches by Monetary Policy Framework and by Market type

Notes: Each panel reports the distribution of governors' speeches in the dataset. The left panel groups speeches by monetary policy framework and the right panel groups them by market type. Monetary policy frameworks follow standard categories such as inflation targeting, exchange rate targeting, and monetary aggregate targeting. Market types follow the IMF classification of advanced economies, emerging markets, and low-income developing countries.

The press release data consists of 7,315 monetary policy committee press release statements across 86 countries spanning from the period between 2005–2023. These documents are then split into 447,453 sentences. On average the press releases contain 82 sentences and 2,330 words per document. Figure 5.5 reports the distribution of press releases across monetary policy frameworks and market types. The left panel shows that most press releases come from inflation-targeting central banks, with fewer documents produced under exchange-rate targeting or monetary-aggregate frameworks. This reflects both the wider adoption of inflation targeting and the greater emphasis it places on regular communication. The right panel shows that advanced economies contribute the largest number of press releases in the corpus, followed by emerging markets and a smaller number from low-income developing countries. These patterns indicate that the availability of press releases is shaped by institutional capacity and communication practices across monetary policy regimes and country groups.



(A) Monetary Policy Framework



(B) Market Type

FIGURE 5.5: Distribution of Press Releases by Monetary Policy Framework and by Market type

Notes: Each panel reports the distribution of press releases in the dataset. The left panel groups speeches by monetary policy framework and the right panel groups them by market type. Monetary policy frameworks follow standard categories such as inflation targeting, exchange rate targeting, and monetary aggregate targeting. Market types follow the IMF classification of advanced economies, emerging markets, and low-income developing countries.

The speech and press release documents are separated into individual sentences containing at least 14 characters, which are then used directly as input for sentence classification. Table 5.1 provides a descriptive statistic of the distribution of sentences used for the classification exercise.

TABLE 5.1: Summary Statistics of the Distribution of Sentences Per Document

Statistic	**Central Bankers' Speeches**	**Press Releases**
Average	122	82
Maximum	801	960
Minimum	1	1
Standard Deviation	98	65
Total number of sentences	2,066,036	447,453

Notes: This table reports summary statistics for the number of sentences per document for central bank speeches and press releases. The average, maximum, minimum, and standard deviation are calculated across all documents in each category. The final row shows the total number of sentences contained in the full corpus for each document type.

We complement the textual data with macroeconomic data obtained from the International Financial Statistics (IFS) database of the International Monetary Fund (IMF), and indirectly from Haver Analytics. The Foreign Exchange intervention dataset is sourced from Adler et al. (2021), which contains monthly public data and proxies for Foreign Exchange interventions for 122 central banks from 2000Q1 through 2022Q4.

Lastly, while the dataset covers many countries, a key limitation is that the analysis relies primarily on English language communications. For several non-English speaking central banks, the English texts often correspond to externally oriented summaries or press releases prepared for international audiences. This creates a selection bias because these documents place more weight on global themes, external stability, and exchange rate developments, while domestic details that appear in the native-language versions are often shortened or omitted. As a result, the English corpus may over-represent messages aimed at foreign investors and under-represent domestic policy discussions. A sensitivity check on a small translated subsample suggests that the meaning of the original communication is largely preserved when translated, although the English versions are more concise. This sensitivity check provides a direct way to examine whether relying on English texts meaningfully distorts the policy content captured in the analysis.

Figure 5.6 compares the official English versions of selected central bank documents with machine translated versions of the corresponding native-language texts. South Africa is included as a benchmark case because the South African Reserve Bank publishes its policy statements directly in English. As expected, the English and translated versions for South Africa are almost identical. This provides a useful control and helps interpret the results for countries where English releases are summaries rather than full translations. The left panel reports cosine similarity between the official English text and the machine translated version. The similarities are high across all countries, indicating that the English texts preserve most of the underlying meaning. The strongest alignment appears in monetary policy statements, which tend to follow a consistent and structured style. The right panel shows the ratio between the length of the official English statement and the translated native-language version. Ratios close to one indicate little compression. South Africa fits this pattern, as expected for a country that communicates in English. In contrast, countries such as Brazil, Chile and China show more pronounced compression. The English versions for the People's Bank of China are much shorter than the native statements, which is consistent with its external communication style. As such, the sensitivity test shows that while English statements can be more concise, the core policy message is preserved. Some selection bias remains because English releases for non-English speaking central banks are aimed at international audiences and may emphasise global themes. Even so, the results suggest that the main policy content is stable across languages, and the central findings of the analysis are unlikely to be driven by language-related distortions.

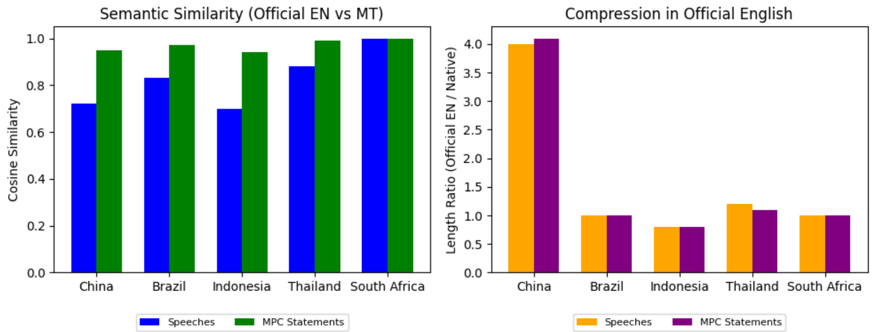


FIGURE 5.6: Sensitivity tests

Notes: This figure summarises the sensitivity check comparing official English versions of central bank communications with machine-translated versions of their native-language texts. The left panel reports cosine similarity scores between the English and translated statements, and the right panel shows the ratio of document lengths across the two versions. South Africa is included as a benchmark country where English is the primary language of communication. Higher similarity scores and ratios close to one indicate closer alignment between the two versions.

5.4.2 Difference Between Press Releases and Governors' Speeches

Central bank speeches are typically delivered by the governor and serve as direct communication channels with the media. They aim to clarify issues related to the policy strategy and address any potential misunderstandings. Press releases, on the other hand, convey information about policy decisions, new regulations, and comments on relevant economic data. To analyse these two forms of communication and explore differences in their content, we constructed a dataset comprising a collection of speeches and press releases sourced from the official websites of central banks in selected countries. The documents included in the dataset were chosen based on their accessibility in English to ensure consistency and reliability in the analysis. We examine the difference between the content of the governors' speeches and the press releases by employing the Latent Dirichlet Allocation (LDA)[9] , a topic modelling technique to uncover underlying topics of discussion. The process involves minimal pre-processing, including tokenization and removal of stop words, followed by training the LDA model to identify clusters of words that frequently occur together. By specifying the number of topics, LDA helps us understand the primary themes in central bank communications, which are then interpreted by analysing the top words associated with each topic to align them with known issues and policy discussions. The trained LDA model assigned a distribution

[9]See Blei et al. (2003) for a more detailed explanation on LDA. See also Jelodar et al. (2017).

of topics to each document, allowing us to analyse the thematic composition of both speeches and press releases. The interpretation of these topics involved examining the top words associated with each one and assigning meaningful labels aligned with known policy issues and economic discussions, such as ”inflation,” ”exchange rates,” and ”economic growth.”

In our analysis, we applied Latent Dirichlet Allocation (LDA) to the speeches and press releases separately, rather than pooling them together. This distinction was made to explore whether the themes in speeches differ from those in press releases, given their different purposes and audiences. Specifically, the speeches, typically delivered by the governor, serve as a more narrative form of communication with the public, while press releases focus on formal policy decisions and economic data. By analysing these two types of documents separately, we can more accurately capture the unique topics that arise in each context.

The number of topics in the LDA model was determined based on exploratory analysis, which involved testing different topic numbers and selecting one that balanced thematic depth with clarity. The final number of topics used in the analysis, as depicted in Figures 5.7 and 5.8, was 10. This number was chosen to provide a balance between sufficiently capturing thematic diversity and ensuring there is clarity in the interpretation of the topics. To evaluate the importance of each topic, we focused on the dominant topic for each document, that is, the topic with the highest proportion within a given document. Based on this, we ranked the topics according to how frequently they were discussed across the entire corpus. Figure 5.7 and 5.8 presents this ranking, showing the distribution of documents according to the most talked-about topics, such as Topic 1, Topic 9, and so on. This allows us to see which topics were most prominent in the speeches and press releases, allowing us to understand the key issues communicated by various central banks over the study period. We further illustrate the content of these topics by displaying the top 30 keywords associated with each one as shown in the word cloud. This helps interpret the nature of the discussions and provides context for the rankings given below.

The results indicated clear thematic differences between the two types of communication. Governors’ speeches were more focused on broader narratives about inflation and policy direction, emphasizing effective communication with the media and the public, while press releases concentrated on specific policy decisions and updates on macroeconomic data. Each topic is represented by word clouds reflecting the top words, where the size of the keyword illustrates its importance in the topic. For press releases (figure 5.7), we find that the discussion mainly focuses on inflation and economic forecasting, emphasizing the central banking policies and their impact on inflation, interest rates, and financial stability.

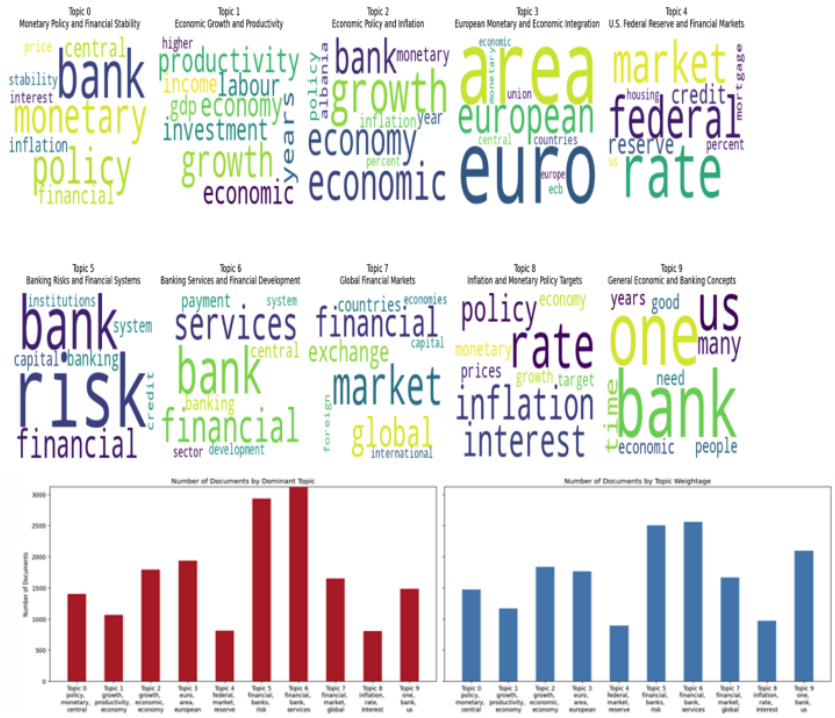


Figure 5.7: Top 10 Topics Discussed in Press Releases

Notes: This figure displays the ten most frequent topics identified in central bank press releases using the LDA model. Each topic label summarises the dominant terms within that topic, and the bars show the relative prominence of each topic across the full set of speeches. Values reflect the proportion of sentences assigned to each topic in the model's output.

Figure 5.8 discusses the dominant topics discussed in speeches. We find a shift in focus to banking services and financial sector development, including the evolving role of central banks. Speeches also discuss risks in the banking sector, such as financial stability and capital requirements.

Therefore, by applying LDA, we were able to systematically identify differences between communication in speeches and press releases, providing valuable information into the distinct roles that speeches and press releases play in central bank communications. We find that press releases are focused on the policy decision and its justification as compared to speeches, which cover a broader set of considerations less directly linked with the policy decision. Press releases can thus be useful in guiding economic agents on the future path of policy rates by giving financial markets, economists, and the public some form of guidance on the central bank's future policy intentions. As compared

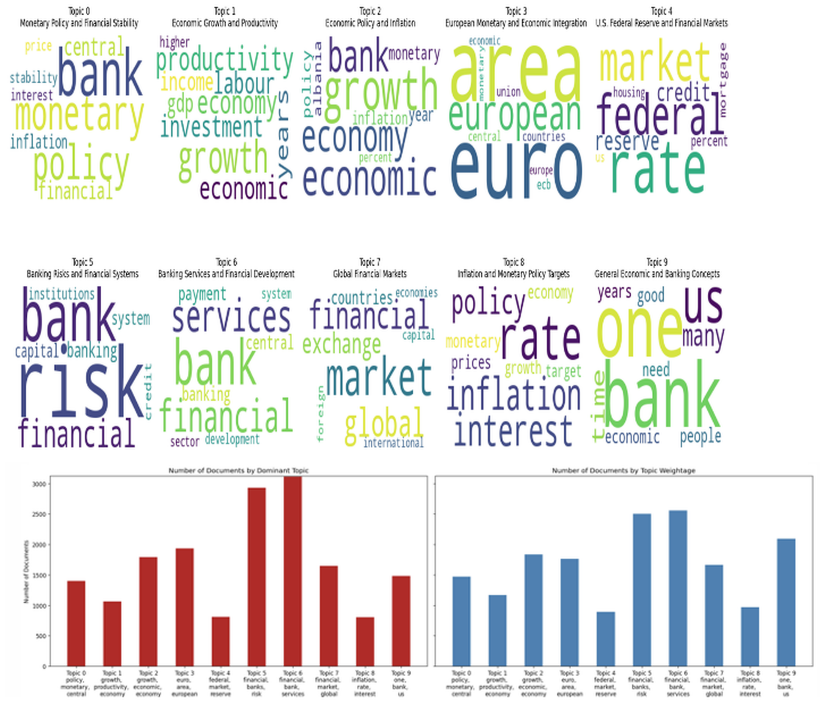


FIGURE 5.8: Top 10 Topics Discussed in Speeches

Notes: This figure displays the ten most frequent topics identified in central bank speeches using the LDA model. Each topic label summarises the dominant terms within that topic, and the bars show the relative prominence of each topic across the full set of speeches. Values reflect the proportion of sentences assigned to each topic in the model's output.

to speeches, press releases are a primary tool for communicating changes in policy rates, economic forecasts, and other key decisions and because they are published online and widely accessible, information is disseminated quickly and consistently to the financial markets and the public. This transparency thus helps stabilize expectations and supports economic decision-making especially during uncertain times.

