University of Liège

Monetary Policy and Uncertainty: The Higher-Order Nexus

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Chapter 1

Introduction

"[...] there is still much about uncertainty about which we remain uncertain."[1]
— Nicholas Bloom, (2014)

Since the dawn of the twenty-first century, the global economy has undergone a series of profound *structural transformations* and been subject to a series of *unprecedented events*. Technological advancements, particularly in digitalization and artificial intelligence, have fundamentally reshaped information flows and production networks. The deepening of globalization in trade and finance has intensified cross-border interdependencies, rendering national economies more tightly coupled than at any previous time (Kose et al., 2003; Bruno and Shin, 2014; Miranda-Agrippino and Rey, 2020). A prolonged period of historically low, and at times negative, interest rates—coupled with a secular decline[2] in the natural rate of interest—has compelled central banks to expand their toolkit beyond conventional instruments, incorporating balance sheet policies and forward guidance (Bernanke, 2020). More recently, the COVID-19 pandemic brought global mobility to a halt and severely disrupted supply chains, while rising geopolitical tensions and the proliferation of trade restrictions have triggered a reconfiguration of global production systems. The transition to renewable energy has raised questions about resource scarcity, giving rise to macroeconomic risks, including inflationary pressures and heightened vulnerability to energy market disruptions. Finally, the resurgence of inflation across advanced and emerging economies has necessitated an abrupt policy tightening cycle, complicating the communication strategies of monetary authorities and amplifying uncertainty about their intended actions.

Taken together, the trajectory of the global economy has been far from stable or predictable. These developments instead underscore a stark reality: **uncertainty** is not merely present but *omnipresent*, an inescapable feature of the economic landscape whose contours remain only partially understood. Uncertainty has not only entered the lexicon of scholars; it also dominates headlines and political discourse. Yet, despite its ubiquity, its meaning remains elusive. *What, precisely, do we mean by uncertainty?*

Uncertainty is not a single, well-defined object. Since Knight (1921) and Keynes (1921, 1936), economists have recognized that it extends beyond risk in the narrow sense of quantifiable probabilities. Knight emphasized that risk can be described by known probability distributions, whereas uncertainty arises when no such distribution can be spec-

[1]These words have been written by Bloom (2014) when closing its seminal survey paper on uncertainty fluctuations.

[2]See among others Laubach and Williams 2003; Del Negro et al. 2017; Holston et al. 2017 for studies on the evolution and determination of the equilibrium real interest rate (r_t^*).

ified. Keynes went further, stressing the pervasiveness of fundamental uncertainty and the fragility of probabilistic reasoning itself. Uncertainty now exceeds the bounds of this taxonomy, encompassing ambiguity about likelihoods, incomplete information, unstable structural parameters, and even doubt about the very models that map policies to outcomes.[3]

Economists therefore confront multiple layers: data uncertainty, arising from measurement error and subsequent revisions; parameter uncertainty, concerning the magnitude and persistence of responses; and model uncertainty, surrounding the appropriate theoretical framework. Each of these layers creates distinct challenges. Data uncertainty undermines the reliability of real-time policy assessment. Parameter uncertainty complicates forecasting and often blurs the line between transitory and persistent shocks. Model uncertainty is deeper still, destabilizing the very foundations upon which policy advice and structural interpretation rest. Nor do empirical measures offer a single resolution: news-based indices, surveys, econometric factors, and market-implied measures look at different horizons and often diverge[4], reminding us that "uncertainty" is not a single object but a family of related ideas. For these reasons, it is best treated as a **higher-order**, multidimensional phenomenon—analytically demanding, empirically plural, and central to modern macroeconomics.

This elusiveness also complicates how we fold uncertainty into quantitative business cycle frameworks and into the decisions of households, firms, as well as other economic agents. Different structural mechanisms, such as precautionary motives (Basu and Bundick, 2017), wait-and-see behavior (Bernanke, 1983; Bloom, 2009), financial frictions (Christiano et al., 2014; Gilchrist et al., 2014), and limits to information (Veldkamp, 2011; Fajgelbaum et al., 2017), can pull in different directions, so that the pass-through varies across episodes and microfoundations. Surveys and reviews [5] find that economic uncertainty is typically countercyclical and moves with activity, yet it can both trigger downturns and reflect other shocks; what one sees depends on the measure used and the identification approach. The type of uncertainty also matters: real, macro, or financial; as each differs in its dynamics and connections with output and financial conditions (Ludvigson et al., 2021). In short, we are, to some extent, still *uncertain about uncertainty*.

Against this backdrop of pervasive and multifaceted uncertainty, **monetary policy** itself has also undergone profound transformations. Over the past two decades, central banks have had to navigate not only conventional interest rate instruments but also an expanded toolkit that includes large-scale asset purchases, forward guidance, and liquidity

[3]For further developments and distinctions, see Ellsberg (1961) on ambiguity aversion; Lucas (1976) on structural parameter instability; Hansen and Sargent (2007) on robust control and model uncertainty; and Sims (2003) on rational inattention. These contributions highlight that uncertainty can involve ambiguity in beliefs, incomplete or asymmetric information, evolving structures, and skepticism about the models themselves.

[4]See Bloom (2014) for an accessible overview of common proxies and their countercyclical comovement; Cascaldi-Garcia et al. (2023) for a taxonomy of news-, survey-, econometric-, and market-based measures and how horizons/real-time availability differ; Kozeniauskas et al. (2018) on why macro uncertainty, disagreement, and micro dispersion are conceptually and statistically distinct; and Bianchi et al. (2023) for evidence that leading proxies are only imperfectly correlated.

[5]See among others Bloom 2014; Fernández-Villaverde and Guerrón-Quintana 2020; Castelnuovo 2023; Cascaldi-Garcia et al. 2023. for surveys on economic uncertainty and the business cycles.

interventions.[6] These innovations have blurred the line between monetary policy and financial market conditions, making the channels of transmission[7] more complex and the reactions of markets more immediate. Financial markets, in turn, have become exceptionally attentive to policy signals: even subtle changes in tone, timing, or composition of policy decisions are now quickly reflected in asset prices and risk premia.[8] Beyond accounting for monetary policy transmission, contemporary DSGE modeling embeds financial intermediation and accelerator, balance-sheet and collateral constraints, risk-premium and liquidity channels—features[9] that collectively underscore the centrality of the financial sector in amplifying business-cycle volatility and shaping macro-financial comovements.

This heightened interaction between monetary policy and financial markets brings two fundamental perspectives that unite the thesis. On the one hand, monetary policy does not merely operate under uncertainty but also actively shapes the perception and dynamics of uncertainty in financial markets. Understanding how monetary policy, through its many facets, affects financial uncertainty is thus central to understanding its transmission to financial markets and the broader economy. On the other hand, a different but equally fundamental perspective arises when one considers that monetary policy itself is *designed* and *evaluated* in a world of *model uncertainty*. As macroeconomic models have grown richer—integrating financial frictions, heterogeneous agents, and more elaborate structures—the range of models informing central banks has broadened; yet this proliferation has also heightened uncertainty about the different *structural representations* of the economy within these models. This raises the problem of *policy design* and *robust-control* in such an environment, where the search for robust frameworks built on simple, implementable rules takes precedence over fully optimal, highly complex, model-specific strategies.

Taken together, these developments underline the importance of studying the *nexus* between *higher-order uncertainty* and *monetary policy*. They also motivate the arc of this dissertation: from the *roles* of monetary policy on financial uncertainty developments across different markets, measures or instruments, to the *implications* of *structural* and *model uncertainty* for the *design* and *robustness* of *rule-based policy frameworks*.

An important feature that unifies this thesis is its empirical focus on the euro area. As highlighted by Altavilla et al. (2024), European macroeconomies remain relatively underexplored despite their global influence, and many open questions about monetary policy warrant further investigation. Over the years, the ECB's monetary policy has provided a particularly rich setting, given its experience with a wide range of unconventional instruments and its operation within a unique structural environment. This context motivates

[6]See notably (Bhattarai and Neely, 2022) for a survey of the literature on the effects of unconventional monetary policy measures.

[7]See notably Kashyap and Stein (2023) for a more recent and more explicit discussion on this.

[8]See, among others, Gürkaynak et al. (2005), Campbell et al. (2012), Gagnon et al. (2011), and Nakamura and Steinsson (2018).

[9]See Gertler and Kiyotaki (2010) on financial intermediation, Kiyotaki and Moore (1997) and Iacoviello (2005) on collateral constraints, Bernanke et al. (1999) for the financial accelerator, Rudebusch and Swanson (2012); Christiano et al. (2014); Amisano and Tristani (2023) on risk-premium channels, and Brunnermeier and Sannikov (2014) on liquidity spirals.

us to place, in addition to the analysis of the interaction between monetary policy and uncertainty, a particular emphasis on the euro area. This emphasis also serves as a common thread across the chapters.

The next section delineates major strands of the literature within which the different chapters are established. It is not intended to be exhaustive; each chapter provides a more detailed treatment of the relevant research and its scope. Section 1.2 outlines the specific research gaps, questions, and contributions that this thesis seeks to tackle. Finally, Section 1.3 details the structure of the dissertation.

1.1 Monetary Policy and the New Uncertain World

Since the seminal work of Bloom (2009), research on *economic uncertainty* and its interaction with *business cycles* has expanded massively. Spurred by the empirical observation that uncertainty typically rises during recessions, both empirical and theoretical literature has proceeded in tandem to clarify how uncertainty is intertwined with macroeconomic fluctuations. Due to the lack of a single agreed-upon definition, the literature has developed a broad set of empirical measures and proposed a variety of microfoundations and transmission mechanisms. Bloom (2014); Kozeniauskas et al. (2018); Fernández-Villaverde and Guerrón-Quintana (2020); Cascaldi-Garcia et al. (2023) and Castelnuovo (2023) are examples of surveys and works that provide a more detailed description of the state of research on uncertainty and its role in economic dynamics. The causal status of uncertainty, *driver* or *consequence*[10] of downturns, remains an open question. Much of the empirical literature has, explicitly or implicitly, treated uncertainty as *exogenous* to other fundamentals, often via SVARs with recursive identification, ruling out potential contemporaneous feedback from other structural shocks. Departing from this practice, Ludvigson et al. (2021) decomposes uncertainty à la Jurado et al. (2015) and shows that distinguishing between real, macro, and financial uncertainty is consequential for business-cycle analysis. A growing body of work supports the view that uncertainty, particularly financial uncertainty, can be endogenous.[11] However, the scale and the timing of the responses depend on the measures employed and the identification strategy. Concerning the role of monetary policy, an early and influential exception is Bekaert et al. (2013), who decompose the VIX into components associated with risk aversion and uncertainty. Most of these empirical works rely on methods that predate recent advances in structural identification in macroeconometrics[12], notably based on higher moments (see Lewis (2025b) for a review), which are becoming increasingly popular for empirical business cycles research and could be beneficial for analyzing linkages among monetary policy, uncertainty, and aggregate dynamics. These methods, however, raise a complementary challenge: being largely data-driven, they often require careful ex-post *economic labeling* of the identified shocks. This difficulty

[10] See Ludvigson et al. (2021) for a thorough discussion on uncertainty as a driver or consequence of business cycles.

[11] See notably Bachmann et al. (2011, 2013); Carriero et al. (2021); Bianchi et al. (2023) as example works on endogenous uncertainty.

[12] See Ramey (2016) for a review on the identification of macroeconomic shocks and their propagation.

becomes more pronounced when differentiating *conventional* from *unconventional* policy actions in the context of monetary policy.

Understanding how monetary policy influences financial uncertainty also engages a large body of macro-finance literature. Building on the foundational works of Cook and Hahn (1989); Kuttner (2001); Cochrane and Piazzesi (2002); Bernanke and Kuttner (2005) or Gürkaynak et al. (2005), high-frequency surprises[13] around policy announcements have been used to identify policy shocks and to trace their effects on yields (Swanson and Williams, 2014), risk premia (Hanson and Stein, 2015), and asset prices (Faust and Rogers, 2003; Rogers et al., 2018; Swanson, 2021); these surprises have also served as instruments in SVARs (Faust et al., 2004; Gertler and Karadi, 2015; Jarociński and Karadi, 2020) and in local-projection frameworks (Jordà, 2005; Plagborg-Møller and Wolf, 2021). With the advent of the ZLB and the introduction of asset purchases and forward guidance, identification of monetary policy shocks has become more challenging and *multidimensional* than ever before. Rossi (2021) discusses the econometric challenges posed by the ZLB, as well as the use of novel methods for identifying monetary policy shocks and assessing their macro-financial effects. In the spirit of Gürkaynak et al. (2005), recent works Altavilla et al. (2019); Swanson (2021) extract multiple policy factors from changes in asset prices around announcements. A complementary perspective proposed by Inoue and Rossi (2021) models policy shocks through movements in the yield curve's *level*, *slope*, and *curvature*, building on Nelson and Siegel (1987) and Diebold and Li (2006), thereby unifying conventional and unconventional dimensions within a single term-structure framework. Despite substantial progress, most of this literature focuses on first-moment (mean) effects on prices and returns. By contrast, the effects of policy on second moments—that is, on financial uncertainty itself—and their *heterogeneity* across *asset classes* (e.g., bonds, equities, or exchange rates) and *policy dimensions* (short-rate, QE, FG, etc.) have received comparatively less systematic attentionBauer et al. (2022).[14]

Finally, the question of monetary policy under model uncertainty links to foundational research on policy design (Taylor, 1999; Blinder, 1999; Clarida et al., 1999; Svensson, 2003; Mishkin, 2007) and robust control (see e.g., Hansen and Sargent 2001, 2003; Walsh 2004; Giannoni 2007), as well as to the evaluation of simple interest rules, notably legacy rules as Taylor (1993a). Taylor and Williams (2010) survey evidence that simple interest-rate rules are practical and robust, often more robust than model-optimal rules, even under measurement error, and various forms of expectations mechanisms. Much of that evidence, however, was mainly developed in earlier generations of models. In a post-GFC era, advances in quantitative methods and an evolving macroeconomic landscape have produced a *new generation* of DSGE frameworks that embed richer financial sectors and a range of frictions. This new generation of models, highlighted in the works of Wieland et al. (2016)

[13] See Bauer and Swanson (2023b) for a thorough discussion on high-frequency identification of monetary policy shocks and their effects.

[14] As written by Bauer et al. (2022): *"In order to better understand the transmission of monetary policy to financial markets, a large literature has studied the effects of changes in expected policy rates in event studies of FOMC announcements with high-frequency data. However, the role of second moments and uncertainty has received much less attention in this context."*, page 1.

and Binder et al. (2019), tends to amplify shocks and alter transmission channels in ways that can shift stabilization trade-offs. In such an evolving model space, the robustness properties of simple monetary-policy rules warrant re-assessment. Despite earlier existing comparative exercises (Taylor and Wieland, 2012; Orphanides and Wieland, 2013), comparative evaluations across families of models with financial frictions or new structures remain relatively scarce, leaving open how rule performance generalizes when the underlying model is itself uncertain and relies on more complex, perpetually evolving structural representations of the economy.

Together, these three broad strands of literature—uncertainty and business cycles fluctuations (empirical macro and macroeconometrics), high-frequency identification of monetary policy shocks and their impacts on financial markets (macro-finance), and policy design and robustness (normative, theory-based policy evaluation) under model uncertainty—pave the way of this dissertation, and advances our understanding of the nexus between monetary policy and higher-order uncertainty motivated earlier. In the following section, we define the main research questions and contributions the thesis aims to cover, and indicate how they map onto the different chapters.

1.2 Research Questions and Contributions

Our central inquiry, the nexus between monetary policy and higher-order uncertainty, arises at the intersection of these three major strands of the academic literature. Despite evident complementarities, these strands have largely evolved in parallel in the scope of macroeconomics and finance. The principal contribution of this thesis is to unify them within a monetary-policy-centered focus.

General Question: *How does monetary policy interact with uncertainty from a higher-order perspective—by shaping financial uncertainty across markets, measures, instruments and by remaining robust under structural/model uncertainty in rule-based design?*

More specifically, from this general question, we derive the following research questions, pursued in subsequent chapters:

A: *Does monetary policy endogenously affect financial uncertainty, and with what implications for business cycles?*

Most empirical studies on uncertainty and business cycles treat uncertainty as an *exogenous* factor influencing macroeconomic fluctuations, often neglecting the *endogenous* role of other economic fundamentals like *conventional* and *unconventional* monetary policy dimensions in shaping these dynamics. This leaves open whether policy endogenously affects uncertainty, especially financial uncertainty, and how this feeds back into macro-financial dynamics. We address this in the context of the Euro area, by proposing a novel econometric framework in the SVAR tradition that allows for a proper *econometric identification* and *economic labeling* of *multiple* monetary policy shocks, in a *statistical* identification context. This is achieved by combining information from the non-Gaussianity of structural shocks (Lanne et al., 2017) and a single external instrument/proxy, traditionally used in proxy-SVAR applications (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and

Karadi, 2015). Empirically, we show that, as Bekaert et al. (2013), monetary tightening raises market-implied financial uncertainty, with distinct impact and persistence profiles across the two policy dimensions, and that financial uncertainty acts as a transmission channel through which monetary policy has an *indirect* influence. A detailed structural analysis also reveals that the properties of these shocks are consistent with known monetary policy narratives (Assenmacher-Wesche and Gerlach, 2010; Hartmann and Smets, 2018) related to the ECB, while also revealing distinct contributions to fluctuations in financial uncertainty over time.

B: *Are the effects of monetary policy on financial uncertainty heterogeneous across asset classes and yield-curve dimensions?*

A large body of literature in macro-finance documents that the effects of monetary policy on financial markets and the term-structure are not uniform, varying according to the type of instrument used and channels involved. As highlighted by Inoue and Rossi (2021), the effects of these different tools, mainly short-rate revisions, forward guidance or asset purchases, manifest differently on the shape of the *yield curve*, making them multidimensional in nature. Using *high-frequency identification*, major existing studies (Gürkaynak et al., 2005; Altavilla et al., 2019; Swanson, 2021) focus mainly on *first-order* (mean) effects on asset prices and and other pricing fundamentals. What remains less understood is how policy dimensions translate into *second-order* variations of asset prices and returns—that is, how policy shapes financial uncertainty—and whether these effects are asset-specific rather than uniform. To address this, we adapt the yield-curve perspective of Inoue and Rossi (2021) by recovering policy's level, slope, and curvature components from high-frequency (announcement-window) surprises and linking each component to a stochastic-volatility measure of uncertainty, interpreted as expected conditional volatility. Methodologically, this provides a portable bridge that carries familiar *high-frequency surprises* from first-moment analysis to the second-moment domain. Empirically, the framework delivers a multi-asset, component-level map from policy to uncertainty across bonds, equities, and exchange rates in the euro area, revealing systematic *heterogeneity* by *asset class* and *policy dimension*. This heterogeneity also manifests in dynamic responses of uncertainty to shock types, the type of monetary policy regime considered, and time-varying contributions to uncertainty, with different effects around key monetary-policy episodes. In doing so, our analysis provides an empirical contribution to characterizing how euro area monetary policy shapes financial uncertainty across markets and regimes.

C: *Which simple interest-rate rules remain robust when the model of the economy is itself uncertain—especially in the presence of new-generation models with financial frictions?*

The literature shows that simple interest-rate rules can be practical and often *robust* guides to policy, but most evidence and prescriptions come either from single-framework evaluations or from *earlier generations* of models. With modern advances in DSGE modeling, a new (third) generation of New Keynesian models has appeared, featuring more complex architectures and an explicit characterization of the financial sector (Wieland et al., 2016; Binder et al., 2019). In this context, *model uncertainty* (about structure and parameters) becomes first-order for policymakers and raises new questions for *policy design* and the *robustness* of policy rules. Using the systematic comparison framework of Wieland et al. (2012), we reassess this question of robustness and study how these modeling advances affect the performance of simple rules. Building on Orphanides and Wieland (2013) and Binder et al. (2019), our model set contains a wide spectrum of structural representations of the Euro Area economy, spanning from the first, second, and third generations of models. Our work lies at the intersection of Orphanides and Wieland (2013) and Binder et al. (2019), where we extend the comparison exercise of Orphanides and Wieland (2013) by explicitly incorporating post-crisis macro-financial DSGEs with different financial frictions mechanisms that were not part of their analysis, and we complement Binder et al. (2019) by providing a systematic normative evaluation of simple monetary policy rules across this richer model set, covering both fixed and optimized formulations of such rules. We further identify a robust-optimal simple rule via Bayesian model averaging, translating robustness into implementable coefficient profiles. The analysis shows that financial frictions alter policy trade-offs compared to earlier-generation models and weaken the performance of legacy rules, but also that robust simple designs—highly inertial with moderate inflation responses—continue to provide credible and resilient guidance.

Overall, uncertainty is taken throughout the chapters, either as an object to be **identified** and **measured**, an **economic channel** through which monetary policy propagates, and a **policy-design constraint** when the structural representation of the economy is unknown. The development of methods to address these questions aims to provide the most informative answers while staying rooted in the conventions of each research literature. In the following section, we outline the structure of the dissertation and the organization of the different chapters.

1.3 Structure of the Dissertation

The dissertation is written as a compilation of articles: each chapter is presented as an original research paper that investigates a specific question previously outlined. A more concrete description of these chapters is provided below.

In Chapter 2, we investigate the role of monetary policy in shaping financial uncertainty and its interaction with the business cycles in the euro area. Our contribution is to provide new empirical evidence on how euro area monetary policy endogenously moves financial uncertainty and how this, in turn, feeds back into macro-financial dynamics. We make use of SVAR methods to empirically investigate this question for the euro area. Our main objective is to characterize the effects of two different types of monetary policy innovations, respectively *conventional* and *unconventional* monetary policy shocks. Given the lack of consensus regarding uncertainty, its role in economic fluctuations, and its relationship with monetary policy, choosing an identification method suitable for this application requires identification methods that are *agnostic* with respect to economic theory. Statistical identification methods (see Lewis (2025b)) fulfill this role, where the identification of structural shocks and the type of restrictions imposed is solely based on the statistical properties of the data and do not require restrictions based on economic theory. However, this comes at the cost of giving a sound economic interpretation of the identified shocks, something often referred as the *shock labeling problem*. While different avenues to overcome this problem have been proposed, these latter are not sufficient given the problem at hand, where we aim to label *multiple* economic shocks with close structural natures and similar (sign) pattern of responses. To address this problem, our econometric framework extends Lanne et al. (2017), where we make use of both (i) non-Gaussianity of the data (ICA) to achieve identification and (ii) include a proxy/instrument (Stock and Watson, 2012; Mertens and Ravn, 2013) correlated with the two shocks of interest. The inclusion of the instrument, as well as an *inequality restriction* based on the *magnitude* of its response to the two shocks, is sufficient to solve this shock labeling problem for the block of shocks considered. Moreover, an added benefit is that the instrument induces over-identifying restrictions testable via LR tests, allowing a joint check of the proxy's relevance and exogeneity conditions. In Monte Carlo experiments calibrated to our setting, such a method reduces mislabeling and even sometimes sharpens identification relative to other competing benchmarks, depending on the strength of the instrument and of the inequality. The method is complementary to Schlaak et al. (2023), who propose a similar type of framework but for an identification based on heteroskedasticity and for an application on a single monetary policy shock. Using the high-frequency surprises of Altavilla et al. (2019), we choose our proxy as long-term German yield surprises around ECB policy announcements, and assume an inequality for the labeling stating that, in line with empirical studies (Gagnon et al., 2011; Campbell et al., 2012; Wright, 2012; Joyce et al., 2020) on the effects of UMPs, unconventional shocks have more pronounced effects on the instrument. The SVAR model contains macro measures such as the level of output or prices, as well as other financial indicators (interest rates, exchange rates, stock prices). Financial uncertainty is captured via a market-implied option volatility index (VSTOXX). Our empirical analysis shows that shocks have distinct implications for uncertainty dynamics and for its pass-through to real activity, notably output. We find that monetary policy's pass-through to financial uncertainty is predominantly indirect, operating via financial conditions, so overlooking this channel distorts conclusions about the effects of uncertainty shocks on output fluctuations and calls into question the widespread practice of treating uncertainty as exogenous.

In Chapter 3, we refine our understanding of how monetary policy affects *heterogeneously* financial uncertainty across *asset classes* and different *dimensions* of monetary policy, captured by variations in *level, slope*, and *curvature* of the yield curve around monetary policy announcements. Whereas Inoue and Rossi (2021) recover these components from daily term-structure movements using the framework of Nelson and Siegel (1987) and Diebold and Li (2006), we implement their perspective with high-frequency yield-curve surprises (Altavilla et al., 2019) in tight announcement windows. This *high-frequency* design limits contamination from non-policy factors moving rates and thereby sharpens the identification of monetary-policy effects. We then embed these three policy shock components in a stochastic-volatility framework in which they affect the expected stochastic volatility of asset returns. Unlike the preceding chapter, where uncertainty is observed (market-implied), here it is *latent* and *modeled* as the stochastic, time-varying dispersion of asset returns. Moreover, under standard assumptions regarding the efficiency of markets, we show that this conceptualization of uncertainty accords with the one proposed by Jurado et al. (2015). The representation of the model enables a rich characterization of the effects of monetary policy on financial uncertainty. Indeed, the state-space representation lets us quantify both impact effects and dynamic responses of uncertainty via generalized impulse responses (GIRFs) à la Koop et al. (1996). The model is estimated by Bayesian MCMC; in particular, we rely on the NUTS algorithm (Hoffman et al., 2014), which adapts during sampling and requires little tuning, yielding faster, more reliable mixing than random-walk Metropolis (Metropolis et al., 1953) and Gibbs sampling (Geman and Geman, 1984). We apply this framework to a euro-area of 47 financial instruments, a multi-asset panel spanning sovereign bonds, corporate bonds, equities, and major foreign exchange rates. The panel deliberately covers instruments with distinct risk profiles, maturities, liquidity conditions, and information sensitivities, enabling a granular assessment of heterogeneous uncertainty responses across euro-area markets. Overall, we document heterogeneous responses of asset-specific uncertainty across policy shock components. This heterogeneity manifests along several margins: impact effects, impulse responses, contributions to uncertainty fluctuations, and counterfactual market reactions to particular key ECB policy episodes. We also show that the ZLB materially shapes the transmission of these shocks across markets, where uncertainty appears to respond more synchronously in periods of low interest rates. These findings bring a new perspective on the effects of monetary policy on financial markets, highlighting the importance for central banks of the composition of their policy tools and their influence on the yield curve.

In Chapter 4, we examine the uncertainty–monetary policy nexus from the standpoint of policymakers who face uncertainty regarding the economy's true structural representation and must design optimal policy in that context. The literature accordingly favors *simple policy rules* as instruments and guides for policy design in this setting, owing to their transparency, simplicity, and robustness across alternative models and structural assumptions. Against the backdrop of newer frameworks, particularly those featuring an active financial sector and multiple frictions, this chapter reassesses the performance and robustness of several simple monetary-policy rules. Our work contributes and builds upon both Orphanides and Wieland (2013) and Binder et al. (2019) by bridging the rule-robustness tradition with some DSGE models of the "third" generation (Binder et al., 2019), who features financial frictions. More specifically, we explicitly incorporate certain post-crisis models with banking/accelerator mechanisms into a *normative and cross-model* assessment of simple rules, thereby complementing the analysis in Binder et al. (2019), which focuses primarily on the implications of financial frictions more broadly, without such a pronounced focus on rules as we do. Using the systematic comparison framework of Wieland et al. (2012), our analysis compares a common family of five different simple rules (Taylor-type, difference-type, and inertial variants) across ten structural macroeconomic models spanning pre- and post-crisis vintages. This comparison exercise is achieved at low cost using some euro-area (calibrated or estimated) models of the Macroeconomic Model Database (MMB). We evaluate the stabilization performance of each rule under a harmonized quadratic loss and for different central bank's stabilization preferences, and proceed in three main layers: (i) benchmark fixed-coefficient (non-optimized) rules model-by-model to reassess legacy prescriptions once frictions are present; (ii) compute model-optimal coefficients and policy frontiers to quantify how financial frictions steepen the inflation–output volatility trade-off and tilt optimal responses; and (iii) conduct a Bayesian Model Averaging to obtain *robust-optimal* coefficient profiles that translate robustness into implementable guidance. In a nutshell, we find that legacy Taylor-type rules deteriorate when financial frictions are admitted, whereas a family of highly inertial rules with moderate inflation responses and an explicit level measure of economic slack remain consistently robust across models.

Chapter 2

Unveiling Endogenous Financial Uncertainty

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Abstract. We investigate the impact of monetary policy shocks on financial uncertainty using a structural vector autoregressive framework. However, this analysis is hindered by the need to distinguish between structural shocks stemming either from conventional policies or from unconventional ones, although there are no clear expected sign differences in their impacts that would facilitate their labeling. To address this issue, we combine an identification framework based on the non-normality of the data with a single external instrument, supposed to be correlated with both shocks. We then rely on an inequality condition for the estimated effects of the shocks on the instrument to properly label the two shocks. We showcase the good performance and robustness of the proposed method with respect to several existing methods in realistic simulation studies. Then, using this method, we reveal that financial uncertainty is endogenous to monetary policy shocks, especially those stemming from conventional tools.

Keywords: Independent Component Analysis (ICA), unconventional monetary policy, uncertainty, proxy SVAR.

2.1 Introduction

Over the last decades, understanding the effects of monetary policy and its transmission channels to the real economy has become a crucial need for policymakers and macroeconomists. However, measuring these effects in today's macroeconomic context remains challenging. Indeed, since the Global Financial Crisis (GFC) and the emergence of the zero lower bound (ZLB), the conduct of monetary policy has been drastically modified. Central banks rely nowadays heavily on unconventional (non-standard) tools such as quantitative easing (QE) or forward guidance (Bernanke, 2020). Concomitantly, a strand of the academic literature[1] pioneered by the work of Bloom (2009) has explored the role of uncertainty in explaining business cycles, spurred by empirical evidence that uncertainty rises

[1] A non-exhaustive list of this literature encompasses Bachmann et al. (2013); Bekaert et al. (2013); Jurado et al. (2015); Baker et al. (2016); Caldara et al. (2016); Basu and Bundick (2017); Kozeniauskas et al. (2018); Bloom et al. (2018); Jo and Sekkel (2019); Forni et al. (2021).

during recessions (Ludvigson et al., 2021). This literature highlights the importance of uncertainty—whether financial, macroeconomic, or policy-related—as a critical driver of business cycles.

While both monetary policy and uncertainty are drivers of business cycles, they have mostly been studied separately. Existing research (Carriero et al., 2018b; Ludvigson et al., 2021) acknowledges that uncertainty responds to broader economic shocks, yet the specific role of monetary policy—particularly unconventional (non-standard) measures—in driving financial uncertainty remains underexplored. In light of these considerations, we investigate how monetary policy shocks affect financial uncertainty and the real economy in the Euro area, distinguishing between conventional and unconventional monetary policy shocks. By conventional monetary policy shocks, we refer to unexpected changes in the short-term policy rate, whereas unconventional monetary policy shocks encompass unexpected policy changes that go beyond traditional interest rate adjustments, such as quantitative easing or forward guidance.[2]

To do so, we build on the recent works of Ludvigson et al. (2021), Carriero et al. (2018a,b, 2021), and Mumtaz and Theodoridis (2020), and let uncertainty be endogenous in a structural vector autoregressive (SVAR) framework. This approach allows us to explore the role of uncertainty as a potential transmission channel of monetary policy. Specifically, similar to Ludvigson et al. (2021), we focus on financial uncertainty, i.e. uncertainty specific to financial markets, given its central importance in the transmission of unconventional monetary policy through the financial system.

To study simultaneously the effects of conventional and unconventional monetary policy shocks on financial uncertainty, we focus on statistical identification methods of the SVAR model. Given the absence of a clear theoretical consensus on the effects of both conventional and unconventional monetary policy on uncertainty, these methods seem to be the most appropriate ones in the current context[3] since it has limited reliance on economic theory. In particular, identification through independent components (ICA) has proved to be highly flexible and robust to the statistical properties of the data under study (Maxand, 2020; Herwartz et al., 2021). However, when dealing with several shocks of interest (e.g., stemming from conventional and unconventional monetary policies), ICA identification requires the econometrician to take a subjective stance, based on economic theory and impulse-response functions, to give an economic interpretation of the shocks. In a large system of variables, this task is particularly complicated due to the high likelihood that no clear pattern emerges from the data. Thus, to alleviate this concern, we introduce two

[2]The terminology follows the post-GFC empirical literature, which distinguishes (short-term) policy-rate innovations from non-standard actions such as forward guidance and asset purchases. We therefore employ "unconventional" in a single broad sense: unlike other studies such as Jarociński (2024) or Lewis (2025a), it does not represent a precise decomposition of individual tools (e.g. separate QE and forward-guidance shocks), but captures unexpected non-rate policy interventions whose transmission operates mainly through long-term yields, risk premia and expectations (see Rossi (2021) and Bhattarai and Neely (2022) for a review). The label thus reflects the taxonomy used to study how these measures affect asset prices and the real economy, even though they are now increasingly part of the regular monetary policy toolkit Bernanke (2020).

[3]To view a summary of the different identification techniques proposed in the SVAR literature: see notably Rossi (2021) and Herwartz et al. (2021).

refinements to the standard ICA identification approach.

First, in the spirit of Jarociński and Karadi (2020) and Schlaak et al. (2023), we incorporate, within the VAR, high-frequency financial reactions to monetary policy announcements, as an instrumental variable capturing monetary policy shocks.[4] Since these variations are measured during monetary policy announcements, we assume that they are orthogonal to other structural shocks within the system, i.e. structural shocks not related directly to monetary policy, and are solely driven by the two monetary policy shocks of interest.

Second, for labeling simultaneously the two shocks of interest, we introduce a procedure based on the specification of inequalities concerning the response of the instrument itself to these shocks, and not from the other variables of the system, as traditionally done in statistically identified SVARs (Herwartz and Lütkepohl, 2014; Lanne et al., 2017; Lütkepohl and Netšunajev, 2017; Netšunajev and Glass, 2017). As such, we are able to economically label the shocks in situations where no specific patterns are observed empirically among impulse responses, nor provided by economic theory.

Given these aspects, we call our method "non-Gaussian proxy SVAR". It should be noted, however, that our proposition may be exploited with other statistical identification methods than ICA. While the proposed method builds on Schlaak et al. (2023), which combines an external instrument with an identification approach based on heteroscedasticity, and Lanne et al. (2023), which rely on an external instrument and non-Gaussianity in a Bayesian framework, our methodological contribution lies in refining and adapting these techniques to allow for the simultaneous labeling of two different shocks, rather than just one. Thus, it addresses specific challenges in distinguishing shocks with close structural interpretations, such as conventional versus unconventional monetary policy shocks. Moreover, although our empirical analysis focuses on studying the effects of monetary policy on financial uncertainty, the proposed labeling procedure is not restricted to this specific empirical case. It can be readily adapted to other structural analyses aiming to identify several shocks that have similar structural interpretations and belong to the same category, e.g., fiscal policy shocks (Romer and Romer, 2010; Mertens and Ravn, 2013; Keweloh et al., 2023). Before applying this method to real data, we stress the performance of the proposed procedure in a simulation study. We highlight the good small-sample properties and robustness of our new method to small violations of some hypotheses, as well as its advantages over alternatives encountered in the literature.

We then exploit the proposed approach to disentangle the effects of conventional and non-conventional monetary policy shocks on financial uncertainty in the Euro area. We use the database of Altavilla et al. (2019) to construct several instruments, such as high-frequency reactions of long-term German yields around monetary policy announcements. The labeling of the shocks is then based on the existing literature on the respective effects of monetary policy on interest rates (Gürkaynak et al., 2005; Gagnon et al., 2011; Wright, 2012; Campbell et al., 2012; D'Amico and King, 2013; Bauer and Rudebusch, 2014; Inoue and

[4]In a different context, Keweloh et al. (2023) also propose a similar approach for identifying fiscal policy shocks in a Bayesian way.