Figure D.1 to D.3 in the appendix, based on 2023 data, illustrate some areas where press releases could be improved to further strengthen their role in communication. Figure D.1 shows the frequency of press releases by country, and the results indicate that press releases need to be published more frequently, as regular updates would provide more timely guidance to financial markets and the public. Figure D.2 uses the Kincaid-Flesch grade to show that press releases are currently less readable and understandable for some countries compared to others. These countries should therefore aim to make their press releases more readable, ensuring they can be easily understood by a broad audience. In contrast, Figure D.3 shows readability by monetary policy framework. Communications focused on inflation targeting in 2023 were found to be more readable, suggesting that simpler and clearer language makes communication more effective. As such there is therefore need to improve both the frequency and readability of press releases to enhance their transparency and effectiveness in guiding expectations.

5.5 Inflation vs. Exchange Rate Attention in Central Bank Communication

5.5.1 Sentence Classification

TABLE 5.2: A Sample Example of the Classification Task

Sentence	Predicted Label	Probability (Inflation)	Probability (Exchange Rates)	Adjusted Predicted Label with Optimal Threshold
Rental inflation is increasing across all three countries.	Inflation	0.8329	0.1671	Inflation
At the same time, elevated uncertainty about economic development abroad usually leads to a weakening krona exchange rate.	Exchange Rate	0.1647	0.8353	Exchange Rate
There have also been some signs of improvement recently in the euro area.	Exchange Rate	0.4907	0.5093	Other
In contrast, Chinese stocks continued to underperform other markets.	Inflation	0.5003	0.4997	Other

Note: The optimal threshold is obtained using the Youden's J Statistic.

Using a few-shot learning approach, we perform semantic search and classify sentences into two categories, those communicating about inflation and those communicating about exchange rates. A sample for this classification task is shown in Table 5.2. The trained model attempts to understand the context of each sentence and determine whether it relates to inflation or exchange rates. Because we use only two labels, some of the sentences might not match either of the two categories. For example, the final sentence in Table 5.2 does not discuss inflation, yet the model assigns it to the inflation category because it must choose one of the two available labels. This shows the behaviour of a closed classification setup, where the model is required to pick a label even when the sentence does not contain a clear policy signal. To address this, we use probabilities to create an adjusted prediction. A threshold is implemented, where the predicted probabilities must be higher than an optimal threshold. We estimate a Youden's J Statistic[10] for the optimal threshold determination and we obtain an optimal cut-off threshold of 0.8 to accept the prediction of

[10]Youden's J Statistic, Youden's J statistic is defined as:

$$J = \text{sensitivity} + \text{specificity} - 1 \tag{5.1}$$

the model. If the predicted probability for both classes is below the optimal threshold, the predicted class is overwritten with “Other”. This converts the task into an open classification structure, where sentences with weak or mixed signals are no longer forced into the inflation or exchange rate groups. We proceed by using the LLM to predict whether each sentence from speeches or press release data is discussing issues related to inflation or exchange rates. Building on this, the sentence level classification task separates sentences into two policy focused themes, namely inflation communication and exchange rate communication, with an additional “Other” category for cases that do not reach the required probability threshold. This framework isolates the sentences that speak directly to inflation or exchange rate issues, which are the policy themes examined in the empirical analysis. A focused design is required because central bank communication typically includes introductory remarks, broader macroeconomic commentary, institutional updates, and closing statements. The classification therefore concentrates on the specific policy content that is relevant for constructing attention measures. The Other category plays a practical role here since many sentences in central bank documents are descriptive or contextual rather than policy specific. The classification process relies on a probability threshold that governs whether a sentence is assigned to a policy category. A sentence is labelled as inflation related or exchange rate related only when its predicted probability exceeds the chosen threshold. The threshold itself is selected using the Youden’s J statistic, which identifies the cut-off that maximises the sum of sensitivity and specificity. This provides a data driven approach for balancing false positives and false negatives. Sentences that do not reach the threshold are allocated to the “Other” category. This rule has an important methodological role. Many sentences in central bank communication focus on international developments, financial stability, or other macroeconomic topics that are not specific to inflation or exchange rate issues. If the classifier were forced to assign every sentence to one of the policy categories, these broader statements would be attributed incorrectly, and the resulting indicators would exaggerate the degree of policy attention. The threshold therefore ensures that only clearly identifiable policy statements are retained for the construction of the attention measures. This improves the accuracy of the indicators by preventing spillover from non-policy content into the two core themes.

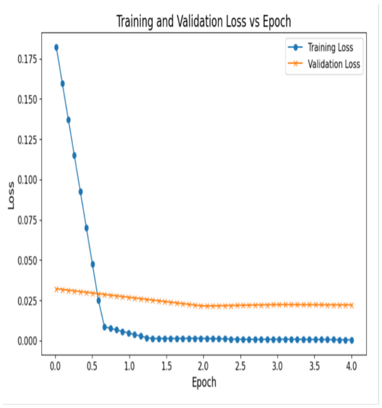
It can be interpreted as the distance between the ROC curve and the “chance line” (the ROC curve of a classifier that guesses randomly). The optimal threshold is that which maximizes the J Statistic.

5.5.2 Model Evaluation

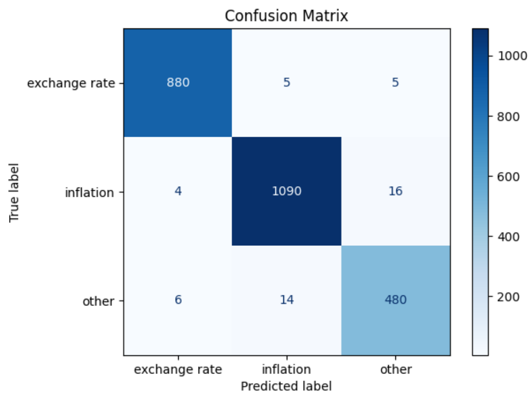
To analyse the effectiveness of the trained model, we evaluate it against the training and validation loss. We record the training and validation loss against each epoch and show the results below. The training loss measures how well the model's predictions match the true labels during training whilst the validation loss measures how well the model generalizes the data it has not seen during training. The training loss indicates whether the model is learning from the training data effectively. A decreasing training loss suggests that the model is improving. On the other hand, a validation loss measures how well the model will perform on unseen data. A decreasing validation loss indicates improved generalization. From the graph below, the training loss decreases and later becomes stable showing that the model is effectively learning from the data. The validation loss also decreases and becomes stable after two epochs showing that the model might perform well on untrained data. We also use a confusion matrix to evaluate the performance of our classification model by comparing the actual labels with the predicted labels. The confusion matrix indicates that the classifier performs strongly across all three categories. Most sentences labelled as "exchange rate" or "inflation" by human annotators are correctly identified by the model, reflecting accurate separation of the two main policy topics. Misclassifications are limited and intuitive. A small number of sentences originally labelled as "inflation" or "exchange rates" are assigned to the "other" class, suggesting that these sentences contain more general economic commentary rather than explicit references to inflation or exchange rate dynamics. This pattern is expected, as the "other" category captures broader monetary or macroeconomic content that does not contain clear linguistic markers of the two policy topics.

Finally, to evaluate the performance of our model against other models in literature, we benchmark our model against the Zero-Shot approach that uses SetFit and Transformers. The results are summarized in Table 5.3, which provides a comprehensive overview of the performance metrics.

The results illustrate the performance of our SetFit (Few Shot) model, which achieves strong and consistent scores across all metrics such as accuracy, F1 score, precision, and recall. This outperforms both SetFit (Zero Shot) and Transformers (Zero Shot) models. While SetFit (Zero Shot) and Transformers (Zero Shot) models demonstrate strong performance with high accuracy and F1 scores, our SetFit (Few Shot) model excels with perfect metrics, emphasizing its superior capability in leveraging few-shot learning.



(A) Training and validation loss



(B) Confusion matrix

FIGURE 5.9: Model performance metrics

Notes: Panel (a) plots the evolution of training and validation loss over epochs for the SetFit model. Lower loss indicates better fit. Panel (b) reports the confusion matrix for the three-class classification task (exchange rate, inflation, and other). Values represent the number of sentences assigned to each predicted category. Darker shading indicates higher counts.

TABLE 5.3: Model Evaluation Against Other LLM Models

Model	**Accuracy**	**F1 Score**	**Precision**	**Recall**
SetFit (Few-shot)	0.98	0.98	0.98	0.98
SetFit (Zero-shot)	0.96	0.96	0.96	0.96
Transformers (Zero-shot)	0.97	0.97	0.97	0.97

Notes: Accuracy measures the proportion of correct classifications. Precision reports the share of predicted sentences in a given class that are correctly assigned, while recall measures the share of true sentences in that class that the model successfully identifies. The F1 score is the harmonic mean of precision and recall. The SetFit (Few-shot) model achieves the strongest overall performance, with higher scores than both Zero-shot approaches.

Accuracy measures the overall proportion of correctly classified instances, with our SetFit (Few Shot) model achieving a score of 0.98, indicating good performance. The F1 Score combines precision and recall into a single metric, providing a balanced measure of a model's effectiveness; here, our SetFit (Few Shot) model also scores 0.98, reflecting its superior balance between precision and recall. Precision quantifies the accuracy of positive predictions, while Recall measures the model's ability to identify all relevant positive cases. Both metrics are perfect for our SetFit (Few Shot) model, further reflecting its exceptional performance. In comparison, while the SetFit (Zero Shot) and Transformers (Zero Shot) models show strong results, with high accuracy and F1 scores, our SetFit (Few Shot) model demonstrates superior effectiveness across all evaluated metrics. These results show the effectiveness of our approach and its advantageous position relative to other advanced models in the field.

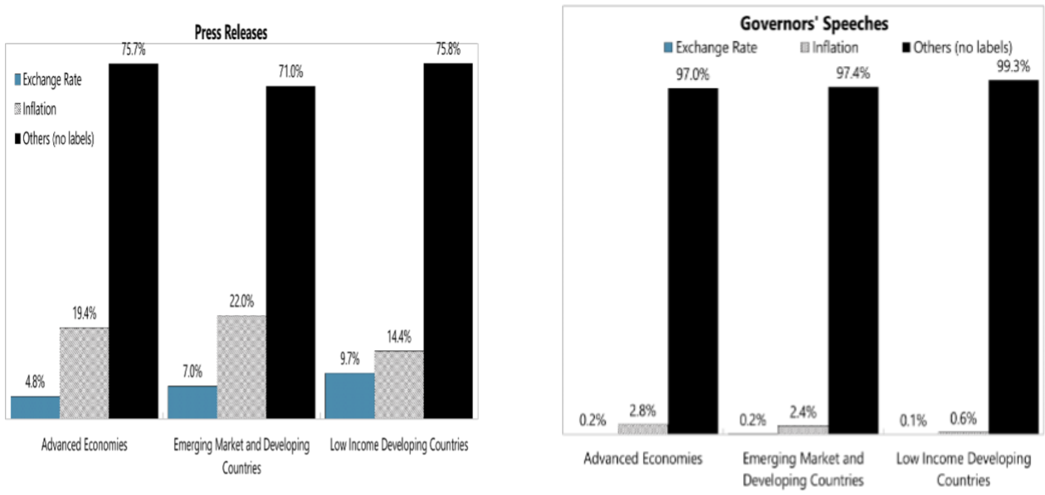
5.6 Results

We analyse policy language relating to inflation and exchange rates. From the governor's speeches, 28.72 percent of the total sentences communicate about inflation, whilst 2.93 percent communicate about exchange rates. In comparison, when analysing press release data, we find that 55.32 percent of the sentences relate to communication about inflation, whilst 5.04 percent communicate about exchange rates.