Rossi, 2021; Rossi, 2021). In particular, we assume that unconventional monetary policy shocks affect high-frequency long-term rate variations relatively more than conventional shocks. Under this postulate, we easily label the two monetary policy shocks of interest according to the relative magnitude of their estimated effects on the instrument, a result not possible to obtain if we had used instead sign patterns on the system variables. With this setting, we find that financial uncertainty responds to monetary policy shocks and is mainly affected by conventional shocks. Although less strong at impact, unconventional shocks appear to have a more persistent effect on uncertainty than conventional ones. Our results are in line, to some extent, with the findings of Ludvigson et al. (2021) and Bekaert et al. (2013). A confirmatory analysis based on the time series properties of the identified shocks brings additional support to the correctness of our labeling.

Studies closest to ours are the ones of Mumtaz and Theodoridis (2020) and Bekaert et al. (2013). Theoretical and empirical evidence from Mumtaz and Theodoridis (2020) highlights how monetary policy affects macroeconomic volatility, while Bekaert et al. (2013) investigates the effects of monetary policy on components of the VIX, specifically risk aversion and uncertainty, uncovering significant interconnections. However, these studies do not explicitly take into account the unconventional effects of monetary policy or their potentially distinct impacts on financial uncertainty. Thus, in addressing this gap, this paper contributes to this empirical literature by dissociating the effects of conventional and unconventional monetary policy shocks on financial uncertainty and their broader macroeconomic implications.

The questions explored throughout this analysis have particular policy implications. First, this paper sheds new light on the role of financial uncertainty as a transmission of monetary policy to the economy, confirming that it is particularly significant in shaping output dynamics. Second, our results confirm the idea that central banks, concerned about the financial system's stability, should account for the effect of their monetary policies on the fluctuations in financial uncertainty.

The paper is organized as follows: Section 4.3 explains our identification method in more detail and describes how we deal with the "shock labeling" problem. In Section 2.3, we analyze the statistical implications of this identification through a simulation study. Section 2.4 is devoted to the empirical analysis. Section 2.5 concludes.

2.2 Methodology

This section describes our econometric approach, which will subsequently be exploited in our empirical analysis. Specifically, we detail how to include an instrumental variable correlated with one or, as in our case, multiple structural shocks of interest, to solve the shock labeling problem of a statistically identified SVAR, as outlined in Lanne et al. (2017). While our framework builds upon the SVAR model depicted by Lanne et al. (2017) and an identification scheme based on independent non-Gaussian structural shocks (ICA), our contribution lies in refining these methods to address challenges in labeling multiple shocks with close structural natures. By integrating an external instrument with novel inequality constraints, we provide a systematic approach to shock labeling that enhances the robustness and flexibility of the framework. This methodology is not restricted to ICA and can be generalized to other statistical identification methods, such as heteroscedasticity (see Schlaak et al., 2023), and applied to various economic contexts. For the specific case of monetary policy shocks, identification via non-Gaussianity was recently put forward by Lanne and Luoto (2020), Jarociński (2024) and Anttonen et al. (2024).

2.2.1 *Econometric framework*

Let us consider a K-dimensional VAR (p) model following:

$$
\begin{aligned}
y_t &= \gamma + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t, && (2.1)\\
&= \gamma + A_1 y_{t-1} + ... + A_p y_{t-p} + B\varepsilon_t, && (2.2)\\
B^{-1} y_t &= B^{-1}\gamma + B^{-1} A_1 y_{t-1} + ... + B^{-1} A_p y_{t-p} + \varepsilon_t, \qquad t = 1, ..., T, && (2.3)
\end{aligned}
$$

for which $A(L) = I_K - A_1 L - ... - A_p L^p$ captures the autoregressive parameters of the model, γ contains intercepts and other deterministic terms, and $y_t = (y_{1t}, ..., y_{Kt})'$ is a vector of observable macroeconomic and financial variables at a point in time. For simplicity, we consider that the VAR is stable ($\det(A(z)) \neq 0$) with time-invariant deterministic terms. The vector u_t denotes the reduced-form residuals serially uncorrelated with $\mathbb{E}(u_t) = 0$ and $\text{Cov}(u_t) = \Sigma_u$. The matrix B is non-singular and summarizes the contemporaneous effects among the variables. This matrix connects the structural shocks $\varepsilon_t = B^{-1} u_t$ to the reduced-form errors u_t. While reduced form coefficients of the VAR in (2.1) can be estimated easily, the structural representation of the model requires estimating the structural matrix B, which is unknown without additional identifying restrictions. In this paper, the identification of B and the structural shocks relies on the identification scheme proposed by Lanne et al. (2017), where the shocks ε_{it} are statistically identified assuming they exhibit non-Gaussian features and are mutually independent.[5] In this context, identification of B is unique up to sign and column permutation. The primary motivation for utilizing this specific identification scheme is derived directly from the findings of Herwartz et al. (2021). Their recent extensive simulation experiment has shown that identification via ICA proved to be the most flexible one among the principal statistical identification methods encountered in the SVAR literature.

While statistical identification has gained popularity in the macroeconometric literature (see Lewis, 2025b for a review), these methods encounter the fundamental challenge of economically labeling the identified structural shocks. Indeed, identification of the structural model (2.2) relies on certain statistical assumptions, such as non-normality of the shocks Lanne et al. (2017), but it does not directly assign an economic interpretation to the shocks. A potential solution to address this issue consists of exploiting the local uniqueness property of statistical identification to rearrange the columns of B in such a way that it forms a unique sign pattern, thus enabling the researcher to economically characterize

[5]See Appendix A.1 for more details on the identification scheme proposed by Lanne et al. (2017).

the shocks. This approach, combined with the use of additional external economic information (e.g., impulse responses, time series of structural shocks, or FEVDs), is considered a common strategy for dealing with this labeling problem (Herwartz and Lütkepohl, 2014; Lanne et al., 2017; Lütkepohl and Netšunajev, 2017; Netšunajev and Glass, 2017). The local uniqueness property of statistical identification ensures that the structural matrix B is identified up to sign and column permutation, but this alone does not resolve the labeling problem. Further information or assumptions are necessary to connect the shocks to their economic interpretations.

Nevertheless, the effectiveness of this aforementioned approach and the severity of the labeling issue depend heavily on the specific economic application under study. While the labeling method based on sign patterns may be feasible in simplistic scenarios, specifying such patterns for multiple shocks of interest becomes challenging in applications like ours, characterized by higher-dimensional systems and unknown reactions of certain variables to shocks. In particular, as in our study and that of Lakdawala (2019), dissociating monetary policy shocks into two or multiple economic natures becomes increasingly complex, if not impossible, with this approach. Indeed, focusing solely on sign responses to these shocks intrinsically provides the same type of information for labeling, leaving us in a situation of indeterminacy concerning their labeling.

To address this issue, we rely on an instrumental variable and leverage this external information to economically label multiple shocks in the context of a statistically identified SVAR. In contrast to Schlaak et al. (2023), who discusses the labeling of a single monetary policy shock identified with heteroscedasticity, we propose a labeling method in the case where several shocks are of interest, and the shocks are identified with ICA.

Let us consider, in addition to the model depicted above, an external instrument that relates to the structural shocks according to

$$w_t = \beta \varepsilon_t + \eta \nu_t, \tag{2.4}$$

where ε_t is the $K \times 1$ vector of structural shocks, $\beta = (\beta_1, ..., \beta_K)$ is a $1 \times K$ parameters vector, ν_t is a measurement error with $\mathbb{E}(\nu_t) = 0$ and variance σ_m^2. The coefficient η scales the variance of the noise. Equation (2.4) constitutes a generic representation of how the instrument (w_t) connects with the vector of statistically identified but not labeled structural shocks (ε_t). Combining (2.1) with (2.4), one can augment the VAR(p) according to:

$$z_t = \delta + \Gamma_1 z_{t-1} + ... + \Gamma_p z_{t-p} + e_t, \tag{2.5}$$

with $z_t = (y_t, w_t)'$ being a $(K+1)\times 1$ vector of variables, $\Gamma_1, ..., \Gamma_p$ the lag matrices capturing both the autoregressive structure of y_t and w_t, δ is a vector of constants, and e_t is now a $(K+1)\times 1$ vector of serially uncorrelated residuals. The relation between structural shocks and reduced form errors is then defined by

$$e_t = D\mu_t, \tag{2.6}$$

$$= \begin{pmatrix} B_{(K\times K)} & 0_{(K\times 1)} \\ \beta_{(1\times K)} & \eta \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \nu_t \end{pmatrix}. \tag{2.7}$$

From these equations, we can rewrite model (2.5) under its structural representation:

$$z_t = \delta + \Gamma_1 z_{t-1} + ... + \Gamma_p z_{t-p} + D\mu_t. \tag{2.8}$$

Under this representation, the instrument is incorporated within the VAR with β summarizing the contemporaneous reaction to the structural shocks ε_t. As in the case of Schlaak et al. (2023), the inclusion of w_t renders our SVAR model overidentified. Any additional restrictions on D, and more specifically on β, provide the econometrician with further information for the labeling of shocks. Moreover, as those restrictions are overidentifying, they have the advantage of being testable. Consequently, depending on the context and the type of instrument we have at our disposal, one can make a priori some statements about how the instrument is connected with the shocks we seek to label.

To clarify this point and illustrate how our approach differs from that of Schlaak et al. (2023) regarding the assumptions made about our instrument, let us consider the example where w_t represents high-frequency responses of long-term yields to monetary policy announcements. We assume that w_t contains valuable information on two different monetary policy shocks bearing different economic interpretations (e.g., stemming from conventional or unconventional policies). The instrument (w_t) is thus assumed to be linearly related to two elements of ε_t (i.e., the shocks of interest), denoted unconventional (ε_t^u) and conventional (ε_t^c) monetary policy shocks:

$$w_t = \beta^u \varepsilon_t^u + \beta^c \varepsilon_t^c + \eta\nu_t, \tag{2.9}$$

where ν_t is the measurement error component associated with the instrument. As such, we assume that this instrument is only correlated with these shocks of interest we seek to label. Moreover, in light of the nature of the instrument at hand (here high-frequency responses of long-term yields to monetary policy announcements), we formulate the following statement about the *magnitudes* of the coefficients:

$$|\beta^u| > |\beta^c| \ \text{ or } \ |\beta^u| - |\beta^c| > 0. \tag{2.10}$$

The economic interpretation behind (2.10) is that unconventional shocks affect more high-frequency changes of long-term rates, in absolute terms, than conventional shocks. This economic postulate has been supported by a large strand of the literature[6]. An alternative

[6]See notably, Vayanos and Vila (2021); Gagnon et al. (2011); Campbell et al. (2012); Wright (2012); Bauer and Rudebusch (2014); Joyce et al. (2020); Inoue and Rossi (2021); Rossi (2021), among others. In line with this view, Rossi (2021) emphasizes: *"Overall, the literature agrees that the empirical effects of unconventional monetary policy are significant on long-term yields and other asset prices,"* page 16.

strategy could, in principle, be based on the slope of the yield curve, similar to Goodhead (2024), where we distinguish the shocks according to their relative impact on short- and long-term interest rates. In our setting, however, this type of rule is not well-suited. First, identification of structural shocks in our context is limited to permutation and sign, so that any labeling scheme that relies on the sign of the short- or long-end responses is inherently fragile. The permutation of signs can considerably complicate the economic interpretation associated with shocks when it relies on the slope of the yield curve. In our context, a positive response of the slope can arise from a contractionary unconventional shock as well as from an expansionary conventional shock, and vice versa, so that it becomes difficult to unambiguously associate a given slope pattern with a specific type of monetary policy shock. A labeling based on magnitude avoids this potential confusion, even though it still requires an ex post assessment of the shock dynamics to interpret their contractionary or expansionary nature.

For notational convenience and without loss of generality, we assume that the two shocks to be labeled ($\varepsilon_t^u, \varepsilon_t^c$) are first and second in the system, i.e., correspond to ε_{1t} and ε_{2t}. In this context, conditions that prevail for labeling monetary policy shocks are therefore

$$\beta_3, ..., \beta_K = 0, \tag{2.11}$$

$$\beta_1, \beta_2 \neq 0, \tag{2.12}$$

$$|\beta_1| > |\beta_2|. \tag{2.13}$$

Thanks to the last inequality condition (2.13), we may use the estimated quantity $|\hat{\beta}_1| - |\hat{\beta}_2|$, to label the shocks. In our case, it effectively distinguishes between what we refer to as conventional and unconventional monetary policy shocks. Similarly to Schlaak et al. (2023), conditions (2.12) and (2.11) stand for the relevance and exogeneity conditions. These restrictions are necessary for instrument validity and are essential in our framework to detect the shocks subject to labeling. Finally, beyond addressing the labeling problem, the inclusion of the instrument may enhance the estimation of the impacts of the shocks and thus improve their identification.

2.2.2 *Practical considerations*

The framework described in Section 2.2.1 relies on the hypothesis that the chosen instrument is solely correlated with two innovations of the model (2.9). Under assumptions (2.10) to (2.13), we impose some restrictions on β and label the shocks economically. However, we do not know in practice which columns of D are consistent with the structural shocks of interest since local uniqueness implies that D is identified up to signs and columns permutation.[7] Thus, specifying the restrictions on β and identifying the columns of D related to our two structural shocks of interest require in practice testing whether the

[7] In this paper, we decided to follow the ordering proposed by Lanne et al. (2017) to pick one particular structural representation of the model among a set of equivalent classes to obtain a unique identification of B (or D).

instrument w_t satisfies the exogeneity and relevance conditions given by (2.11) and (**??**) for all possible specifications of β. For a VAR model of order $K+1$ as in (2.5), this consists in testing $\binom{K}{2} = \frac{K!}{2!(K-2)!}$ different specifications on β, each exhibiting only 2 free coefficients, while the remaining $K-2$ entries are set to 0.

Since our identification relies on the likelihood-based method of Lanne et al. (2017), we use likelihood ratio tests (LR tests) to test over-identifying restrictions on D. Thus, testing (2.11) is done by comparing the likelihood of a restricted version of the model, i.e. imposing a model with zeros restrictions $\beta_0 = (\beta_1, \beta_2, 0, ..., 0)$, and a model without restrictions $\beta = (\beta_1, \beta_2, ..., \beta_K)$. Imposing those restrictions on β enables us to formalize this test:

$$H_0 : \beta_3 = \ldots = \beta_K = 0, \quad H_1 : \exists j \in \{3, \ldots, K\} : \beta_j \neq 0. \tag{2.14}$$

The rejection of the null hypothesis indicates the endogeneity of the instrument. In addition, this framework also allows us to test the relevance of w_t (2.12) by comparing two restricted versions of the model. We compare the likelihood of a model where $\beta = (\beta_1, \beta_2, 0, ...0)$ against a model where $\beta_0 = (0, 0, ..., 0)$. That is, we test

$$H_0 : \beta = \beta_0, \quad H_1 : \beta_1, \beta_2 \neq 0. \tag{2.15}$$

The rejection of the null hypothesis indicates that the instrument is relevant, i.e., correlated with two targeted structural shocks of the model. The distribution of the statistic underlying the LR-tests is a χ^2 with degrees of freedom equal to the number of restrictions. Hence, not rejecting the first test and rejecting the second one simultaneously leads to the conclusion that the instrument fulfills the relevance and exogeneity conditions, i.e., that the zero restrictions placed on β are well-founded.

The labeling of the shocks is therefore done after having tested all possible combinations of β containing restrictions. Ideally, if our assumptions are respected, we should retain only one specification of β. However, the tests may reveal that several specifications of β make the instrument valid, which leaves us in an indeterminate case for the labeling. Such situations could arise for different reasons. For example, it could indicate that the hypothesis underlying the instrument is false, i.e., the instrument is correlated with either more or fewer shocks than those assumed. Moreover, the hypothesis made on the instrument can be true, but such indeterminacy arises due to the lack of power of the LR-tests. When dealing with those cases, the safest way to proceed is to retain all the specifications of β that pass the testing procedure. Then, the choice of a particular specification has to be motivated by another kind of information available to the researcher, for example, the resulting impulse responses, the time series of the structural shocks, or the forecast error variance decomposition (FEVD).

2.3 Simulation Study

As shown in Section 2.2.1, the two main advantages of our framework are that (i) it partially solves the shock labeling problem inherent to the statistical identification of SVARs, and (ii) it sharpens the identification of the shocks of interest if their correlations with the instrument are sufficiently high. In this section, we aim to quantify through a simulation study the extent to which the proposed framework improves upon these two aspects.

As a first simulation exercise, we specify a generic SVAR model with a clear sign pattern among the shocks of interest. In this setting, it is possible to use these expected sign patterns (usually provided by theory) to label the shocks of interest a posteriori. However, we show that labeling the shocks according to a sign structure is not as optimal as our labeling method, due to estimation uncertainty. Then, in a second scenario, we consider a framework closer to what we expect in our empirical analysis. More precisely, we specify a model with two shocks of interest, however exhibiting an identical expected sign pattern. In this situation, the sign pattern labeling strategy does not work, but we show that our instrument-based labeling approach performs satisfactorily.

For both scenarios, we also investigate the effectiveness of our proposed method in enhancing the identification of the shocks of interest compared to the classical ICA approach (Lanne et al., 2017) and the proxy-SVAR identification methods (External IV) proposed by Stock and Watson (2012) and Mertens and Ravn (2013).

Section 2.3.1 outlines the simulation settings applied to the previously mentioned scenarios. Sections 2.3.2 and 2.3.3 describe in more detail the data generation processes (DGPs) used in each scenario. Section 2.3.4 describes the performance criteria used to assess the quality of the labeling of the shocks of interest, as well as the accuracy of their identification. Section 2.3.5 details the instrument generation. Section 2.3.6 presents and discusses the simulation results.

Notice that, similar to our empirical analysis, we focus on the study of scenarios where we aim to correctly label and identify two specific shocks of interest.

2.3.1 Simulation setting

We conduct our simulation study under different sample sizes and distributional assumptions for the structural shocks ε_t. We set the sample size to $T = (250, 500, 750, 1000)$. As in Lanne et al. (2017), each structural shock ε_{it} is drawn independently and identically from the following two (marginal) distributions:

- Standardized Student-*t(df)* with *df* = 5;
- Centered and standardized $\mathcal{X}^2_{(4)}$.

In addition, as a robustness check, we report in Appendix A (sections A.2 and A.3) a third case where the shocks follow a Gaussian distribution.

We consider the case of homoscedastic structural shocks $\text{Cov}_t(\varepsilon_t) = I_k$ for all $t = 1, ..., T$. The number of Monte Carlo replications is set to $L = 500$. Finally, we assume that the lag order (p) is known when estimating the reduced form of the VAR.

2.3.2 *Case 1 (DGP 1): SVAR with target shocks exhibiting a recursive sign pattern*

We consider first the following generic structural VAR:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{pmatrix} = A_1 \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{pmatrix} + A_2 \begin{pmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-3} \end{pmatrix} + B \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}, \tag{2.16}$$

where the autoregressive matrices A_1, A_2, and the structural B matrix are

$$A_1 = \begin{pmatrix} 1.24 & -0.09 & -0.16 \\ 0.13 & 0.94 & -0.06 \\ 0.24 & 0.30 & 1.03 \end{pmatrix}, A_2 = \begin{pmatrix} -0.37 & 0.05 & 0.08 \\ -0.07 & 0.22 & 0.03 \\ 0.12 & -0.15 & -0.27 \end{pmatrix}, \tag{2.17}$$

$$B = \begin{pmatrix} -0.48 & -0.41 & 2.32 \\ 2.32 & -0.22 & 0.72 \\ 1.57 & 0.76 & 0.98 \end{pmatrix}.$$

This SVAR model is calibrated similarly as Herwartz and Plödt (2016). In this model, the three structural shocks $(\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t})'$ are distinct from each other in terms of the direction of their respective effects on the system variables $(y_{1,t}, y_{2,t}, y_{3,t})'$. The structural matrix B shows a unique and recognizable sign pattern among the three shocks, which can be exploited to label them economically. When we focus on labeling shocks based on a sign pattern, we exploit the recursive sign pattern among the columns of B to calculate the frequency[8] for which we can uniquely label two shocks simultaneously according to the sign pattern of the first two columns: $(- + +)$ and $(- - +)$.

2.3.3 *Case 2 (DGP 2): SVAR with target shocks exhibiting the same sign pattern*

In this second case, we aim to closely align with the context of our empirical application, where the goal is to identify and label two shocks of interest that (a priori) exhibit identical or at least very similar sign patterns. Labeling these shocks based solely on the sign of the responses thus becomes an obsolete strategy, prompting us to rely more on information from an instrument to label the shocks. To achieve this, we slightly adapt the structural matrix B of (2.17) to artificially introduce the presence of two shocks of interest exhibiting the same sign pattern. The matrix B is now calibrated as follows

$$B = \begin{pmatrix} 0.48 & -0.41 & 2.32 \\ 1.23 & -0.22 & 0.72 \\ -0.17 & 0.76 & 0.98 \end{pmatrix}. \tag{2.18}$$

[8]This approach to quantifying the performance of labeling methods based on a sign pattern is similar to that employed by Herwartz et al. (2021).

2.3.4 *Performance criteria*

For both scenarios, we assess the accuracy of the proposed method in labeling the two specific shocks of interest, denoted as $(\varepsilon_{1,t}, \varepsilon_{2,t})$, and in estimating their structural effects. Regarding the labeling process, we compare our approach in the first scenario with a method based solely on sign patterns (i.e., without employing an instrument). We quantify the frequency of correct labeling achieved by each method. For the second scenario, since the model does not exhibit a clear and recognizable sign pattern among the first two shocks, it becomes meaningless to calculate the frequency of correct labeling as in the first DGP. Instead, we calculate the complementary frequency, i.e., the occurrence of incorrectly labeling two shocks using a recursive sign scheme between two columns of B. Concerning the performance in estimating the structural effects, we compare, for each identification scheme, the MSE of the impact response coefficients associated with $(\varepsilon_{1,t}, \varepsilon_{2,t})$.

2.3.5 *Instrument generation*

We compare the robustness of our method in labeling and sharpening the identification of $(\varepsilon_{1,t}, \varepsilon_{2,t})$ according to (i) the endogeneity level of the instrument and (ii) the difference in (2.13). To do so, we calibrate the vector $\beta = (\beta_1, \beta_2, \beta_3)$ such that we introduce the presence of no ($\beta_3 = 0$), weak ($\beta_3 = 0.05$) and strong ($\beta_3 = 0.3$) instrument endogeneity. For each case, we set the value of $\beta_2 = 0.25$ and let β_1 vary $\in \{-0.4, -0.7, -0.9\}$, to study how the difference $|\beta_1| - |\beta_2| = (0.15, 0.45, 0.65)$ affects the labeling accuracy. The measurement error associated with the instrument (ν_t) is distributed according to a standard normal distribution and we set the variance of the noise such that $\eta = 1$. Unlike our method, which uses a single instrument to characterize two shocks of interest simultaneously, the classical proxy SVAR method requires at least the use of two instruments to identify the first two columns of B. To allow a meaningful comparison between our method and this latter approach, we simulate two instruments, using the values of (β_1, β_2) to summarize the correlation of the instruments with the two shocks of interest. In cases where endogeneity is introduced, we introduce a source of correlation between the instruments and the third shock by setting $\beta_3 \in \{0.05, 0.4\}$.

2.3.6 *Results*

In this section, we discuss the results of a simulation exercise carried out with our method and assess its performance for labeling and estimating the structural shocks of interest. First, we highlight, for both DGPs, the performance of our labeling method (2.13) with respect to a labeling approach based on a sign pattern. Second, we report the MSE in estimating the structural impacts[9] of $(\varepsilon_{1,t}, \varepsilon_{2,t})$. We compare our method to the ICA approach of Lanne et al. (2017) and the classical proxy SVAR.

[9] We report an aggregate measure of MSE. We sum the MSEs of coefficients of the first two columns of B.

Labeling performance

Tables 2.1 and 2.2 compare the labeling performance of our method (NG proxy columns) with a labeling method based on a sign pattern. Several observations can be drawn from these results. First of all, frequencies reported in Table 2.1 for DGP I show that our labeling method is superior to the one based on a sign pattern. This is true even in cases with small samples ($T = 250$) and including endogeneity (e.g. $\beta_3 = 0.3$). Labeling using an instrument improves with an increase of the difference $|\beta_1| - |\beta_2|$, and is robust to the presence of endogeneity in the instrument. These findings also apply to DGP II (Table 2.2). Notice that, for DGP II, the frequencies associated with columns "sign pattern" indicate the occurrence of mistakenly recognizing a recursive sign pattern between two shocks. Consequently, the interpretation of performance is reversed, with higher frequencies indicating a higher risk of nonsensical shock labeling. Although this risk decreases asymptotically with T, it remains particularly high in smaller samples ($T = 250$) and the Student cases. In these cases, the size of this risk is substantial (ranging from 35 to 40%), thus showing the limitation of labeling shocks according to a sign pattern under conditions similar to what we expect in our empirical application. Additional results for shocks following a Gaussian distribution can be found in Appendix A (Tables A.1 and A.2) and do not contradict the results of DGP I and DGP II. The labeling performance is still found to be superior to labeling through a sign pattern, although logically lower compared to the non-Gaussian cases, since the non-normality of the shocks is respected.

Mean squared errors (MSE)

Figure 2.1 summarizes the MSEs associated with each method and across all Monte Carlo experiments. As in the previous section, we focus on reporting only the non-Gaussian cases[10]. The figure is composed of six panels. Panels (a), (b), and (c) compare the evolution of the MSE for the first DGP and, respectively, for cases of no ($\beta_3 = 0$), weak ($\beta_3 = 0.05$), and strong ($\beta_3 = 0.3$) endogeneity. Panels (d), (e), and (f) do the same for the second DGP. From these graphs, we observe that adding the instrument according to our method (see red lines) yields lower MSE figures than traditional proxy SVAR methods of Stock and Watson (2012) and Mertens and Ravn (2013) (see green lines). Except for a few singular cases, it holds for nearly all settings of the simulation study. Additionally, a second advantage over proxy SVAR identification is its greater robustness and reduced sensitivity in cases of endogenous instruments.[11]

[10]Results for Gaussian cases can be found in Figure A.1 in Appendix A.

[11]This is true for the two non-Gaussian cases. Under Gaussianity, the identification of the shocks is weaker than proxy SVAR methods. However, we are still superior to the identification of shocks over the identification of Lanne et al. (2017).

Table 2.1: Comparison of labeling performance: DGP 1 (sign pattern vs NG proxy).

	$\beta_3 = 0$				$\beta_3 = 0.05$				$\beta_3 = 0.3$			
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.15$	$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.694	0.828	0.618	0.736	0.716	0.858	0.604	0.790	0.722	0.784	0.612	0.788
500	0.880	0.930	0.730	0.902	0.890	0.912	0.768	0.922	0.856	0.908	0.766	0.902
750	0.910	0.978	0.852	0.952	0.924	0.974	0.846	0.956	0.928	0.972	0.844	0.950
1000	0.972	0.972	0.914	0.972	0.972	0.992	0.870	0.972	0.966	0.990	0.886	0.970
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.45$	$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.710	0.970	0.628	0.962	0.740	0.970	0.598	0.942	0.738	0.956	0.582	0.946
500	0.868	0.998	0.780	0.986	0.880	0.998	0.750	0.986	0.878	0.990	0.766	0.984
750	0.940	0.998	0.858	0.996	0.928	0.998	0.854	0.994	0.944	0.998	0.846	0.998
1000	0.960	1	0.884	1	0.956	1	0.894	1	0.964	0.998	0.884	1
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.65$	$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.710	0.988	0.632	0.980	0.700	0.992	0.636	0.990	0.692	0.992	0.596	0.990
500	0.876	0.998	0.742	0.998	0.870	1	0.752	0.996	0.880	1	0.746	0.996
750	0.944	1	0.852	1	0.928	1	0.838	1	0.932	1	0.830	0.998
1000	0.958	1	0.884	1	0.964	1	0.886	1	0.968	1	0.884	1

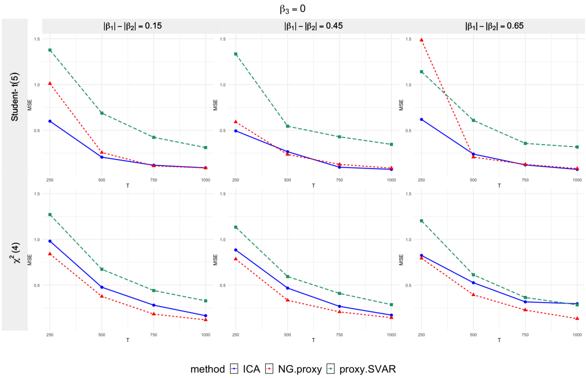
Table 2.2: Comparison of labeling performance: DGP 2 (sign pattern vs NG proxy).

	$\beta_3 = 0$				$\beta_3 = 0.05$				$\beta_3 = 0.3$			
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.15$	$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.368	0.870	0.470	0.846	0.310	0.896	0.528	0.824	0.390	0.844	0.508	0.828
500	0.138	0.948	0.314	0.930	0.110	0.962	0.278	0.946	0.128	0.920	0.322	0.922
750	0.058	0.986	0.214	0.980	0.044	0.978	0.174	0.978	0.050	0.954	0.200	0.948
1000	0.024	0.998	0.116	0.988	0.020	0.994	0.102	0.992	0.024	0.970	0.116	0.958
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.45$	$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.342	0.988	0.544	0.966	0.328	0.992	0.534	0.978	0.376	0.970	0.510	0.974
500	0.126	1	0.276	0.996	0.126	0.998	0.334	0.994	0.132	1	0.292	0.998
750	0.062	1	0.162	1	0.038	1	0.178	0.998	0.054	1	0.194	1
1000	0.020	1	0.108	1	0.020	1	0.106	0.998	0.022	1	0.126	1
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.65$	$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$		$t_{(5)}$		$\mathcal{X}^2_{(4)}$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.346	0.994	0.510	0.984	0.390	0.986	0.516	0.976	0.376	0.990	0.500	0.970
500	0.134	1	0.308	0.996	0.134	1	0.264	0.990	0.132	0.998	0.284	1
750	0.048	1	0.188	0.998	0.038	1	0.134	1	0.054	1	0.182	0.998
1000	0.032	1	0.098	1	0.024	1	0.110	1	0.024	1	0.110	0.998

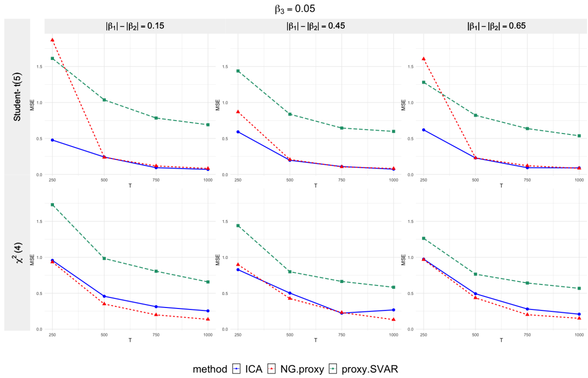
Comparing our method to the identification approach of Lanne et al. (2017), which does not employ any instruments (see blue lines), our method performs equally well or even better asymptotically (in Chi-squared cases) in the absence of instrument endogeneity. However, we do not find strong evidence in small samples (i.e., for $T = 250$) that incorporating the instrument into our framework enhances the identification of the two shocks of interest when the likelihood is correctly specified.

Figure 2.1: Evolution of MSEs across methods and simulation settings in non-Gaussian cases.

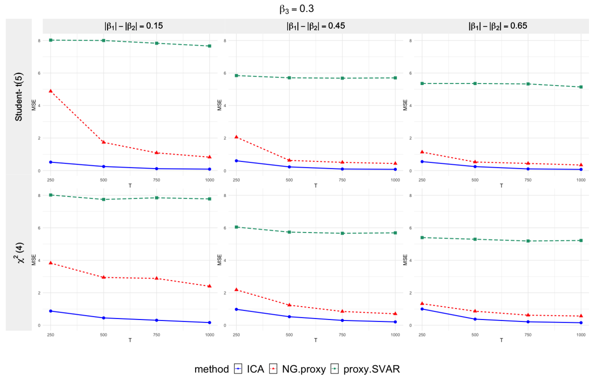
(a) **DGP 1:** No endogeneity, $\beta_3 = 0$.



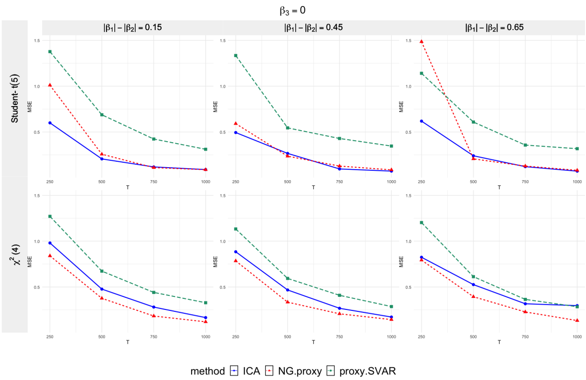
(b) **DGP 1:** Weak endogeneity, $\beta_3 = 0.05$.



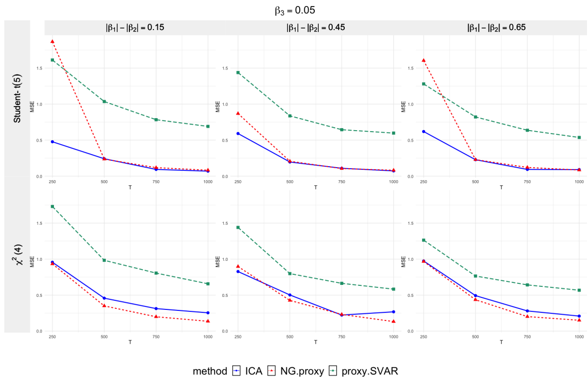
(c) **DGP 1:** Strong endogeneity, $\beta_3 = 0.3$.



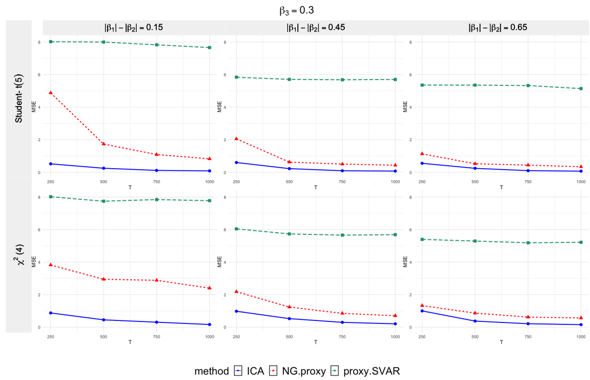
(d) **DGP 2:** No endogeneity, $\beta_3 = 0$.



(e) **DGP 2:** Weak endogeneity, $\beta_3 = 0.05$.



(f) **DGP 2:** Strong endogeneity, $\beta_3 = 0.3$.



2.4 Monetary Policy Shocks and Uncertainty in the Euro Area

We now apply our framework to study the links between monetary policy, financial uncertainty, and the macroeconomy. We restrict our analysis to the Euro area. So far, limited empirical evidence is available in Bekaert et al. (2013) and Mumtaz and Theodoridis (2020), which focused on the United States, not Europe. Notice also that their identification of monetary policy shocks does not make use of a proxy and does not take into account the non-conventional effects of monetary policy. We use the dataset of Altavilla et al. (2019) to construct proxies (instruments) of monetary policy shocks. This dataset contains high-frequency reactions of financial markets around monetary policy announcements, making them a priori relatively good proxies for the two shocks we are looking for. The following section explains in detail the choice of our instrument, as well as a description of the variables used in our empirical analysis.

2.4.1 Data and model choices

We collect data for the Euro area from January 1999 to January 2020 at a monthly frequency, with $T = 253$ observations. The choice of this period is justified by the lack of available instruments before January 1999 and the intention to exclude the Covid-19 crisis. The event window chosen when recording high-frequency surprises is the *"monetary event window"* defined by Altavilla et al. (2019). This event window captures both press releases and press conferences made on monetary policy announcement dates. Our baseline model corresponds to the model in (2.5) where z_t contains eight variables: seven (low frequency) macro-financial variables (y_t) and one instrument (w_t). The variables contained in y_t are respectively: industrial production (log x 100), HICP (log x 100), the nominal EUR/USD exchange rate, long-term (10-year) government bond yields, VSTOXX, EURO STOXX 50 (log x 100), 2-year German government bond yield.

We use the VSTOXX index to measure financial uncertainty, the equivalent of the VIX for the Euro area. We follow in that respect Bekaert et al. (2013). To measure the monetary policy stance during the ZLB period, we use the 2-year German bond rate, a rate with a longer maturity than the central bank funds rate, as suggested notably by Rossi (2021), Gertler and Karadi (2015) and Jarociński and Karadi (2020). As a measure of GDP, we use the monthly industrial production index, while HICP is used as a measure of the level of prices. Besides financial uncertainty, the model features the presence of other financial variables, namely a stock price index, an exchange rate measure (EUR/USD), and a measure of long-term interest rates.

In addition, we need an instrumental variable w_t which, under (2.9) and (2.10), helps us to characterize the effects of the two monetary policy shocks and to label them based on the magnitude of their responses to the shocks, as given by (2.10). We choose w_t as high-frequency surprises in the 20Y German yield reported in the database of Altavilla et al. (2019). Figure 2.2 shows the evolution of the instrumental variable over time. Our underlying assumption is that high-frequency variations in the 20Y German yield are affected

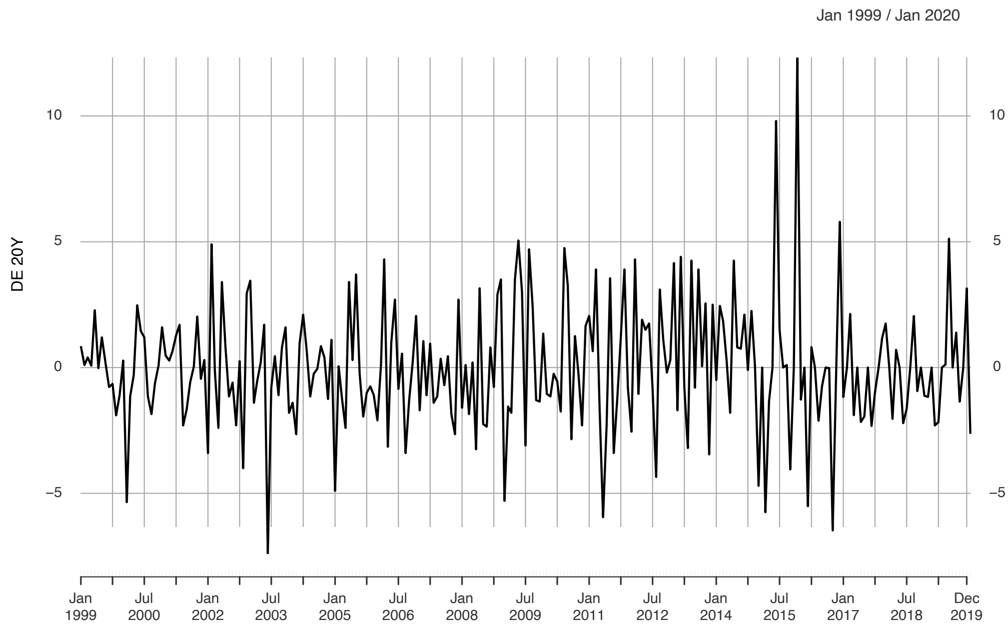


Figure 2.2: High-frequency responses in German yield (20Y) of Altavilla et al. (2019).

by both types of monetary policy shocks. Notice that choosing a 20-year maturity is not arbitrary. Although both conventional and unconventional measures are known to affect interest rates (Kuttner, 2001; Gürkaynak et al., 2005, 2007; Wright, 2012), unconventional measures such as quantitative easing or forward guidance have proven to be particularly effective in pushing down the long end of the yield curve, making long-term interest rates relatively more affected by unconventional policies than conventional ones. As such, we may formulate a hypothesis similar to (2.9) and label the shocks accordingly, for a particular specification of D selected by the LR tests.To strengthen our confidence level in the labeling of the shocks, we investigate in the second step the dynamics of the impulse responses and the time series of shocks implied by the model[12]. Further discussions and analyses about the labeling of the shocks are provided in the next subsection.

The number of lags included in the baseline model is set to two ($p = 2$) as suggested by the Akaike information criterion (AIC). This lag order seems appropriate due to the size of the VAR and the short sample at hand. This order is close to the order $p = 1$ suggested by the Bayesian information criterion (BIC) and the Hannan-Quinn information criterion (HQC).

Finally, we restrict some reduced-form parameters to zero so that the instrument does not have an autoregressive structure, and past values of y_t do not affect w_t. This specification is consistent with Jarociński and Karadi (2020), which, as in our case, uses an instrument internally but identifies structural shocks via sign and zero restrictions. Since

[12]The proposed labeling method makes use of point-wise estimates of β only, and does not take into account estimation uncertainty. This might potentially yield a labeling error. However, this risk is relatively small even for small samples, as long as w_t shows a relatively stronger degree of correlation with one shock compared to the other.

our identification relies on non-Gaussianity, we also check that our model exhibits non-Gaussian features by performing Jarque-Bera tests (see Figure A.2 in Appendix A). Both univariate and multivariate versions of the test lead us to reject the Gaussianity of the innovations.

2.4.2 Results

Impulse responses

After estimating the reduced form of the model by least-squares, we perform a constrained ML estimation of the matrix D and obtain our two shocks of interest. We specify the matrix D such that the fourth and the seventh columns are free from zeros. Under this specification, we do not reject the exogeneity condition (2.11) and reject (2.12), suggesting that the instrument is relevant. Moreover, this specification has the lowest AIC among all other specifications satisfying the relevance and exogeneity conditions. The results of these tests can be found in Table A.3 in Appendix A.

In Figure 2.3 we display the impulse responses of the variables for this particular specification. We label the shocks according to (2.10). Given the magnitude of the instrument's responses and the dynamics of y_t, we interpret the left-hand column (or first shock) as the responses obtained after a contractionary conventional monetary policy shock, while the right-hand column (second shock) can be characterized as a contractionary unconventional monetary policy shock.

Focusing on the conventional monetary policy shock, a one standard deviation change in the shock is accompanied by an increase in the instrument and the level of interest rates (both short and long), a drop in stock prices, an appreciation of the euro, as well as a decrease in output and the price level. The responses to the unconventional monetary policy shock are quite similar, although different in magnitude, except for the level of prices (HICP). This surprising response of prices to unconventional shocks can be potentially interpreted as a reflection of the information effects embedded in these monetary policy announcements. Specifically, such announcements may convey the central bank's private assessment of future economic outlook, impacting market expectations of inflation and demand. Andrade and Ferroni (2021) show that monetary policy communication can encompass both Delphic shocks (news about future economic conditions) and Odyssean shocks (policy commitments), which influence inflation expectations through signaling mechanisms. Similarly, Miranda-Agrippino and Ricco (2021) argue that high-frequency monetary policy surprises often reflect a combination of monetary shocks and the central bank's private forecasts, leading markets to revise their expectations upward. These considerations collectively highlight how these shocks labeled simply as "unconventional" in our empirical setting could generate such effects on prices. Given the critical importance of labeling in our empirical framework, we also conduct an additional confirmatory analysis, building on the results presented in this section. This analysis examines the time-series properties of the identified shocks and discusses to what extent the imposed labeling is consistent with observed dynamics and established monetary policy narratives; its main implications are developed in the discussion that follows. Apart from this point, which merits a detailed discussion beyond the scope of this paper, we nevertheless observe that the responses to this second shock manifest by a stronger reaction of the instrument and long-term yields, with a negligible response of the 2-year German rate. Similar to the responses observed for conventional shocks, the impulse responses to unconventional monetary policy shocks show an appreciation of the nominal exchange rate, a decline in stock prices, and a reduction in production, with these effects materializing a few periods after the monetary policy tightening.

Looking at the response of the VSTOXX, we notice that the degree of uncertainty perceived by financial markets varies according to the nature of the monetary policy shocks. Although financial uncertainty increases following contractionary monetary policy shocks, conventional shocks appear to have stronger effects. Indeed, we observe a sharp rise in the VSTOXX a few periods after the occurrence of a contractionary conventional shock, with a peak reaching 0.9 at horizon $h = 7$. The response to the unconventional shock is quite similar, while being lower in magnitude. We observe again a rise in financial uncertainty in the months following the impact. The response reaches a peak of 0.3 at horizon $h = 13$. Analyzing the dynamics of uncertainty, it is interesting to observe it in connection with the evolution of long-term yields and the dynamics of stock prices. Indeed, independently of the nature of the shock, contractionary monetary policy shocks are associated with a rise in the level of interest rates over the months following the shock. As financial conditions tighten, we observe a drop in stock prices and a rise in financial uncertainty.

Our findings align with the recent and expanding body of literature supporting the view that uncertainty is endogenous to economic fundamentals and external shocks, particularly monetary policy. Prior studies such as Ludvigson et al. (2021) and Carriero et al. (2018a,b, 2021) emphasize the endogenous nature of uncertainty and its importance in shaping economic fluctuations. While these studies broadly explore the implications of uncertainty within the economy, our research specifically investigates the link between monetary policy shocks and financial uncertainty. This complements earlier contributions by Bloom (2009), Bachmann et al. (2013), and Gilchrist et al. (2014), which focus on uncertainty as a driver of business cycles.

Unlike Ludvigson et al. (2021) and Carriero et al. (2018b), we do not differentiate explicitly between macroeconomic and financial uncertainty. Instead, we consider the VSTOXX to be a closer measure of financial uncertainty, given its specific connection with financial markets. This focus on financial uncertainty particularly aligns with the findings of Carriero et al. (2018b), who emphasize the endogeneity of financial uncertainty to economic fundamentals. By linking financial uncertainty to monetary policy shocks, this present paper provides a focused perspective on how central banks influence financial market perceptions of uncertainty, reinforcing the importance of the financial dimension in understanding uncertainty dynamics. In addition, our analysis extends the results of Bekaert

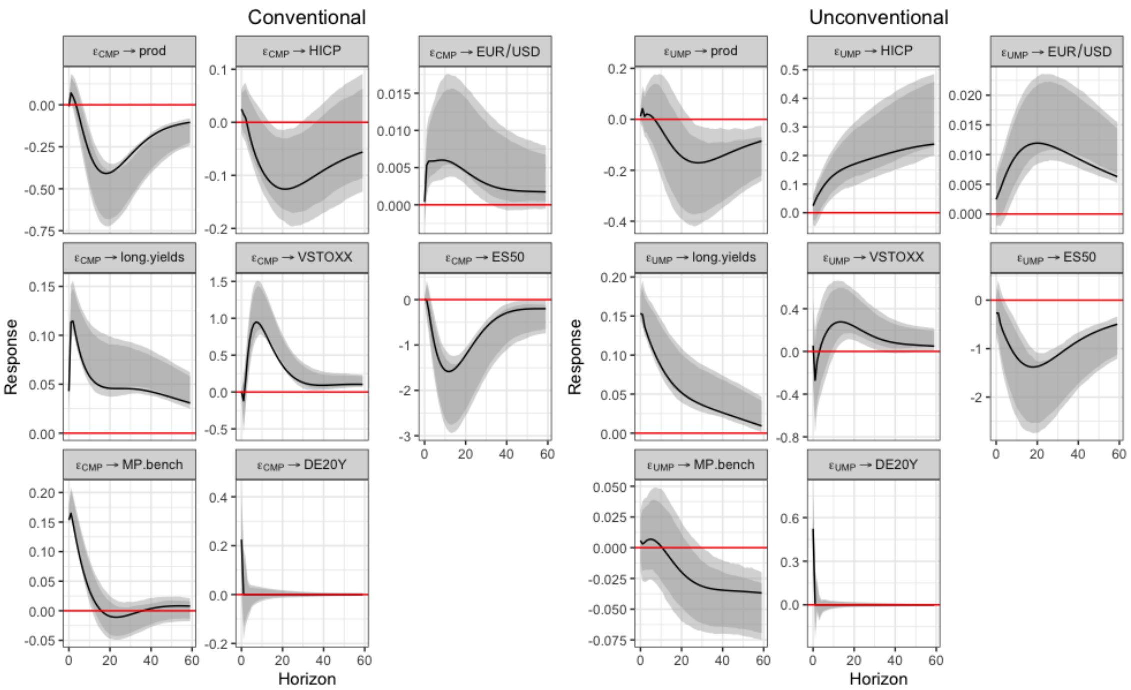


Figure 2.3: Impulse responses to monetary policy shocks.

Notes: Impulse responses (baseline model) to contractionary conventional (left column) and unconventional (right column) monetary policy shocks. The variables depicted correspond to those used in the model (2.5) and described in 2.4.1. Specifically, the model includes industrial production (denoted as "prod" as a proxy for GDP, log x 100), HICP (log x 100, as a measure of prices), the nominal EUR/USD exchange rate, the 2-year German bond yield (denoted as "MP.bench", a measure of short-term interest rates and monetary policy stance), long-term (10-year) government bond yield (denoted as "long.yields"), the VSTOXX index (as a measure of financial uncertainty), and the EURO STOXX 50 index ("ES50" log x 100, as a measure of stock prices). The chosen instrument is "DE20Y", representing high-frequency surprises in the 20-year German yield, as reported in the database of Altavilla et al. (2019). Confidence bands are obtained using a moving block bootstrap (block length = $T^{1/3}$) with 16-84 (darker band) and 10-90 (lighter band) Hall's percentiles.

et al. (2013), who investigate the effects of monetary policy on financial uncertainty and risk aversion, but do not focus on the unconventional dimension of monetary policy. Our study extends their framework for the Euro Area and gives new insights into the distinct roles of conventional and unconventional monetary policy shocks. Furthermore, we achieve this through a totally different identification scheme, with the advantage of avoiding any recursive (Cholesky) ordering in the identification of shocks.

Finally, evidence of this link carries several important policy implications for central banks. It points out the role of uncertainty in the transmission of monetary policy, offering a finer understanding of how central banks' actions affect both the financial system and the broader economy. As highlighted in Bekaert et al. (2013), this connection is also important for financial stability purposes, as preventing disruptions caused by excessive financial uncertainty has become a second and complementary objective of central banks. Finally, by clarifying the role of monetary policy shocks in shaping financial uncertainty, this research contributes to ongoing discussions on the interaction between monetary policy, financial stability, and economic dynamics.

To further ensure the robustness of our findings, we analyzed the sensitivity of the results using alternative instruments with different maturities, as detailed in Section A.3.3 of Appendix A. This robustness part reveals that impulse responses and labeling of shocks remain consistent across different instrument choices, providing additional confidence in the validity of our results. In addition, Table A.5 compares the properties of our two shocks with an identification strategy based on a set of sign restrictions imposed on high-frequency surprises, following the approach proposed by Goodhead (2024).

Labeling of the shocks: confirmatory analysis

In addition to looking at the effect of monetary policy shocks on the instrument, looking at the magnitude of certain impulse responses is a relevant feature that characterizes the nature of the monetary policy innovations underlying the model. In particular, impulse responses (see Figure 2.3) show differences in the responses of interest rates to shocks. We have seen that long-term yields are more sensitive to unconventional shocks, while short-term yields are more sensitive to conventional ones. Although characterizing the effect of unconventional monetary policies on financial markets and the economy is a challenging task, the consensus in the literature is that unconventional monetary policies affect relatively more long-term rates (Rossi, 2021). Since our results are in line with this consensus, it gives us another reason to believe that our shock labeling is correct.

A second way to assess the correctness of our labeling is to look *a posteriori* at the obtained time series of the shocks, and at the features of these time series. Figure 2.4 plots the time series of shocks labeled as "conventional" and "unconventional", respectively, while in Figure 2.5 we display rolling window estimates of the variance of the shocks. The estimation window is set to 24 months. From these time series, we detect several elements in favor of our labeling. First, we notice a change in the variance of the shocks before and after the GFC crisis. The variance of the shocks labeled as "unconventional" increases from 0.95 to 0.99, while the variance of shocks labeled as "conventional" falls from 1.05 to 0.8. This change in variance suggests that we have labeled the shocks in an economically sound manner. Indeed, central banks reduced the use of conventional monetary policies after the 2008 financial crisis and the apparition of the ZLB, leading to the emergence of unconventional measures and the decline in the variance of conventional monetary policy shocks. Even though central banks also used unconventional measures before the crisis (Rossi, 2021), reliance on those policies increased during the ZLB period, i.e., after the GFC and the Eurozone debt crisis.

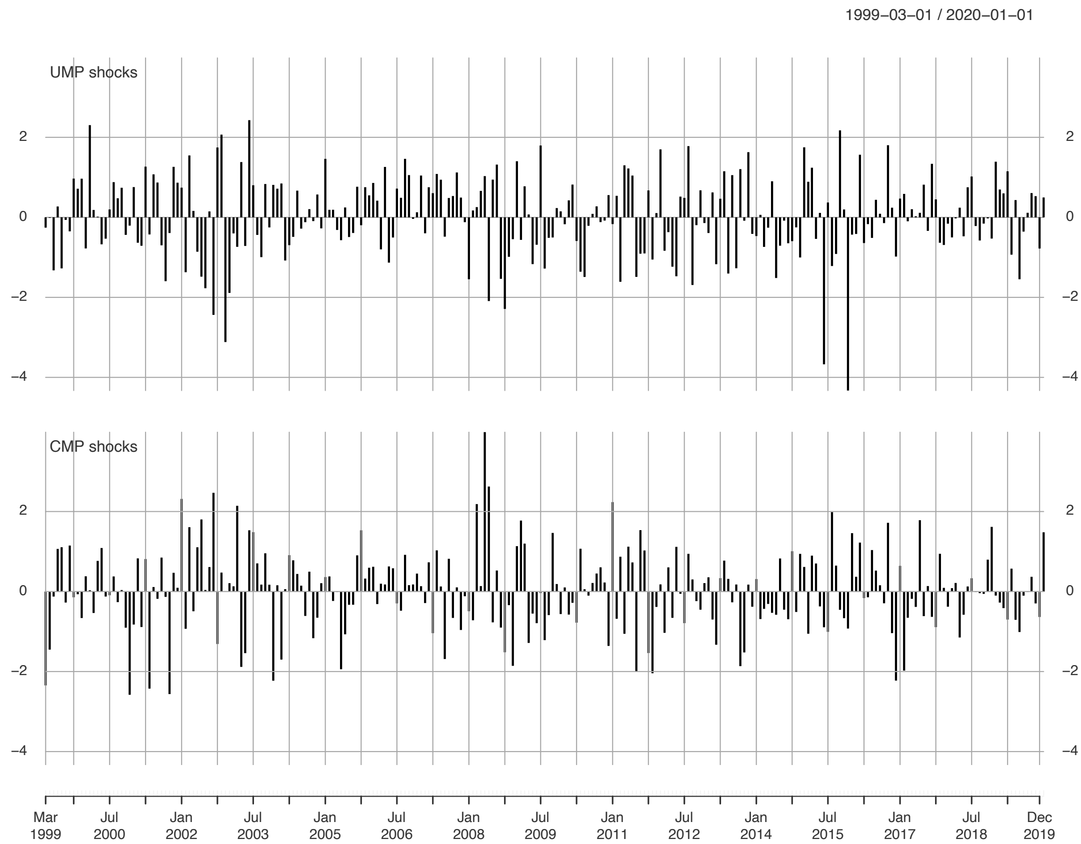


Figure 2.4: Time series of monetary policy shocks. Upper panel: unconventional monetary policy shocks. Lower panel: conventional monetary policy shocks.

Besides this, Figure 2.5 also plots the variance of the shocks on a rolling window of 24 months. We notice from this figure large variations over time in the (rolling) variance of the shocks. For the vast majority of the time preceding the financial and sovereign debt crises, the variability of unconventional shocks was lower than that associated with conventional shocks. However, it changed from 2013 onwards, as the variance of the unconventional shocks exceeded the variance of the conventional shocks. In particular, the gap between variances widened from 2015 to 2017, periods throughout which the ECB intensified its use of unconventional tools, notably via the expanded APP.

Note that these fluctuations in the variance of the shocks match the episodes mentioned in the analysis of Hartmann and Smets (2018), which provides an extensive overview of the major economic, monetary, and financial developments since the inception of the euro in 1999. Similarly, Rogers et al. (2014) and Gagnon and Sack (2018) also depict how unconventional monetary policies have been conducted after the financial crisis in Europe and other major countries. According to Hartmann and Smets (2018), four major episodes (or cycles) summarize the evolution of the ECB's monetary policy: (i) the end of a "technology cycle" characterized by the collapse of the dot-com bubble, a fall in economic activity and a weak euro (1999-2003); (ii) a period of loosing in monetary policy causing the buildup of instabilities and considered as the prelude of the financial crisis (2003-2007); (iii) the reces-

Figure 2.5: Rolling window estimates of the variance of the shocks. Dashed: conventional monetary policy shocks. Solid: unconventional monetary policy shocks. Vertical lines: four major economic cycle episodes of Hartmann and Smets (2018).

sions following the US financial crisis and the sovereign debt crisis in Europe (2007-2013); and (iv) the period of a "low-inflation recovery" accompanied by the presence of the ZLB and the intensification of unconventional tools as economic stimulus (2013-2018).

This figure allows us to track the periods of monetary expansions and contractions over time for both types of shocks. In particular, we can see that both series followed a downward trend after 2008, which means that most of the shocks that occurred afterward were expansionary. Note also that the trend lasts longer (until 2015) for unconventional shocks than for conventional shocks. These latter observations coincide with the conduct of ECB monetary policy during this period, which was particularly accommodating after the financial crisis, with the ECB having to make greater use of unconventional tools for a longer period in response to the ZLB constraint.

To conclude this discussion on the labeling of shocks, we can state that our labeling of shocks is not in contradiction with the elements highlighted above. Indeed, both the responses (magnitude and dynamics in particular) of the variables, as well as the time series properties of the structural shocks, do not contradict the labeling done on the shocks.

Historical decomposition and forecast error variance decomposition

While the impulse responses summarize the system's reactions to monetary policy shocks, the historical decomposition of the VSTOXX series and its forecast error variance decom-

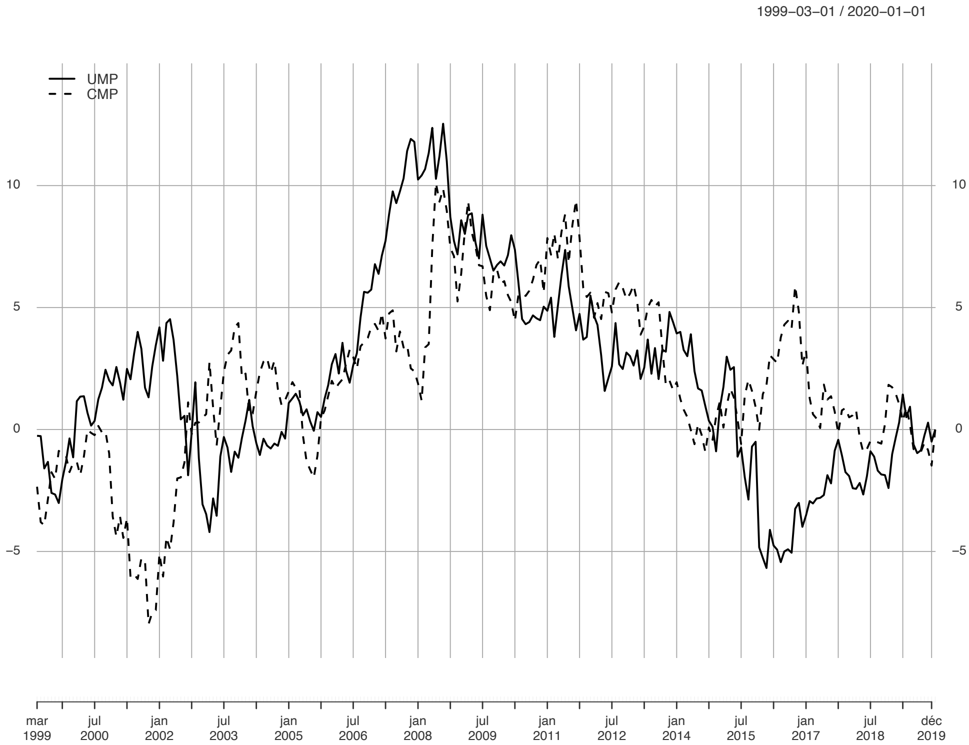


Figure 2.6: Cumulative sum of shocks over time. Dashed: conventional monetary policy shocks. Solid: unconventional monetary policy shocks.

position (FEVD) provide additional information to economically quantify the links between monetary policy and financial uncertainty. In Figure 2.7, we show the historical decomposition between monetary policy shocks (green for conventional shocks, red for unconventional ones) and all other shocks (gray) of the mean-centered financial uncertainty. Overall, we find that conventional shocks are more important than unconventional ones in explaining deviations of financial uncertainty from its historical mean. In particular, in the run-up to the financial crisis (2005-2007), we find that monetary policy innovations played an important role in explaining fluctuations in financial uncertainty. From 2005 to mid-2006, the conduct of monetary policy reduced the level of uncertainty, while thereafter it increased it. From a historical perspective, this phenomenon can be explained by the fact that, between mid-2003 and the end of 2005, monetary policy was particularly accommodative following the aftermath of the burst of the dot-com bubble (Hartmann and Smets, 2018). Over that period, the ECB kept interest rates unchanged at around 2% for more than two years, while the economic context in Europe was characterized by a recovery in output growth, an expansion in credit and money, as well as inflation above its target in mid-2005. It was only at the end of 2005 that the ECB started a series of interest rate hikes to counteract inflationary risks. Concomitantly, concerns arose about the possible emergence of asset price imbalances, particularly in the housing sector, as a result of the robust expansion of monetary aggregates and credit availability. This notably led policymakers to discuss a “lean against the wind” policy to preserve financial stability (Assenmacher-Wesche and Gerlach, 2010; Gambacorta and Signoretti, 2014; Herwartz et al., 2018; Smets, 2018).

On the contrary, before 2008, the contributions of unconventional shocks are smaller than those of other structural shocks. This result supports our previous observations regarding the magnitude of uncertainty responses to monetary policy shocks. Nevertheless, we observe that between 2013 and 2020, the contribution of these shocks increased. This period was mainly characterized by the prevalence of a low inflation environment, spurring the ECB to keep interest rates close to zero and to launch several asset purchase programs (APPs). In particular, starting in 2013, the ECB adopted more explicit forward guidance and policy communication (Hartmann and Smets, 2018). Concerning this adoption, we observe that monetary policy during this period has contributed to an increase in the level of financial uncertainty while between 2015 and 2017 and the implementation of the Expanded Asset Purchase Programme (EAPP), the massive expansion of the ECB balance sheet lowered the level of uncertainty in financial markets[13] and improved financial conditions, as shown by the historical decompositions (see Figure A.3 in Appendix A) of the EURO STOXX 50 and long-term yields series.

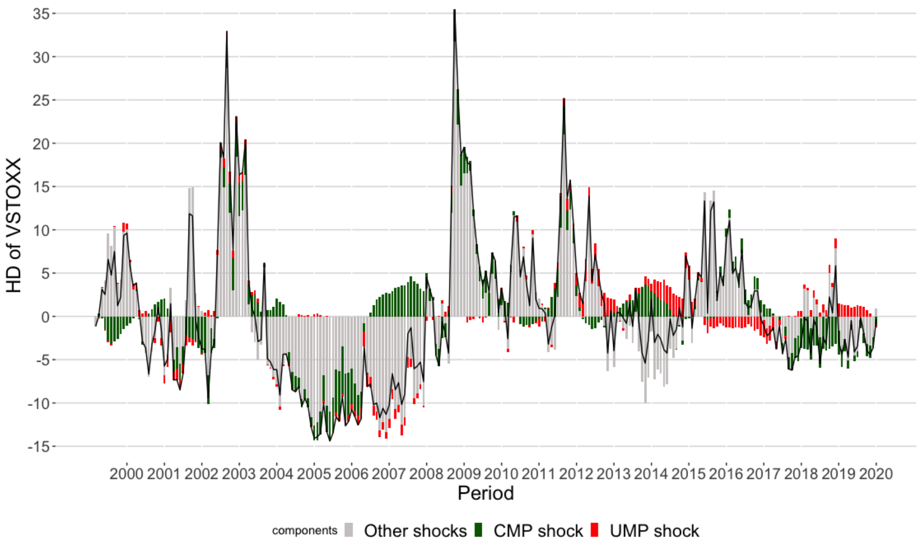


Figure 2.7: Historical decomposition of financial uncertainty (VSTOXX).

Finally, in Figure 2.8 we display the FEVD for financial uncertainty. We show that conventional shocks contribute largely (up to 15 percent) and more than unconventional shocks. Nevertheless, monetary policy innovations labeled as unconventional have a much larger contribution to the FEVD of long-term interest rates and stock prices (see Figure A.4 in Appendix A).[14]Therefore, we postulate that the response of the VSTOXX to such shocks,

[13]Note also that this observation coincides with the sign restrictions imposed by Gambacorta et al. (2014) to identify unconventional monetary policy shocks. Gambacorta et al. (2014) captures unconventional monetary policy shocks by using sign restrictions on central bank assets and the VIX. When identifying these shocks, they assume that expansionary unconventional shocks (mainly materialized by exogenous increases in the central bank's total assets) are accompanied by a fall in the VIX.

[14]This result, along with additional results presented in Appendix A, supports the correctness of the shock labeling procedure underlying our framework.

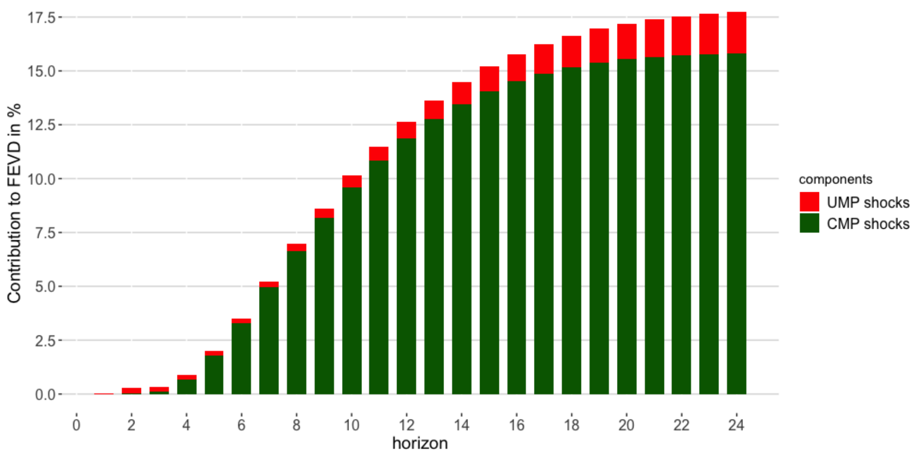


Figure 2.8: FEVD of financial uncertainty (VSTOXX).

as discussed earlier, is affected indirectly through the other variables of the system.

The role of uncertainty in the transmission of monetary policy shocks

What explains the responses of uncertainty to monetary policy shocks? Is it the rationale of a direct link between uncertainty and monetary policy, or the result of an indirect transmission between monetary policy and other variables in the system? To what extent is the uncertainty channel crucial in the transmission of monetary policy to financial markets and macroeconomic conditions? To answer those questions, we estimate the same VAR model as before while imposing uncertainty to be exogenous at the impact of the shocks, similarly to Bloom (2009) and Jurado et al. (2015). To do so, we impose additional restrictions on the structural matrix. Ordering VSTOXX first, we now assume that uncertainty is affected only by a single type of shock, namely uncertainty shocks. Moreover, when drawing impulse responses, we restrict uncertainty from having any feedback role on the dynamics of the other variables in the model[15], leading us to draw "counterfactual" impulse responses. It also enables us to (i) determine whether the previously identified link originates from a direct fundamental nexus between monetary policy and financial uncertainty and (ii) assess more explicitly the role of uncertainty, i.e., the uncertainty channel, in the propagation of monetary policy shocks.

We report the results of the model estimated under this specification (see Figure 2.9). Overall, comments made previously about the shape and the dynamics of the responses to the shocks still hold. Focusing on uncertainty, we note from the response of the VSTOXX that uncertainty surrounding financial markets is affected by monetary policy shocks, particularly those described as "conventional". However, since we prevent the uncertainty channel from playing a role in the propagation of shocks, it underscores that uncertainty is affected by monetary policy innovations, but that the nature of this link is mainly the result of an indirect transmission, mediated through other economic and financial fundamentals.

[15]This is carried out by imposing zero restrictions on the VAR companion matrix $A(L)$.

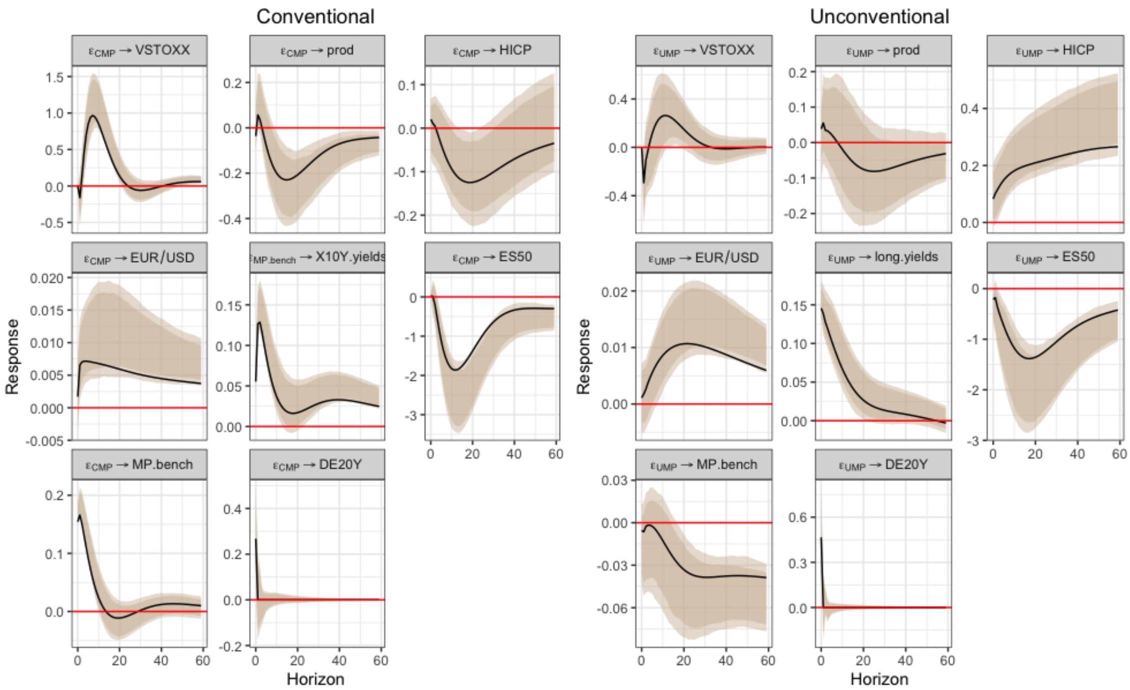


Figure 2.9: Impulse responses when "closing" the uncertainty channel.

Notes: Responses are similar to Figure 2.3 except that we specify uncertainty to be exogenous at impact (i.e. not affected by MP shocks) and that the latter has no feedback in the dynamics of the other variables in the model. Methods for the construction of confidence bands and variable labels are similar to those of Figure 2.3.

To delve deeper into the importance of financial uncertainty in the monetary policy pass-through and its role in shaping macro-financial conditions, we illustrate in Figure 2.10 the disparity in responses between those obtained in the baseline analysis (see Figure 2.3) and those obtained just beforehand (see Figure 2.9). We find that, except for industrial production, the importance of financial uncertainty in transmitting monetary policy shocks is rather small and not significant for the majority of the variables in the system. Our observation that industrial production is more sensitive to the presence of an uncertainty channel is not surprising, since the latter has been shown to play a substantial role in output deviations (Bloom, 2009, 2014; Jurado et al., 2015; Bloom et al., 2018). However, our results show in addition that (i) fluctuations in uncertainty can arise from additional economic disturbances, such as monetary policy shocks, beyond those originating solely from uncertainty shocks, and (ii) the uncertainty channel plays a particularly significant role in the transmission of monetary policy shocks, especially those considered as "conventional", to medium-term output fluctuations.