Overall, these results suggest that central bank communication about policy rates tends to discuss inflation more as compared to exchange rates. This disparity implies that while exchange rates are crucial, they may not be as frequently addressed in official communications as compared to inflation.

When evaluating the overall emphasis on policy rates, it becomes apparent that inflation dominates the discourse across both governor's speeches and press releases. This emphasis reflects central banks' primary mandate to manage inflation expectations and maintain price stability. To provide a more comprehensive analysis, we further analyse the results by market type and by monetary policy framework. This approach helps us explore and look into how different central banks prioritize and communicate about inflation and exchange rates, thereby enhancing our understanding of their respective policy orientations and objectives.

The Figure 5.10 shows the percentage of predicted labels by market type for both press releases (left) and speeches(right). The figure illustrates that advanced economies discuss more about inflation as compared to exchange rates in their monetary policy committee press releases. Similarly, low income developing economies also have more sentences discussing inflation than exchange rates in their press releases. This is because advanced economies typically have well-established central banks with inflation-targeting monetary policies. As a result, discussions and policies often revolve around managing inflation rates within a target range. Low income developing countries on the other hand, have high volatile inflation that is harder to control due to various factors such as political instability and less developed financial markets. Therefore, central banks in these regions also focus heavily on inflation in their communications. Similarly, the figure above (right) also shows that advanced economies have more sentences discussing inflation than exchange rates in



(A) Press Releases

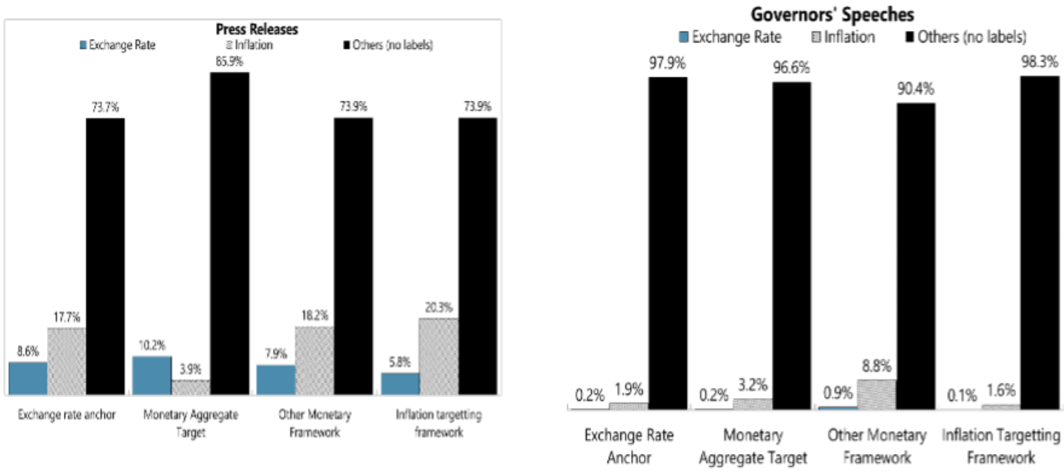
(B) Governors' Speeches

FIGURE 5.10: Percentage of Predicted Labels by Market Type

Notes: Each panel reports the percentage of sentences classified as discussing inflation or exchange rates, grouped by market type. The left panel shows results for press releases and the right panel shows speeches.

their speeches. This might be because speeches by central bank officials are often directed at a broader audience that includes financial markets, policymakers, academics, and the public. These speeches serve as a platform to provide an explanation about what the central bank's thinks in terms of its assessment of economic conditions, and its policy intentions. Discussing both inflation and exchange rates in speeches allows central banks to communicate their stance on international economic relations, currency policies, and responses to global economic developments. Figure 5.11[11] shows the percentage of predicted labels by Monetary Policy framework for both press releases (left) and speeches (right). In terms of press releases, inflation targeting economies discuss inflation more compared to exchange rates. Inflation targeting economies prioritize inflation discussions in their press release statements due to their explicit inflation targets and policy tools aimed at achieving these targets. The figure also shows that almost all countries in our sample except for those using the monetary aggregate target, discuss and communicate more about inflation than exchange rates.

[11] As shown in Table A2, only three countries fall under the monetary aggregate target regime. Notably, China is one of these countries, and its significant economic size and global influence may disproportionately affect the results for this regime in Figure 5.11. Therefore, it is important to consider that the findings for the monetary aggregate target regime could be largely driven by the data from China. This should be taken into account when interpreting the results for this regime, and future research may benefit from a more detailed investigation into the specific role that China's policy stance plays in shaping these outcomes.



(A) Press Releases (B) Governors' Speeches

FIGURE 5.11: Percentage of Predicted Labels by Monetary Policy Framework
Notes: Each panel shows the percentage of sentences classified as discussing inflation or exchange rates, grouped by monetary policy framework. The left panel reports press releases and the right panel covers speeches by the central bank governor.

This is because monetary aggregate target economies discuss money supply growth and liquidity management as primary policy concerns, focusing less on inflation. In terms of government speeches, our results illustrate that central banks communicate less about inflation and exchange rates in their speeches and focus more on other issues. These differences highlight how different policy frameworks address economic challenges and objectives based on their unique circumstances and goals. The market type and monetary policy framework thus affect the content of press releases and speeches. These factors collectively influence how central banks communicate policy decisions, economic outlooks, and strategies to manage economic challenges and promote sustainable growth.

5.6.1 Sentiment Analysis

Sentiment analysis is a technique in natural language processing (NLP) used to determine the emotional tone behind a body of text. It involves classifying text into categories such as positive, negative, or neutral, thereby uncovering the sentiment expressed. For our study, we utilize a large language model (LLM) known as FinBERT, which is specifically designed for sentiment analysis in the financial domain. FinBERT has been trained in an extensive corpus of financial texts, equipping it with the precision needed to interpret and classify sentiments accurately within financial contexts.

In our case, FinBERT processes central bank communications (press releases and speeches), by outputting probabilities for each sentiment class, that is, positive, negative, and neutral. This probabilistic approach allows us to classify each sentence based on the highest probability. The sentiment score for each sentence is calculated using the formula:

$$\text{FinBERT Sentiment Score} = P(\text{positive}) - P(\text{negative}) \tag{5.2}$$

This score provides a quantitative measure of the sentiment, where a higher positive score indicates stronger positive sentiment, and a higher negative score reflects stronger negative sentiment. The sentiment scores are then aggregated to assess the overall tone of the central bank communications. This method enables us to quantify how central bank messages are perceived and their potential impact on market behaviour. Table 5.4 below illustrates an example of sentences and their sentiment.

TABLE 5.4: A Sample Example of the Sentiment Analysis Task

Sentiment	Sentence
Positive	• The recent economic data support our optimistic outlook, indicating robust growth and price stability in the coming quarters. • The latest inflation data reflects our successful monetary policies, showing a healthy balance that supports sustainable economic growth.
Neutral	• We will continue to monitor inflation closely and adjust our policy as needed to ensure economic stability. • Exchange rate fluctuations are being monitored to ensure that they do not adversely affect our economic targets.
Negative	• Current inflation challenges necessitate cautious monetary policies to mitigate risks and ensure long-term stability. • The recent volatility in exchange rates is a cause for concern and may impact economic stability if not addressed promptly.

Notes: This table presents illustrative examples of the three sentiment categories used in the analysis. Positive sentences express favourable assessments of economic or policy developments, neutral sentences provide factual or balanced statements without clear tonal direction, and negative sentences highlight risks, concerns, or adverse developments related to inflation or exchange rate conditions.

In analysing central bank communication, sentiment can be categorized into three primary types: positive, neutral, and negative.

Positive sentiment often reflects optimism and confidence about the economic outlook, which can boost market confidence and reduce the perceived need for intervention. For example, a governor might say, ”The recent economic data support our optimistic outlook, indicating robust growth and price stability in the coming quarters,” signalling a favourable economic environment.

Neutral sentiment conveys factual and procedural information without strong emotional undertones, focusing on ongoing monitoring and adjustments to policy based on economic indicators. An example of this might be, ”We will continue to monitor inflation closely and adjust our policy as needed to ensure economic stability,” indicating a balanced and measured approach.

Negative sentiment indicates concern or caution, reflecting economic challenges or risks that necessitate careful policy measures. A statement such as, ”Current inflation challenges necessitate cautious monetary policies to mitigate risks and ensure long-term stability,” reflects a more guarded stance and may prompt a more proactive intervention strategy. Each type of sentiment thus plays a crucial role in shaping market expectations and guiding central bank actions.

In our methodology, sentiment is calculated at the sentence level to capture detailed syntax within the text. These sentence-level sentiments are then aggregated to form a document-level sentiment score. For months with no documents, we treat these as missing variables and use imputation methods to estimate the missing sentiment values. This approach ensures that our analysis remains comprehensive and accounts for all time periods. FinBERT’s domain-specific training makes it particularly adept at understanding financial jargon and context, enhancing its accuracy in sentiment classification. Its ability to handle the complexities of financial language makes it an invaluable tool for analysing market sentiment, predicting stock movements, and assessing investor sentiment. By applying FinBERT to central bank communications, we gain a detailed and comprehensive view of how these messages might influence exchange rate dynamics and market stability.

5.7 Empirical Analysis

Our analysis examines the influence of central bank communication tone on foreign exchange dynamics. It utilizes a panel dataset to capture both cross-sectional and time-series variations. This dataset includes multiple observations for a range of countries over time, allowing us to explore the effects of central bank communication across different economic contexts and regimes. We apply a panel regression model with fixed effects to control unobserved heterogeneity and account for country-specific factors that might impact exchange rate dynamics. The use of panel data in this study provides several advantages. Panel data, which includes observations across multiple time periods for the same countries, allows us to analyse both cross-sectional and time-series variations. This comprehensive approach helps in understanding how central bank communication influences exchange rates over time and across different economic environments. The fixed effects model employed in our analysis controls for unobserved heterogeneity by accounting for country-specific characteristics that could otherwise bias the results. This method ensures that our findings reflect the true impact of central bank communication on exchange rate dynamics, rather than being confounded by omitted variables or country-specific factors.

5.7.1 Foreign Exchange (FX) Volatility

We explore the effect of central bank communication tone on exchange rate returns and volatility by employing a panel regression model with fixed effects. This approach allows us to control for unobserved heterogeneity and capture country-specific factors that may influence exchange rate dynamics. By using the fixed effects model, we ensure that our results are not biased by omitted variables or country-specific characteristics. We use the following regression model:

$$\sigma(\text{FX})_{it} = \alpha_i + \tau_t + \beta_1 \,\text{Policy}_{i,t-1} + \beta_2 \,\text{Policy}_{i,t-1} + Z_{it-1}\gamma' + \varepsilon_{it} \tag{5.3}$$

The dependent variable, $\sigma(\text{FX})_{it}$, is the exchange rate volatility of country i in month t. It is measured by the standard deviation of the monthly real exchange rate. The main explanatory variable, *Policy*, is the policy language sentiment, which we extract from central bank communication. Z_{it} refers to control variables used in the model such as the trade balance, inflation, the real effective exchange rate, and the change in the real effective exchange rate. ε_{it} is the error term.

Table 5.5 presents the results obtained from analysing the impact of policy language sentiment on exchange rate returns and volatility derived from speeches. The table is organized with Columns 1, 3 and 5 representing returns, while Columns 2, 4 and 6 reflect volatility. Specifically, Column 1 shows the returns of exchange rates against the US dollar, Column 3 displays the returns for the real effective exchange rate (REER) and Column 5 displays the returns for the nominal effective exchange rate (NEER). Columns 2, 4 and 6 capture the volatility associated with these returns. The results reveal that an increase in positive inflation sentiment leads to a significant increase in FX returns, as shown in Column 1, with significance at the 10 percent level. This might be because an increase in positive inflation sentiment reflects expectations of stable or improving economic conditions, which can lead to higher investor confidence and appreciation of the currency against the US dollar. Investors often respond favourably to positive economic signals, thus driving up the returns on the currency. In contrast, positive inflation sentiment results in a significant decrease in REER returns, detailed in Column 3, with significance at the 5 percent level. This suggests that while positive sentiment tends to boost returns for FX rates against the US dollar, it concurrently diminishes returns for the REER. As such, while domestic inflationary pressures could influence bilateral exchange rates favourably, they may not be as beneficial on a broader scale when considering the REER. The REER accounts for trade-weighted exchange rates and adjusts for relative inflation, so an increase in domestic inflation could erode the real value of the currency on an international scale, leading to decreased REER returns. In terms of exchange rate sentiment, an increase in positive exchange rate sentiment decreases FX returns. This result is significant at a 10 percent significance level. An increase in positive exchange rate sentiment typically reflects expectations of a strengthening or stabilizing currency in the foreign exchange market. As market participants anticipate a more stable or stronger currency, the immediate returns on FX investments might decrease due to the reduced likelihood of short-term speculative gains, hence a decrease in exchange rate returns. On the other hand, the results for NEER returns show that inflation sentiment has an insignificant effect, with a coefficient close to zero and a p-value greater than 0.1. This suggests that changes in inflation sentiment do not significantly influence the nominal effective exchange rate returns. Unlike exchange rates against the US dollar, which are more directly impacted by domestic inflation expectations, the NEER, as a trade-weighted index, appears less sensitive to inflation sentiment alone. This suggests that the NEER is influenced by a wider range of economic factors, such as the economic performance of trading partners and global inflation trends, rather than just domestic inflation pressures. Similarly, the results for exchange rate sentiment on NEER returns show an insignificant negative relationship. Positive sentiment towards exchange rates, which typically reflects expectations of a stronger or more stable currency, is associated with a slight decrease in NEER returns, though this effect is not statistically significant. This suggests that while positive sentiment may influence short-term movements in bilateral exchange rates, it does not have a meaningful impact on the NEER. Since the NEER is a broader measure, its returns are less likely to be strongly affected by sentiment that is more relevant to bilateral exchanges or short-term speculation.