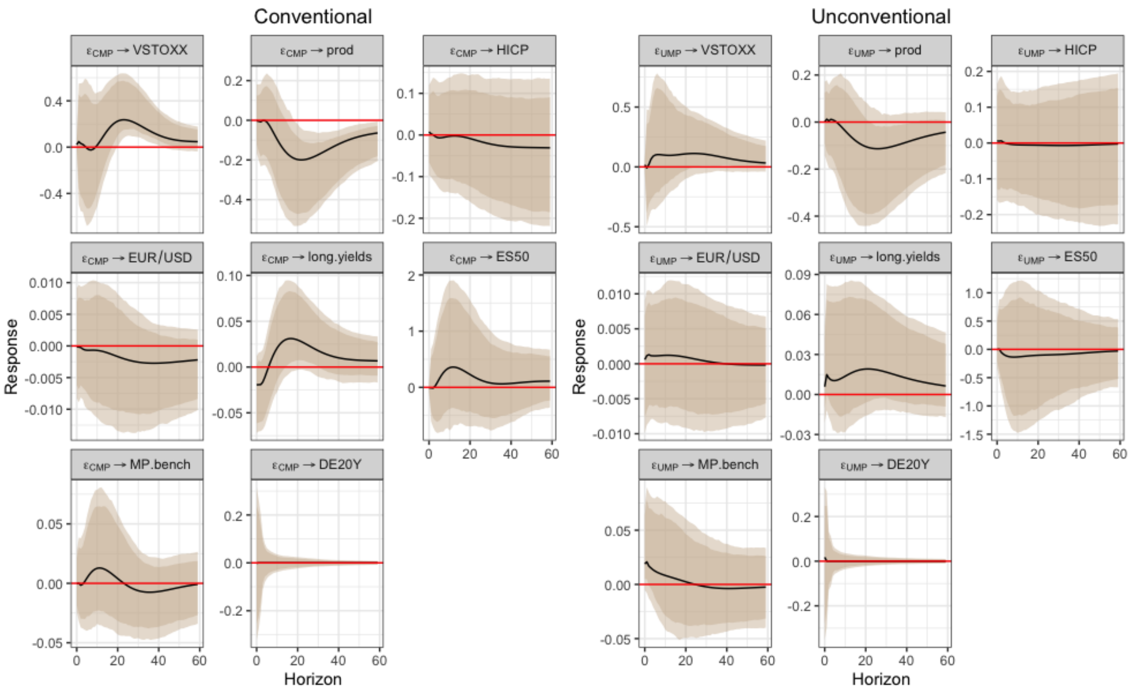


Figure 2.10: Difference of responses to monetary policy shocks under an "open" (Figure 2.3) and a "closed" uncertainty channel (Figure 2.9).

Notes: Difference of responses to monetary policy shocks under an "open" and a "closed" uncertainty channel. Variable labels are similar to those in Figure 2.3 and Figure 2.9. Confidence bands are set to 16-84th and 10-90th percentiles.

2.5 Conclusion

In this paper, we present a novel econometric approach to simultaneously disentangle and label conventional and unconventional monetary policy shocks in SVAR models. This framework combines both the non-Gaussian properties of the data and the presence of an instrumental variable. While we specifically apply this method to study the interaction between monetary policy shocks and financial uncertainty dynamics, the framework is versatile and can be adapted to other settings, provided the assumptions on the instrumental variable, particularly those about its relationship with the shocks being identified, remain valid.

In a detailed simulation study, we highlight that using an external instrument (i) improves upon the "shock labeling" problem encountered with ICA identification schemes, and (ii) achieves similar or better accuracy than the identification approach of Lanne et al. (2017) and the proxy SVAR approach of Stock and Watson (2012) and Mertens and Ravn (2013). Additionally, our method is robust to relaxing the strict exogeneity condition of the instrument.

We apply this framework to study the effects of monetary policy on financial uncertainty in the Euro area. Our results highlight important distinctions between the two types of monetary policy shocks. Financial uncertainty tends to rise in response to contractionary monetary policy shocks, with the effect being more pronounced for conventional shocks. Consistent with Bekaert et al. (2013), we find that conventional contractionary monetary policy significantly increases the level of uncertainty perceived by investors. Unconventional monetary policy shocks, on the other hand, exert a smaller but more persistent effect on financial uncertainty.

Our findings align with the growing literature, including Ludvigson et al. (2021), Carriero et al. (2018a), and Carriero et al. (2018b), which underscores the endogeneity of uncertainty to economic fundamentals and external shocks. Specifically, we provide evidence that financial uncertainty is notably influenced by monetary policy innovations. This suggests the existence of financial uncertainty as a potential transmission channel of monetary policy. However, we find that this channel primarily operates indirectly through its effect on financial conditions, rather than as a distinct and direct mechanism amplifying monetary policy shocks. This conclusion aligns with the broader findings of Bloom (2009), Bachmann et al. (2013), and Jurado et al. (2015), which emphasize the indirect role of uncertainty in shaping economic dynamics.

Finally, evidence of the relationship between monetary policy and financial uncertainty provides valuable insights into the transmission of monetary policy and the role of central banks in ensuring financial stability. The endogenous nature of uncertainty observed in this study highlights the importance of integrating uncertainty dynamics into monetary policy design. It also calls for a reconsideration of the role and magnitude of uncertainty shocks in driving business cycles, a topic extensively studied in previous literature. These findings underscore the critical interplay between monetary policy, financial conditions, and economic stability, suggesting future research on their interaction.

Chapter 3

The Heterogenous Response of Financial Uncertainty to Monetary Policy

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Abstract. Understanding monetary policy transmission to financial markets is crucial for policymakers and investors, but existing literature focuses on first-order effects and market-wide aggregated measures. To address this gap, the present paper investigates the responses of asset class-specific financial uncertainty to distinct dimensions of monetary policy shocks. We conduct our analysis with a Bayesian extended stochastic volatility model, allowing for the effect of monetary policy shocks on second-order moments used to compute our uncertainty measures. Then, we decompose monetary policy shocks into changes in the yield curve's level, slope, and curvature during a high-frequency time window around policy announcements, refining previous approaches relying on daily changes. Applying this approach to a wide array of 47 sovereign bonds, corporate bonds, stocks, and exchange rates in the euro area, we document heterogeneous and persistent effects of these shocks on asset-specific financial uncertainty.

Keywords: high-frequency identification, uncertainty, stochastic volatility.

3.1 Introduction

Over the past two decades, a substantial body of research has examined how financial markets respond to monetary policy (see Bhattarai and Neely, 2022 and Bernanke, 2020, for a review). Understanding how monetary policy influences asset prices and other major financial developments is essential for both macroeconomics and finance[1]. In macroeconomics, interest in this question has been particularly reinforced after the Great Financial Crisis (GFC) and the emergence of the zero lower bound (ZLB), a low-interest rate environment spurring central banks all over the world to rely more extensively on so-called unconventional monetary policies (UMPs) to stabilize disrupted financial markets. In addition, structural macroeconomic models (Bernanke et al., 1999; Adrian and Shin, 2014; Brunnermeier and Sannikov, 2014; Christiano et al., 2014; Adrian et al., 2019) attach increasing

[1] This fundamental research question has also been notably addressed by Eichenbaum and Evans (1995); Kuttner (2001); Cochrane and Piazzesi (2002); Rigobon and Sack (2004); Bernanke and Kuttner (2005); Gürkaynak et al. (2005); D'Amico and King (2013); Hanson and Stein (2015); Neely (2015); Swanson (2021), among others

importance to financial conditions in explaining real business cycles, making the financial sector a particularly dominant element in the transmission of monetary policy (Gertler and Karadi, 2015; Bernanke, 2020; Swanson, 2021). The importance of such a question also applies to finance, where understanding the impact of monetary policy on the term structure of interest rates and risk premia is fundamental for asset pricing models (see, e.g., Campbell and Cochrane 1999; Bansal and Yaron 2004; Bekaert et al. 2009; He and Krishnamurthy 2013; Greenwood et al. 2018).

While the existing literature provides extensive theoretical and empirical insights into how monetary policy shapes the functioning of financial markets and the pricing of securities, a notable feature is that these studies typically focus on first-order (mean) effects. Surprisingly, much less is known about how and the extent to which monetary policy influences uncertainty (i.e., the second-order effects) surrounding asset prices, especially at the disaggregated level. This paper addresses this gap by analyzing how monetary policy affects daily asset-specific financial uncertainty, explicitly measured as future expected conditional stochastic volatility of asset returns. We do so for multiple asset classes in the euro area, thereby characterizing possible heterogeneity in uncertainty responses to monetary policy at the asset class level. In addition, this paper offers a new perspective by analyzing how these responses vary according to the dimension of the yield curve that is impacted by specific monetary policy actions, including traditional interest rate setting, forward guidance, large-scale asset purchases, or liquidity measures (Gürkaynak et al., 2005; Inoue and Rossi, 2021; Swanson, 2021; Bernanke, 2020). Indeed, since these various tools affect the yield curve in different ways, such as influencing future short-term rates expectations or altering term and risk premia between maturities, it results in variations in the level, slope, or curvature of the yield curve, reflecting different channels of transmission of monetary policy to the financial markets. Our analysis explicitly accounts for these various mechanisms, along the lines advocated by Inoue and Rossi (2021).

Evidence for the existence of an effect of monetary policy on financial uncertainty can be found in existing macro-financial theories. For example, by shaping the long-run and near-term expectations of future short-term rates, monetary policy directly affects the level and slope of the yield curve, altering discount rates applied to future cash flows over time (Gürkaynak et al., 2005; Bernanke and Kuttner, 2005). Simultaneously, adjustments in the slope and curvature can reveal changes in the expected economic outlook and revisions of future short rates (Christensen and Rudebusch, 2012; Bauer and Rudebusch, 2014) as well as more complex adjustments in term (or risk) premia (Rogers et al., 2014; Hanson and Stein, 2015; Rogers et al., 2018), driven notably by a modified supply-demand balance for duration risk (Vayanos and Vila, 2021; Greenwood and Vayanos, 2014). These various effects on the yield curve, in turn, map into broader monetary policy transmission channels. In particular, persistently low yields encourage risk-taking and portfolio rebalancing (Gagnon et al., 2011; Swanson, 2011; Borio and Zhu, 2012; Vissing-Jorgensen and Krishnamurthy, 2011; Greenwood and Vayanos, 2014; Bauer et al., 2023), prompting shifts into riskier assets, compressing risk premia, and amplifying price responses. The signaling component of forward guidance and asset purchases (Woodford et al., 2012; Bauer and Rudebusch, 2014) shapes medium- to long-term expectations, often triggering pronounced market reactions, particularly when guidance reveals new information about future policy paths and economic outlook (Campbell et al., 2012; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2021; Andrade and Ferroni, 2021). Finally, variations in yield curve components trigger exchange rate movements, notably through interest rate differentials and international risk premia, transmitting policy shocks in foreign markets through capital flows (Rey, 2015; Gabaix and Maggiori, 2015; Rogers et al., 2018). Therefore, all these forces, taken together, do not merely shift the average trajectory of asset prices but also influence the dispersion of responses that define how markets simultaneously incorporate new information about economic fundamentals and re-price future risks. Thus, it suggests a connection with second-order effects.

Empirically, however, evidence is scarcer. Using the VIX, Bekaert et al. (2013) uncovers significant interconnections between monetary policy, risk aversion, and uncertainty. More recently, Bauer et al. (2023) offers further insights into this, showing that high-frequency policy surprises[2] affect the aggregate risk appetite and the VIX itself, with expansionary shocks lowering implied equity volatility and contractionary shocks raising it. In addition, Kang and Park (2024) examines the effects of monetary policy shocks on macro and financial uncertainty indices in a structural VAR framework, using empirical uncertainty measures of Jurado et al. (2015). Note that, unlike Bekaert et al. (2013) and Bauer et al. (2023), uncertainty is found to decrease after a policy tightening. Closer to our modeling approach, Carriero et al. (2021) uses a structural VAR with stochastic volatility to capture uncertainty endogenously from the data, but they do not study its response to monetary policy. Contrary to the present paper, these studies investigate financial (or macro) uncertainty dynamics either at the aggregate level of the economy or assuming a single dimension of monetary policy.[3] This approach neglects the fact that assets differ in their sensitivities to various policy-driven shifts in interest rates, liquidity conditions, and credit spreads, implying that the aforementioned effects may not be uniform across asset classes. Hence, the same yield curve surprises can lower uncertainty in low-risk government bonds while heightening it in riskier corporate debt or equity markets. Accordingly, to provide a deeper and finer understanding of the macro-financial implications of monetary policymaking over the financial system, we conduct our analysis at the asset class level, examining how uncertainty around asset class-specific prices evolves across different dimensions of changes in the yield curve.

The perspective taken in this paper, to consider three novel dimensions of analysis (second-order effects, disaggregation at the asset-class level, and decomposition in level-,

[2]Note that Bauer et al. (2023) relies on Bauer and Swanson (2023b) for the identification of policy shocks, and summarizes the four different types of monetary-policy news (based on four principal components of Eurodollar rates) in a single number. Consequently, the authors do not explicitly dissociate the respective effect of each of these components (contrary to the present paper) in their empirical analysis of the risk-taking channel.

[3]To a lesser extent, Lewis (2025a) also documents effects of policy surprises on uncertainty and proposes a decomposition of policy announcement surprises into multiple dimensions. However, his approach, based on exploiting the heteroskedasticity of intraday data, differs from what is proposed in our paper.

slope-, and curvature-related monetary policy events), is essential, not only for understanding monetary policy transmission towards financial markets (Krishnamurthy et al., 2018; Bauer et al., 2023; Kashyap and Stein, 2023), but also for macroprudential considerations. In particular, the proposed mapping may help identify emerging financial imbalances and guard against the buildup of systemic risks or vulnerabilities (Adrian and Shin, 2014; Adrian et al., 2019). Moreover, this paper also echoes significant strand of the macro literature which recognizes uncertainty as a central driver of business cycle fluctuations (Bloom, 2009, 2014; Gilchrist et al., 2014; Jurado et al., 2015; Baker et al., 2016; Ludvigson et al., 2021), and emphasizes the importance of distinguishing between macroeconomic and financial uncertainty, given their distinct origins, transmission channels, and endogenous responses to monetary policy (Jurado et al., 2015; Ludvigson et al., 2021; Carriero et al., 2018a, 2021; Castelnuovo, 2023).

From a methodological standpoint, assessing the multidimensional effects of monetary policy on financial uncertainty calls for two essential elements: an explicit statistical model for modeling uncertainty from the data, as well as a rigorous identification of exogenous policy changes. To do so, we employ a Bayesian stochastic volatility framework augmented with exogenous covariates (denoted SV-X), which allows us to quantify the effects of distinct dimensions of monetary policy shocks in asset price dispersion dynamics. In our framework, changes in financial uncertainty associated with monetary policy are defined as changes in expected stochastic asset-price dispersion (stochastic volatility) due to monetary policy shocks. To identify monetary policy shocks and decompose their effects along various dimensions, we rely on the bulk of the literature making use of high-frequency surprises.[4]

In particular, our methodology for recovering monetary policy shocks follows Inoue and Rossi (2021). Indeed, we exploit information on changes in factors of the term structure, respectively, level, slope, and curvature, around monetary policy announcements. The major advantage of using this approach lies in the fact that we can capture multiple dimensions of monetary policy, as monetary policy shocks are defined as shifts in factors (level, slope, and curvature) defining the yield curve. However, while Inoue and Rossi (2021) records those changes on the day of the monetary policy announcement dates, we adapt their methodology and record variations of the term structure at a higher frequency (i.e., a couple of hours) by exploiting the database of Altavilla et al. (2019). As such, our approach strengthens the economic identifications of the functional shocks proposed in Inoue and Rossi (2021).

Covering the period 1999–2020, we conduct our empirical analysis using 47 daily series of financial returns, encompassing a wide spectrum of financial instruments across European markets, following the call of Altavilla et al. (2024) to improve our understanding of policy transmission heterogeneity in the euro area. Our dataset comprises sovereign

[4] A non-exhaustive list of this strand of literature encompasses Kuttner 2001; Bernanke and Kuttner 2005; Gürkaynak et al. 2005; Faust et al. 2007; Gertler and Karadi 2015; Nakamura and Steinsson 2018; Cieslak and Schrimpf 2019; Jarociński and Karadi 2020; Miranda-Agrippino and Ricco 2021; Swanson 2021; Bauer and Swanson 2023a. See also Bauer and Swanson (2023b) for a thorough discussion on this.

and corporate bond indices, equity indices disaggregated by country, sector, and market capitalisation, as well as major exchange rates relative to the Euro. Our objective is not limited to measuring the immediate effects of these shocks, but to extend our understanding of how they shape the dynamics of uncertainty. We follow a stepwise approach to progressively uncover how the different dimensions of monetary policy shape financial uncertainty at a granular, asset-level: We first estimate the response of asset-specific uncertainty to monetary policy–induced shifts in the entire yield curve. These responses are then decomposed into the contributions of the level, slope, and curvature dimensions, with the respective impact of each evaluated separately for conventional (pre-ZLB) and ZLB regimes. In the latest part, we employ impulse response functions (à la Koop et al., 1996), historical variance decompositions, and counterfactual exercises to quantify the dynamics, historical importance, and episodic relevance of each component.

Our empirical findings reveal significant effects and heterogeneity across asset classes and yield curve dimensions (level, slope, curvature), offering some insights into the broad existing channels, such as discount rate revisions and risk-premium adjustments, through which monetary policy shapes financial uncertainty differently across assets. Furthermore, we also observe that the structural dynamics associated with monetary policy regimes, both before and during ZLB, affect the relationship under study. Finally, in historical decomposition exercises, we document a major influence of monetary policy on uncertainty fluctuations beyond standard time series dynamics, especially when it affects the curvature of the yield curve. Notably, in a counterfactual analysis, we estimate that the 2015 expanded Asset Purchase Program led to a reduction of financial uncertainty for country-specific stock indices up to -7.7 percentage points compared to a no-intervention scenario.

Notice that, although our framework will treat variations in the level, slope, and curvature factors of the yield curve as economically meaningful dimensions of policy surprises, we do not aim to uncover the structural determinants of these movements or disentangle the specific channels through which these latter connect with asset prices and uncertainty[5]. Instead, as explained in Section 3.2.2, we will interpret variations in these factors as empirically tractable measures of different components of monetary shocks and analyze their implications in reduced-form terms.

The paper is organized as follows: Section 3.2 describes both the features of the stochastic volatility model and our approach to recovering monetary policy shocks. Section 3.3 details the data used for the empirical part of the paper. Section 3.4 reports and discusses the results. Section 4.5 concludes.

3.2 Methodology

In this section, we outline the methodology used to estimate the dynamic effects of monetary policy on financial uncertainty. We first specify our general modeling approach in

[5]See Hanson and Stein (2015), Rogers et al. (2014), and Rogers et al. (2018) for examples of studies that explicitly decompose the effects of monetary policy into changes in expected short rates (the expectations hypothesis component) and adjustments in term premia. Bauer and Rudebusch (2014) similarly disentangles these components and contrasts the signaling and portfolio rebalancing channels.

Subsection 3.2.1 before detailing our identification strategy for the monetary policy shocks in Subsection 3.2.2.

3.2.1 *Modeling strategy*

Our approach is based on an extended stochastic volatility (SV) framework for daily data, which allows us to capture the time-varying nature of uncertainty in financial asset returns[6], while explicitly incorporating the role of monetary policy shocks. We specify a daily stochastic volatility for financial asset returns as:

$$r_t = \exp\{h_t/2\}\xi_t, \tag{3.1}$$

where ξ_t follows a standard normal distribution with mean zero and variance one, i.e. $\xi_t \sim \mathcal{N}(0,1)$. The logarithm of the conditional variance, denoted as h_t, follows a stochastic process given by:

$$h_t = \mu_h + \phi(h_{t-1} - \mu_h) + \mathbf{x}_t^* \theta + \nu_t, \tag{3.2}$$

where ν_t is an independent and identically distributed innovation, normally distributed with zero mean and variance ω^2, i.e. $\nu_t \sim \mathcal{N}(0, \omega^2)$. In line with traditional specifications in the SV literature (Taylor, 1986; Jacquier et al., 1994; Kim et al., 1998), we assume that ξ_t and ν_t are serially independent and mutually uncorrelated, and that the monetary policy shocks $\mathbf{x}_t^*$ are exogenous and orthogonal to (ξ_t, ν_t). The term μ_h captures the long-run mean of log variance (h_t), while ϕ accounts for the persistence of volatility over time, ensuring that the process is stationary when $|\phi| < 1$. The vector $\mathbf{x}_t^*$ encompasses the different components of monetary policy shocks, which are, similar to Inoue and Rossi (2021), defined as the changes in factors of the yield curve around monetary policy announcements. These shocks are included in the transition equation with coefficients θ, allowing us to measure how monetary policy affects financial uncertainty. The motivation for using a stochastic volatility model stems from the theoretical conceptualization of uncertainty as proposed by Jurado et al. (2015). According to their definition, financial uncertainty at a given horizon h should be understood as the conditional standard deviation of the unforecastable component of a given economic or financial variable for the same horizon. Formally, for a return series r_t, h-period ahead uncertainty measure (ending in $t+h$) is given by:

$$\mathcal{U}_t^r(h) = \sqrt{\mathbb{E}\left[(r_{t+h} - \mathbb{E}[r_{t+h}|\mathcal{I}_t])^2 \mid \mathcal{I}_t\right]}. \tag{3.3}$$

This definition highlights that financial uncertainty represents the degree of unpredictability of future realizations of r_t, given past information. As advocated in Jurado et al. (2015), the use of stochastic volatility in calculating (3.3) explicitly accounts for the time

[6]Throughout this section, r_t and h_t denote a generic asset return and its (log) conditional variance. In the empirical application, the same specification is estimated separately for each index or asset k in our sample. Formally, for asset k we have $r_{k,t} = \exp\{h_{k,t}/2\}\xi_{k,t}$ and $h_{k,t} = \mu_{h,k} + \phi_k(h_{k,t-1} - \mu_{h,k}) + \mathbf{x}_t^*\theta_k + \nu_{k,t}$, with all assets indexed by k. For expositional simplicity, we suppress the asset index in the derivations and work with a representative return series.

variation and the stochastic nature of the conditional variance of r_t, aligned with their definition. It also permits the construction of a shock to the second moment that is independent of innovations to r_t itself, an important feature in the theoretical literature on uncertainty (Bloom, 2009; Christiano et al., 2014; Gilchrist et al., 2014; Basu and Bundick, 2017) which presumes the existence of such an independent uncertainty shock. GARCH-type models (for example) do not share this feature.

An important feature of Jurado et al. (2015) approach is that $\mathbb{E}[r_{t+h}|\mathcal{I}_t]$ needs to be a forecast of the h-step-ahead conditional expectation of r_t. Indeed, Jurado et al. (2015) are interested in monthly data, for which a certain consensus exists regarding the predictability of the conditional mean (see, e.g. Rapach et al., 2009). At the daily level, however, the consensus goes in the direction of an absence of mean dynamics (Herwartz, 2017), in line with the efficient market hypothesis (Fama, 1970) at short-horizon. Thus, in our setting, since $\mathbb{E}[r_{t+h}|\mathcal{I}_t]$ can be validly set to 0, uncertainty at horizon $h = 0, 1, 2, \cdots$ reduces to:

$$\mathcal{U}_t^r(h) = \sqrt{\mathbb{E}[r_{t+h}^2|\mathcal{I}_t]}. \tag{3.4}$$

By substituting the return equation (3.1), we have

$$\mathbb{E}[r_{t+h}^2|\mathcal{I}_t] = \mathbb{E}[(\exp\{h_{t+h}/2\}\xi_{t+h})^2|\mathcal{I}_t], \tag{3.5}$$

which reduces to:

$$\mathbb{E}[\exp(h_{t+h})\xi_{t+h}^2|\mathcal{I}_t]. \tag{3.6}$$

Since $\xi_t \sim \mathcal{N}(0,1)$, it follows that $\mathbb{E}[\xi_{t+h}^2|\mathcal{I}_t] = 1$ and, under the orthogonality between ξ_{t+h} and h_{t+h}, the conditional expectation factorizes, so that so that:

$$\mathcal{U}_t^r(h) = \sqrt{\mathbb{E}[\exp(h_{t+h})|\mathcal{I}_t]}. \tag{3.7}$$

Consequently, our stochastic volatility model enables us to directly estimate uncertainty as the expected conditional variance of returns, aligning with the definition given by Jurado et al. (2015). Moreover, the stochastic nature of h_t ensures that uncertainty evolves dynamically over time, and can be decomposed between a component depending on past levels of volatility and the influence of monetary policy shocks, and a pure random component (ν_t). For $h = 0$, contemporaneous uncertainty corresponds to observed stochastic volatility. For $h \geq 1$, Eq. (3.7) can be obtained from the generalized impulse function of the model, which we discuss below.

As advocated by Jurado et al. (2015), removing the predictable part $\mathbb{E}[r_{t+h}|\mathcal{I}_t]$ from the return series is essential before estimating the stochastic volatility of the remaining series. This step is simplified by assuming it is equal to zero. Although this assumption seems to contradict Jurado et al. (2015) insights, notice again that here we consider financial returns at a *daily* frequency (contrary to a monthly frequency in the aforementioned article), since we wish to capture the instantaneous effect of monetary policy announcements. In the literature, daily expected returns are usually assumed to be time-invariant (contrary to volatility, sign, or density) and not forecastable, or if forecastable, only over very brief periods (see Farmer et al., 2023 for a recent discussion). Thus, to avoid generating additional detrimental noise in a preliminary mean-forecast estimation step, we set $\mathbb{E}[r_{t+h}|\mathcal{I}_t]$ equal to zero. To assess whether this simplifying assumption is empirically innocuous, Appendix B.4 reports an additional analysis where we test the potential existence of first-order effects of monetary policy shocks on financial returns.

The formulation of our SV model is similar to formulations encountered in the financial literature on stochastic volatility (Kim et al., 1998; Omori et al., 2007), except for the inclusion of shock components in the transition equation (3.2). The inclusion of observable variables or shock components in stochastic volatility modeling has been proposed notably by Hol and Koopman (2000); Koopman et al. (2005); Ulm and Hambuckers (2022); Fu and Mendieta-Munoz (2025) and Fu et al. (2025). We estimate the model using Bayesian methods[7] via Markov Chain Monte Carlo (MCMC). Specifically, we rely on the No-U-Turn Sampler (NUTS) developed by Hoffman et al. (2014), a variant of Hamiltonian Monte Carlo that adapts the path length automatically and improves convergence in high-dimensional or correlated parameter spaces. This approach is well-suited to the nonlinear and latent-state structure of stochastic volatility models with exogenous shocks and allows for efficient exploration of the posterior distribution of the model parameters.

For our analysis, this framework is particularly well-suited, as it enables us to estimate the dynamic response of financial uncertainty to monetary policy shocks $x^*_{i,t}$. Specifically, we define $\boldsymbol{\Psi}^h_i$, the h-ahead generalized impulse response function[8] (GIRF, following Koop et al. 1996) of the log-variance process h_t to a one-unit change in the i-th monetary policy shock component as:

$$\Psi^h_i = \mathbb{E}[h_{t+h} \mid x^*_{i,t} = 1, \mathcal{I}_t] - \mathbb{E}[h_{t+h} \mid \mathcal{I}_t], \quad h = 0, 1, \ldots, H. \tag{3.8}$$

This formulation captures the marginal contributions of respective shock components (level, slope and curvature) to the conditional path of financial uncertainty.[9]

Given our model and the linear structure of (3.2), this impulse response has the following intuitive and analytically convenient closed-form solution:

$$\Psi^h_i = \theta_i \phi^h, \tag{3.9}$$

where θ_i explicitly captures the initial impact of the shock component $x^*_{i,t}$, and ϕ dictates the persistence of responses. The estimation and interpretation of these quantities form the core of our empirical analysis.

In the next Subsection, we explain how we extract monetary policy shocks from high-

[7] See Appendix B.2 for the calibration of the priors model's parameters and additional details regarding the estimation.

[8] At the asset level, the generalized impulse response is $\Psi^h_{k,i} = \mathbb{E}[h_{k,t+h} \mid x^*_{i,t} = 1, \mathcal{I}_t] - \mathbb{E}[h_{k,t+h} \mid \mathcal{I}_t]$ for asset k and shock component i, with closed-form solution $\Psi^h_{k,i} = \theta_{k,i}\, \phi^h_k$. For notational simplicity, we omit the asset index k in the main text.

[9] Although the impulse responses are formulated directly in terms of logarithmic counterparts (h_t), they can easily be translated into economically meaningful uncertainty measures defined earlier in (3.3) and (3.7).

frequency yield curve movements, as they form the basis of our econometric analysis.

3.2.2 Capturing multiple dimensions of monetary policy

In the following, we describe how we identify and construct the vector $\mathbf{x}_t^*$, the exogenous changes in factors implied by pure monetary policy shocks, denoted ε_t^*. We follow Inoue and Rossi (2021) in the way to conceive such shocks. More specifically, we define a pure monetary policy shock as the functional change in the yield curve due to monetary policy announcements d_t. As a monetary policy shock is defined by a change in a function, it influences not only, e.g., the short-term rate, but also the rates at other maturities (denoted by τ), depending on its nature. However, using directly the functional representation ε_t^* in (3.2) would be impractical from an econometric standpoint due to its high dimensionality. Therefore, following Inoue and Rossi (2021), we reduce the dimension of the problem by using the approach of Nelson and Siegel (1987) and Diebold and Li (2006): the variations captured by ε_t^* can be summarized by the variations in three distinct and economically interpretable factors $\boldsymbol{\beta}_t = (\beta_{1,t}, \beta_{2,t}, \beta_{3,t})$. To extract those factors, Inoue and Rossi (2021) model explicitly the dynamics of the yield curve $y_t(\tau)$ according to:

$$y_t(\tau) = \beta_{1,t} + \beta_{2,t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \beta_{3,t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right), \tag{3.10}$$

where the three-dimensional and time-varying parameter vector $\beta_t = (\beta_{1,t}, \beta_{2,t}, \beta_{3,t})$ denotes respectively level, slope and curvature factors. The parameter τ is the maturity associated with each yield to maturity $y_t(\tau)$. Expressing $y_t(\tau)$ as a function, monetary policy shocks for a specific maturity are defined as the shifts in the yield curve ($\Delta y_t(\tau)$) observed on monetary policy announcement dates d_t:

$$\begin{aligned}\varepsilon_t^*(\tau) &= \Delta y_t(\tau)\, d_t, \qquad (3.11)\\ &= \Delta\beta_{1,t}^d + \Delta\beta_{2,t}^d\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \Delta\beta_{3,t}^d\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right), \qquad (3.12)\end{aligned}$$

where d_t is a dummy variable equal to one if there is a monetary policy announcement at time t and $\Delta\beta_{j,t}^d = \Delta\beta_{j,t}\, d_t$ denotes daily changes in factors composing the "functional" monetary policy shock. Using this approach, one can construct the vector x_t^* by taking directly the variations of level, slope, and curvature induced by the monetary policy shock, i.e. $x_t^* = \Delta\beta_t^d = (\Delta\beta_{1,t}^d, \Delta\beta_{2,t}^d, \Delta\beta_{3,t}^d)$, or by taking a linear combination[10] $x_t^* = f(\Delta\beta_t^d)$ of these variations (e.g., the sum or difference) which encompass the different dimensions of the monetary policy shock and do not need to be indexed by the maturity.

Suppose now that, instead of observing $y_t(\tau)$ and extracting $\mathbf{x}_t^*$ on a daily window, we observe directly high-frequency (HF) reactions of yields[11] $\Delta y_t^{hf}(\tau)$ captured around

[10]In particular, $\Delta(\beta_{1,t} + \beta_{2,t})$ corresponds to the change in the instantaneous yield (instrument/short-end dimension), while $\Delta(\beta_{3,t} - \beta_{1,t})$ captures non-parallel shape movements (curvature net of level) that, in an affine-term-structure perspective, load on the expected future path of short rates and/or term premia. We report these for completeness but do not analyze them further.

[11]In our application, $\Delta y_t^{hf}(\tau)$ denotes changes in yields to maturity on benchmark German government

monetary policy announcements for different maturities, i.e., for a short period of intra-day time (e.g., a couple of hours) around the announcement. For example, such surprises $\Delta y_t^{hf}(\tau)$ are provided by Altavilla et al. (2019). Since those variations are captured within monetary policy announcement episodes, we may assume that they constitute solely the response of yields to monetary policy shocks. Consequently, considering that $\Delta y_t^{hf}(\tau) = \frac{\partial y_t(\tau)}{\partial \varepsilon_t^*}$ and following (3.10), we can write explicitly:

$$\begin{aligned}
\Delta y_t^{hf}(\tau) &= \frac{\partial y_t(\tau)}{\partial \varepsilon_t^*}, && (3.13)\\
&= \frac{\partial y_t(\tau)}{\partial \beta_t}\frac{\partial \beta_t}{\partial \varepsilon_t^*}, && (3.14)\\
&= \Delta\beta_{1,t}^{hf} + \Delta\beta_{2,t}^{hf}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \Delta\beta_{3,t}^{hf}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right). && (3.15)
\end{aligned}$$

The representation of the model (3.15) is analogous to (3.12) as it enables, similarly to Inoue and Rossi (2021), to capture variations in level, slope, and curvature associated with ε_t^*. Alternatively to the classical approach of Nelson and Siegel (1987) and Diebold and Li (2006), this representation makes use of variations of the term structure $\Delta y_t^{hf}(\tau)$ for which regression coefficients $\Delta\beta_{1:3,t}^{hf}$ are directly interpreted as variations in level, slope, and curvature to monetary policy shocks. However, a substantial difference is that those factors are identified in a much narrower window.[12] This approach allows for better control over the endogenous responses of the yield curve to other economic or financial developments that may occur simultaneously with monetary policy announcements but are unrelated to the policy itself. In the spirit of Inoue and Rossi (2021), this approach provides a more comprehensive measure of the effects of monetary policy shocks, as it captures multiple structural dimensions of their impacts on the yield curve. These dimensions are summarized by the vector of changes in factors, $\mathbf{x}_t^* = \Delta\boldsymbol{\beta}_t^{hf} = (\Delta\beta_{1,t}^{hf}, \Delta\beta_{2,t}^{hf}, \Delta\beta_{3,t}^{hf})$ which underlie the model shown in (3.15).

Figure 3.1 shows the evolution of our estimated $\Delta\boldsymbol{\beta}_t^{hf}$ over time, describing how monetary policy shocks propagate through the yield curve. Following (3.15), these quantities have been obtained by regressing, for each day of a monetary policy announcement, the intra-day German government bond yield suprises of Altavilla et al. (2019) for 11 maturities (ranging between 2 and 30 years) on the Nelson and Siegel (1987) loadings, in the spirit of Diebold and Li (2006). In Table 3.1, we report associated summary statistics across different policy regimes.[13] The financial implications of the factor variations can be re-

bonds from the EA-MPD database of Altavilla et al. (2019), rather than changes in zero-coupon yields. The representation in (3.10) is formally specified for the zero-coupon yield curve, and Inoue and Rossi (2021) implements it using zero-coupon U.S. Treasury yields data from Gürkaynak et al. (2007). Comparable zero-coupon German yields at high frequency are not available and within the EA-MPD, the German surprises offer the broadest and longest maturity coverage, so we apply the same structure to the cross-section of Bund yields to maturity as an approximation to the underlying term-structure response. Appendix B.1.2 reports goodness-of-fit evidence for this specification based on these high-frequency yield surprises.

[12] In Section B.1.3 of Appendix B, we provide further documentation on the differences and similarities of these shock components with those identified by Altavilla et al. (2019) and Inoue and Rossi (2021).