Lastly, in terms of exchange rate volatility, Columns 2 and 4 indicate that an increase in positive sentiment for both inflation and exchange rates does not significantly affect the volatility of either exchange rates against the US dollar or the REER. These results indicate that while an increase in positive sentiment influences returns, it does not necessarily lead to increased fluctuations in the exchange rate itself. Positive sentiment might stabilize market expectations, reducing the likelihood of volatile responses to economic news. Similarly, positive sentiment does not significantly affect REER volatility. The stability in REER volatility despite changes in sentiment could indicate that broader, aggregate changes in sentiment do not lead to increased uncertainty in the real effective exchange rate. Factors influencing REER volatility might be more complex, involving multiple countries' economic policies and global trade dynamics that sentiment alone does not impact significantly. As such, this lack of significant effect suggests that while policy language sentiment influences returns, it does not similarly impact the stability or variability of exchange rates. Similarly, in terms of volatility, both inflation sentiment and exchange rate sentiment have no significant impact on NEER volatility. The lack of significant coefficients suggests that while sentiment can influence returns, it does not lead to increased fluctuations in the NEER. This stability in volatility suggests that NEER is influenced by a wider array of global factors, such as international trade conditions, economic policies of major trading partners, and geopolitical risks, rather than just the sentiment embedded in policy language. As such, our findings suggest that NEER volatility is less influenced by the tone of central bank communication.

Next, we analyse the impact of central bank communication sentiment extracted from press releases, as shown in Table 5.6. The results indicate that an increase in positive inflation sentiment in press releases does not significantly affect FX returns or volatility. This contrasts with the results observed in Table 5.5, where inflation sentiment in speeches had more noticeable effects. The lack of significant impact in Table 5.6 may reflect the nature of press releases, which are formal and concise, focusing on policy decisions that the market typically anticipates. As a result, press releases tend to confirm existing expectations rather than introduce new information, leading to a muted market response. In contrast, speeches, which often contain broader narratives and forward-looking statements, provide additional context on the central bank's outlook, thus having more potential to influence market sentiment. This is consistent with the findings of Lucca and Trebbi (2009), who stresses the importance of surprises in central bank announcements. Therefore, the limited market reaction to inflation sentiment in press releases suggests that they function primarily as routine policy updates, while speeches play a more dynamic role in shaping market expectations.

Moving on to exchange rate sentiment, Table 5.6 shows that an increase in positive exchange rate sentiment is associated with a rise in FX returns but a decline in REER returns. This suggests that positive sentiment regarding exchange rates boosts investor confidence and short-term FX returns but may have a different impact on trade-weighted measures like the REER. Table 5.6 also shows that positive exchange rate sentiment increases both FX and REER volatility, with these results being statistically significant. This implies that favourable sentiment about exchange rates leads to greater market reactions and fluctuations, reflecting increased speculative activity or market uncertainty. When comparing these results to those in Table 5.5, we observe that exchange rate sentiment from speeches has a negative effect on FX returns, while Table 5.6 indicates a positive effect from exchange rate sentiment in press releases. These opposite signs likely reflect the different roles and audiences of these communication formats. Speeches are more narrative-driven and broader in scope, which can convey caution about economic conditions and lead to negative FX returns. In contrast, press releases are more concise and focused on policy announcements, often signalling confidence and reducing market uncertainty, which can support positive FX returns. Lastly, Table 5.6 shows that positive exchange rate sentiment has a negative but insignificant effect on NEER returns, which is in line with the broader dynamics observed for FX returns. While exchange rate sentiment has significant effects on FX returns and volatility, its impact on NEER returns is weaker. This suggests

TABLE 5.5: Speeches Policy Language Sentiment on Exchange Rate Volatility and Returns

Variables	FX Return	FX Volatility	REER Return	REER Volatility	NEER Return	NEER Volatility
Inflation Sentiment	-0.0000216*	0.0009943	-0.0000054**	-0.0004832	0.0000214	-0.0005328
	(0.0000425)	(0.0007792)	(0.0000255)	(0.0005305)	(0.0000270)	(0.0004764)
Exchange Rate Sentiment	-0.0000413	-0.0002480	-0.0000209	0.0001326	-0.0000254	0.0003022
	(0.0000408)	(0.0007561)	(0.0000249)	(0.0005080)	(0.0000264)	(0.0004711)
FX Return (Lagged)	-0.0036171**					
	(0.0015876)					
FX Return	0.9931083***					
	(0.0016780)					
REER Lag	0.0000030	-0.0001104**	0.0000040***	-0.0000027	0.0000030*	
	(0.0000028)	(0.0000476)	(0.0000013)	(0.0000373)	(0.0000017)	
Change in REER	-0.0000346*	0.0010110***	-0.0001611***	0.0006949***		
	(0.0000203)	(0.0003297)	(0.0000569)	(0.0002020)		
Change in REER (Lagged)	0.0000097	-0.0001600	-0.0000096	0.0000262		
	(0.0000181)	(0.0002810)	(0.0000097)	(0.0001967)		
Trade Balance	-0.0000000	-0.0000001	0.0000000	-0.0000001	-0.0000000	-0.0000001
	(0.0000000)	(0.0000001)	(0.0000000)	(0.0000001)	(0.0000000)	(0.0000001)
Inflation	0.0000362	-0.0000443	-0.0000356**	0.0001959	-0.0000390**	0.0006011*
	(0.0000314)	(0.0004197)	(0.0000144)	(0.0004152)	(0.0000166)	(0.0003099)
FX Return	0.3793922					
	(0.4024862)					
REER Return		1.0174506***				
		(0.0053896)				
NEER Return			1.0224129***			
			(0.0039570)			
Change in NEER			-0.0001895***	0.0003189*		
			(0.0000408)	(0.0001887)		
Change in NEER (Lagged)			-0.0000138	-0.0001738		
			(0.0000098)	(0.0001763)		
NEER Lag			-0.0000042			
			(0.0000222)			
Constant	-0.0005351*	0.0224203***	-0.0005394***	0.0157290***	-0.0004800***	0.0165831***
	(0.0002819)	(0.0049673)	(0.0001275)	(0.0037115)	(0.0001812)	(0.0034135)
Observations	1319	1319	1444	1444	1446	1529
R-squared	0.9996	0.2208	0.3315	0.2076	0.4765	0.2063

Notes: The table reports the coefficient estimates with standard errors in parentheses. The control variables include lagged economic controls (inflation rates, trade balance, FX returns, and REER). Each column shows the result for foreign exchange dynamics (returns vs volatility). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

that the NEER, as a trade-weighted measure, is less sensitive to changes in sentiment regarding bilateral exchange rates, which may reflect market reactions that are more localized to specific currency pairs. Furthermore, the NEER's volatility is not significantly affected by inflation sentiment or exchange rate sentiment, reflecting that the broader set of economic factors influencing the NEER, such as the relative economic performance of trading partners and global inflation dynamics, are likely more influential than market sentiment alone. Therefore, from our findings, the contrast between press releases and speeches is evident in the differing impacts on FX returns and volatility. The NEER, however, appears less sensitive to these forms of sentiment, reflecting its broader, trade-weighted nature and its reliance on more structural economic factors.

TABLE 5.6: Press Release Policy Language Sentiment on Exchange Rate Volatility and Returns

Variables	(1) FX Return	(2) FX Volatility	(3) REER Return	(4) REER Volatility	(5) NEER Return	(6) NEER Volatility
Inflation Sentiment	-0.0001	0.0005	0.0003	0.0234	0.0156**	0.0207
	(0.0001)	(0.0003)	(0.0013)	(0.0225)	(0.0074)	(0.0304)
Exchange Rate Sentiment	-0.0002**	0.0008***	-0.0021*	0.0270	-0.0095	-0.0297
	(0.0001)	(0.0003)	(0.0012)	(0.0214)	(0.0070)	(0.0289)
FX Return (Lagged)	0.0175***					
	(0.0033)					
FX Return	0.9568***					
	(0.0028)					
REER Lag	0.0000***	-0.0000**	-0.0002***	-0.0132***	0.0003	
	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0003)	
Change in REER	-0.0000	-0.0000***	0.0046***	-0.0087***		
	(0.0000)	(0.0000)	(0.0002)	(0.0012)		
Change in REER (Lagged)	-0.0000	-0.0000	0.0004***	-0.0025*		
	(0.0000)	(0.0000)	(0.0001)	(0.0014)		
Trade Balance	-0.0000	-0.0000	-0.0000	-0.0000*	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Inflation	-0.0000**	-0.0000	-0.0001	-0.0045	0.0005	-0.0039
	(0.0000)	(0.0000)	(0.0002)	(0.0037)	(0.0012)	(0.0044)
FX Return	1.3173***					
	(0.0788)					
REER Return		0.4819***				
		(0.0144)				
NEER Return			0.0993***			
			(0.0025)			
Change in NEER			0.0108***	-0.0075***		
			(0.0002)	(0.0007)		
Change in NEER (Lagged)			-0.0004**	0.0035***		
			(0.0002)	(0.0008)		
NEER Lag			-0.0135***			
			(0.0009)			
Constant	-0.0017***	0.0077***	0.0130***	1.3692***	-0.0425	1.4748***
	(0.0005)	(0.0013)	(0.0045)	(0.0892)	(0.0312)	(0.0865)
Observations	918	918	1053	1053	1053	1188
R-squared	0.9967	0.2251	0.9156	0.3245	0.8804	0.2749

Notes: The table reports coefficient estimates with standard errors in parentheses. The control variables include lagged economic controls (inflation rates, trade balance, FX returns, and REER). Each column shows the result for foreign exchange dynamics (returns vs volatility). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.7.2 Foreign Exchange Intervention (FXI)

We define $(FXI)_{it}$ as the foreign exchange intervention of country i in year t. The FXI data, sourced from Adler et al. (2021), provides a comprehensive proxy for foreign exchange interventions at a monthly frequency. Adler et al. (2021) compute their FXI proxy both as a percentage of GDP and in millions of US dollars. Their measure encompasses various components: interventions in the spot market, changes in forward positions (derivatives), and total FXI, which combines both spot market transactions and derivatives. This approach allows for a detailed analysis of foreign exchange interventions, capturing both direct market actions and derivative-based adjustments. Foreign exchange interventions play a role in controlling exchange rate movements. Studies such as Fratzscher et al. (2019) and Bertsch et al. (2024) note that foreign exchange interventions (FXI) are more likely to be successful if complemented with oral communication from central banks. We therefore complement these studies by analysing whether central bank communication sentiment contains information about FXI that can help guide market participants. The regression model used in our analysis is specified as follows:

$$(FXI)_{it} = \alpha_i + \tau_t + \beta_1 \text{ Policy}_{i,t-1} + \beta_2 \text{ Policy}_{US,t-1} + Z_{it}\gamma' + \varepsilon_{it} \tag{5.4}$$

The dependent variable, $(FXI)_{it}$, is the foreign exchange intervention measure for country i at time t. The main explanatory variable, *Policy*, represents the policy language sentiment extracted from central bank communication. α_i and τ_t represent country-specific and time-specific fixed effects, respectively, accounting for unobserved heterogeneity. Z_{it} includes additional control variables such as GDP growth, inflation, and interest rates, which the empirical literature identifies as significant determinants of foreign exchange interventions. Finally, ε_{it} is the error term capturing unobserved factors affecting $(FXI)_{it}$. This model allows us to isolate the effect of central bank sentiment on foreign exchange interventions while controlling for key economic factors and accounting for fixed effects. We summarize our findings regarding the influence of central bank communication tone on foreign exchange interventions below. Our results, categorize the effects based on the type of central bank communication (press releases vs. speeches) and the exchange rate regime on a monthly frequency. Table 5.7 below reports the results of a panel regression analysis assessing the impact of central bank press release sentiment on foreign exchange interventions. The regression model includes fixed effects and examines the influence of inflation and exchange rate sentiment on foreign exchange interventions. The analysis controls for factors such as the GDP growth, inflation, the effective real exchange rate, and interest rates. Additionally, the model accounts for country and time specific fixed effects. The dependent variables in columns 1 through 4 represent different measures of foreign exchange interventions expressed as a percentage of the GDP.

When analysing central bank press releases (Table 5.7), we find that positive sentiment about inflation and exchange rates derived from press releases has distinct effects on foreign exchange interventions (FXI). Specifically, our results show that when central banks express an increase in positive sentiment regarding inflation, there is a noticeable decrease in FXI as a percentage of GDP. This can be attributed to increased market confidence and expectations of economic stability, which reduces the demand for hedging against inflationary risks. This suggests that a more favourable outlook on inflation boosts market confidence and expectations of economic stability. An increase in positive sentiment regarding exchange rates, particularly under a flexible exchange rate regime, leads to a reduction in total FXI. This is true for both spot and derivative positions. This shows heightened market confidence and expectations of currency stability, diminishing the perceived need for intervention. These findings thus suggest that the tone of central bank communication not only influences market perceptions but also impacts the scale and nature of foreign exchange interventions, with increased positive sentiment leading to a more stable FXI posture. This is consistent with Beine et al. (2009) who suggests that central bank communication and FX purchases are related and that FX communication works best when economic agents expect it to be followed by action.

To further investigate this, we analyse the impact of inflation and exchange rate sentiment obtained from speeches on FXI measured as a percentage of GDP. The impact of central bank speeches with increased positive sentiment about exchange rates depicted in Table 5.8 demonstrates a complex relationship with foreign exchange interventions (FXI). When central bank speeches convey a positive outlook on exchange rates, there is a decrease in FXI (forward positions) as a percentage of GDP. This suggests that in favourable market conditions, central banks may reduce their forward market engagements, reflecting a lower need to hedge or stabilize the currency.

TABLE 5.7: Press Releases Policy Language Sentiment on Foreign Exchange Interventions

	(1) FXI Broad Proxy (GDP)	(2) FXI Spot Proxy (GDP)	(3) FXI Derivative Proxy (GDP)
Inflation sentiment	-0.0928		-0.1062*
	(0.0983)		(0.0622)
Exchange rate sentiment	0.2894	-0.3808	-0.1565
	(0.1947)	(0.3875)	(0.1235)
Crawl-like × exchange rate sentiment		0.5756	
		(0.4035)	
Floating × exchange rate sentiment	-0.4709**	0.3001	0.1216
	(0.2147)	(0.3904)	(0.1361)
Free floating × exchange rate sentiment	-0.4785**	0.1948	0.1556
	(0.2407)	(0.4033)	(0.1527)
Pegged × exchange rate sentiment	0.0795	0.5292	0.1512
	(0.5387)	(0.5571)	(0.3418)
Stabilized arrangement × exchange rate sentiment	-0.1114	0.4615	0.1463
	(0.2741)	(0.4059)	(0.1739)
Crawling peg × exchange rate sentiment		0.9038	
		(0.5991)	
Other managed arrangement × exchange rate sentiment		0.5546	
		(0.5631)	
Constant	1.7737	1.2245***	-0.4911
	(1.6753)	(0.4103)	(1.0599)
Controls	Y	Y	Y
Time Fixed Effects	Y	Y	Y
Country Fixed Effects	Y	Y	Y
Observations	1320	2313	1325
R-squared	0.21	0.12	0.20

Notes: The table reports coefficient estimates of regression (5.4) with standard errors in parentheses, clustered at the central bank level. The control variables include interest rates, inflation rates, and real GDP growth rates, as well as central bank and time fixed effects. Each column shows the result for foreign exchange interventions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

However, this dynamic shifts in countries with flexible exchange rates. Here, higher positive sentiment often correlates with an increase in total FXI (spot and derivatives) as a percentage of GDP. This indicates that central banks might amplify their interventions to either reinforce their monetary policies or leverage favourable market conditions, despite prevailing market confidence.

The positive association between exchange rate sentiment and foreign-exchange intervention in flexible regimes may seem counterintuitive but it can be explained by the fear-of-floating hypothesis. That is, many central banks that describe their regimes as flexible still respond to exchange rate movements when these threaten price stability or financial conditions. More optimistic communication about the exchange rate may therefore coincide with intervention aimed at stabilising expectations or limiting volatility. This behaviour is consistent with evidence that inflation-targeting banks often smooth exchange rate fluctuations to maintain credibility.

The results suggest that communication tone forms part of the policy toolkit. By adjusting the sentiment in press releases and speeches, central banks can influence expectations in ways that complement traditional instruments. A neutral tone during temporary currency pressures can reduce the need for costly intervention, while positive language during periods of strong fundamentals can strengthen confidence without direct market action. The findings also connect to the open-economy trilemma. Monetary autonomy, exchange-rate stability, and capital mobility cannot all be achieved at once. The language used by central banks shows how communication helps them manage these competing objectives.

While positive sentiment can signal reduced intervention in some contexts, it may also prompt increased activity in others, depending on the exchange rate regime and the central bank's strategic objectives.

As a test for robustness, we examine the relationship between policy sentiment and foreign exchange interventions measured in US dollars. Table 5.9 illustrates the analysis results obtained from press release documents. Similar to the results obtained in Table 5.9, we find that an increase in positive inflation sentiment decreases FXI as measured by derivatives. However, this result is insignificant at a 5 percent level. We also find that an increase in positive sentiment about exchange rates in countries with a flexible exchange rate system decreases FXI. This is consistent with the results we found before.

Table 5.10 illustrates the analysis results obtained from central bank speeches. FXI is measured in US dollars. Inflation sentiment has no significant effect on foreign exchange interventions, similar to results in Table 5.8. We also find

TABLE 5.8: Central Bank Speeches Policy Language Sentiment on Foreign Exchange Interventions

	(1) FXI Broad Proxy (GDP)	(2) FXI Spot Proxy (GDP)	(3) FXI Derivative Proxy (GDP)
Inflation sentiment	0.0619		-0.1219
	(0.2013)		(0.1695)
Exchange rate sentiment	-0.6402*	0.0765	-0.6726**
	(0.3245)	(0.2968)	(0.2732)
Floating × exchange rate sentiment	1.5257***	0.5326	0.8813**
	(0.4518)	(0.3964)	(0.3802)
Free floating × exchange rate sentiment	1.0099**	0.1351	0.7982**
	(0.4331)	(0.3954)	(0.3645)
Stabilized arrangement × exchange rate sentiment	-0.1008	-2.3182	1.8383
	(3.1264)	(2.8843)	(2.6315)
Constant	-4.7993	0.3959	-5.9946
Controls	Y	Y	Y
Time Fixed Effects	Y	Y	Y
Country Fixed Effects	Y	Y	Y
Observations	1291	1307	1291
R-squared	0.76	0.72	0.42

Notes: The table reports coefficient estimates of regression (5.4) with standard errors in parentheses, clustered at the central bank level. The control variables include interest rates, inflation rates, and real GDP growth rates, as well as central bank and time fixed effects. Each column shows the result for foreign exchange interventions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5.9: The Impact of Central Bank Press Releases Policy Language Sentiment on Foreign Exchange Interventions

	(1) FXI Broad Proxy (USD)	(2) FXI Broad Proxy (USD)	(3) FXI Spot Proxy (USD)	(4) FXI Derivative Proxy (USD)
Inflation sentiment	350.5545		751.2292*	-398.2349
	(477.3640)		(427.9086)	(283.5430)
Exchange rate sentiment	2688.1907***	7141.7439***	3942.2238***	-1263.4615**
	(945.5285)	(1175.0452)	(847.5708)	(562.6473)
Floating × exchange rate sentiment	-2877.2943***	-7473.7367***	-4103.8359***	1230.6337**
	(1042.2357)	(1318.8188)	(934.2590)	(620.0165)
Free floating × exchange rate sentiment	-3709.2942***	-7963.6363***	-5027.4975***	1325.6508*
	(1168.7340)	(1495.4906)	(1047.6519)	(695.5344)
Pegged (within bands) × exchange rate sentiment	548.1110	-4575.3081	-1268.2251	1827.7998
	(2615.2910)	(3522.7055)	(2344.3441)	(1556.2743)
Stabilized × exchange rate sentiment	-2594.9797*	-6746.0261***	-3602.4194***	1018.1622
	(1330.7265)	(1724.3017)	(1192.8610)	(791.8199)
Constant	-5883.0680	14157.3974	-535.2139	-5180.8217
	(8131.9896)	(10629.4537)	(7289.5075)	(4825.8265)
Controls	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Country Fixed Effects	Y	Y	Y	Y
Observations	1320	1369	1320	1325
R-squared	0.1765	0.2089	0.1742	0.1504

Notes: The table reports coefficient estimates of regression (5.4) with standard errors in parentheses, clustered at the central bank level. The control variables include interest rates, inflation rates, and real GDP growth rates, as well as central bank and time fixed effects. Each column shows the result for foreign exchange interventions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

that an increase in positive sentiment about exchange rates decreases FXI. When accounting for different exchange rate regimes, we find that an increase in exchange rate sentiment for countries with a flexible exchange rate regime increases FXI. This is not the case for countries with a fixed exchange rate regime, as they portray insignificant results. This is in line with the results we found in Table 5.8.

In summary, the results suggest that inflation sentiment does not significantly affect FXI, but that exchange rate sentiment does. This is because central

TABLE 5.10: The Impact of Central Bank Speeches Policy Language Sentiment on Foreign Exchange Interventions

	(1) FXI Broad Proxy (USD)	(2) FXI Broad Proxy (USD)	(3) FXI Spot Proxy (USD)	(4) FXI Derivative Proxy (USD)
Inflation sentiment	743.2783		1262.2476	-518.9690
	(1170.4214)		(1149.0086)	(813.2300)
Exchange rate sentiment	-3626.7427*	-3480.6644*	-348.8281	-3277.9141**
	(1886.4329)	(1867.1279)	(1851.9206)	(1310.7277)
Floating × exchange rate sentiment	8599.5993***	8625.6554***	4205.7980	4393.8013**
	(2625.8520)	(2618.2003)	(2577.8120)	(1824.4896)
Free floating × exchange rate sentiment	5930.6497**	5726.6330**	2080.5187	3850.1304**
	(2517.1326)	(2489.5763)	(2471.0816)	(1748.9494)
Stabilized arrangement × exchange rate sentiment	4399.5083	2509.0656	-6700.3241	11099.8331
	(18170.2361)	(17874.6797)	(17837.8116)	(12625.0095)
Constant	-10381.6914	-9756.6708	18923.2063	-29304.9106
	(30439.7896)	(30338.9231)	(29882.8935)	(21150.1178)
Controls	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Country Fixed Effects	Y	Y	Y	Y
Observations	1291	1291	1291	1291
R-squared	0.7815	0.7807	0.7598	0.4390

Notes: The table reports coefficient estimates of regression (5.4) with standard errors in parentheses, clustered at the central bank level. The control variables include interest rates, inflation rates, and real GDP growth rates, as well as central bank and time fixed effects. Each column shows the result for foreign exchange interventions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

banks address inflation through monetary policy rather than through direct foreign exchange interventions. The results being consistent with previous results that measured FXI as a percentage of the GDP suggests that the relationships observed are robust across different analyses. It reinforces the idea that the central bank's response to sentiment is influenced by the underlying exchange rate regime. The consistency implies that the central bank's intervention strategies are systematically aligned with the type of exchange rate regime in place. Our findings about inflation and exchange rate sentiment from central bank communication can assist central banks in their policy making in several ways. Firstly, since exchange rate sentiment has a more significant impact on FXI (foreign exchange interventions) compared to inflation sentiment, central banks might prioritize communication strategies that address and manage exchange rate expectations. This can involve clearer and more frequent communication about exchange rate policies and interventions to stabilize market expectations. Central banks should therefore aim to be more proactive in their communication than reactive. The results also suggest that the central bank's interventions are aligned with the exchange rate regime in place. Central banks can use this understanding to tailor their intervention strategies according to the regime they are operating under (e.g., fixed, floating, or managed float). This alignment might help in managing exchange rate stability more effectively. Furthermore, by understanding that exchange rate sentiment impacts FXI more significantly, central banks can work towards consistent messaging that aligns with their intervention strategies. This consistency helps in building credibility and making their policy actions more predictable to the market. Overall, understanding the differential impacts of inflation and exchange rate sentiment on FXI enables central banks to refine their policy communication, intervention strategies, and overall approach to managing monetary and exchange rate policies more effectively.

5.8 Conclusion

This study set out to examine how central bank communication shapes foreign exchange interventions (FXI), with a focus on the role of sentiment about inflation and exchange rates. While much of the existing literature has concentrated on a small group of advanced economies, the analysis here broadens the scope by introducing a novel dataset that captures a wider range of countries and time periods.

The results show that both the channel of communication and the sentiment conveyed influence FXI and market outcomes. Using large language models within a few-shot learning framework, central bank speeches and press releases were classified into inflation and exchange rate related content, and their sentiment was extracted. The findings indicate that speeches exert more influence than press releases. Positive inflation sentiment in speeches is followed by higher FX returns and lower REER returns, whereas press releases show little measurable effect. By contrast, positive exchange rate sentiment is associated with higher FX returns and greater REER volatility, pointing to a broader role in shaping market fluctuations. These findings underline the importance of distinguishing between communication channels when analysing the impact of central bank messages.