[13] We also report two standard linear combinations used to give a structural reading of curve movements: $\Delta(\beta_{1,t} + \beta_{2,t})$, which equals the change in the instantaneous yield as $\tau \to 0$ and thus approximates an instru-

trieved from (3.10): with λ set at the usual value of 0.609, a one-unit level shock shifts all maturities by 100 basis points (so 0.1, as observed in 2016, corresponds to a 10 bps parallel move); a one-unit slope shock raises yields by about 75 bps at 1-year, 31 bps at 5-year, and 16 bps at 10-year (so 0.1 implies roughly $+7.5$, $+3.1$, and $+1.6$ bps at those maturities); and a one-unit curvature shock produces a hump centered at 2–3 years, lifting those maturities by about 28–30 bps (about 27 bps at 5-year and 16 bps at 10-year; hence 0.1 maps to ≈ 3 bps near the hump). Moreover, this visualization allows us to give an economic interpretation to each shock component, depending on its relationship with the factors, as well as the influence of monetary policy on the yield curve. For example, the level component ($\Delta\beta_{1,t}^{hf}$) captures parallel shifts across all maturities, generally shows smoother changes, and reflects broad-based monetary policy adjustments associated with expectations regarding the long-term stance of monetary policy. In contrast, the slope component ($\Delta\beta_{2,t}^{hf}$) accounts for changes in the steepness of the yield curve, driven by differences between short- and long-term rates. This factor relates notably to expectations about the future path of policy rates and growth prospects. Positive changes in the slope indicate a steepening of the yield curve, which is often interpreted as an indicator of anticipated economic expansion. Conversely, negative changes indicate flattening, typically associated with policy tightening and concerns about economic downturns. Finally, the curvature component, displaying higher volatility in the figure, reflects effects on medium-term yields, often associated with risk premia.

To gauge how our shocks relate to other existing measures, we regress $\Delta\beta_t^{HF}$ (level, slope, curvature) on the conference-window policy factors of Altavilla et al. (2019). As shown in Figure B.12 in Appendix B, statistically significant correlations arise mainly along a few dimensions: the level shocks are most strongly associated with QE surprises ($R^2 \approx 0.39$); slope shocks correlates with both Timing and, more prominently, QE surprises ($R^2 \approx 0.01$ and $R^2 \approx 0.31$, respectively); and curvature shocks are most correlated with FG surprises ($R^2 \approx 0.32$, with a negative slope) and, to a lesser extent, with Timing ($R^2 \approx 0.03$). These patterns indicate that our shock measures share non-negligible co-movements with policy surprises commonly used in the high-frequency identification literature (Kuttner, 2001; Gürkaynak et al., 2005; Altavilla et al., 2019; Swanson, 2021), even though the underlying identification schemes differ.

Beyond factor dynamics, the plot also reveals notable differences across monetary policy regimes. Pre-ZLB, monetary policy shocks predominantly influenced the level and slope factors, consistent with the reliance on conventional policy tools targeting short-term interest rates. In the post-ZLB period, the prominence of the slope and curvature factors underscores the increased use of unconventional tools, such as forward guidance and quantitative easing, which primarily impacted medium- and long-term yields. These results highlight the unique and evolving nature of monetary policy transmission across

ment (short-end) shock; and $\Delta(\beta_{3,t} - \beta_{1,t})$, which holds the level fixed and isolates non-parallel (curvature-net-of-level) movements associated with revisions to the expected policy path and/or term premia. These combinations aid interpretation only and are not used in our empirical analysis. See Inoue and Rossi (2021) for more details.

the yield curve, emphasizing how different policy tools affect the yield curve via multiple dimensions.

Nevertheless, certain conceptual and methodological limitations remain, particularly regarding the identification of monetary policy shocks. Unlike Hanson and Stein (2015) or Rogers et al. (2018), our approach provides a reduced-form characterization of monetary policy shocks through changes in the level, slope and curvature of the yield curve, rather than through a structural decomposition into expected future short rates and term (risk) premia. Such structural decompositions typically rely on no-arbitrage affine term-structure models and macro-finance DTSMs,[14] as in Duffie and Kan (1996), Dai and Singleton (2000, 2002), Rudebusch and Wu (2008), Adrian et al. (2013) or Joslin et al. (2014), which specify a stochastic discount factor and price the full term structure under no arbitrage. Other representations of the term structure could in principle also be used. The Svensson (1994) extension of Nelson and Siegel (1987) provides additional parametric flexibility by allowing a second curvature component, while models such Diebold et al. (2006), Ang and Piazzesi (2003), Moench (2012) and Altavilla et al. (2017) combine yield-curve factors with macroeconomic dynamics, in some cases within a no-arbitrage framework. Such alternatives provide a more structural understanding of the determinants of yield curve movements, offering a clearer decomposition between expectations and risk premia, but at the cost of additional parameters, stronger identifying assumptions, and increased complexity in high-frequency settings. By contrast, following Inoue and Rossi (2021), our approach provides a parsimonious and interpretable summary of the yield curve's joint high-frequency response to monetary policy announcements.

Furthermore, high-frequency surprises may also embed central bank information effects (Nakamura and Steinsson, 2018; Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023a)[15], such that non-parallel movements can arise even without a pure instrument change or forward guidance about the future policy path. While these considerations would further investigations beyond the scope of this paper, our stance is to focus on a reduced-form identification strategy: we use high-frequency yield curve responses to monetary announcements as exogenous policy-induced shocks, summarizing their multidimensional effects on the term structure. It summarizes the responses to monetary policy in an economically meaningful way, allowing us to assess their impact on the uncertainty (stochastic volatility) surrounding asset prices, although this approach does not isolate structural components behind yield curve movements.

[14]DTSMs: Dynamic Term Structure Models.

[15]The literature on "information effects" in high-frequency surprises has offered many competing views: (i) a *private-information* view in which central bank announcements reveal new private information on economic outlook, so markets adjust simultaneously and stocks and yields move together (e.g., Nakamura and Steinsson, 2018; Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020); (ii) a *public-news* view where co-movements mainly reflect data known before the meeting, so empirical analyses should control for pre-announcement news (Miranda-Agrippino and Ricco, 2021); and (iii) a *Fed-response-to-news* channel for which surprises mostly reflect how the Fed systematically reacts to public data that markets under-anticipate (Bauer and Swanson, 2023a,b). For a clear overview, see Bauer and Swanson, 2023a,b.

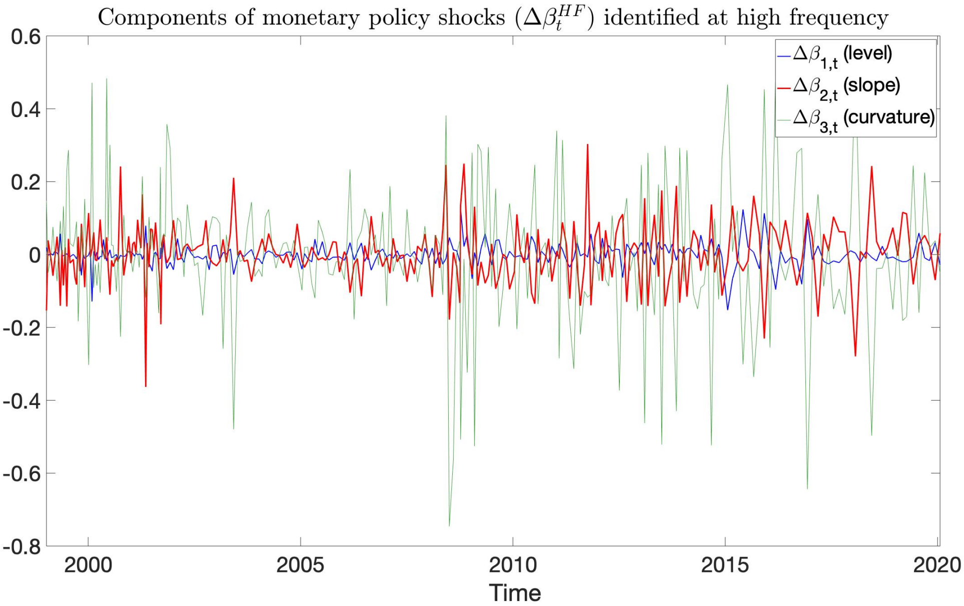

Figure 3.1: Components of monetary policy shocks ($\Delta\beta_{1:3,t}^{hf}$) captured at high frequency.

Notes: The figure plots changes in the Nelson and Siegel (1987) factors ($\Delta\beta_{1,t}$: level, $\Delta\beta_{2,t}$: slope, $\Delta\beta_{3,t}$: curvature) extracted from yield curve surprises within a narrow window around monetary policy announcements. The vertical scale can be read in terms of yield changes: with $\lambda = 0.609$, a one-unit variation in the level, slope, or curvature factor maps into shifts of approximately 100 bps in parallel, 72 bps at the short end (1-year), and 52 bps at the medium hump (2–3 years), respectively. Typical observed shocks of 0.1 therefore correspond to yield changes of about 5–10 basis points depending on the factor.

Table 3.1: Summary statistics of shocks by period.

Period	Statistic	$\Delta\beta_{1,t}$	$\Delta\beta_{2,t}$	$\Delta\beta_{3,t}$	$\Delta(\beta_{1,t}+\beta_{2,t})$	$\Delta(\beta_{3,t}-\beta_{1,t})$
Panel A. Full Sample						
1999-01-05 to 2020-01-31	Mean	-0.0001	0.0023	-0.0018	-0.0017	0.0022
	SD	0.0297	0.0827	0.1847	0.1938	0.0794
Panel B. Pre-ZLB Period						
1999-01-05 to 2011-12-31	Mean	-0.0006	-0.0012	0.0045	0.0051	-0.0017
	SD	0.0249	0.0771	0.1611	0.1682	0.0742
Panel C. Post-ZLB Period						
2012-01-01 to 2020-01-31	Mean	0.0013	0.0108	-0.0173	-0.0186	0.0121
	SD	0.0394	0.0953	0.2341	0.2467	0.0909
Panel D. Conventional Period						
1999-01-05 to 2008-10-31	Mean	-0.0019	-0.0003	0.0083	0.0102	-0.0022
	SD	0.0240	0.0714	0.1501	0.1583	0.0681
Panel E. Unconventional Period						
2008-11-01 to 2020-01-31	Mean	0.0024	0.0057	-0.0152	-0.0176	0.0082
	SD	0.0359	0.0959	0.2229	0.2329	0.0923

Notes: $\Delta\beta_{1,t}, \Delta\beta_{2,t}, \Delta\beta_{3,t}$ are (high-frequency) changes in level, slope, and curvature. $\Delta(\beta_{1,t}+\beta_{2,t})$ approximates the instrument (short-end) dimension; $\Delta(\beta_{3,t}-\beta_{1,t})$ captures non-parallel shape movements associated with expected-path and/or term-premium components.

3.3 Data

Table 3.2 describes the time series[16] considered in our analysis. Our dataset comprises daily log returns for a wide cross-section of 47 financial indices spanning five distinct mar-

[16]The data are taken from Reifinitiv. Table B.1 in Appendix B provides summary statistics.

ket segments for the euro area. The sovereign bond group **(Government bonds)** includes benchmark government securities from both core and peripheral euro-area countries, offering variation in credit risk, liquidity conditions, and exposure to interest rate movements. The corporate bond group **(Corporate bonds)** contains investment-grade indices across different maturities, capturing sensitivity to both credit spreads and interest rates. Concerning stocks, the group "**Stocks (countries)**" consists of broad national equity indices for major euro-area economies, reflecting market-wide responses within each country. The other equity group, **"Stocks (sectors)"**, disaggregates equity markets by industry sector (e.g., financials, industrials, consumer goods, etc.) and by size segments (large-cap versus mid/small-cap), enabling us to identify differences related to industry structure and firm size. Finally, the foreign exchange group **(Exchange rates)** contains the euro's bilateral exchange rates against a few major advanced-economy currencies, incorporating assets with different exposures to global risk factors and external monetary conditions. We consider daily log returns (r_t) for a period spanning from January 1999 to January 2020 ($T = 5499$) when available. This segmentation ensures substantial diversity across asset classes, geographies, sectors, and risk profiles, which enables us to examine how monetary policy shocks propagate differently across assets with varying sensitivities to yield curve movements.

3.4 Empirical Results

Our empirical analysis is designed to explore how monetary policy shocks influence financial uncertainty across the various asset classes described in the previous section. To achieve this goal, the analysis is structured into three interconnected subsections that progressively deepen the understanding of these effects.

Section 3.4.1 explores the overall responses of financial uncertainty to monetary policy shocks, where the shocks are represented by the sum of the level, slope, and curvature components of the yield curve. Therefore, in this configuration, $\mathbf{x}_t^*$ and $\boldsymbol{\theta}$ are scalars, which we denote x_t^* and $\tilde{\theta}$ in Subsection 4.1 for clarity. This initial analysis provides a broad perspective on uncertainty responses across sovereign bonds, corporate bonds, exchange rates, and stocks, further disaggregated by countries, sectors, and market capitalization. Observed heterogeneity at this stage motivates further exploration into its potential drivers. Section 3.4.2 disentangles these effects by analyzing the individual contributions of level, slope, and curvature components, shedding light on the transmission mechanisms underlying the observed differences between asset classes. Section 3.4.3 compares the responses across pre- and ZLB periods to examine how the introduction of unconventional monetary policy tools and evolving macro-financial conditions have altered the transmission of monetary policy on yield curve fundamentals and asset prices. Section 3.4.4 concludes our analysis by examining the effects on the uncertainty dynamics of the different financial assets. This includes (generalized) impulse responses (3.9) for each shock component defined earlier, as well as estimates of their historical contributions (see Section 3.4.4) and for particular key monetary policy episodes (see Section 3.4.4).

Table 3.2: Time series description.

Name	Group	Region	Observations	Start date	End date
1. BD BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Germany	5499	1999-01-05	2020-01-31
2. BG BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Belgium	5499	1999-01-05	2020-01-31
3. ES BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Spain	5499	1999-01-05	2020-01-31
4. FR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	France	5499	1999-01-05	2020-01-31
5. GR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Greece	5437	1999-04-01	2020-01-31
6. IR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Ireland	5499	1999-01-05	2020-01-31
7. IT BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Italy	5499	1999-01-05	2020-01-31
8. UK BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	UK	5499	1999-01-05	2020-01-31
9. EMU BENCHMARK 10 YR. DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	EMU	5499	1999-01-05	2020-01-31
10. IBOXX EURO CORPORATES - Cln Prc Indx Today	Corporate bonds	Europe	5499	1999-01-05	2020-01-31
11. IBOXX EURO OVERALL - Cln Prc Indx Today	Corporate bonds	Europe	5499	1999-01-05	2020-01-31
12. IBOXX EURO EUROZONE - Cln Prc Indx Today	Corporate bonds	Europe	5499	1999-01-05	2020-01-31
13. ICE BofA AAA Euro Corporate Index - Clean price	Corporate bonds	Europe	5499	1999-01-05	2020-01-31
14. ICE BofA BBB Euro Corporate Index - Clean price	Corporate bonds	Europe	5239	2000-01-04	2020-01-31
15. ICE BofA 1-3 Year BBB Euro Corporate Index - Clean price	Corporate bonds	Europe	5239	2000-01-04	2020-01-31
16. ICE BofA 1-10 Year AAA Euro Corporate Index - Clean price	Corporate bonds	Europe	5239	2000-01-04	2020-01-31
17. FTSE100PRICEINDEX	Stocks (countries)	UK	5499	1999-01-05	2020-01-31
18. FRANCECAC40PRICEINDEX	Stocks (countries)	France	5499	1999-01-05	2020-01-31
19. IBEX35PRICEINDEX	Stocks (countries)	Spain	5499	1999-01-05	2020-01-31
20. FTSEMIBINDEXPRICEINDEX	Stocks (countries)	Italy	5499	1999-01-05	2020-01-31
21. BEL20PRICEINDEX	Stocks (countries)	Belgium	5499	1999-01-05	2020-01-31
22. ISEQALLSHAREINDEXPRICEINDEX	Stocks (countries)	Ireland	5499	1999-01-05	2020-01-31
23. AEXINDEXAEXPRICEINDEX	Stocks (countries)	Netherlands	5499	1999-01-05	2020-01-31
24. ATHEXCOMPOSITEPRICEINDEX	Stocks (countries)	Greece	5499	1999-01-05	2020-01-31
25. STOXXEUROPE600EPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
26. EUROSTOXX50PRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
27. STOXXEUROPELARGE200PRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
28. STOXXEUROPESMALL200PRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
29. STOXXEUROPEMID200PRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
30. STOXXEUROPE600BASICMATSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
31. STOXXEUROPE600INDUSTRIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
32. STOXXEUROPE600TECHNOLOGYEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
33. STOXXEUROPE600UTILITIESEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
34. STOXXEUROPE600FINANCIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
35. STOXXEUROPE600HEALTHCAREEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
36. STOXXEUROPE600TELECOMEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
37. EUROSTOXXFINANCIALSVSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
38. EUROSTOXXFINANCIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
39. EUROSTOXXHEALTHCAREEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
40. EUROSTOXXINDSGDSSVSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
41. EUROSTOXXINDUSTRIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
42. EUROSTOXXTECHNOLOGYEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
43. EUROSTOXXTELECOMEPRICEINDEX	Stocks (sectors and market cap)	Europe	5499	1999-01-05	2020-01-31
44. USTOEURORFVEXCHANGERATE	Exchange rates	EUR/USD	5499	1999-01-05	2020-01-31
45. SWISSFRANCTOEUROWMREXCHANGERATE	Exchange rates	EUR/CHF	5499	1999-01-05	2020-01-31
46. GBPTOEURBOEEXCHANGERATE	Exchange rates	EUR/GBP	5499	1999-01-05	2020-01-31
47. JAPANESEYENTOEUROWMREXCHANGERATE	Exchange rates	EUR/JPY	5499	1999-01-05	2020-01-31

3.4.1 *Uncertainty responses to yield curve movements across asset classes*

We analyze financial uncertainty responses ($\tilde{\theta}$) to broad yield curve movements, representing monetary policy shocks (x_t^*) as the sum of level, slope, and curvature components. This provides an initial assessment of heterogeneity in uncertainty responses across asset classes, forming the basis for disentangling the specific contributions of each component in the following subsections.

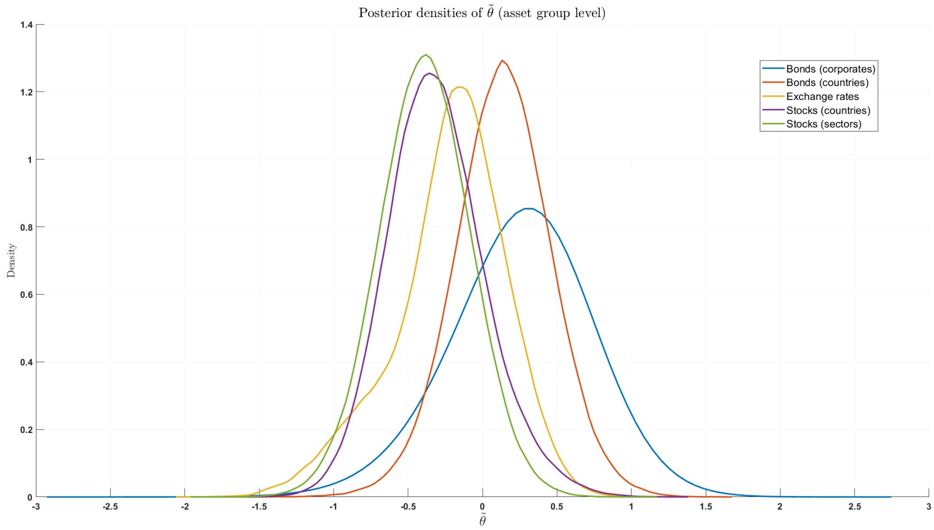

Figure 3.2: Spectrum of uncertainty responses (asset group level).

Figure 3.2 summarizes the posterior densities of $\tilde{\theta}$, aggregated by asset group, capturing the overall spectrum of uncertainty responses to yield curve variations. The modes of these densities reveal significant differences across asset classes. Sovereign bonds (red) and corporate bonds (blue) display positive central tendencies, suggesting that uncertainty increases in response to monetary policy shocks for these asset types. However, the range (dispersion) of responses is notably wider for corporate bonds, reflecting greater heterogeneity within this asset class, potentially attributable to differences in exposures to some underlying risk factors (e.g., credit risk or liquidity conditions). Exchange rates (orange) exhibit a density centered near zero, indicating aggregate neutrality in their sensitivity to overall changes in the yield curve captured in x_t^*. In contrast, the behavior of stock responses is substantially different. Indeed, both country-level indices (purple) and sectoral indices (green) have negative central tendencies and less within-group variation. This suggests that the uncertainty attached to stock prices connects differently to yield curve components summarized in x_t^*.

Figure 3.3 presents the posterior median estimates for individual assets within each different group, alongside their 68% (*), 90% (**), and 95% (***) highest posterior density intervals (HPDIs). Sovereign bonds consistently exhibit positive medians, reflecting a uniform response profile within the group. In contrast, corporate bonds display a wider range of positive responses, indicating greater heterogeneity. For exchange rates, the EUR/CHF

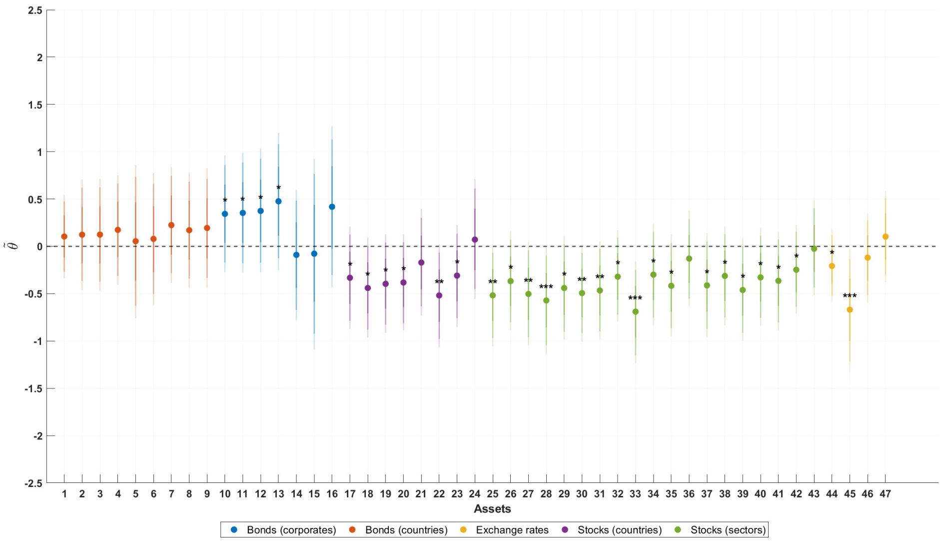

Figure 3.3: Point-wise (posterior medians) estimates of uncertainty responses across all assets.

pair stands out with a notably significant negative response, surpassing that of other currencies. Stocks reveal distinct patterns: country-level indices concentrate around negative responses, while sectoral stocks show broader dispersion, potentially reflecting their more diverse and specific exposure to term-structure fundamentals.

The results presented above highlight significant heterogeneity in uncertainty responses both across and within asset classes. More specifically, sovereign bonds and corporate bonds exhibit positive responses, while equities consistently display negative responses, and exchange rates tend to remain near-neutral on average. Within groups, the broader dispersion observed for corporate bonds, exchange rates, and sectoral equities reflects varying exposures to yield curve dynamics and monetary policy transmission channels. This heterogeneity establishes a foundation for exploring the specific contributions of level, slope, and curvature shocks in the subsequent analysis.

3.4.2 Decomposing yield curve components: level, slope, and curvature effects

We now focus on how asset uncertainty responds to the level (θ_1), slope (θ_2), and curvature (θ_3) components of monetary policy shocks. These three components constitute distinct aspects of monetary policy transmission on the term structure of interest rates, encompassing both changes in expectations about future short-term policy rates and adjustments in term and risk premia. Consequently, as assets valuations are intrinsically linked to expectations about discount rates and risk premia, financial uncertainty is fundamentally shaped by how investors reprice assets in response to revisions in the expected path of interest rates (Gürkaynak et al., 2005; Bauer and Rudebusch, 2014), intermediary constraints (Adrian and Shin, 2010; He and Krishnamurthy, 2013), default and liquidity risk (Duffie and Singleton, 1999; Chen et al., 2007), and time-varying risk aversion (Campbell and Cochrane, 1999; Bansal and Yaron, 2004). While the level factor is primarily related to persistent shifts in the long-run stance of monetary policy, giving long-run anchor to expectations about discount rates across financial assets, slope, and curvature factors can lead to heterogeneous uncertainty responses due to the distinct economic signals they convey. Indeed, shocks to the slope mainly capture revisions in the expected path of short-term interest rates induced by near-term macroeconomic outlook, which can in turn influence uncertainty in credit markets through adjustments in refinancing risks and cyclical credit spreads (Gilchrist and Zakrajšek, 2012). In contrast, monetary policy shocks affecting the curvature account for adjustments in term and risk premia, induced by the use of unconventional measures such as quantitative easing (QE) or targeted credit interventions, which alter the duration and risk structure across maturities. Therefore, decomposing these effects enables a more precise and nuanced understanding of monetary policy's propagation through financial markets, highlighting how the economic signals embedded in different dimensions of the yield curve interact with different channels that can affect financial uncertainty. In the following, we discuss and interpret the empirical results observed both within and across asset classes.

Effects across asset classes

Beginning with the responses at the group level, Figure (3.4) shows that uncertainty responses to shocks in the level component are relatively homogeneous across asset classes. This is consistent with the interpretation of the level factor reflecting shifts in long-run behavior of future interest rates and macroeconomic trends. Since these expectations changes affect the discount rate broadly across maturities, the repricing across assets is relatively uniform, leading to a common response of uncertainty. In contrast, the responses to slope and curvature components display significant heterogeneity. The strongest divergence in uncertainty responses emerges in corporate bonds (blue), which react more strongly and positively to changes in the slope factor, and in equities (purple and green), where the response to the curvature component differs markedly from that of bonds.

The positive response of corporate bond uncertainty to slope shocks is consistent with the heightened sensitivity of credit markets to changes in refinancing conditions. When monetary policy steepens the yield curve, typically by increasing long-term interest rates relative to short-term rates, firms with outstanding (short-term) debt face higher refinancing costs. This elevates refinancing risk, tightens credit conditions, and increases uncertainty about expected returns from holding those bonds. In contrast, sovereign bonds and equities exhibit muted or even negative responses to upward revision (positive slope shock) of the slope. Our interpretation of this pattern aligns with the expectations hypothesis of the term structure, which posits that a steeper yield curve reflects upward revisions in future short-term rate expectations due to anticipated economic expansion (Ang et al., 2006; Wright, 2006). For sovereign bonds, our findings suggest that such revisions reflect improved macroeconomic expectations, which may lower the probability of fiscal stress or sovereign risk default. Overall, this contributes to a decline in uncertainty about sovereign bonds. Similarly, equity markets respond to more favorable economic outlooks with a de-

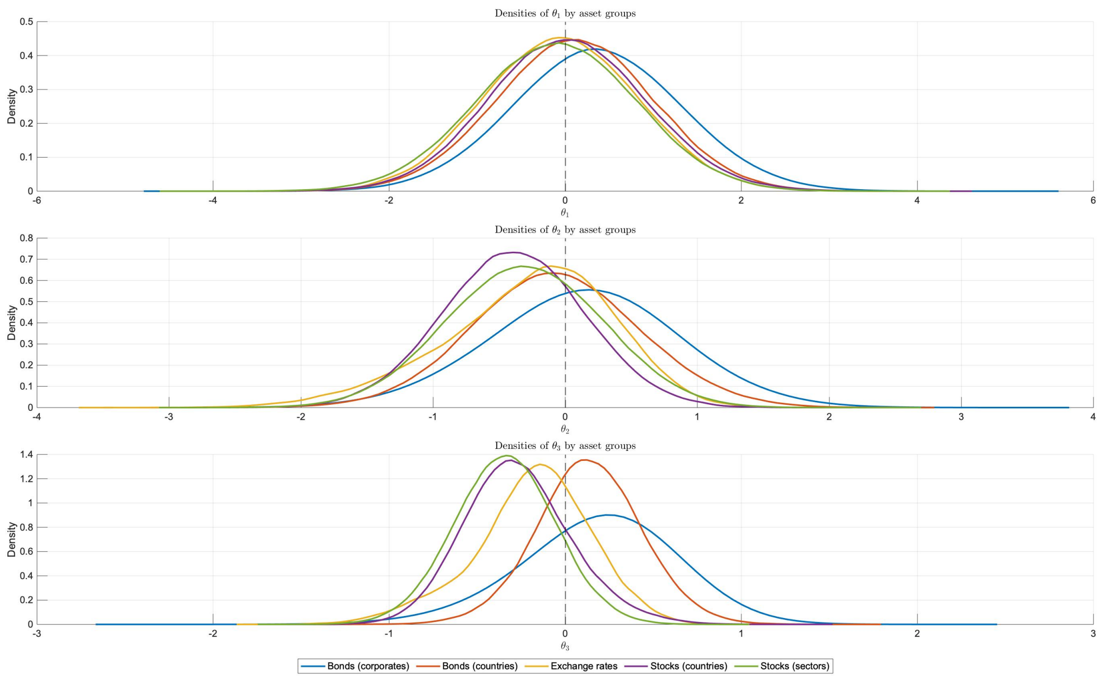

Figure 3.4: Spectrum of uncertainty responses to each component (asset group level).

crease in uncertainty for most indices. A plausible explanation for this pattern is that a steeper yield curve signals stronger near-term growth expectations and reduced macroeconomic risk. In habit formation models (Campbell and Cochrane, 1999), such conditions lower risk aversion, dampening perceived risk. These mechanisms help explain why uncertainty declines for several equity indices following slope shocks.

Concerning responses to the curvature component, our results indicate that positive shocks to the curvature, i.e., disproportionate increases in medium-term yields relative to short and long maturities, lead to increased uncertainty in bond markets and decreased uncertainty in equity markets. This pattern is consistent with term premia adjustments rather than shifts in short-term rate expectations. In the context of ECB monetary policy, such shocks could signal changes in forward guidance or tapering of asset purchase programs, where the central bank moderates its commitment to maintaining low rates in the medium term or signals a slower pace of asset purchases. This prompts investors to demand greater compensation to keep such bonds, raising their yields and increasing uncertainty. Therefore, this observation is consistent with the theoretical framework of Vayanos and Vila (2021), which posits that financial markets are segmented across maturities and that central bank interventions exert targeted effects on term premia by altering the supply-demand balance at specific horizons. If monetary policy announcements suggest reduced intervention at the medium-term segment, term premia at those horizons increase, resulting in higher yield volatility and thus greater bond return uncertainty. This mechanism is amplified when investors with maturity-specific preferences are less willing to absorb duration risk without central bank support. At the same time, the observed decline in equity uncertainty could reflect portfolio rebalancing effects (Gagnon et al., 2011;

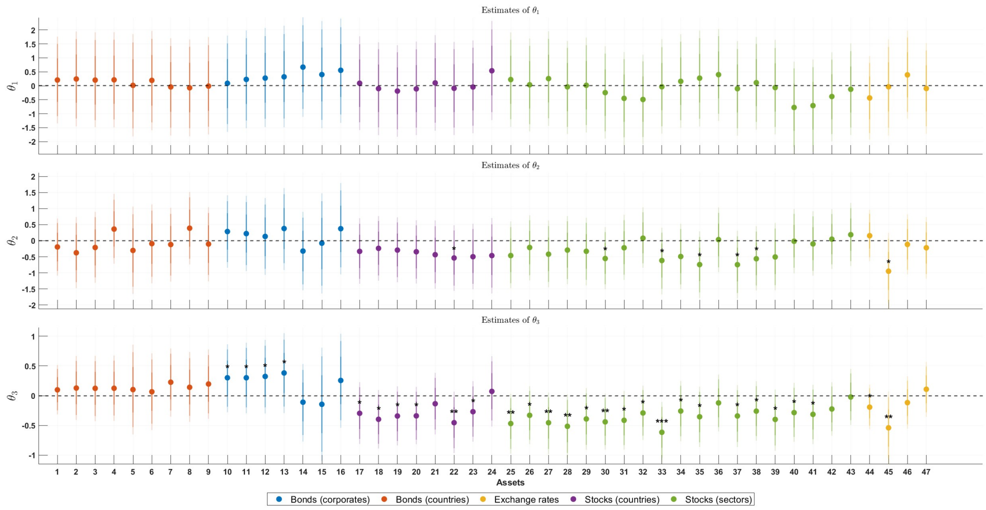

Figure 3.5: Point-wise (posterior medians) estimates of uncertainty responses to each component across all assets.

Vissing-Jorgensen and Krishnamurthy, 2011; Koijen et al., 2021), whereby investors reallocate their portfolios towards riskier assets such as equities.

Effects within asset classes

In addition to differences between asset classes, Figure 3.5 also reveals heterogeneous[17] responses within asset classes. More specifically, at the corporate bond level, differences in uncertainty responses emerge more clearly when comparing indices by credit quality and duration. The ICE BofA Euro AAA Corporate Index (index 13) shows the strongest and most statistically significant response to curvature shocks, followed closely by broader iBoxx indices (indices 10–12). In contrast, lower-rated and shorter-duration bonds, such as the ICE BofA Euro BBB Index and the 1–3 Year BBB Index (indices 14 and 15), exhibit weaker or near-zero responses. These patterns suggest that uncertainty is more sensitive to monetary policy shocks in higher-rated, longer-duration corporate bonds, possibly reflecting their greater exposure to term premium adjustments. Responses to the slope component also appear more pronounced in AAA-rated indices, while the level component elicits uniformly modest effects across credit segments.

For sovereign bonds, uncertainty responds modestly to level shocks, with slightly more pronounced effects in core euro area countries such as Germany (index 1) and Belgium (index 2). Responses to slope shocks show greater dispersion, with Spain (index 3) and Ireland (index 6) exhibiting more pronounced reactions, suggesting some heterogeneity in sensitivity to expected short-term rate revisions. Curvature shocks lead to uniformly weak responses across sovereign indices (indices 1–9), indicating that medium-term term premium adjustments have limited influence on sovereign bond uncertainty

Exchange rates display moderate heterogeneity in their responses to monetary policy shocks, consistent with differential sensitivities to interest rate expectations and risk pre-

[17] See also Figure B.13 in Appendix B for a complementary visualization of the heterogeneity in responses.

mia adjustments (Engel, 2016; Rogers et al., 2018). The EUR/CHF exchange rate (index 45) reacts significantly to slope and curvature shocks, while EUR/USD (index 44) shows a more moderate sensitivity to curvature. In contrast, the EUR/GBP and EUR/JPY currency pairs (indices 46 and 47) exhibit minimal responses across all components, suggesting more muted monetary policy transmission in these exchange rate pairs.

Equity responses exhibit clear within-group heterogeneity, particularly between country and sector indices. Country-level indices (17–24) respond negatively to slope and curvature shocks, suggesting a decline in uncertainty when monetary policy is perceived as signaling improved macroeconomic conditions. In contrast, sector indices (25–43) show more pronounced dispersion, especially in response to curvature shocks. Financials (34, 37), technology (32, 42), and telecom (36, 43) display the largest increases in uncertainty, consistent with their greater sensitivity to interest rate paths and exposure to long-duration cash flows or intermediation margins (especially for banks). These patterns align with the idea that sectors more reliant on forward-looking valuations or net interest spreads may be more affected by shifts in the shape of the yield curve. Defensive sectors, such as healthcare (35, 39) and consumer goods (40), exhibit more moderate responses, though not uniformly muted. Level shocks generate relatively uniform and modest responses across both country and sector indices.

3.4.3 The role of monetary policy regimes: a pre- and ZLB comparative analysis

The GFC and the subsequent emergence of the ZLB marked a major regime shift in the conduct of monetary policy. With short-term interest rates constrained near the effective lower bound, central banks in advanced economies, including the European Central Bank (ECB) and the Federal Reserve (Fed), moved from conventional tools to various non-standard measures, relying more extensively on the financial sector in monetary pass-through (Bernanke, 2020). This novel economic environment and policy framework fundamentally altered the behavior of interest rates (Wright, 2012; Swanson and Williams, 2014; Bauer and Rudebusch, 2016), the pricing of risk (Gourio and Ngo, 2020), and the mechanisms through which monetary policy shocks propagate through financial markets and the broader economy.[18]

To account for these structural changes, we conduct a simple comparative analysis by estimating the same model as in the previous section on two distinct samples: a pre-ZLB period (1999–2012) and a ZLB period (2012–2020). This allows us to examine whether the relationship between shock components and financial uncertainty has evolved between the two regimes, shedding light on potential shifts in monetary policy transmission and its impact on financial markets.

[18] See notably Bhattarai and Neely (2022) for a survey of the literature about the effects and operating mechanisms of UMPs.