An important implication of these results is that communication operates not only as a complement to direct interventions but also as a separate channel through which central banks influence expectations and behaviour in foreign exchange markets. Positive sentiment about inflation tends to reassure markets, reducing the need for intervention, whereas exchange rate sentiment has a more complex influence that varies with the prevailing exchange rate regime. This interaction between tone and institutional setting highlights the need for communication strategies that are adapted to the policy environment.

The results also have practical implications for how central banks manage their forward guidance. Since sentiment in speeches and press releases is associated with FX movements and intervention behaviour, communication can be adjusted to stabilise expectations when exchange rate pressures arise. In flexible regimes, a clear and neutral tone can help limit unnecessary intervention, while in more managed regimes positive language may support confidence when fundamentals are strong. This links the findings to the broader policy trade-offs faced in open economies. The interaction between sentiment, intervention, and the exchange rate regime echoes the classic trilemma where communication becomes one of the tools central banks use to navigate the balance between monetary autonomy, exchange rate stability, and capital flows.

The study also faces several limitations. The dataset is restricted to official speeches and press releases, which may not fully capture informal or off-record communication. Moreover, sentiment classification, while systematic, does not fully capture subtle differences in language or delivery. These limitations suggest that the results should be interpreted as evidence of broad patterns rather than precise estimates. While the panel framework allows us to identify broad links between central bank communication and exchange rate volatility across countries, it does not capture the dynamics of volatility itself. This is because panel regressions treat volatility as an outcome rather than modelling its persistence or clustering. Future research could therefore apply time-series approaches such as GARCH at the country level to complement these findings with a more detailed analysis of volatility behaviour.

A few other avenues remain open for future work. Extending the analysis to additional communication channels, such as interviews or social media, would give a more complete picture of how central banks influence expectations. Comparative studies across emerging and advanced economies would help clarify whether the observed effects are general or context specific. Furthermore, the application of non-linear methods could uncover dynamics that a linear regression cannot, particularly during episodes of market stress when communication interacts more strongly with uncertainty. Lastly, a promising extension could also be to apply volatility models such as GARCH in single-country settings. This would allow researchers to capture the time-varying nature of volatility and examine how communication interacts with volatility dynamics within specific institutional and market environments. Such work would complement the cross-country perspective provided here.

In conclusion, this chapter shows that central bank communication has measurable effects on both foreign exchange interventions and market outcomes. By managing how they present inflation and exchange rate policies, central banks can strengthen their capacity to stabilize foreign exchange markets and pursue their broader economic objectives. In addition, by linking to evidence from Chapter 2 on monetary policy uncertainty and stock market volatility, these findings extend the analysis to the foreign exchange domain and demonstrate the greater importance of communication in shaping financial stability.

Chapter 6

Conclusion

This thesis has investigated the role of monetary policy uncertainty, household perceptions, and central bank communication in shaping financial markets and economic behaviour. Across four empirical chapters, the research has demonstrated that uncertainty is not an abstract construct but a lived reality for households, firms, and policymakers. It is embedded in financial prices, reflected in household choices, and mediated through central bank communication. By combining evidence from an emerging market, novel micro-level household surveys, and cross-country communication analysis using large language models, this thesis provides a broader and more integrated understanding of how monetary policy uncertainty is measured, perceived, and transmitted.
The motivation for this thesis is to understand how uncertainty is perceived and transmitted at both the household and market level. In particular, the analysis focuses on subjective assessments of stock market volatility and forward-looking monetary policy uncertainty. Greenspan have stressed that monetary policy should not react mechanically to movements in financial markets, as this can amplify short-term noise rather than support long-term stability (Greenspan, 1997). This policy view motivates the study of how people and markets interpret uncertainty, and how these interpretations shape behaviour. Central bank communication is central to this process since it provides the information on which expectations are formed. However, the way communication is structured and framed may itself create or reduce uncertainty. In this thesis, modern tools from computational linguistics are used to study this dimension. By applying large language models to central bank texts, we are able to capture tone and emphasis in ways that go beyond traditional keyword methods. This methodological innovation allows us to link communication more directly to perceptions of uncertainty. Recent episodes such as the global financial crisis, the euro area sovereign debt crisis, the COVID-19 pandemic, and the inflation

surge have shown that uncertainty is central to monetary transmission. Against this background, this thesis develops four empirical studies, each addressing a distinct question but contributing to a common narrative.

The four papers in this thesis are written as independent contributions, but they are also closely connected. As a whole, they form a cumulative argument about the role of uncertainty in monetary policy and about the methods required to study it. This section develops the synthesis in detail, tracing how the research progresses across levels of analysis, across empirical methods, and across theoretical debates. In this way, the thesis is presented not as a set of separate studies but as a coherent piece of research on monetary policy uncertainty and central bank communication.

The first paper addresses a practical gap in how monetary policy uncertainty can be measured in an emerging market where traditional instruments are scarce. By constructing a Twitter-based index for South Africa, the chapter demonstrated that it is possible to generate a timely and credible proxy for policy uncertainty using unconventional data. This was more than a technical exercise. It established uncertainty as a measurable phenomenon that fluctuates meaningfully with events and influences markets. The finding that uncertainty shocks raise stock market volatility confirmed the relevance of uncertainty to financial stability in a high-volatility environment.

This starting point prepared the ground for the next stage of the thesis. If uncertainty can be measured and shown to affect markets in an emerging economy, the next question is whether similar dynamics operate at the micro level. Chapter 2 therefore provided the methodological and conceptual foundation for later chapters. It validated the idea that uncertainty is both observable and consequential, while also illustrating the feedback loop between uncertainty and volatility.

The second paper then shifted the lens from markets to households. The motivation was clear. Markets are not the only, or even the main, channel through which monetary policy transmits. Households make borrowing, saving, and investment decisions based on their perceptions of policy. Yet most of the literature has focused on inflation expectations, leaving interest rate expectations underexplored. Chapter 3 addressed this gap by exploiting a novel French survey that directly elicited household beliefs about the policy rate and their associated uncertainty.

Conceptually, this chapter extended the logic of the South African study. If financial markets react to policy uncertainty with higher volatility, do households in an advanced economy perceive and internalise similar links between policy uncertainty and stock market risk? The empirical evidence showed that they do. Households reporting higher uncertainty about monetary policy also reported higher expected stock market volatility. This parallel between macro evidence from markets and micro evidence from households is central to the coherence of the thesis. It shows that uncertainty operates across levels. It is not confined to professional investors but is part of the mental models of ordinary households.

The third paper went further by testing whether these household perceptions conform to the Full Information Rational Expectations benchmark. If households form expectations rationally, then perception gaps and forecast errors should average to zero and show no systematic patterns. The evidence strongly rejected this. Households frequently misperceived the current policy rate and these misperceptions carried over into biased forecasts. Systematic patterns were also uncovered. More educated and higher-income households had smaller errors, while less informed groups systematically overestimated rates. These deviations were not benign. They influenced saving and borrowing behaviour, with larger perception gaps associated with a lower probability of being in higher saving bands.

The final paper shifted perspective once more, from the receivers of information to the senders. If households and markets form perceptions that are biased and heterogeneous, attention must turn to how central banks communicate and how this shapes uncertainty. Chapter 5 addressed this by applying large language models to a large corpus of central bank texts. This was not a departure from the thesis theme but its culmination. This chapter placed communication at the centre of the uncertainty process, recognising that uncertainty is not only experienced by agents but also managed, and at times generated, by institutions. The empirical results showed that communication content and tone vary systematically across central banks, with important consequences for markets. Shifts in emphasis on exchange rates versus inflation influenced exchange rate dynamics, demonstrating that communication priorities are priced by markets. Together, the papers provide a comprehensive account of monetary policy uncertainty as a process that spans measurement, perception, behaviour, and communication. That is, uncertainty is not confined to markets or models but runs through households and institutions as well, shaping behaviour and policy transmission.

Each study required the development and application of new skills, ranging from text mining and time-series econometrics to high-dimensional micro econometrics, behavioural modelling, and machine learning. The diversity of contexts and methods illustrates systematic knowledge-building at the frontier of the field. The research began with time-series econometrics and text mining to construct a new uncertainty index for South Africa. It then advanced to high-dimensional micro econometrics in analysing household survey data, followed by behavioural econometrics to link misperceptions to financial decisions, and finally to natural language processing and large language models for cross-country communication analysis. This sequence illustrates both breadth and depth, moving from macro-financial markets to household microdata and on to institutional communication, while developing expertise at each frontier. In this way, the thesis represents both a contribution to the literature and evidence of independent research capability.

Several themes cut across the four papers and monetary policy uncertainty matters in all contexts examined. In South African markets, in the perceptions and expectations of French households, and in the communication of central banks, uncertainty shapes behaviour and outcomes. Expectations are heterogeneous, with households differing systematically in their perceptions depending on information, education, and exposure. Communication emerges as central, since uncertainty can either be reduced or intensified depending on how policy is conveyed and understood. Furthermore, this thesis also shows that methods evolve, allowing us to draw on social media data and language models alongside traditional econometrics to capture uncertainty in real time. Finally, the comparative perspective demonstrates that although institutional contexts differ between emerging and advanced economies, the underlying dynamics of uncertainty remain widely shared. These themes provide the basis for the theoretical, empirical, and policy contributions that follow.

The four papers collectively advance theoretical debates in three areas. First, they deepen the understanding of uncertainty itself. Since Knight (1921), economists have distinguished measurable risk from unmeasurable uncertainty, yet much of the modern literature continues to treat uncertainty as an exogenous disturbance. The findings in this thesis suggest a different view, that uncertainty is endogenous, shaped by communication, amplified by misperceptions, and feeding back from markets to policy decisions. The bidirectional relationship between monetary policy uncertainty and volatility documented in South Africa provides evidence of this mechanism. This perspective calls for models in which uncertainty is not only a background condition but also a determinant of economic dynamics.

Second, they challenge the benchmark of full-information rational expectations. Evidence from French households shows that perception gaps and forecast

errors are systematic and correlated with socioeconomic traits. These deviations from the rational benchmark are not simply survey noise, they influence real outcomes, including saving decisions. The findings therefore support frameworks of bounded rationality, rational inattention, and heterogeneous expectations, where limited information and selective attention shape behaviour. This challenges the assumption that policy transmission can be modelled through a representative, fully informed agent, and suggests that expectation heterogeneity should be embedded more explicitly in macroeconomic models.
Third, they reposition communication as a central component of policy. Analysis of central bank texts using modern language models shows that communication is not a neutral disclosure of information but an instrument that can stabilise or destabilise expectations. Shifts in emphasis and tone affect how markets and households interpret policy, sometimes anchoring beliefs and sometimes generating uncertainty. These results align with theories of central bank credibility that treat communication as endogenous to policy effectiveness. They also illustrate the need to study communication not only as a complement to policy but as part of the transmission mechanism itself.

This thesis also contributes empirically by expanding the data and methods available for studying uncertainty. Paper 1 constructed the first Twitter-based index of monetary policy uncertainty for an African country, demonstrating the feasibility of using social media as a high-frequency information source. This innovation provides policymakers in data-scarce environments with a low-cost tool to monitor sentiment. Paper 4 extended the toolkit further by applying large language models to central bank texts, moving beyond dictionary methods to capture nuance and tone. These applications show how big data and machine learning can complement traditional surveys and financial indicators.
Methodologically, the thesis employed shock-restricted structural VARs, high-dimensional IV-Lasso, distributional tests, and behavioural econometrics. These approaches addressed identification and endogeneity concerns while maintaining links to theory. They illustrate how modern econometrics can be combined with new data sources to yield credible evidence. Importantly, the use of household survey microdata alongside macro-financial time series emphasises the value of multi-level analysis. By bringing together macro-financial time series, micro-level survey responses, and central bank communication, the empirical work demonstrates that monetary policy uncertainty is a multi-layered phenomenon. Each level provides different but complementary evidence, that is, markets reveal how uncertainty is priced, households show how it is perceived and acted upon, and central banks illustrate how it is communicated. This integration strengthens

the robustness of the findings and points to the importance of multi-method approaches in applied macroeconomics.

The findings carry several implications for central banks. In emerging markets, uncertainty can be monitored with unconventional data, but it also has more severe effects due to thinner financial markets and greater exposure to shocks. This calls for proactive communication and integration of financial stability into policy frameworks. In advanced economies, household misperceptions weaken transmission, suggesting that communication should be clearer and more targeted to different audiences. More broadly, the analysis shows that communication is an important policy tool. Central banks must not only decide rates but also manage how those decisions are perceived. This means that communication strategies need to be evaluated systematically, much like interest rate decisions themselves. Credibility depends on consistent alignment between words and actions, and central banks that anticipate and address uncertainty proactively are more effective than those that respond only after volatility has already risen.

No empirical project is without limitations and acknowledging them is important for understanding the scope of the findings and for motivating future research. The limitations of this thesis fall into three broad categories: data availability, methodological constraints, and the pace of technological change.
Firstly, The South African Twitter-based index offers a novel way to capture monetary policy uncertainty, but it has inherent limitations. Twitter users represent only a subset of the population, typically younger, urban, and more affluent groups, which may bias the measure toward the concerns of that demographic. Moreover, Twitter data are available only from 2006 onward, preventing long historical analysis, and since 2023 access to Twitter's full archive requires costly subscriptions or restrictive API access. This reduces the replicability and scalability of the approach, especially for cross-country comparisons. Household survey data also pose a different set of limitations. The French TNS survey used here was limited to a single wave, which means the results reflect a snapshot rather than dynamic adjustments in household expectations over time. Earlier survey waves did not include questions on policy rates. As a result, this left us without a longer series for comparison. More generally, most consumer expectation surveys focus heavily on inflation rather than policy rates, which restricts the ability to study household-level monetary policy uncertainty in a broader range of countries. Central bank communication data also have gaps. The dataset relied primarily on English-language press releases and speeches,

which may miss nuances in multilingual contexts or countries where the local language carries more weight in shaping perceptions. Therefore, obtaining reliable archives across countries can be challenging, especially for smaller or less transparent central banks. These gaps thus limit the scope of comparative cross-country analysis.
Secondly, For the communication analysis, large language models (LLMs) represent a significant methodological advance over dictionary-based approaches, but they are not without problems. LLM outputs are sensitive to training data, prompt design, and language bias, and they can misclassify complex statements. Therefore, it is important to fine tune and evaluate the models used.
Lastly, a further limitation arises from the rapid pace of technological change. When the Twitter-based index was first developed in 2021, transformer-based large language models were not yet available. Since then, advances in natural language processing have opened up more powerful methods for text classification and sentiment analysis, making earlier techniques appear dated in retrospect. Similarly, econometric methods evolve quickly, and approaches considered state-of-the-art just a few years ago may soon be replaced by more flexible machine learning tools. This creates a moving target for researchers, where methodological choices are inevitably shaped by the tools available at a given time. In sum, while the thesis introduces new data sources and methods, it also operates within the constraints of representativeness, coverage, and evolving technology. These limitations temper the generalisability of the findings but also highlight opportunities for future research to extend, refine, and improve upon the approaches taken here. Despite these limitations, the findings presented in this thesis are robust within the scope of the available data and provide a credible basis for advancing both academic debate and policy discussion on monetary policy uncertainty.

The limitations discussed above naturally point to promising avenues for future work. At the same time, the findings of this thesis open new questions that extend beyond its immediate scope. Together, these suggest a broad research agenda at the intersection of monetary policy uncertainty, expectations, perceptions, and communication. Future research could expand the range of data sources used to study monetary policy uncertainty. For emerging markets, where conventional instruments such as option markets are underdeveloped, alternative digital traces remain underexploited. Social media platforms beyond Twitter (e.g. Reddit, Facebook, or news-comment sections) and search engine query data could be used to triangulate measures of uncertainty. This would help reduce reliance on a single platform and provide more representative signals of public sentiment. On the household side, longitudinal surveys are essential. The French survey used in this thesis provided a valuable snapshot, but a panel design would allow researchers to track how perceptions and expectations evolve over time and how households update beliefs after policy shocks. Expanding household-level surveys to other advanced and emerging economies would also allow meaningful cross-country comparisons of monetary policy uncertainty. For central bank communication, efforts should be made to gather more multilingual corpora, particularly in countries where English is not the primary medium of policy communication. Analysing statements in local languages, alongside English, would capture more accurately the information environment that households and firms actually face.

Furthermore, this thesis employed a combination of econometrics and machine learning methods, but the rapid evolution of technology creates scope for refinement. Nonlinear econometric frameworks such as threshold VARs or Markov-switching VARs could capture the state-dependent effects of policy uncertainty, which may be stronger during downturns or crises. Machine learning methods beyond Lasso such as random forests, gradient boosting, or neural networks could be applied to survey and behavioural data to capture nonlinearities and interactions. For communication analysis, future work could pair central bank statements with data on media reporting and social media reactions. This would allow researchers to study not only what central banks say but also how those messages are received and interpreted in real time. Advances in natural language processing, including multilingual large language models, will continue to improve the ability to detect tone, emphasis, and framing across contexts.

In addition, the household studies in this thesis show that perception gaps and forecast errors are associated with saving and borrowing behaviour. Future work could extend this to other financial decisions such as investment in risky assets, housing choices, or pension contributions. Linking survey data on expectations with administrative or transaction-level financial data would allow more direct tests of how beliefs shape outcomes. Parallel work could be undertaken on firms, building on new surveys of business expectations and uncertainty, to explore how managers' perceptions of policy affect investment, hiring, and pricing decisions.

The dual focus on South Africa and France was deliberate but necessarily limited. Future research should broaden this scope. Constructing MPU indices for other emerging markets such as Brazil, India, or Nigeria would help establish whether the South African patterns are generalisable. Similarly, applying household surveys in other advanced economies would test whether the French results hold more broadly or are context specific. On the communication side, expanding the analysis to a wider set of central banks, including those with pegged exchange rates or unconventional policy mandates, would provide a fuller picture of how communication priorities differ across regimes.

An important lesson is that uncertainty is not confined to monetary policy. Fiscal policy uncertainty, political uncertainty, and climate policy uncertainty all interact with monetary policy and may amplify or offset its effects. Future work could model these interactions more explicitly, particularly in economies where fiscal dominance or climate shocks are relevant. Likewise, the rise of digital currencies presents a new dimension of uncertainty. For example, how central bank digital currencies will affect the transmission of policy, and the expectations of households and markets remains largely unexplored.

Lastly, there is scope for institutional development. Central banks themselves could adopt real-time uncertainty monitoring tools, integrating social media, survey, and market-based indices into their policy dashboards. Collaborations between central banks and academic researchers could improve methodological transparency and ensure that such tools are robust. Over time, these measures could become part of the routine toolkit of central banking, much like inflation forecasts or stress tests.

In short, future research should build on the contributions of this thesis by widening the data base, refining the methods, and extending the scope across countries and policy domains. As new technologies and shocks continue to reshape the global economy, the study of monetary policy uncertainty will remain central to both academic inquiry and policy practice.

All in all, this thesis has argued that monetary policy cannot be understood without recognising uncertainty, perceptions, expectations, and communication. Uncertainty is not only a by-product of shocks but also a determinant of how policy is transmitted. Expectations are heterogeneous and often biased, challenging rational benchmarks. Communication is therefore not ancillary but integral to managing uncertainty.

By addressing these issues across markets, households, and central banks, the research provides a more complete picture of monetary transmission. It combines new data sources with modern econometrics to push the boundaries of measurement and analysis. It shows that monetary policy is as much about managing perceptions as about adjusting policy rates. For scholars, the work contributes to the theoretical and empirical literature on uncertainty and expectations. For policymakers, it shows the importance of communication and the need to recognise household misperceptions. For future research, it points to the opportunities opened by big data and machine learning.

In conclusion, this thesis provides new evidence on how monetary policy uncertainty can be measured in an emerging market, how it is perceived and acted upon by households in an advanced economy, and how it is conveyed through central bank communication. The findings show that uncertainty influences financial markets, household behaviour, and policy credibility, demonstrating that it is a central element of monetary transmission rather than a background condition.

Appendix A

Chapter 2

A.1 Data Collection Methodology

This appendix outlines the steps taken to collect Twitter data and construct a Twitter-based index of monetary policy uncertainty (MPU) for this study.

1. Defining Keywords and Search Criteria

To capture tweets related to monetary policy uncertainty, a set of keywords was defined based on terms most commonly associated with economic policy uncertainty and central bank actions. The following criteria were applied:

- **Keywords:** The search included a combination of terms related to monetary policy (e.g., “interest rates,” “central bank,” “inflation,” “policy,” “rate hike”) and terms related to uncertainty (e.g., “uncertain,” “risk,” “volatility,” “uncertainty”).
- **Geographic Focus:** Tweets were filtered to include those originating from South Africa.
- **Timeframe:** The analysis covered the period from **January 2017 to December 2020**, with specific focus on key political and economic events that might have influenced public perceptions of monetary policy uncertainty.

2. Data Collection Process

The following steps were followed to collect tweets:

- **Twitter API Access:** The study used the official Twitter API to retrieve tweets based on the defined keywords. This was done using the `Tweepy` library (for Python) and the `Twitter Developer API`.
- **Rate Limits and Sampling:** The API's rate limits were adhered to, meaning that tweet retrieval was split into several requests. To manage the volume, a random sampling method was employed to avoid bias toward highly frequent terms or specific time periods.
- **Filtering and Preprocessing:** Once the tweets were retrieved, they were pre-processed to:
  - Remove duplicates
  - Filter out irrelevant tweets (e.g., spam or unrelated topics)
  - Extract only the relevant text content (ignoring metadata such as URLs and hashtags)

3. Data Cleaning and Preprocessing

The collected tweet dataset underwent several preprocessing steps to ensure data quality:

- **Text Cleaning:** All tweets were cleaned by removing punctuation, stop words, and irrelevant symbols (e.g., emoticons and links).
- **Language Filtering:** Since the study focused on South African policy, tweets in languages other than English were excluded. This was done using a language detection tool.
- **Normalization:** The text was normalized by converting all characters to lowercase to avoid duplicate counting of words that differed only by case (e.g., ”Risk” and ”risk”).

4. Twitter Based Index

- **Validation:** The constructed MPU index was validated by comparing it against known policy events and market reactions. Peaks in the index were compared to major policy announcements and political events that were likely to influence market sentiment. The index was also compared to other monetary policy uncertainty measures found in literature.

5. Data Limitations and Biases

- **Sampling Bias:** While attempts were made to randomize the sample of tweets, Twitter's user base is not fully representative of all demographics, meaning that the index may reflect a skewed sample of public sentiment, especially among more active or vocal user groups.
- **Data Completeness:** Some policy-related events may not have been adequately reflected due to limitations in the data collection (e.g., Twitter's API rate limits or missing data).

6. Tools and Software Used

- **Tweepy:** Python library used to interact with Twitter's API.
- **NLTK:** Used for text cleaning .
- **Python Pandas & NumPy:** For data manipulation and processing.
- **Matplotlib & Seaborn:** Used for visualizing the time series data.

A.2 Stock Market Volatility

Daily returns of the closing stock prices of the Johannesburg Stock Exchange are obtained from the Eikon Reuters database. The daily returns are constructed as follows:

$$R_{n,t} = \ln\left(\frac{X_{n,t}}{X_{n-1,t}}\right) \times 100 \tag{A.1}$$

Where $R_{n,t}$ denotes the stock market return on day n for the month t.
As a proxy for stock market volatility, we measure monthly realized volatility using daily squared returns (Gospodinov and Jamali, 2015). The realized volatility is given by:

$$vol_t = \sqrt{252 \cdot \frac{1}{N}\sum_{n=1}^{N} R_{n,t}^2} \tag{A.2}$$

Where N is the number of trading days in month t.

A.3 Correlations between shocks and external variables

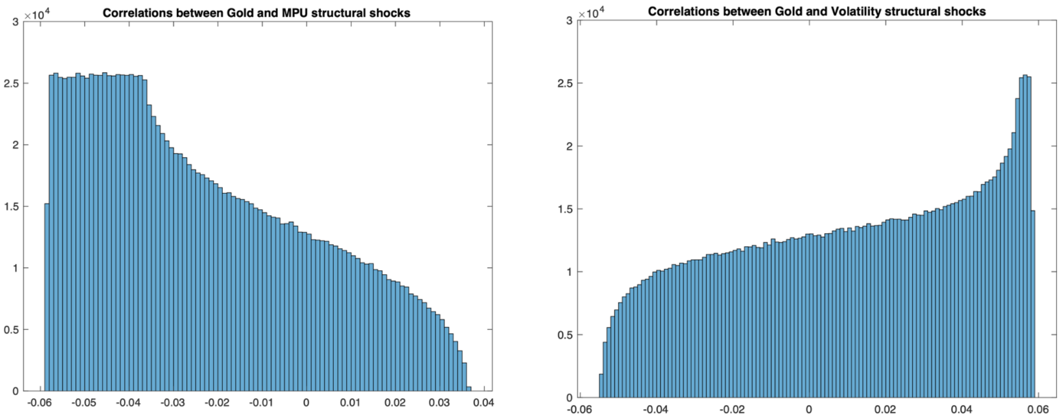


Figure A.1: The Distribution of the Correlations Between Gold and Structural Shocks

Notes: Following Ludvigson et al. (2021), external variables are not assumed to be valid instruments in the sense of exogeneity, but they should display systematic comovement with the shocks they are intended to capture. Gold prices are commonly used in this context because they respond strongly to uncertainty episodes. Significant correlations provide support for the interpretation of the identified shocks.