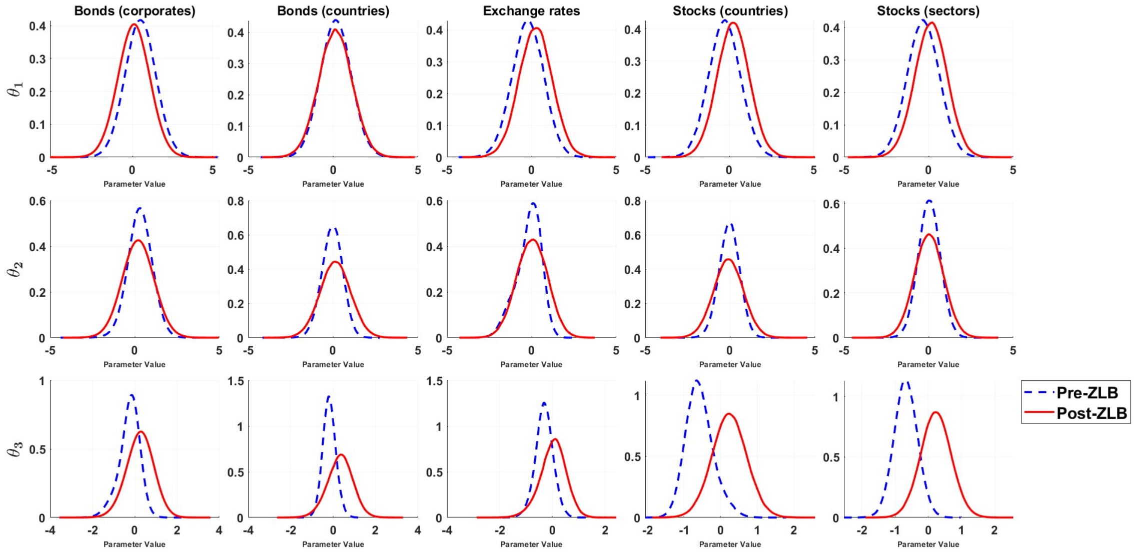

Figure 3.6: Spectrum of uncertainty responses to each component (Pre- vs ZLB, asset group level).

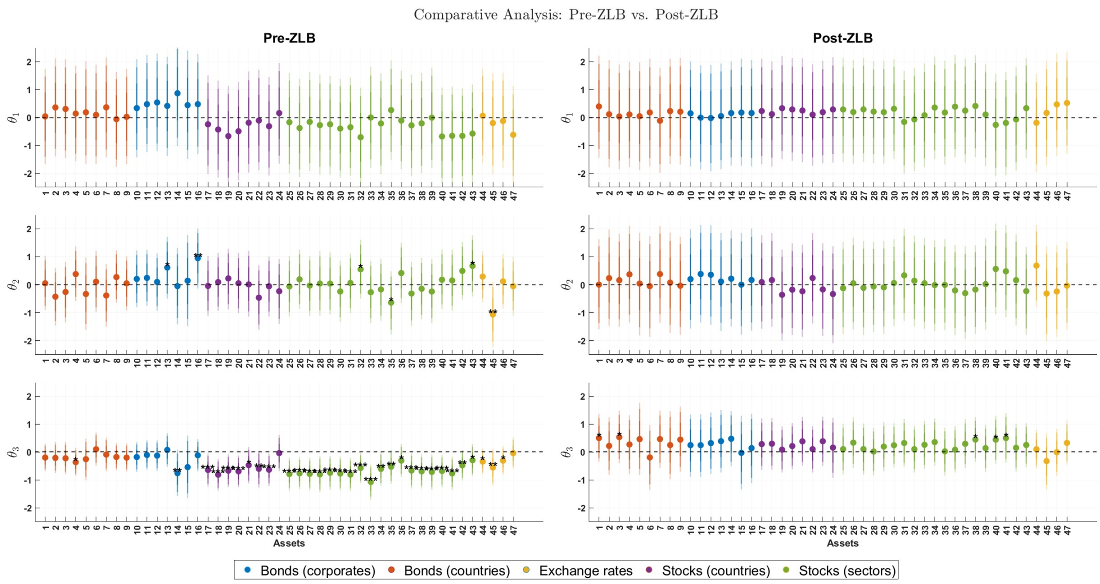

Figure 3.7: Comparison of uncertainty impact responses estimates (θ) between (left) pre- and (right) ZLB.

Figures 3.6 and 3.7 contrast uncertainty responses to shocks across pre- and ZLB periods, both at the aggregate group level and at the more granular asset level. Multiple patterns emerge from this analysis. At the group level, responses to level shocks (θ_1) exhibit relatively modest changes between the two regimes. Corporate bond responses appear to decline slightly for ZLB, sovereign bond responses remain broadly stable, while uncertainty responses for equities and exchange rates increase moderately. For slope shocks (θ_2), responses are broadly similar across periods and asset classes, although cross-asset heterogeneity observed in Section 3.4.2 appears somewhat reduced during ZLB. Slope shocks tend to generate more uniform responses in the ZLB period. The most notable difference concerns curvature shocks (θ_3). Indeed, uncertainty responses to these shocks become notably more pronounced in the ZLB period. This increase is visible across all asset classes, but is particularly evident in equities, where curvature shocks emerge as a dominant source of uncertainty. These patterns are confirmed and further refined when examining asset-level responses in Figure 3.7. Pre-ZLB, uncertainty responses to curvature shocks displayed a more pronounced dispersion across assets, most notably between bonds and equities, reflecting strong within-group and cross-asset heterogeneity. In contrast, ZLB estimates reveal more uniform increases in uncertainty across individual assets, suggesting financial uncertainty across markets respond more synchronously to these type of shocks. The bond-equity dichotomy previously observed in earlier (3.4.2) is no longer evident, and responses appear more synchronized across and within asset classes.

Interpreting these patterns requires considering the broader shifts in monetary policy frameworks and financial market conditions associated with the ZLB and unconventional policy period. The reduced heterogeneity in responses to level and slope shocks during ZLB may reflect, at least in part, the stronger anchoring of interest rate expectations in this environment. With short-term rates constrained by the effective lower bound and central banks relying increasingly on forward guidance, the scope for surprises in expected short-term policy rates may have diminished. This could result in more homogeneous uncertainty responses across assets, as markets place less weight on divergent interpretations of short rate trajectories. In contrast, the greater prominence and uniformity of responses to curvature shocks across asset classes after the introduction of the ZLB indicates the rising importance of medium-term risk pricing and term premia dynamics in monetary transmission. In an environment characterized by large-scale asset purchases and expectations of low interest rates, investors may have become more sensitive to shifts in the perceived risk compensation embedded in medium-term yields. As a result, curvature shocks appear to have become a more systematic driver of financial uncertainty across markets.

Overall, these patterns suggest that monetary policy transmission to financial uncertainty became increasingly shaped by medium-term yield and risk premia channels during the ZLB period and unconventional times. However, given the reduced-form nature of our empirical framework, these interpretations should be viewed as suggestive and consistent with, rather than definitive evidence of, underlying structural mechanisms.

3.4.4 Monetary policy shocks and uncertainty dynamics

This section extends and complements our analysis carried out so far by (i) understanding the dynamic effects of monetary policy shocks components on uncertainty (h_t), (ii) assessing the historical contribution of shocks to fluctuations in financial uncertainty, and (iii) performing counterfactual exercises on certain key historical monetary policy announcements. We analyze and discuss this in the following sections.

Dynamic responses to shocks

We rely on (3.8) and (3.9) to quantify uncertainty responses to each shock component and compute it for the different asset categories encompassing our dataset. Beyond the heterogeneity in responses at impact, i.e., when $h = 0$, Figure (3.8) also reveals substantial differences, across and within groups, on the enduring impact of each distinct type of shock.[19]

Each response corresponds to a one-percentage-point change in the level, slope, or curvature factor driven by the monetary policy shock. Given (3.10), each shock component loads differently on the yield curve. A shock to the level shifts all yields uniformly across all maturities, causing a one-percentage-point increase in yields at both short and long horizons. A unit shock to the slope steepens the yield curve, leading to a larger rise in short-term rates (e.g., around 0.7 percentage points at 1 year) than in long-term yields (e.g., 0.27 percentage points at 5 years). A shock to the curvature component leads to a more localized movement, with intermediate maturities (e.g., 2 years) shifting by about 0.3 percentage points relative to short- and long-term rates.

We notice some differences regarding the speed at which uncertainty (h_t) dissipates. Corporate bond uncertainty declines more quickly, suggesting a faster resolution of uncertainty in credit markets. However, responses of sovereign bonds remain elevated for a longer period, indicating a slower resolution of monetary policy effects. Exchange rate uncertainty exhibits the slowest decay, reflecting prolonged adjustments in currency markets. Concerning equities, uncertainty returns faster to its steady state compared to bonds and exchange rates, with sectoral stocks showing more heterogeneous persistence across industries. From our model, the overall duration of uncertainty effects is determined by the persistence parameter ϕ, which dictates how long uncertainty remains elevated after a shock in level, slope, or curvature dimension. It should be noted that the above patterns are shaped by the structure of our model. Exploiting models with richer persistency dynamics, or other channels, could offer further insights into the transmission of monetary policy shocks to financial uncertainty.[20]

Historical contribution of shocks to financial uncertainty fluctuations

To what extent has monetary policy contributed to historical fluctuations in financial uncertainty? To explore this more closely, we decompose, for each monetary policy announcement, uncertainty deviations attributed to monetary policy shocks and random noise (ν_t). This approach reveals how policy-driven uncertainty has evolved across asset classes, highlighting periods dominated by specific shock dimensions. Figure (3.9)

[19] The responses, expressed in terms of deviations of h_t, show the dynamic evolution of uncertainty to a unit change of shock components $\Delta\beta^{HF}_{1:3,t}$. As h_t expresses log variations, they represent uncertainty deviations in percentage from a state, with responses that can be linked to the actual level of uncertainty: a response of magnitude Δh_t translates into a multiplicative effect of $e^{\Delta h_t}$ on the uncertainty level of the underlying financial asset. This allows us to quantify not only the direction and magnitude of uncertainty shifts but also their persistence over time.

[20] See notably Alessandri and Mumtaz (2019) regarding this point.

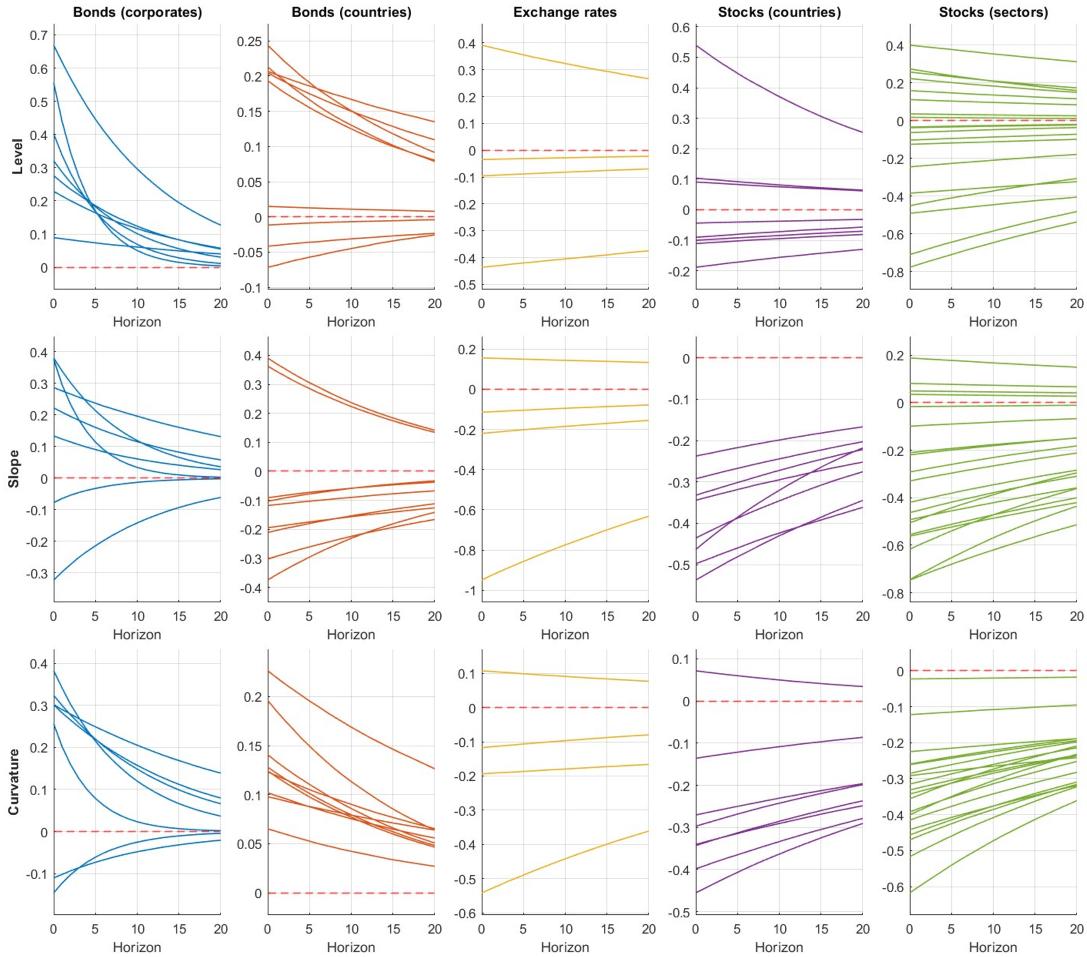

Figure 3.8: Uncertainty responses to monetary policy shocks components over time.

visualizes these contributions for five assets representative of their group, respectively, the **BD Benchmark 10-Year DS Govt. Index** (Germany, index 1), the **ICE BofA BBB Euro Corporate Index** (index 14), the **FTSE100 Price Index** (UK, index 17), the **EUROSTOXX Technology Price Index** (index 42), and the **EUR/USD** exchange rate (index 44), offering a historical perspective on the impact of monetary policy shocks on financial uncertainty fluctuations beyond usual time series dynamic, denoted h_t^*. Formally, we define this quantity by

$$h_t^* = h_t - (\mu - \phi(h_{t-1} - \mu)) = \theta \mathbf{x}_t^* + \nu_t,$$

and report the relative contributions of level, slope, curvature, and stochastic noise to deviations from the long-run uncertainty trajectory.

Figure (3.10) and Table (B.2) provide further insights regarding this, summarizing respectively: (i) the average historical contribution of shocks to uncertainty fluctuations (h_t^*) across all assets considered in our analysis, and (ii) a measure of their dispersion across assets and groups for each respective component, i.e., level, slope, curvature, and noise.

The observed results suggest that shock contributions, taken together, account for a non-negligible and greater proportion of h_t^* deviations than noise contributions (52.74%

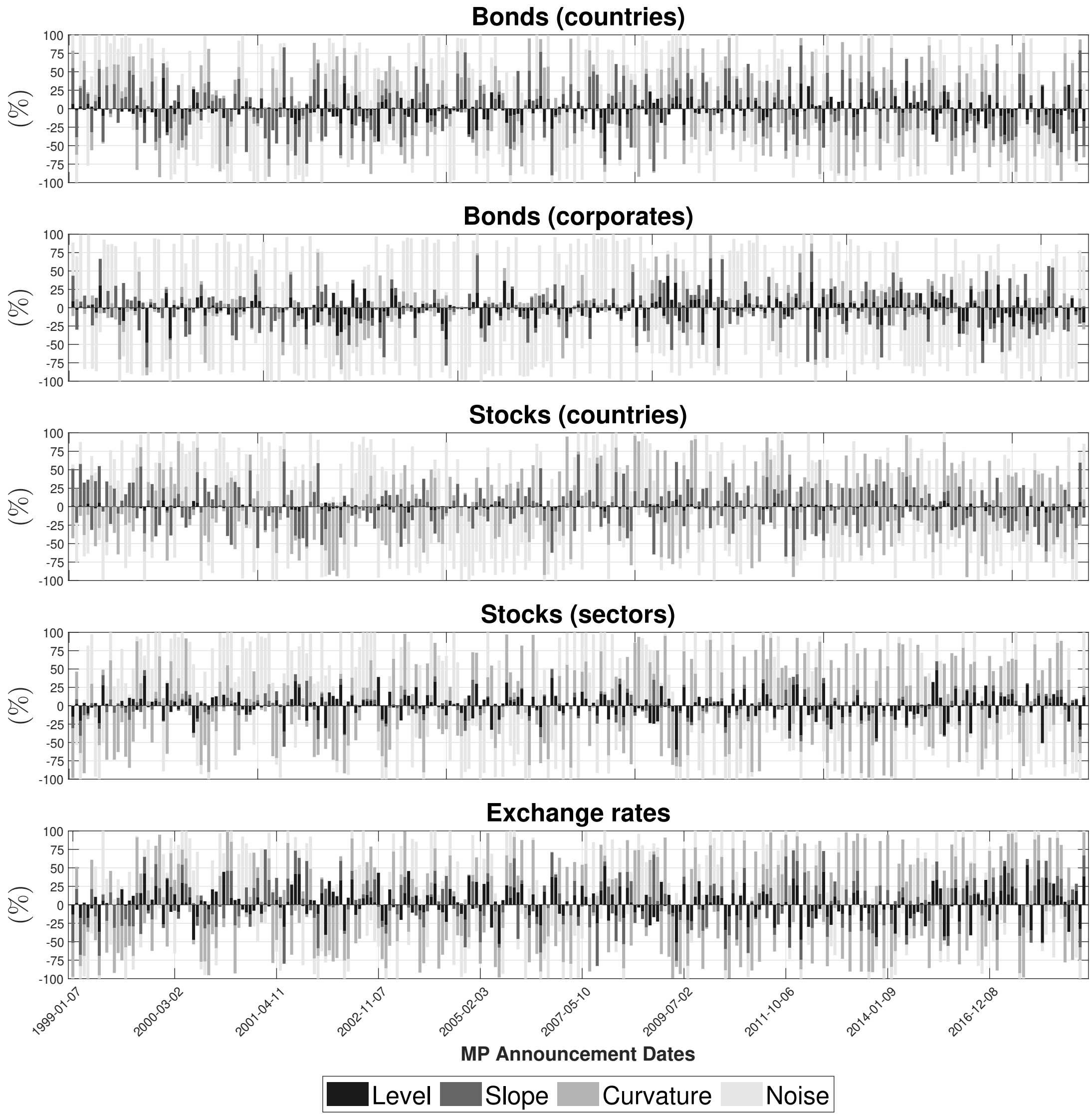

Figure 3.9: Historical relative contributions (in %) of shock components and noise to uncertainty fluctuations. Each panel corresponds to a representative asset from each asset class group: (i) Bonds (countries): BD Benchmark 10-Year DS Govt. Index (Germany, index 1); (ii) Bonds (corporates): ICE BofA BBB Euro Corporate Index (index 14); (iii) Stocks (countries): FTSE100 Price Index (UK, index 17); (iv) Stocks (sectors): EUROSTOXX Technology Price Index (index 42); and (v) Exchange rates: EUR/USD exchange rate (index 44). See Table 3.2 for more details about these time series.

vs 47.26% on average). Among the three components, curvature has the highest mean contribution across all groups (28.77%), followed by slope (18.37%) and level (5.60%), underscoring its dominant role in explaining yield curve adjustments and affecting financial uncertainty. Moreover, the level component displays lower dispersion, involving more uniform effects across assets, while slope and curvature show greater variability, suggesting a higher heterogeneity regarding their contributions. In particular, the mean contribution of the slope factor ranges from 10.96% for corporate bonds to 23.48% for country-level stocks. The curvature component also differs, with contributions between 19.77% for sovereign bonds and 34.82% for sector-level stocks.

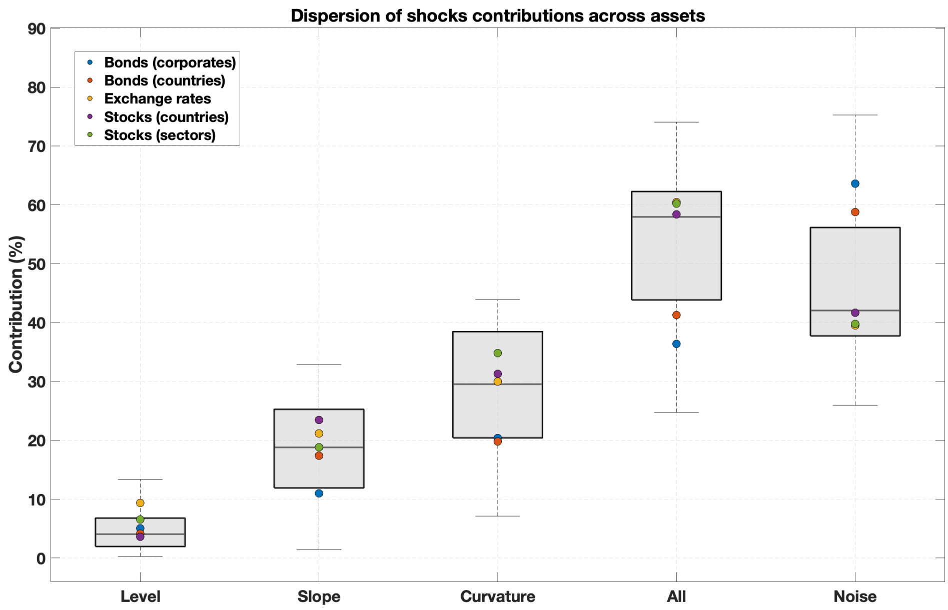

Figure 3.10: Boxplots of shocks contributions and noise across assets.

Counterfactuals and monetary policy episodes

The high-frequency surprises of Altavilla et al. (2019) encompass a range of key policy announcements and significant episodes in the ECB's monetary policy history[21]. This enables us to quantify further the monetary policy's role in shaping financial uncertainty during some specific historical episodes. To achieve this, we assess the contribution of shocks to financial uncertainty for particular key historical dates. More specifically, given the baseline model estimates (see Section 3.4.2), we conduct a series of counterfactual exercises and estimate how financial uncertainty would have evolved in the absence of these shocks. We focus on four particular monetary policy announcements: two unconventional announcements, the Securities Markets Programme (SMP) on 4/08/2011, and the announcement of the (expanded) Asset Purchase Programme (APP) 22/01/2015; and two during conventional periods (5/06/2003 and 2/07/2009) as detailed in Table B.3. Figures (3.11) and (3.12) plot respectively the counterfactual uncertainty level trajectories (dashed dotted for the full effect, expressed in terms of h_t and σ_t) alongside their actual realized paths (thick solid) for the same five representative assets as before (see Subsection 3.4.4). Analyzing these counterfactual trajectories reveals distinct effects of monetary policy shocks on uncertainty. These differences highlight how the specific components (level, slope, and curvature) have shaped diverse uncertainty responses across financial markets and policy announcements.

[21] Table B.3 in Appendix B provides a detailed description of the key policy announcements and episodes, including decisions made during the "conventional" period (before the zero lower bound, ZLB) and the "non-conventional" period, characterized by the adoption of non-standard policy measures.

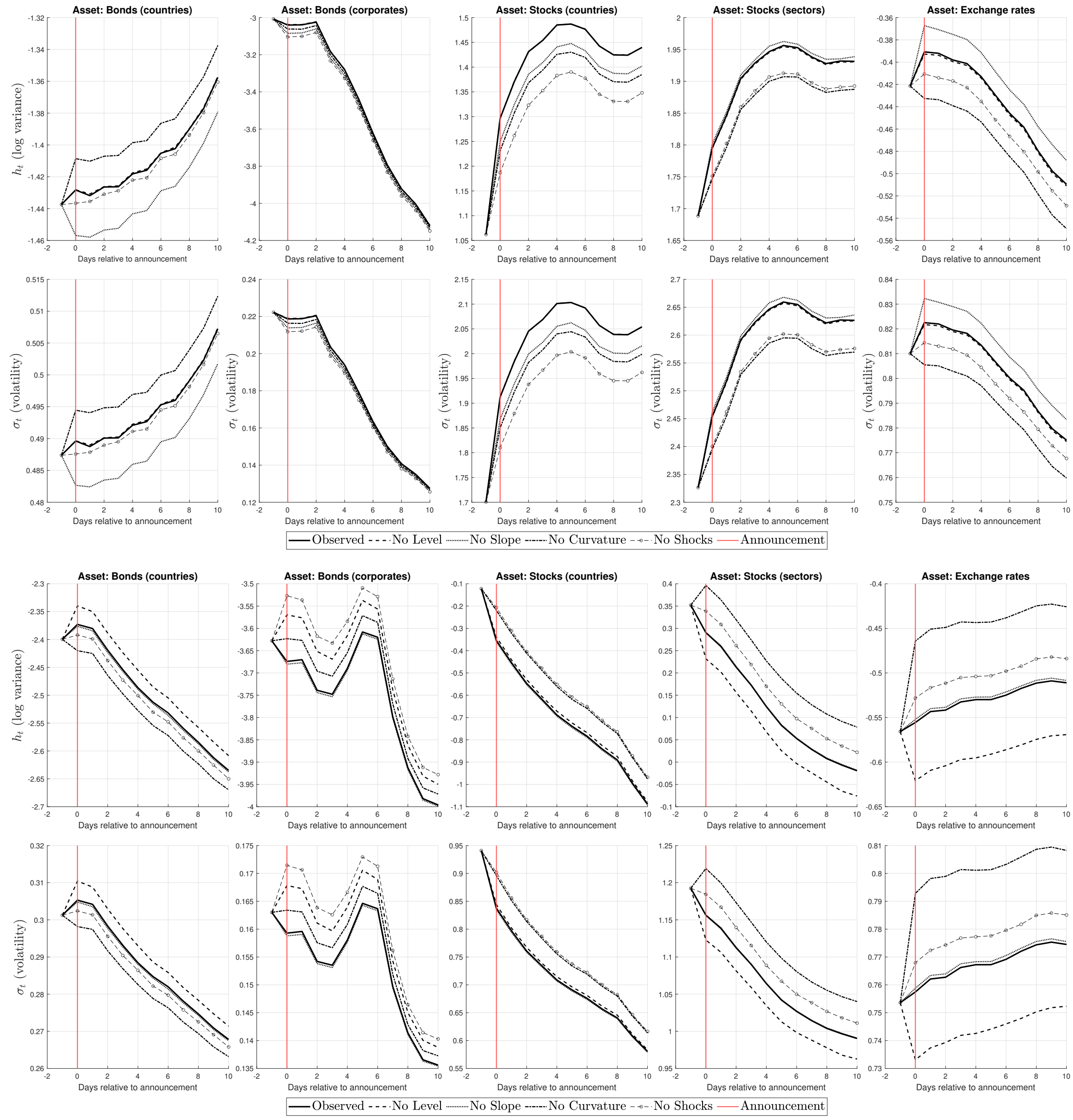

Figure 3.11: Counterfactual uncertainty trajectories for two unconventional policy announcements: SMP (4/08/2011, top) and APP (22/01/2015, bottom). See Table B.3 for more information about these announcements. The counterfactuals are computed on the same five representative assets as those in Figure 3.9.

For the SMP announcement (Figure 3.11, upper panel), monetary policy shocks collectively led to significant increases in uncertainty, notably by approximately +4.94% for country-level stocks, +2.4% for sector-level stocks, and +4.76% for sovereign bonds[22]. These effects were primarily driven by slope and curvature components, reflecting substantial shifts in risk premia and interest rate expectations. Conversely, the QE announcement (Figure 3.11, lower panel) substantially reduced uncertainty, with notable decreases of around -7.77% in country-level stocks and -6.98% in corporate bonds. The curvature dimension of the shock particularly contributed to this stabilization, reflecting QE's effectiveness in stabilizing financial markets and calming investor concerns about future risks.

[22]The magnitude of these effects are obtained from the vertical distances between thick solid and dashed-dotted lines at day zero, for the graphs expressed in terms of σ_t.

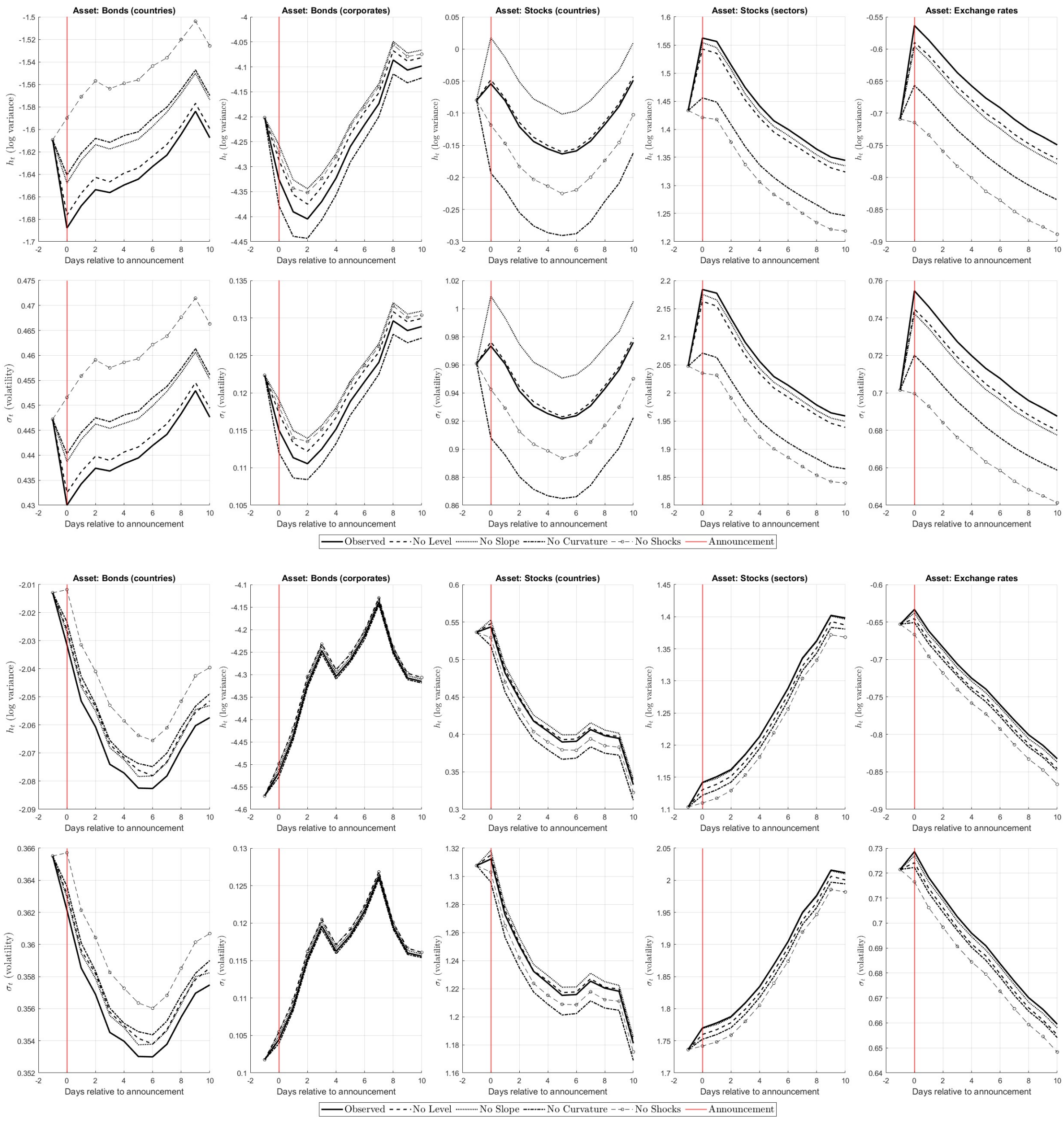

Figure 3.12: Counterfactual uncertainty trajectories for two conventional policy announcements (5/06/2003, top) 2/07/2009, bottom). See Table B.3 for more information about these announcements. Counterfactuals are computed on the same five representative assets as those in Figure 3.9.

For the conventional policy announcement on 05/06/2003 (3.12, upper panel), the observed impacts on uncertainty varied significantly across asset classes. Sovereign bonds experienced a notable reduction of approximately -4.87%. However, other asset classes showed moderate increases: country-level stocks (+2.64%), sector-level stocks (+6.86%), and exchange rates (+7.85%). The announcement on 02/07/2009 (lower panel) exhibited smaller uncertainty changes, with minimal effects on sovereign bonds (-0.82%), moderate increases in sector-level stocks (+1.72%), and exchange rates (+1.1%). Thus, the largest uncertainty impact among all episodes analyzed occurred during the QE announcement, particularly in country-level stocks, where uncertainty decreased by approximately -7.77% relative to the no-shocks baseline.

Overall, the findings observed in this section, as well as those in Subsection 3.4.4, offer a complementary and historical perspective regarding the role of monetary policy shocks in affecting financial uncertainty. By focusing on these specific policy announcements, our analysis illustrates that monetary policy has influenced financial markets through varying combinations of yield curve components across time. While curvature-related shocks tend to dominate on average, the contributions of level and slope components exhibit meaningful variations across episodes and asset classes. These results, consistent with the heterogeneous sensitivities documented previously, highlight that monetary policy shocks have historically materialized through different dimensions of the yield curve, with differentiated implications for financial uncertainty across market segments.

3.5 Conclusion

This paper brings a different perspective on the effects of monetary policy on financial markets. We empirically investigate how monetary policy shocks influence financial uncertainty in various asset classes in the euro area. We highlight distinct responses to shocks manifesting on various yield curve dimensions, specifically through level, slope, and curvature components.

To do so, we measure financial uncertainty, conceived explicitly as the expected stochastic time-varying dispersion of asset returns arising from yield curve shifts driven by monetary policy shocks. The various marginal effects of these shifts are estimated through a standard reduced-form stochastic volatility model augmented with empirical measures of monetary policy shocks extracted from high-frequency yield curve variations around policy announcements provided by Altavilla et al. (2019).

We highlight the relevance of considering second-order effects in the transmission of monetary policy on financial markets. The decomposition into level, slope, and curvature components provides a tractable way to empirically characterize how different dimensions of monetary policy shape the yield curve and are associated with changes in financial uncertainty. This framework highlights the importance of recognizing the multidimensional nature of monetary policy surprises and their differentiated influence across asset classes.

Observed empirical results reveal heterogeneous uncertainty responses across shock dimensions and asset classes. Sovereign bonds tend to show moderate increases in uncertainty following level shocks, which may reflect adjustments in long-term expectations about future policy rates. In contrast, corporate bonds display more pronounced increases in uncertainty in response to slope shocks, potentially indicating heightened sensitivity to short-term refinancing risks and liquidity conditions. Equity markets, broadly, exhibit reductions in uncertainty following monetary policy shocks, particularly those associated with the curvature component. Nevertheless, these patterns appear to differ across monetary policy regimes, with curvature shocks gaining prominence during the ZLB period. While these findings suggest possible interpretations related to changes in risk premia or expectations, we remain cautious about making strong structural claims and acknowledge that the observed heterogeneity may stem from a range of underlying mechanisms that merit further investigation.

Future research could rely on prior works, notably those of Rogers et al. (2014); Hanson and Stein (2015); Rogers et al. (2018); Swanson (2021), and extend this analysis by considering a framework capable of jointly identifying changes in expectations and risk premia behind the yield curve's factor surprises. Integrating these elements more explicitly, as well as the role of the ZLB, into fully-fledged macro-finance dynamic term structure models (DTSMs) as Rudebusch and Wu (2008); Christensen and Rudebusch (2012); Joslin et al. (2014); Swanson and Williams (2014); Wu and Xia (2016) would further clarify the expectations vs risk-based components of monetary policy transmission on financial uncertainty. Finally, taking into account any potential information effects (Bauer and Swanson, 2023a,b) in high-frequency surprises is a natural extension of our empirical analysis that merits further investigation.

Chapter 4

Robust Monetary Policy Design Under Uncertain Business Cycles

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Abstract. In recent years, monetary policy analysis has increasingly relied on a new generation of structural models that extend the standard New Keynesian framework. These advances account for explicit macro-financial linkages, banking sector frictions, and balance-sheet constraints. These refinements have expanded policymakers' analytical toolkit but also increased model uncertainty, as policy transmission now varies widely across different financial structures. This paper investigates how such advances affect robustness properties of simple interest-rate rules for monetary policy design. Focusing on the Euro Area, our comparative analysis makes use of ten macroeconomic models spanning from older to newer generations. We compare the performance of traditional and optimized simple interest-rate rules under a unified evaluation framework. We show that financial frictions steepen inflation–output trade-offs and diminish the efficiency of legacy rules such as Taylor (1993), while high-inertia, moderate-inflation-response rules with an explicit level measure of slack remain consistently robust. A model averaging exercise confirms that such designs balance performance across heterogeneous models, providing central banks with transparent and resilient rule-based strategies in the face of evolving macroeconomic paradigms.

Keywords: robust monetary policy design, model uncertainty, policy rules.

4.1 Introduction

Effective monetary policy must navigate through complex and evolving economic conditions, often under elevated uncertainty about the structure of the economy and the nature of shocks that affect the business cycles. However, how should central banks design their policies in this context? Do they have to commit to simple rules or value discretion? Monetary policy design has constituted a fundamental area of research in macroeconomics for decades, and one of the most important concerns of central banks. Previous extensive research (Taylor, 1993a, 1999; Blinder, 1999; Clarida et al., 1999; Svensson, 2003; Mishkin, 2007, 2018) has contributed to this question, debating and contrasting the merits of discretionary frameworks, which allow for flexibility and real-time judgment to current economic conditions, versus simple rule-based frameworks, which enhance commitment, credibility, and transparency.

The growing complexity of modern economies and the plethora of new models used by central banks have elevated the importance of policy strategies that are robust across alternative structural representations of the economy (Orphanides and Wieland, 2013). In environments where policymakers face multiple layers of uncertainty, including model misspecification, measurement errors, imperfect knowledge of natural rates, and various types of expectations, the limitations of purely optimal, model-specific strategies become apparent (Taylor and Williams, 2010). Under model uncertainty, the quest for designing a fully optimal policy within a particular model is hampered in favor of identifying robust policy frameworks, i.e., policy strategies that perform reasonably well across a set of different economic environments. In this context, simple interest rate rules have emerged as robust candidates. Despite their simplicity, simple rules are found to be superior in this regard as they deliver good stabilization performance across a range of macroeconomic models featuring different structural properties. Such valuable advantages in terms of robustness, implementation, and communication have led to their adoption as benchmarks in central banks' internal models and policy discussions.

Most of the findings on policy rules and robustness were established in an earlier macroeconomic landscape, primarily based on models of early generations in the 1990s and early 2000s. As documented by Taylor and Williams (2010), the literature consistently identified policy principles that performed well across different structural representations of the economy, namely a strong response to inflation, moderate interest rate inertia, and reduced reliance on unobservable level gaps. These models, despite being used by central banks for policy evaluation or forecasting, often abstract from key features that became substantial after the global financial crisis (GFC). Such features include notably explicit macro-financial linkages, balance sheet constraints, and unconventional policy instruments. In the aftermath of the GFC, the modeling frontier shifted toward a new generation of DSGE frameworks. As documented by Binder et al. (2019) and Wieland et al. (2016), these models differ by incorporating banking sectors, credit spreads, collateral constraints, and other mechanisms that amplify and reshape the transmission of monetary policy. These advances have revealed greater heterogeneity in policy transmission and a stronger role for financial frictions in propagating shocks, yet the robustness of traditional simple rules has not been systematically re-examined in this richer environment.

In this paper, we revisit the question of the robustness of monetary policy rules in light of these modeling advances. Building on earlier systematic comparison exercises of Orphanides and Wieland (2013), we conduct a large-scale evaluation of monetary policy rules across a rich set of models for the Euro Area. Our focus is not just on overall performance, but on the robustness properties of different rules, both simple and optimized across models, with a particular emphasis on the third generation of models with financial frictions defined by Binder et al. (2019). We extend the work of Orphanides and Wieland (2013) by incorporating a new set of models for the Euro Area, many of which reflect post-crisis realities such as balance sheet effects and financial accelerator mechanisms. Using the systematic comparison approach of Wieland et al. (2016), we compare model outcomes on a common basis and assess the relative performance of different policy rules in terms of loss functions, volatility trade-offs, and model-by-model outcomes. To identify a robust-optimal simple rule that balances performance across the heterogeneous model set, we also perform model averaging (MA) based on the losses obtained for each model. Our work extends the systematic comparison of Orphanides and Wieland (2013), who did not explicitly incorporate post-crisis models with financial frictions in their analysis. At the same time, while Binder et al. (2019) emphasizes the relevance of this new generation of models for macroeconomic dynamics such as impulse responses and forecasting performance, they do not provide a systematic normative assessment of simple monetary policy rules. Our contribution is precisely to fill this gap by integrating these post-crisis macro-financial models into a harmonized comparison framework, evaluating the robustness of both fixed and optimized rules, and identifying a robust-optimal rule through model averaging. In doing so, we contribute to the ongoing debate on the merits and limitations of rule-based policy in a world where the true model is unknown and evolving. We also provide updated evidence on whether the classic conclusions about simple rules remain valid in the more complex and constraint-prone monetary environment that central banks now face.

The remainder of the paper is structured as follows. Section 4.2 reviews the literature on policy rules and robustness, with particular attention to models with financial frictions. Section 4.3 outlines our methodology, including the models, rules, and evaluation criteria used in the comparison exercise. Section 4.4 presents our results on the performance and robustness of policy rules across models. Section 4.5 concludes with a discussion of the policy implications of our findings and directions for future research.

4.2 Literature Review

The modern literature on monetary policy rules emerged in the early 1990s from the debate on rules versus discretion. Taylor (1993a), Clarida et al. (1999) formalised the case for systematic interest rate rules within the New Keynesian (NK) framework, with the "Taylor principle" as a central guideline. This strand of research demonstrated that relatively simple interest rate feedback rules could approximate the performance of fully optimal policies while being easier to implement and communicate. A key step was the shift from complex, model-specific optimal control to simple, robust rules. At that time, the prevailing policy prescriptions called for strong responses to inflation, moderate interest rate inertia, and cautious use of output gaps produced stable and effective outcomes in a wide variety of models. By the eve of the Global Financial Crisis (GFC), a certain consensus had emerged around these design principles.

Beyond their tractability, simple rules gained prominence because they performed well under model uncertainty. Levin and Williams (2003) showed that certain Taylor-type rules are robust across a range of structural models, including those with differing expectations structures. Orphanides and Williams (2002, 2007, 2008) highlighted the dangers of natural-rate misperceptions: rules with heavy reliance on unobservable level gaps can lead to systematic policy errors. They advocated difference rules, which respond to changes in activity rather than levels, combined with moderate inertia to dampen the effects of mismeasurement. Complementary work by Bullard and Mitra (2002) and Evans and Honkapohja (2003a,b) added the criterion of learnability, showing that rules satisfying the Taylor principle with moderate smoothing are more likely to yield determinate and stable equilibria when agents form expectations adaptively. As a result, robustness, defined as satisfactory performance across models and expectation formations, became an explicit objective in monetary policy design.

The GFC altered the research agenda. With policy rates constrained by the lower bound, attention shifted toward the make-up of different (unconventional) policy instruments (Bernanke, 2020) and new strategies such as price-level targeting, average-inflation targeting, and lower-for-longer forward guidance (Bernanke et al., 2019). In parallel, the modeling frontier moved toward "third-generation" DSGE models incorporating macro-financial linkages, such as bank capital regulation, credit spreads, and collateral constraints. Examples of comparison exercises made by Wieland et al. (2016) and Binder et al. (2019) document these advances and the construction of the Macro Model Database (MMB) to facilitate systematic model comparisons. A key insight that emerges from this new vintage is that monetary policy transmission mechanisms are more heterogeneous than in earlier generations, and that financial frictions can amplify and reshape the effects of shocks on business cycles. Despite these developments, the question of whether pre-GFC prescriptions for simple, robust rules still hold in this richer environment has received little direct attention.

Earlier research delivered consistent guidance: respond strongly to inflation, include moderate interest rate inertia, and reduce reliance on unobservable level gaps, potentially by using difference-type rules. Nevertheless, these prescriptions have not been systematically and sufficiently challenged in macro-financial models. This paper addresses that gap. Using a large set of euro-area macroeconomic models from the MMB, including third-generation models with explicit financial frictions, we conduct a like-for-like comparison of leading simple rules under the systematic comparison framework of Wieland et al. (2012). Based on loss metrics, we evaluate both model-specific performance and cross-model robustness. We also employ model averaging (MA) to identify a robust simple rule that performs well across heterogeneous structures, policy preferences, and expectation formations. In doing so, we revive the policy rules research agenda in a new macroeconomic landscape and provide updated guidance for robust policy rule design under contemporary policy constraints.

4.3 Methodology

The evaluation policy rules robustness is a well-established area of policy analysis in which model comparison exercises have played a central role (see e.g., Kuester and Wieland, 2010; Taylor and Wieland, 2012; Orphanides and Wieland, 2013, among others). A key requirement for meaningful cross-model evaluation is that the performance criteria, often measured via welfare loss measures, are defined consistently across models. Without such harmonization, differences in outcomes may reflect structural specificities of the models rather than the intrinsic properties of the policy rule under evaluation. To conduct our comparison of rules across models, we rely on Wieland et al. (2012) and their systematic comparison framework to evaluate policy outcomes soundly. In practice, we leverage the *Macroeconomic Model Database (MMB)*, a ready-to-use model comparison platform suited for large-scale and low-cost comprehensive comparison exercises.

The following sections present the models and rules that compose the two main dimensions (rules and models) of our comparison exercise. The models encompass different generations of NK frameworks, including pre-crisis benchmark models as well as models of the third generation advocated by Binder et al. (2019), exhibiting an explicit characterization of the financial sector. Regarding the rules, we limit ourselves to a simple generic class of rules and select five particular specifications belonging to this class. These latter differ in terms of inertia, as well as the degree of reaction to past, current, and expected inflation and output gap. An explicit description of these rules follows in Section 4.3.2.

In the context of our comparison exercise, we assess the performance of each rule r in a given model m by focusing on a common quadratic loss function and a different set of central bank preference configuration $\lambda = (\lambda_\pi = 1, \lambda_y)$:

$$\mathcal{L}_{r,m}^{(\lambda)} = Var(\pi_{r,m}) + \lambda_y Var(y_{r,m}), \tag{4.1}$$

where $\mathrm{Var}(\pi_{r,m})$ and $\mathrm{Var}(y_{r,m})$ are the unconditional variances of inflation and the output gap generated by rule r in model m. We consider a grid of preference parameters λ_y given by:

$$\lambda_y \in \{0, 0.25, 0.5, 0.75, 1, 2, 4, 8\},$$

which allows us to assess the sensitivity of rule performance to varying central bank preferences for output gap stabilization over inflation. Note that this specification is notably consistent with the one used in Levin et al. (2003). This one does not include an explicit penalty on interest-rate volatility. We follow the rest of our analysis in evaluating rules in terms of inflation and output-gap stabilisation only. Nevertheless, interest-rate volatility is a relevant policy concern in practice, and we therefore comment in the results on how our robust rules perform along this dimension.

4.3.1 Set of models and classification

We make use of the MMB and the large set of models available to conduct our analysis. The selection of models encompasses 10 different models representing economies of the Euro Area. The models selected are consistent with those examined in earlier studies on policy rule robustness and in model comparison exercises, such as in Kuester and Wieland (2010); Orphanides and Wieland (2013); Wieland et al. (2016) or Binder et al. (2019). More specifically, the model classification is similar to Orphanides and Wieland (2013) and Binder et al. (2019), where we categorize models into three chronologically successive "generations" that mirror the methodological advances in modern macroeconomics and the different historical developments. Table 4.1 provides a detailed description of the specific features of each model in our set.[1]

The first generation encapsulates predominantly small-to medium-scale, largely calibrated models that rely on backward-looking dynamics or only partly forward-looking elements. In this class, on the basis of estimated parameters of Peersman and Smets (1999) for the Euro Area, the Rudebusch and Svensson (1999) model *(US_RS99)* features a compact structure with lagged expectations and a simple Taylor-type rule, without full microfoundations. The *G7_TAY93* framework (Taylor, 1993b) extends those ideas to a calibrated multi-country setting with staggered wage contracts, partial price adjustment, and disaggregated consumption and investment. Finally, the Coenen and Wieland (2003) model (*G3_CW03*) applies a three-region open-economy New Keynesian prototype, with Calvo (1983) staggered pricing and rational expectations, to pre-crisis policy simulations. While *G3_CW03* retains the small-scale, policy-focused orientation of first-generation models, its adoption of Calvo stickiness and fully rational expectations anticipates the micro-founded, fully forward-looking structures that came to define the second generation.

The second generation introduces fully forward-looking, optimizing behavior and richer nominal rigidities, typically estimated via Bayesian techniques on pre-2008 data. Smets and Wouters (2003) (*EA_SW03*) and the Riksbank's *EA_SR07* model (Adolfson et al., 2007) anchor this class, embedding Calvo-style wage and price stickiness alongside habit persistence and investment adjustment costs. The European Commission's QUEST III of Ratto et al. (2009) model (*EA_QUEST3*) further incorporates rule-of-thumb households and a fiscal sector, while the ECB's New Area-Wide Model (*EAUS_NAWM08*), developed by Coenen et al. (2008), links the Euro Area and the United States a stylized (non-microfounded) financial intermediation wedge and differentiated wage-setting across labor types.

Finally, the post-crisis "third generation" (see Binder et al., 2019) augments the New Keynesian framework with an explicit and heterogeneous characterization of the financial sector. Although all these models introduce credit spreads and balance-sheet channels, they do so through different types of frictions. Gerali et al. (2010) (*EA_GNSS10*) and Darracq Paries et al. (2011) (*EA_DKR11*) embed imperfectly competitive banks that face regulatory-type capital constraints and lend against collateral. In these models, loan and deposit rates are set with markups over the policy rate, bank capital adjusts only gradually, and collateral constraints limit the amount of credit that can be extended. As a result, shocks to bank capital, funding conditions or collateral values translate into persistent movements in credit spreads and loan supply. By contrast, the Villa-style variant (*EA_VI16bgg*; Villa, 2016) retains the real and nominal core of Smets and Wouters (2007) but introduces the Bernanke et al. (1999) (BGG) financial accelerator: firms finance investment

[1] The presentation of the specific features and microfoundations of each model is not exhaustive. For further details, the reader may consult Orphanides and Wieland (2013), Binder et al. (2019), as well as the descriptive vignettes of the models provided in the MMB (https://www.macromodelbase.com/download).

Table 4.1: Overview of models by generation and structural features.

Model	Generation	Region	Scale	Expectations	Category	Key Features
US_RS99	First Gen / Traditional Keynesian	US	Small	Backward-looking	Semi-structural	Backward-looking IS–PC–Taylor structure with persistent dynamics; no microfoundations.
G7_TAY93	First Gen / NK1	G7	Large	Rational (partial)	Baseline NK w/ RE	Calibrated multi-country NK with staggered wages, Calvo prices, richly disaggregated demand.
G3_CW03	First Gen / NK1	US, EA, Japan	Medium		Open economy	Three-region DSGE under rational expectations, Calvo pricing, and zero-lower-bound policy experiments.
EA_SR07	Second Gen / Pre-Crisis NK-DSGE	Euro Area	Medium		Open economy	Small-scale open-economy DSGE with sticky prices/wages, habit formation, and exchange-rate channels.
EA_SW03	Second Gen / Pre-Crisis NK-DSGE	Euro Area	Medium	Rational	Baseline NK w/ RE	Smets-Wouters benchmark: habit formation, investment adjustment costs, calibrated shock processes.
EA_QUEST3	Second Gen / Pre-Crisis NK-DSGE	Euro Area	Large		Baseline NK w/ RE	QUEST III: non-Ricardian households, fiscal sector, simple financial accelerator, large-scale structure.
EAUS_NAWM08	Second Gen / Pre-Crisis NK-DSGE	EA + US	Medium		Open economy	Two-region EA–US DSGE with stylized finance block, heterogeneous households, labor frictions.
EA_GNSS10	Third Gen / Post-Crisis Macro-Financial	Euro Area	Medium	Rational	Macro-financial	Gerali et al.: banking sector, capital constraints, loan spreads, collateralized lending channels.
EA_DKR11	Third Gen / Post-Crisis Macro-Financial	Euro Area	Medium	Rational	Macro-financial	BGG financial accelerator, macroprudential regulation, multi-branch banking.
EA_VI16bgg	Third Gen / Post-Crisis Macro-Financial	Euro Area	Medium	Rational	Macro-financial	Villa (2016) BGG variant: endogenous risk premia, external finance premium on firm leverage.

with external borrowing, and a costly-state-verification problem generates an endogenous external finance premium that rises with leverage and default risk. In this setup, financial frictions operate primarily through firms' balance sheets and the pricing of corporate debt rather than through explicit bank capital regulation. Taken together, these models capture three broad classes of microfoundations for incorporating financial frictions.

By spanning purely backward-looking semi-structural setups, medium-scale forward-looking DSGEs, and richly parameterized macro-financial architectures, our model set furnishes a comprehensive laboratory in which to test the resilience of simple monetary rules to fundamentally different propagation mechanisms. These differences affect how strongly and how long shocks propagate through output and inflation and thus how sensitive each model is to a given policy rule. These structural microfoundations ultimately map into different slopes of the New Keynesian Phillips curve and the IS equation: variations in nominal rigidities, habits, adjustment costs, openness, and financial wedges change how strongly inflation responds to the output gap and how sensitive demand is to interest rates and spreads. As a result, each model embodies a distinct stabilization trade-off for a given simple rule, even when the rule is formally identical across specifications.

The following sections formalize the different types of rules implemented in each model and for our stochastic simulations.

4.3.2 Monetary policy rules

This section describes the monetary policy rules evaluated in our comparative analysis. Similar to Taylor and Williams (2010); Orphanides and Wieland (2013) or Binder et al. (2019), all the rules can be interpreted as variants of a generic rule specification that defines the class of linear (simple) interest rate feedback rules. This unified representation facilitates comparison and serves as a basis for identifying both model-specific and robust optimal rules. We distinguish three categories: (i) simple rules with fixed coefficients drawn from the literature, (ii) model-optimal rules, and (iii) robust optimal rules under model uncertainty. In the following, we introduce the generic class of policy rules and specific policy formulations encountered in the literature. We also explain how we construct, from this scheme, optimal rules and apply model averaging (MA) to assess robustness under model uncertainty.

General rule specification

All monetary policy rules considered in the analysis are represented as special cases of a general linear feedback rule, which allows for policy inertia, forward-lookingness, and differentiated responses to inflation and output gap dynamics. Following Orphanides and Wieland (2013), we define a generic rule formulation specified as follows:

$$i_t = \rho i_{t-1} + \alpha\, \pi^{(4)}_{t+h} + \beta\, y_{t+h} + \tilde{\beta}\, (y_{t+h} - y_{t+h-4}), \tag{4.2}$$

where i_t is the nominal interest rate, $\pi^{(4)}_{t+h}$ denotes the four-quarter-ahead inflation rate, defined as $\pi^{(4)}_{t+h} \equiv p_{t+h} - p_{t+h-4}$ with p_t the log price level, and y_t is the output gap (the deviation of output from its flexible-price equilibrium). The term $(y_{t+h} - y_{t+h-4})$ captures the four-quarter change in the output gap. The parameter $\rho \in [0, 1]$ measures the degree of interest rate smoothing, while α, β, and $\tilde{\beta}$ govern the responses to inflation, the level of the output gap, and the change in the output gap, respectively. The horizon $h \geq 0$ indicates whether policy reacts to current conditions ($h = 0$) or to model-consistent forecasts at longer horizons ($h > 0$). This specification encompasses a broad class of forward-looking and inertial rules.[2]

Simple rules from the literature

Relying on ready-to-use rules within the MMB architecture, we consider five simple policy rules that have been widely used in monetary policy research and in earlier robustness comparisons. They differ in their degree of inertia, responsiveness to inflation and output gap variables, and in the timing of the information set. Three of these rules can be expressed as special cases of the general rule in equation (4.2), while the remaining two include dynamic features (e.g., one-period lagged output gap) that require a slight extension

[2] Two of the rules considered, Levin et al. (2003) and Smets and Wouters (2007), include additional terms such as one-period lagged output gap responses that fall outside the scope of equation (4.2). We document these cases in Section 4.3.2.

of the generic formulation.

For clarity, we define a variant of the general rule that introduces an additional lagged output gap term:

$$i_t = \rho i_{t-1} + \alpha \pi_{t+h}^{(4)} + \beta_0 y_{t+h} + \beta_1 y_{t+h-1} + \tilde{\beta}\,(y_{t+h} - y_{t+h-4}). \tag{4.3}$$

This extension nests all five rules considered. However, for the analysis and model averaging, we restrict optimization to the original class defined in equation (4.2).

Table 4.2 presents the coefficients and horizons for each rule. For rules that include lagged terms not covered by the benchmark specification, we mark them with an asterisk and retain their original structure.

Table 4.2: Specification of simple rules relative to general formulation.

Rule	ρ	α	β_0	β_1	$\tilde{\beta}$	h
Taylor (1993)	0.00	1.50	0.50	0.00	0.00	0
Orphanides & Wieland (2008)	0.00	2.34	0.765	0.00	0.00	3
Orphanides & Wieland (2013)	1.00	0.50	0.00	0.00	0.50	0
Levin et al. (2003)*	0.76	0.60	1.18	-0.97	0	0
Smets & Wouters (2007)*	0.81	0.39	0.97	-0.90	0	0

* Includes additional terms (e.g., one-period lagged output gap) that fall outside the definition of equation (4.2).

The Taylor (1993a) rule serves as the canonical benchmark, responding to current inflation and output gap without interest rate smoothing. The Orphanides and Wieland (2008) rule is forward-looking, using three-quarter-ahead forecasts for both inflation and the output gap. The Orphanides and Wieland (2013) rule is specified in first differences, with the change in the policy rate responding equally to the four-quarter change in inflation and output gap, and featuring unit interest rate smoothing. The Levin et al. (2003) and Smets and Wouters (2007) rules incorporate interest rate smoothing and include, beyond contemporaneous responses, reactions to lagged output gap values.

In all our stochastic simulations, each rule is evaluated with its original structure and forecast horizon. This is also the same for the derivation of model-specific optimal rules (see Section 4.3.2), in which we optimize reaction coefficients conditional on a fixed horizon h.

Optimal simple rules

To benchmark the performance of these fixed-coefficient simple rules, we derive model-optimal rules by estimating the parameters of (4.2) that minimize the loss function (4.1) for each model and central bank's stabilization focus. More specifically, we search for the optimal coefficients $(\rho, \alpha, \beta, \tilde{\beta})$ which minimize (4.1). These optimal rules serve as performance benchmarks and allow us to quantify the (loss) gap between simple (fixed-coefficients) rules and model-specific optimized rules.

Robust optimal rules and model averaging

Finally, we construct robust optimal rules using model averaging (MA). Each model m is assigned a weight w_m, and the performance of a rule r is evaluated via its MA loss:

$$L_r^{\mathrm{MA}} = \sum_m w_m \cdot L_{r,m}, \tag{4.4}$$

where $L_{r,m}$ is the loss of rule r in model m. We then identify the configuration of parameters $(\rho, \alpha, \beta, \tilde{\beta})$ in (4.2) that minimizes the weighted average loss across models:

$$\theta^* = (\rho^*, \alpha^*, \beta^*, \tilde{\beta}^*) = \arg \min_{\rho,\alpha,\beta,\tilde{\beta}} \sum_m w_m \cdot L_{r,m}. \tag{4.5}$$

This robust optimal rule reflects the trade-offs inherent in monetary policy design in the context of model uncertainty, and enables us to compare traditional simple rules with an optimal rule explicitly designed to perform well across a range of plausible models. For simplicity, and contrary to Orphanides and Wieland (2013), we set the value of $h = 0$ and did not allow the horizon to vary when performing this model averaging procedure. We also assume, as in Levin and Williams (2003) or Taylor and Wieland (2012), that all models in our set are equiprobable with $w_m = \frac{1}{M} = 0.1$. Alternatively, it is also possible to let these weights vary according to how, a posteriori, a given model m fits the data (Cogley et al., 2011). Although this procedure is used in a context of uncertainty regarding the model, the determination of a robust optimal rule, often named as a"Bayesian rule", can also encompass other levels of uncertainty. For example, Cogley et al. (2011) also considers uncertainty regarding the values of structural parameters governing these models.[3]

4.4 Results

This section reports the results of our comparative analysis and draws policy insights regarding rules. We begin by comparing the performance of simple rules across models (Section 4.4.1) to identify those with the strongest robustness properties. We then put a particular focus on optimal simple rules (cfr. Section 4.3.2) and third-generation models, analyzing how they reshape policy trade-offs and shift optimal rule designs compared to models of earlier generations. Finally, Section 4.4.3 is devoted to a model averaging exercise where we study the design of a simple monetary policy rule robust to model uncertainty. We contrast earlier benchmarks against this standard.

[3]In our case, we fixed for each model the values of parameters to their estimated or calibrated values in models reported by the MMB.

4.4.1 *Performance and robustness of simple rules*

Table 4.3 depicts the losses attached to each rule in our comparison exercises and stochastic simulations. We compare the losses across rules and models for a baseline value of $\lambda_y = 0.5$. Observed results suggest heterogeneity in rule performance across models. The

Table 4.3: Losses by model and rule at baseline preferences ($\lambda_\pi = 1$, $\lambda_y = 0.5$).

Model	taylor93	sw2007	ow2008	ow13	levin2003
EA_SW03	2.61	2.78	2.46	1.31*	1.90
G7_TAY93	0.0015	0.0008	0.0011	0.0006*	0.0009
EA_QUEST3	0.0016	0.0006	0.0007	0.0002*	0.0004
G3_CW03	0.0015	0.25	0.0014*	0.68	0.08
EAUS_NAWM08	0.08*	0.55	0.69	0.40	0.51
US_RS99	14.47	15.04	8.52	**0.3976**	11.9140
EA_SR07	14.27	7.36	10.33	5.17*	7.33
EA_VI16bgg	23.156	12.20	15.13	5.61*	9.05
EA_DKR11	NA	7.53	13.87	2.32*	4.99
EA_GNSS10	NA	13.48	20.98	7.53*	10.89

table reveals just how much the performance of simple monetary policy rules depends on the structure of the economy. No single rule consistently dominates. For example, the Taylor (1993a) rule performs the best in the EAUS_NAWM08 model but performs worst in the EA_VI16bgg model, which features Bernanke et al. (1999) financial accelerator mechanism and frictions. The effectiveness of a rule is therefore highly model-dependent, shaped by the structure and frictions embedded in each framework. However, we notice that Orphanides and Wieland (2013) rule stands out, as it delivers the lowest loss in 7 out of the 10 models, even for models belonging to the last generation. Its performance across diverse environments suggests that it offers a good compromise between simplicity and adaptability. Moreover, it is also worth noting that losses tend to be higher and the variation in performance more pronounced in models with financial frictions. This suggests that these new models pose additional challenges for monetary policy design, in particular, a more pronounced disparity in the relative performance of simple rules. Building on these initial insights on rules performance, we now turn our focus to the evaluation of their robustness. The literature has proposed two different, yet complementary, approaches for evaluating policy robustness. The first approach, rooted in robust control theory (Hansen and Sargent, 2001; Walsh, 2004; Giannoni, 2007), adopts a min-max perspective, identifying the rule that minimizes the worst-case loss across all models. The second approach consists of evaluating average performance (cfr. section 4.4.3) and variability as indicators of robustness. This can be done by assuming that all models have the same weight or not.[4] Levin and Williams (2003) or Taylor and Wieland (2012) are examples who employ this approach. According to both criteria, the rule of Orphanides and Wieland (2013) emerges as the most robust among the five rules considered. The rule not only attains the lowest loss in the

[4] See section 4 in Taylor and Williams (2010) for more discussion on this.

model characterized by the highest overall loss (EA_VI16bgg), thus performing best under the worst-case scenario, but also reports the lowest average loss and the smallest standard deviation across the full set of models. These latter findings suggest that this rule maintains strong performance even with the inclusion of third-generation models (see Table 4.3), indicating that the earlier prescriptions and results of Orphanides and Wieland (2013) in favor of this simple robust rule still hold amid the increased complexity introduced by macro-financial interactions. One might find it potentially surprising that such a rule still performs well in third-generation models. There is, however, a potential interpretation for this result. The rule implies very gradual changes in the policy rate and reacts to changes in inflation and the output gap rather than to their levels. In models where financial conditions and balance sheets matter, abrupt interest-rate movements may create strong swings in the amplification of credit and activity. A very high-inertial rule like Orphanides and Wieland (2013) naturally limits this amplification while still leaning against the cycle.

Table 4.4: Robustness summary of simple rules across models.

Rule	**Max Loss (Worst Case)**	**Mean Loss**	**Std. Dev.**
Taylor93	23.156 (EA_VI16bg)	6.82	8.54
SW2007	15.04 (US_RS99)	5.91	5.71
OW2008	20.98 (EA_GNSS10)	7.20	7.27
OW2013	**7.53** (EA_GNSS10)	**2.34**	**2.60**
Levin2003	11.914 (US_RS99)	4.66	4.56

Notes: This table reports the maximum loss (worst-case across all models), average loss, and standard deviation of loss for each policy rule from Table 4.3. According to the min-max criterion, **OW2013** is the most robust, as it minimizes the worst-case loss across models. It also performs best on average and shows the lowest variability in performance.

4.4.2 *Trade-offs, robustness, and optimal rules in a new macroeconomic landscape*

While the previous section focused on analyzing the outcomes and robustness of simple (fixed-coefficient) rules, this section focuses on analyzing them with respect to their optimized version. In line with recent contributions, such as Binder et al. (2019) and Wieland et al. (2016), we deepen our investigation into third-generation models by examining (i) the structure of policy trade-offs between inflation and output stabilization, (ii) the evolution of optimal rule coefficients across different central bank preferences, and (iii) the loss gaps that quantify the performance distance between simple and optimized rules. This analysis and orientation are mainly motivated by the results and discussions of Wieland et al. (2016) and, more recently, Binder et al. (2019), who put an emphasis on the richer and more heterogeneous transmission mechanisms these models involve, as well as new perspectives for macroeconomic policymaking. This also complements the previous section on rule performance, taking into account several ways of evaluating rule performance and, consequently, their robustness across different dimensions.

Moreover, we contrast these different outcomes with earlier-generation benchmarks to assess whether financial frictions lead to structurally different trade-offs in terms of monetary policy making. Our analysis relies on two complementary outputs: policy frontiers for optimized rules, which map the best achievable volatility combinations, and the sensitivity of rule coefficients, which reveals how policymakers' preferences for output gap stabilization (λ_y) influence optimal responses.

Policy frontiers and performance gaps in financial frictions models

Figure 4.1 portrays the policy frontiers across the five optimized simple rules specific to the EA_VI16bgg model, a representative framework incorporating financial frictions.[5] Each curve traces the minimum achievable combinations of inflation and output gap volatility under optimal rule coefficients as the policymaker's preference parameter λ varies. All five frontiers exhibit the expected convex, downward-sloping shape, confirming the canonical trade-off between inflation and output gap stabilization. That is, enhancing inflation control (moving left along the x-axis) systematically entails higher volatility in the output gap (rising along the y-axis), and vice versa.

Nevertheless, despite this common structure, the steepness and curvature of the frontiers vary significantly across rules, revealing important differences in how each rule mediates this trade-off under financial frictions. Notably, the rules of Orphanides and Wieland (2013) and Levin and Williams (2003) produce very steep frontiers when $\lambda = 0$, i.e., when inflation stabilization is the sole main objective. This indicates that any improvement in inflation outcomes under these rules entails disproportionately large sacrifices in output stability in this type of configuration of policymakers' preferences. As the value of λ increases and more weight is placed on output gap stabilization, the trade-off becomes markedly flatter. This suggests that these rules perform more efficiently when the central bank adopts a more balanced set of objectives. The rule of Smets and Wouters (2007) exhibits the same kind of behavior as that of Taylor (1993a), although it displays a relatively higher trade-off in the case of full inflation-targeting.

The red markers in each subplot denote the performance of simple fixed-coefficient rules discussed in the earlier section under baseline preferences $\lambda_y = 0.5$. Their position, strictly above the efficient frontier in all cases, demonstrates their suboptimality within the EA_VI16bgg model. However, the size of the gap[6] to optimality varies. The Taylor (1993a) rule is furthest from its efficient frontier, with a loss gap of 13, reflecting its poor adaptability to the structural features of financial frictions. In contrast, more parametrized rules such as those of Orphanides and Wieland (2013) or Levin and Williams (2003) lie close to their frontiers, suggesting their original versions remain remarkably efficient even without re-optimization. This last observation suggests that modern rule specifications

[5]The selection of this representative model is motivated by the fact that it is the only model for which the five non-optimized rules offer a computational solution (cfr. Table 4.3) for determining the value of the loss functions.

[6]By loss gap, we compare here the difference between the loss of each simple, non-optimized, with the minimum loss (across λ) of their optimized counterparts.

are not only better suited to the modern model paradigm but also achieve better welfare performance for most stabilization focus preferences.

To further explore what these policy findings imply for central banks, Figure 4.2 presents the evolution of estimated reaction coefficients across the preference grid. The results point to systematic changes in optimal rule design. Across most rules, the inflation coefficient α declines with higher λ values, consistent with a reallocation of policy focus toward output gap stabilization. Meanwhile, the interest rate smoothing term ρ remains persistently high, often exceeding 0.9, reflecting the stabilizing role of gradualism in economies with financial frictions. Concerning optimal reaction to output gap developments $(\beta_0, \beta_1, \tilde{\beta})$, we observe that, as central bank preferences shift toward greater output stabilization, the strength of the response to the output gap tends to increase. However, the degree of responsiveness depends on the structure of the rule.

For instance, the Orphanides and Williams (2008) rule, which responds to the expected output gap, shows a sharp upward adjustment in β_0. By contrast, rules like Taylor (1993a) or Smets and Wouters (2007), which feature contemporaneous or lagged responses to output gap, exhibit a more gradual rise in β_0. The rule of Orphanides and Wieland (2013), which responds to output gap growth ($\tilde{\beta}$), also exhibits a strong and rapid rise in this parameter. Finally, the case of Levin and Williams (2003), which allows for both current and lagged output responses (β_1, β_2), shows more complex, non-monotonic profiles for these coefficients, reflecting a more complex type of feedback.

Overall, these results suggest that, for this type of model, optimal simple rules require a central bank reaction function that combines high inertia, flexible responsiveness to output gaps, and, in some cases, forward-looking response to output gap developments. Furthermore, optimal rules are highly sensitive to stabilization preference settings, and the structure of the model itself can significantly alter the nature of monetary prescriptions. This last point is the subject of the following analysis.

Comparing trade-offs across generations of models

Are there any differences in terms of policy trade-offs (inflation vs output gap) across generations of models? And are these differences consistent across policy rule formulations? These questions are crucial for our analysis and constitute a critical aspect for policy evaluation. Figure 4.3 contrasts the policy frontiers obtained earlier with the *EA_SR07* model, belonging to the second generation. For all rules, the presence of financial frictions embedded in the *EA_VI16bgg* model modifies the shape and slope of the policy frontiers, altering the nature of trade-offs faced by policymakers.