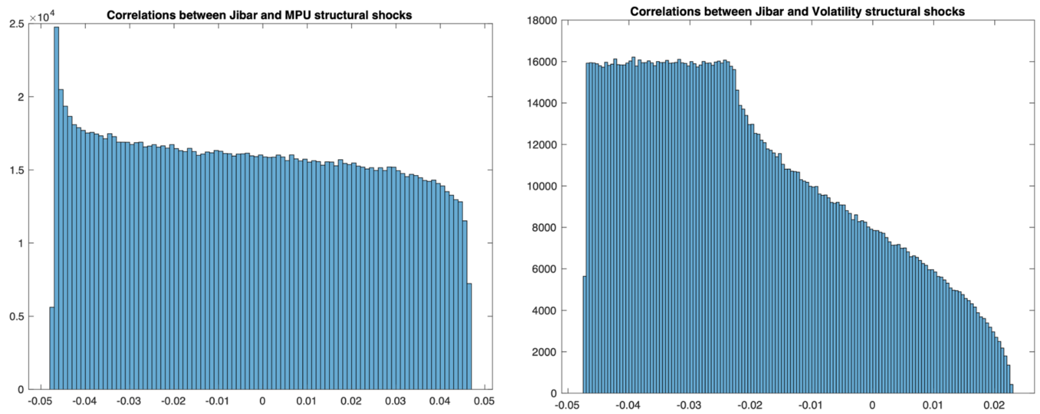


Figure A.2: The Distribution of the Correlations Between Jibar and Structural Shocks

Notes: This figure shows the distribution of correlations between the Johannesburg Interbank Agreed Rate (JIBAR) and the identified structural shocks. Two relationships stand out. First, shocks to stock market volatility are positively correlated with JIBAR, suggesting that episodes of financial turbulence spill over into higher short-term funding costs in the interbank market. Second, monetary policy uncertainty (MPU) shocks also display a positive correlation with JIBAR, consistent with the idea that heightened uncertainty about future policy actions raises risk premia in money markets. Following Ludvigson et al. (2021), these external correlations are used as informative restrictions, without requiring JIBAR to be strictly exogenous to the shocks of interest.

A.4 Tests for Stationarity

TABLE A.1: Augmented Dickey-Fuller (ADF) Stationarity Tests

	MPU	SMV	Industrial Production (log)
Test statistic	-8.548	-5.107	-4.017
1% critical value	-3.578	-3.585	-3.584
5% critical value	-2.925	-2.928	-2.929
10% critical value	-2.601	-2.602	-2.602
p-value	0.0000	0.0001	0.0002
Observations	47	47	47
Lag length	0	0	0

Notes: The table reports Augmented Dickey-Fuller unit root tests for monetary policy uncertainty (MPU), stock market volatility (SMV), and log industrial production. The null hypothesis is the presence of a unit root. All three series reject the null at the 1% significance level, confirming stationarity. Lag length selected by SIC, with maximum lag of 9.

Appendix B

Chapter 3

Appendix A: Survey Questions (TNS 2015)

This section shows the key survey questions used in the analysis.

Stock Market Expectations

B1a. In five years from now, do you think the stock market (CAC-40) will have... (Please write probabilities from 0 to 100. The sum must be 100.)

- Risen more than 25%
- Risen 10% to 25%
- Risen less than 10%
- Remained at the same level
- Fallen less than 10%
- Fallen 10% to 25%
- Fallen more than 25%

Current Debt Status

E1. Do you currently have any outstanding debt?

- Yes
- No

Policy Rate Perceptions

E6a. Would you say that the interest rate of the Bank of France (or ECB) is today… (Please write probabilities from 0 to 100. The sum must be 100.)

- Less than 0.5%
- Between 0.5% and 1.5%
- Between 1.5% and 2.5%
- Between 2.5% and 3.5%
- Between 3.5% and 4.5%
- More than 4.5%
- I don't know

Policy Rate Expectations

E6b. In five years from now, do you think the European Central Bank interest rate will be… (Please write probabilities from 0 to 100. The sum must be 100.)

- Less than 0.5%
- Between 0.5% and 1.5%
- Between 1.5% and 2.5%
- Between 2.5% and 3.5%
- Between 3.5% and 4.5%
- More than 4.5%
- I don't know

Household Savings

E11. In the last 12 months did you or your spouse/partner save any money (excluding loan or mortgage repayments)?

- No, we haven't saved
- Yes, less than €500
- Yes, from €500 to less than €1,000
- Yes, €1,000 to €2,000
- Yes, €2,000 to €5,000
- Yes, €5,000 to €10,000
- Yes, more than €10,000

Appendix C

Chapter 4

TABLE C.1: Appendix: Full regression results for forecast errors on perception gaps (corresponding to Table 4.2)

	(1) OLS	(2) Median Reg.	(3) PDS-Lasso
Perception Gap (PG)	0.640***	0.733***	0.637***
	(0.041)	(0.036)	(0.035)
Constant (α)	0.700**	0.360	0.746***
	(0.314)	(0.292)	(0.075)
Gender (Male=1)	0.004	-0.019	–
	(0.069)	(0.071)	
Income (ref: $<$12k)			
12–20k	0.150	0.107	–
	(0.134)	(0.122)	
20–30k	0.212	0.159	–
	(0.128)	(0.115)	
$>$30k	0.325**	0.247**	0.156**
	(0.129)	(0.122)	(0.075)
Assets (ref: $<$75k)			
75–225k	0.022	0.028	–
	(0.113)	(0.104)	
225–450k	0.036	0.088	–
	(0.120)	(0.106)	
$>$450k	0.135	0.196*	0.180**
	(0.123)	(0.117)	(0.081)
Employment (ref: Other)			
Retired	-0.007	0.156	–
	(0.210)	(0.221)	
Unemployed	0.227	0.177	–
	(0.189)	(0.212)	
Employed	-0.079	0.107	–
	(0.162)	(0.186)	
Education (ref: $<$HS)			
High School	-0.146	-0.284	–
	(0.284)	(0.243)	
Technical/Prof.	-0.368	-0.275	–
	(0.237)	(0.190)	
College+	-0.259	-0.195	-0.012
	(0.245)	(0.195)	(0.069)
Age (ref: $<$35)			
35–44	0.146	0.091	–
	(0.108)	(0.115)	
45–65	0.175	0.212*	–
	(0.104)	(0.116)	
80+	0.354**	0.299*	–
	(0.167)	(0.168)	
Observations	626	626	626
R^2 / Pseudo R^2	0.393	0.299	0.372
Joint test $\alpha = \beta = 0$	F=147.72	F=224.65	χ^2=1502.62
p-value	0.000	0.000	0.000

Notes: Robust standard errors are reported for OLS; bootstrap standard errors for the median regression; and valid standard errors for the PDS–Lasso specification. Significance levels are denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All specifications include controls for income, assets, employment, education, and age. Out of the full set of 118 controls, the PDS–Lasso procedure selected income $>$30k, assets $>$450k, and college education.

Appendix D

Chapter 5

TABLE D.1: Analyzed Countries

MP Framework	Count	Countries
Exchange Rate Anchor	13	Aruba, Bhutan, Eswatini, Gambia, Lesotho, Morocco, Namibia, Nigeria, Oman, Singapore, South Africa, Tanzania, Trinidad and Tobago
Inflation Targeting Framework	31	Australia, Bahamas, Botswana, Brazil, Colombia, Dominican Republic, Georgia, Ghana, Hungary, Iceland, Indonesia, Jamaica, Japan, Kazakhstan, Kenya, Korea, Mexico, New Zealand, Norway, Peru, Philippines, Poland, Rwanda, Seychelles, South Korea, Sri Lanka, Sweden, Thailand, Türkiye, United Kingdom, Uruguay
Monetary Aggregate Target	3	China, Liberia, Samoa
Other Monetary Framework	33	Argentina, Austria, Belgium, Cyprus, Egypt, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Kyrgyz Republic, Latvia, Lithuania, Luxembourg, Malawi, Malaysia, Malta, Mauritius, Mongolia, Mozambique, Netherlands, Pakistan, Portugal, Slovakia, Slovenia, Spain, Switzerland, Taiwan, United States, Zambia, Zimbabwe

Notes: The table lists all countries included in the analysis, grouped by their monetary policy framework as classified by the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Counts refer to the number of economies in each category.

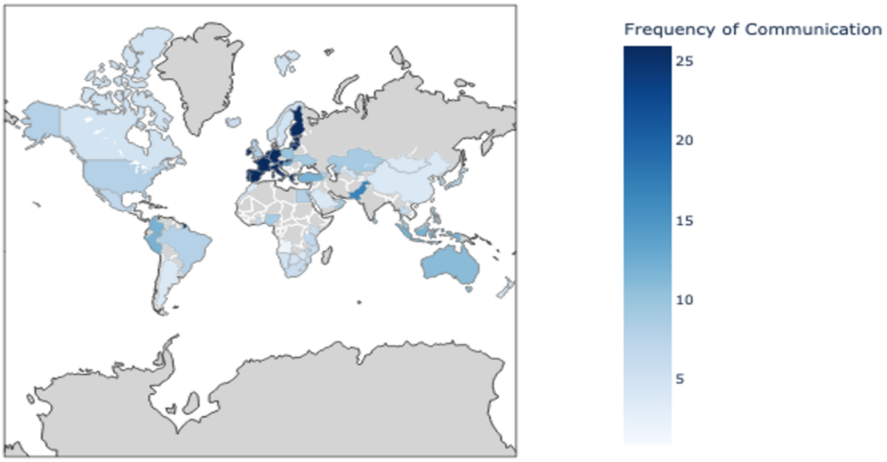


FIGURE D.1: Frequency of Press Release by Country

Notes: The figure shows the number of monetary policy press releases published by each central bank in our dataset. Counts reflect the availability of English-language documents on official central bank websites.

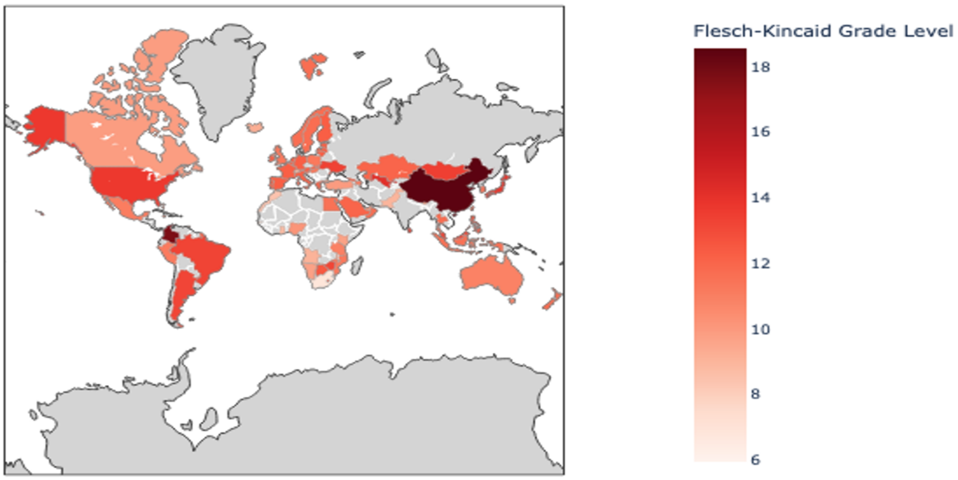


FIGURE D.2: Readability of Press Releases by Country (Average 2023)

Notes: The figure reports average readability scores for press releases in 2023, based on standard text-complexity measures. Higher values indicate easier to read communication.

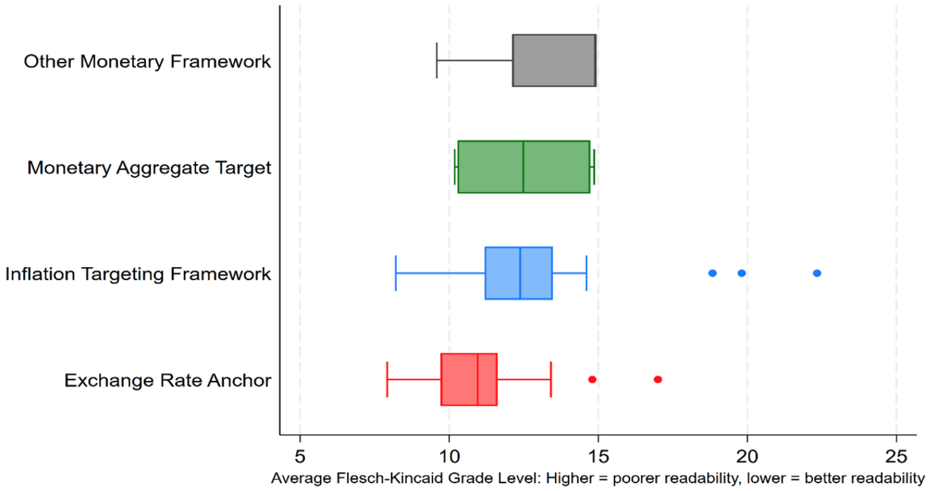


FIGURE D.3: Readability of Press Releases by Monetary Policy Framework (2023)

Notes: The figure compares average 2023 readability across monetary policy frameworks as classified in the IMF AREAER. Readability scores summarise the linguistic clarity of policy statements.

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