In this structural representation of the economy, policy frontiers tend to flatten more rapidly as the preference weight on output gap stabilization (λ) increases. This implies that, once a moderate degree of output stabilization is targeted, additional improvements in inflation outcomes can be achieved at a lower marginal cost. In contrast, under strict inflation targeting ($\lambda = 0$), these models exhibit significantly steeper policy frontiers, with high output volatility required to maintain low inflation. In contrast, a different pattern

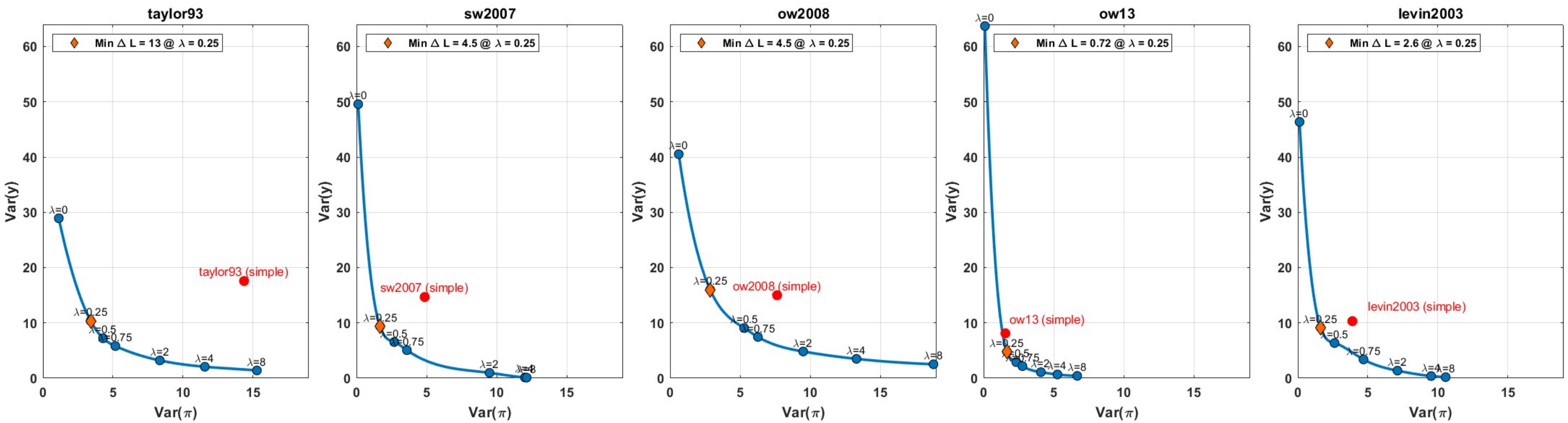


Figure 4.1: Policy frontiers for optimal simple rules (EA_VI16bgg model). Each panel shows the variance trade-off between inflation and output gap for a given rule under optimal coefficients. The red point indicates the outcome of the fixed-coefficient simple rule (as used in Section 4.4.1), while the blue frontier shows outcomes for optimized rules across preference weights. Orange diamonds mark the configuration where the simple rule has the lowest loss gap.

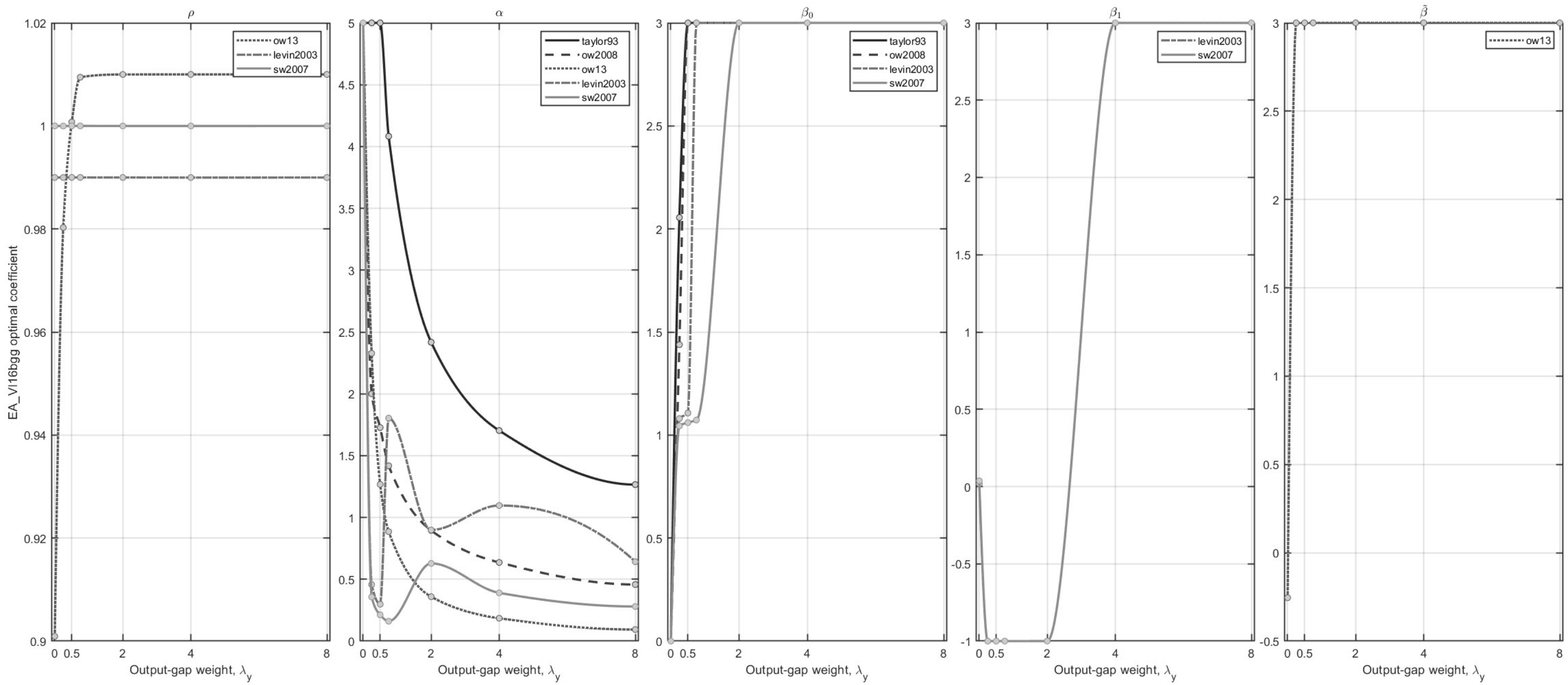


Figure 4.2: Evolution of optimal rule coefficients across preference configurations (EA_VI16bgg model). Each subplot tracks the optimal value of a specific policy parameter across the preference grid for output gap stabilization (λ). The results show how model-specific optimal simple rules respond to varying policy objectives, with differences across rule specifications depending on which output gap dynamics they include (contemporaneous, lagged, forward-looking, or differenced).

emerges in the earlier-generation *EA_SR07* model, where output stabilization becomes more costly relative to inflation control.

Table 4.5: Efficiency of simple rules: minimum loss gaps and optimal preferences.

Model	Rule	Min. Rel. Gap (%)	λ^*	Abs. Gap at λ^*	Ranking
EA_QUEST3	taylor93	114.670	8.00	0.0021	5
	sw2007	82.691	4.00	0.0008	4
	ow2008	51.064	8.00	0.0010	3
	ow13	**15.750**	**0.75**	**0.0000**	**1**
	levin2003	47.401	4.00	0.0004	2
EA_SR07	taylor93	41.190	2.00	8.5851	5
	sw2007	22.521	0.50	1.3533	3
	ow2008	**17.730**	0.75	1.9873	2
	ow13	22.836	**0.25**	**0.5586**	**1**
	levin2003	18.502	0.75	1.5011	4
EA_VI16bgg	taylor93	189.120	0.75	18.0200	5
	sw2007	104.780	0.50	6.2418	4
	ow2008	54.215	0.50	5.3188	3
	ow13	**25.111**	**0.25**	**0.7190**	**1**
	levin2003	56.229	0.50	3.2584	2

Notes: For each rule and model, the table reports: (i) the minimum *relative loss gap* in percent, defined as $(L^{\lambda}_{\text{simple}} - L^{\lambda}_{\text{opt}})/L^{\lambda}_{\text{opt}} \times 100$; (ii) the corresponding preference weight λ^*; and (iii) the *absolute loss gap* at that λ^*. Bold entries highlight the most efficient rule per model.

Among the rules considered, the one Orphanides and Wieland (2013) stands out by exhibiting a relatively stable policy frontier across model generations. Its structure, which includes full inertia and responses to inflation and output gap growth, delivers robust performance even in the presence of financial frictions.

This robustness along this perspective is further quantified in Table 4.5, which summarizes the minimum relative and absolute loss gaps attained by each rule, as well as the preference weight λ^* at which these minima occur. While earlier-generation models such as *EA_QUEST3* allow several rules to lie near the efficient frontier, performance gaps widen markedly in the presence of financial frictions. In *EA_VI16bgg*, the absolute loss associated with legacy rules like Taylor (1993a) rises sharply, while the Orphanides and Wieland (2013) rule maintains the lowest loss across all models and preference settings.

Overall, the findings discussed in this section multiple implications regarding the nature of monetary policy design. First, our results show that the third generation of NK models (Binder et al., 2019), exhibiting here more complex macro-financial linkages, alter the nature of stabilization trade-offs and call for a re-evaluation of optimal objective weights. The comparative analysis of policy frontiers across model generations reveals that financial amplification mechanisms alter the slope and curvature of achievable trade-offs, making strict inflation targeting more costly in terms of output volatility. In this type of economic structure, it is preferable for policymakers to set their policy objectives towards higher degree of output gap stabilization than full inflation targeting, as it delivers

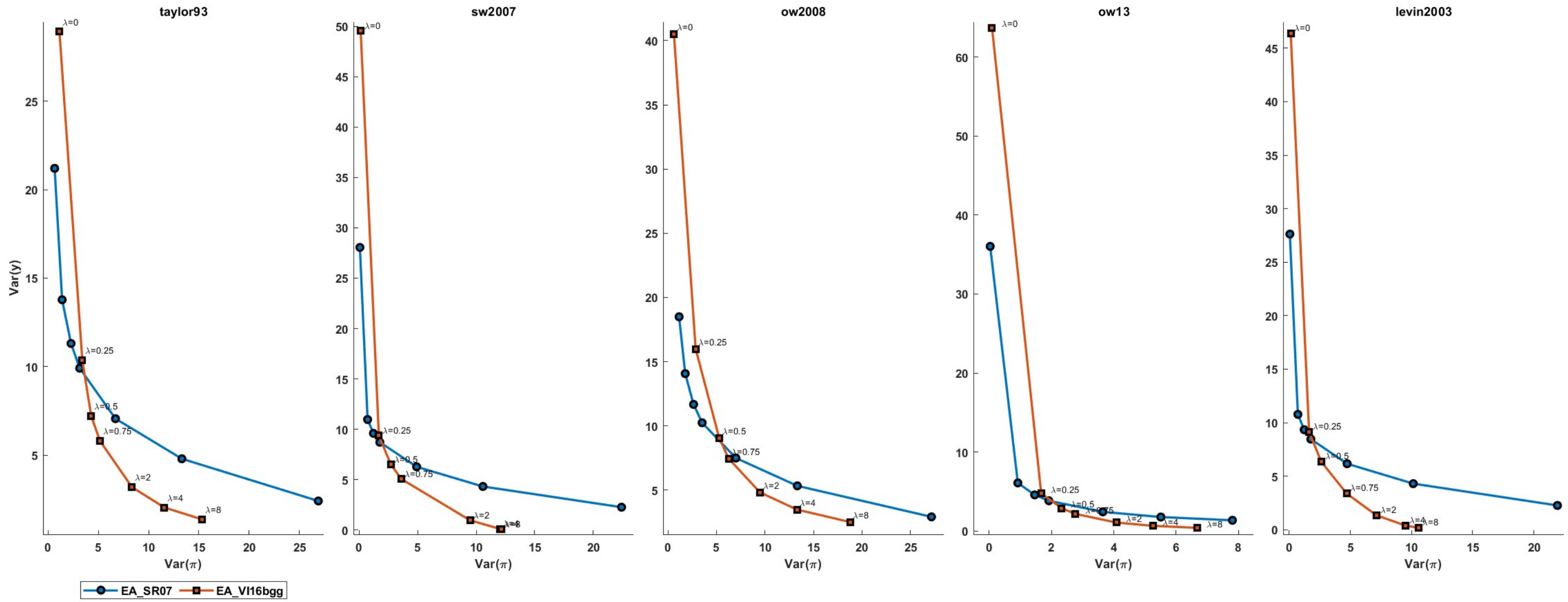


Figure 4.3: Policy frontiers across model generations: output-inflation trade-offs for optimized simple rules.

Notes: Each panel shows the policy frontier in terms of the variance of inflation (Var(π)) and output gap (Var(y)) under a given rule, comparing outcomes across the second-generation model *EA_SR07* (blue) and the financial frictions model *EA_VI16bgg* (red). For each λ value in the preference grid, rules are re-optimized. Lower positions on the frontier indicate better stabilization performance. In models with financial frictions, the frontier flattens more rapidly as λ increases, implying that output stabilization can be improved with relatively small increases in inflation variability. Conversely, strict inflation targeting ($\lambda = 0$) becomes more costly in terms of output volatility. Among rules, the specification Orphanides and Wieland (2013) shows the most consistent frontier shape across models, suggesting greater robustness to structural change.

better welfare outcomes. Second, the efficacy of legacy rules, such as Taylor (1993a), deteriorates under financial amplification mechanisms, resulting in larger loss gaps relative to their optimized counterparts. This confirms that policy rule effectiveness is contingent not only on the structure of the rule but also on the features of the model in which it operates. Finally, it is worth emphasizing that the rule of Orphanides and Wieland (2013) stands out in both visual and quantitative assessments: it maintains a relatively stable frontier across model types and in diverse environments. Its structure delivers consistent robustness in performance, captured alongside different dimensions, even under modern complexity and model uncertainty.

4.4.3 Robust optimal rules and model averaging

Although third-generation models reflect recent advances in macroeconomic modeling, central banks and policymakers rarely place full confidence in a single class of model for policy exercises. Indeed, many forms and types of structural uncertainties (shocks, parameters, model structural equations) make it risky to tailor policy tightly to any single specification. This present section addresses the practical challenge of designing a simple monetary policy rule (defined as in 4.2), which accounts for model uncertainty and performs well across the whole spectrum of models listed in Table 4.1. More specifically, we ask whether a simple reaction function can deliver three desirable features: (i) near-optimal outcomes under model uncertainty, (ii) good performance when applied to a post-GFC financial-frictions environment, and (iii) structural similarity in central banks' optimal reaction functions, which reduces policy-switching costs and enhances communication. Each dimension informs a different layer of policy evaluation and is representative of actual challenges policymakers can face in a perpetual, evolving macroeconomic landscape.

Evaluating the robust optimal rule

We begin by identifying the optimal robust rule, which solves the problem outlined in (4.5). This rule minimizes the weighted average loss across models, for each different value of λ_y. Solutions to this problem are shown in Table 4.6 and Figure 4.4, which respectively report the MA-optimal losses and evolution of parameters θ^* underpinning this problem. These MA-optimal coefficients represent a coherent target for rule design under uncertainty. They offer policymakers a feasible, well-performing structure grounded in diverse models and preferences. These results define a hard performance benchmark for policy evaluation.

Table 4.6: MA-optimal losses across preference weights.

Preference Weight λ_y	MA-Optimal Loss
0	0.2348
0.25	1.3038
0.50	2.5636
0.75	2.4411
1	4.6117
4	7.8649
8	6.9846

These results reveal particular policy insights: inertia is consistently high ($\rho \approx 0.95$–0.99), inflation responses remain moderate ($\alpha \approx 0.5$ at $\lambda_y = 0.5$), while the output gap is addressed via a level term around one ($\beta_0 \approx 1.1$) and a small positive growth term ($\tilde{\beta} \approx 0.5$) at moderate preferences. These features capture a reaction profile that is both responsive and smooth, tailored for policy under model uncertainty.

Comparison with suboptimal rules

A natural question is whether earlier off-the-shelf rules (see Section 4.4.1), applied without re-optimization, can deliver robustness comparable to this optimal benchmark. Table 4.7 compares, at the baseline $\lambda_y = 0.5$, the average loss of several such rules to the MA-optimal loss. Once again, the Orphanides and Wieland (2013) stands out: it delivers a loss close to the MA benchmark. This result echoes their earlier prescriptions: despite modern complexity associated with third-generation models, their guidance on the robustness of this type of rule remains valid. In contrast, classic level rules such as Taylor (1993a) and Orphanides and Wieland (2008) are more than four units above the MA-optimal loss. These differences are economically meaningful, especially in a robustness setting.

Table 4.7: Average losses: fixed rules vs. MA at $\lambda_y = 0.5$.

Rule	Avg. Loss (Fixed-Coeffs)	MA Loss	Difference
Taylor93	6.82	2.5636	4.2564
SW2007	5.91	2.5636	3.3464
OW2008	7.20	2.5636	4.6364
OW2013	2.34	2.5636	**-0.2236**
Levin2003	4.66	2.5636	2.0964

Balancing model uncertainty and financial frictions in optimal policy reaction functions

While comparing policy outcomes (loss measures) provides a basis for evaluating the performance and robustness of policy rules, it offers limited insight into the nature of their design and the policy effort required to achieve those outcomes. Examining the *structural proximity* of policy reaction functions adds a further layer of analysis that is essential for the

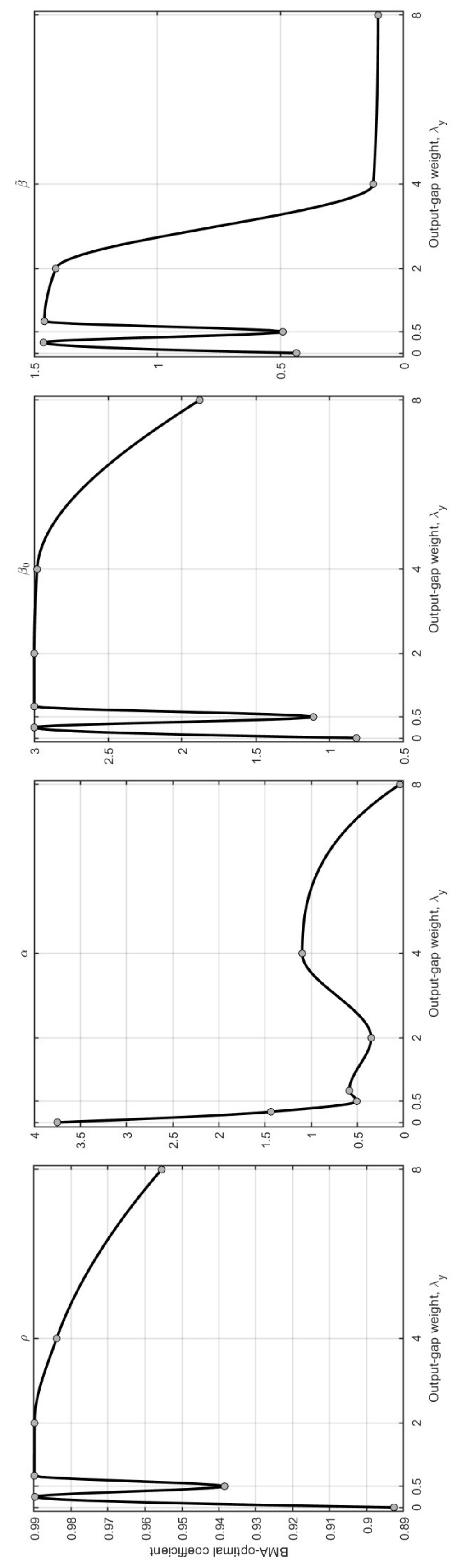


Figure 4.4: MA-optimal reaction coefficients across λ_y. Notes: coefficients shown in canonical order $(\rho, \alpha, \beta_0, \tilde{\beta})$; lines are smoothed interpolations through $\lambda_y \in \{0, 0.25, 0.5, 0.75, 2, 4, 8\}$.

evaluation and formulation of monetary policy. This section contrasts optimal policy reaction functions between models with financial frictions and the model-uncertainty (MA) benchmark, with the aim of identifying a type of design, or policy space, that can deliver effective stabilization in both contexts.[7] Such a rule design would allow policymakers to address the amplification effects of financial frictions while remaining robust in the face of broader structural uncertainty; thereby avoiding the (switching) costs associated with frequent policy reformulations.

Figure 4.5 shows, for each parameter and value of λ_y, the absolute differences in reaction coefficients. Table 4.8 reports the results for the baseline case of $\lambda_y = 0.5$ and includes the corresponding loss values. From this, we highlight three main patterns. First, inertia terms (ρ), when included in rule specifications, align closely with the MA benchmark (gaps around 0.05–0.06). Second, inflation responses vary markedly: Taylor (1993a) and Orphanides and Wieland (2008) are substantially more aggressive than the uncertainty-robust (MA) benchmark, while those of Smets and Wouters (2007) and Levin et al. (2003) remain close. Third, the largest structural divergence concerns the reaction to output-gap terms: the MA rule uses a level term (β_0), whereas Orphanides and Wieland (2013) responds to a difference term ($\tilde{\beta}$), producing a large coefficient gap despite good loss performance.

Table 4.8: Baseline ($\lambda_y = 0.5$): coefficient gaps and losses

	$\lvert\theta^*_{EA\_VI16bgg} - \theta^*_{\mathrm{MA}}\rvert$				Optimal Losses at $\lambda_y = 0.5$		
Rule	ρ	α	β_0	$\tilde{\beta}$	EA_VI16bgg	MA	Diff
Taylor93	–	4.492	1.890	–	7.9014	2.5636	5.3378
SW2007	0.062	0.295	0.050	–	5.9568	2.5636	3.3932
OW2008	–	1.219	1.890	–	9.8106	2.5636	7.2470
OW2013	0.062	0.760	–	2.510	3.7751	2.5636	1.2116
Levin2003	0.052	0.209	0.003	–	5.7949	2.5636	3.2313

Overall, this comparison of optimal reaction functions in a context of model uncertainty and in a financial-frictions environment reveals that a small set of simple rules, most particularly those of Levin et al. (2003) and Smets and Wouters (2007), align closely across both problems. These rules combine high inertia, moderate inflation responses, and a level-based output-gap term, features which appear critical for balancing robustness under model uncertainty with effectiveness in the presence of financial frictions. By contrast, rules specified as in Taylor (1993a) or Orphanides and Wieland (2008) exhibit substantial inflation-response gaps relative to the MA benchmark, indicating that they would require significant recalibration in a robustness-oriented framework. Finally, despite showing more pronounced differences on the (growth) output-gap term $\tilde{\beta}$, the Orphanides and Wieland (2013) still delivers low losses, indicating that certain departures from the benchmark can be accommodated without compromising stability.

[7] For consistency with the approach adopted in the preceding sections, the model *EA_VI16bgg* (Villa, 2016) is retained as the reference framework for third-generation models and for this comparison.

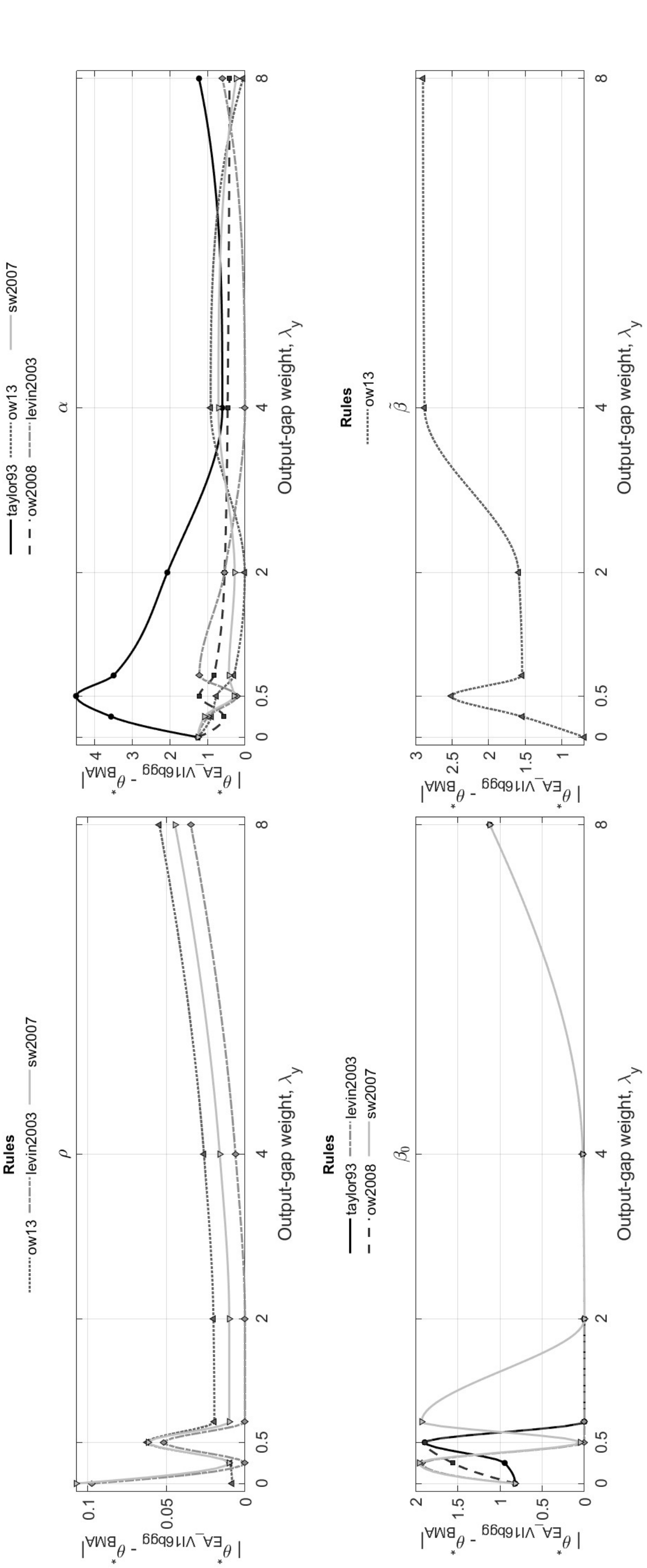


Figure 4.5: Structural proximity: absolute coefficient gaps $|\theta^*_{\mathrm{EA\_VI16bgg}} - \theta^*_{\mathrm{MA}}|$ by λ_y. Notes: each subplot tracks one parameter; curves show rules including that parameter.

The pattern observed above is consistent with what the theoretical body of work made by Woodford (2003) suggests about optimal monetary policy in New Keynesian models. In its textbook *Interest and Prices*, Woodford (2003) shows that when private agents are forward-looking, and policy is set under commitment, the optimal policy is history-dependent and can be approximated by highly inertial interest-rate rules. In that framework, interest-rate smoothing (gradualism) is not just an empirical regularity observed but a device for managing expectations, stabilizing the forward-looking IS and Phillips curves, and avoiding excessive volatility in response to shocks.

An immediate implication of this high inertia is that the policy rate moves smoothly over time. Even though our loss function does not explicitly penalize interest-rate volatility, rules that perform best in terms of inflation and output stabilization also imply relatively gradual and predictable rate adjustments. This connects to the policy debate on the benefits of gradualism (Alati et al., 2025) and activism (Dupraz et al., 2023) for monetary policy making. Central banks often prefer not to move rates aggressively, because large rate changes can unsettle financial markets and, in the presence of financial frictions, trigger strong movements in credit, spreads, and balance sheets. Our results suggest that such gradualism is not only a matter of communication or style, but is also consistent with good stabilization performance in our model set.

Policy takeaways

Based on the results discussed in the above section, three broad policy takeaways emerge from our analysis.

Section 4.4.1 (simple non-optimized vs. model-optimal rules) has revealed that, across models and Keynesian paradigms, no single simple (non-optimized) rule systematically dominates, and the dispersion in losses widens in the presence of financial frictions. Nevertheless, difference-type rules (such as Orphanides and Wieland (2013)) still travel comparatively well across generations of models, making them a pragmatic starting point when model uncertainty is high..

Section 4.4.2 (policy frontiers and optimal simple rules) offers further policy insights. Compared to earlier-generation models, strict inflation targeting in financial-frictions models entails steeper inflation–output trade-offs, with output volatility bearing most of the cost. Optimal policy reactions tilt toward pronounced gradualism and moderated inflation responses, with stronger, but rule-specific, attention to output-gap (economic slacks) developments. The policy implication is that aggressive inflation responses are harder to sustain when financial amplification is active; designs that privilege smooth adjustments and disciplined responses to output-gap variations are more efficient in such environments.

Section 4.4.3 (robust optimal rule) provides further policy insights, distinguishing between policy outcomes and the underlying structure of optimal rules when policy is set under model uncertainty. The robust, model-averaged benchmark emerging from our analysis exhibits a particular structure, characterized by high inertia, a moderate response to inflation, and an explicit response (in level) to output deviations, with the growth-of-output deviations term playing a secondary role. In contrast, the financial-frictions optimum associated with rules relying on output-gap growth specification (Orphanides and Wieland, 2013) frequently requires stronger responses on output-gap growth compared to the optimal robust benchmark. Comparing reaction coefficients highlights complexity in policy design under both objectives: some legacy rules like Taylor (1993a) display excessive responsiveness to inflation relative to the robust benchmark, while others, such as Levin et al. (2003) or Orphanides and Wieland (2013), remain structurally close. From a policy perspective, minimising "switching costs" between a single-model stance and an uncertainty-aware stance favours rules that retain the level-gap term alongside high inertia, even though growth-gap variants may remain effective in particular policy preference settings. These policy prescriptions are, of course, contingent on our methodological framework: they reflect a finite set of representative models and a narrow class of linear interest-rate rules under quadratic losses.

4.5 Conclusion

Throughout this paper, we reassess the robustness properties of simple interest-rate rules when policy is evaluated under uncertainty and with new-generation types of models. Using a vintage of different euro area models, spanning pre- and post-GFC generations, we follow a systematic comparison framework (Wieland et al., 2012) and analyse the robustness properties of five different policy rules under different layers of policy analysis. This layered approach contributes in two ways by identifying simple rules that balance model-specific performance with robustness to model uncertainty and by clarifying which policy structures remain most stable across the environments and problems considered in this research.

Three broad conclusions emerge from our analysis. First, performance varies across models, but certain types of rules travel well. In our comparison exercise, a non-optimized version of the rule of Orphanides and Wieland (2013) remains the most robust on average and under a min–max lens. Second, financial frictions reshape best achievable policy outcomes of such rules (policy frontiers) and push optimal coefficients toward high interest-rate inertia with moderate inflation responses. Stabilization gains in these models require policymakers to place stronger emphasis on output deviations. Third, under model uncertainty, the optimal reaction function delivers a certain type of structure featuring high inertia, a moderate inflation coefficient, and a more pronounced reaction to the level of output gap. These findings extend classic robustness results to modern macro-financial settings and connect with comparison exercises that emphasise transmission heterogeneity and model uncertainty.

Several limitations are, however, still worth noting. These broad policy insights emerge on the basis of our chosen models and rule class. The analysis relies on a non-exhaustive euro-area set, linear interest-rate rules evaluated with simple (non-microfounded) quadratic losses, certainty regarding structural parameters within models, and non-adaptive weights. Outcome-based proximity metrics (e.g., IRFs or forecast-error variances) could complement our comparison of optimal reaction coefficients, and real-time data exercises would speak to implementability.

Finally, this research offers new perspectives for policy robustness research. A natural extension beyond the scope of this paper would be to widen the type of models in the "third-generation". Example of such avenues could include models from the Heterogeneous-Agent New Keynesian (HANK) literature, as Debortoli et al. (2018); Kaplan et al. (2018) or Bilbiie (2024), which may lead to different implications for (robust) optimal policy. Finally, as contemporary monetary policy is multi-instrument Bernanke (2020) and increasingly more complex with many forms of forward guidance and asset purchases, the study of robustness could also turn to these other forms of policy rather than simple rules.

Chapter 5

Further Research

The preceding chapters have provided a deeper understanding of the interaction between monetary policy and uncertainty from a higher-order perspective, as well as the implications of this nexus for academic research in macroeconomics and finance. These chapters have examined this broad question through various lenses and methodological approaches, each contributing to distinct yet interconnected strands of the literature. Nevertheless, within the scope of the three main research streams outlined above, and for each of the individual chapters, we can identify several promising avenues for future research that could further enhance our understanding of the issues addressed in this dissertation. Below, we expose a series of further developments for each respective chapter.

5.1 Monetary Policy, Uncertainty and the Business Cycles

Chapter 2 has provided empirical evidence that financial uncertainty should not be treated as an exogenous source of fluctuations, but rather as a variable that responds endogenously to other macroeconomic shocks, particularly to monetary policy innovations. This finding contributes to a growing body of literature emphasizing the endogenous nature of uncertainty, as recently documented by Castelnuovo (2023) and Cascaldi-Garcia et al. (2023). Building on our econometric framework or other methods, future research could investigate more systematically how different types of shocks, e.g., monetary, fiscal, or financial, affect the behavior of uncertainty over time.

An important direction involves deepening our understanding of how uncertainty is perceived and transmitted across agents. While it is intuitive that economic agents become uncertain in response to news or policy signals, it remains challenging to formally capture this behavioral response using macroeconomic data. In that regard, the empirical literature relies on a range of proxies based on forecast errors (Jurado et al., 2015), financial volatility (Bloom, 2009), or survey-based dispersion measures (Bachmann et al., 2013), whose dynamics and interpretation can diverge. A natural extension would be to apply our framework to a broader set of uncertainty measures[1] to assess the robustness of our conclusions and potentially uncover common underlying drivers, in the spirit of Kozeniauskas et al. (2018). Such work would help clarify to what extent observed uncertainty reflects distinct phenomena versus a shared macro-financial structure.

From a methodological standpoint, it would also be relevant to extend our framework to refine our identification of monetary policy shocks in multiple types of innova-

[1]Given our application on financial uncertainty, it would be natural to rely on the financial uncertainty measure proposed by Jurado et al. (2015) for the Euro Area.

tions, while still using statistical identification schemes. Papers such as Lewis (2025a) or Jarociński (2024) are recent examples that use high-frequency policy surprises and statistical identification to capture different types of economic disturbances. However, unlike our approach, theirs relies on multiple policy surprises around policy announcements rather than a single one, thereby expanding the range of structural shocks that can explain the movements of the surprises and enabling a finer economic interpretation.

Finally, a particularly natural extension of our empirical framework would be to shift the focus from the effects of monetary policy on uncertainty to the uncertainty surrounding monetary policy itself. While Chapter 2 highlights the endogeneity of financial uncertainty to policy shocks, recent research emphasizes that uncertainty about future monetary policy decisions—referred to as *monetary policy uncertainty* (MPU)—can itself become a key driver of macro-financial dynamics. MPU affects the way economic agents form expectations about future interest rates, inflation, and economic conditions, and may thereby impair the transmission and effectiveness of policy actions. Using narrative-based MPU indices, Husted et al. (2020) show that higher uncertainty about monetary policy leads to a decline in output and inflation, as well as a deterioration in financial conditions. Focusing on financial markets, Bauer et al. (2022) also show that uncertainty about future policy rates has pronounced effects on asset prices beyond the respective effects of policy surprises. They also highlight that the level of uncertainty surrounding FOMC announcements determines the magnitude of the effects of surprises about the path of policy rates. As forward guidance becomes increasingly a standard policy tool, these results underscore the need for central banks to tailor their communication to the prevailing level of uncertainty surrounding the course of their actions.

5.2 Heterogeneity in Monetary Policy Transmission to Financial Markets

In Chapter 3, our empirical analysis has shown that the effects of monetary policy on financial markets are heterogeneous: financial uncertainty responds differently both across asset classes and across the activated dimensions of the yield curve. Understanding the heterogeneous effects of monetary policy is essential and aligns with the recent research agenda of Altavilla et al. (2024) for Europe. Yet, although our empirical analysis is grounded in a body of the macro-finance literature, a clear, unified explanation for this heterogeneity remains elusive and calls for a distinct research question. Two major limitations of our analysis warrant emphasis, as addressing them may help clarify the observed heterogeneous pattern.

The first limitation concerns the specification of our stochastic volatility (SV) model. While the model enables us to quantify asset-specific levels of uncertainty, it remains univariate and reduced-form in nature. As such, the estimated coefficients capture only the marginal effects of various components of monetary policy shocks on the state of uncertainty. This restricts our ability to uncover the structural propagation mechanisms through which such shocks influence uncertainty dynamics. In a close framework grounded in stochastic volatility, some studies, such as Alessandri and Mumtaz (2019); Carriero et al.

(2021); Mumtaz and Theodoridis (2020) have adopted SVAR models with stochastic volatility (SVAR-SV), wherein structural shocks can simultaneously affect the conditional volatility of the macro-financial variables (interpreted as uncertainty) and where uncertainty, in turn, feeds back into the first-order dynamics of the system. Although methodologically more demanding, this approach allows for a deeper characterization of the transmission mechanisms through which shocks shape uncertainty dynamics. In addition, it would allow for a more rigorous treatment of the endogenous nature of uncertainty (cfr. Chapter 2), as discussed in the preceding section.

The second limitation concerns the interpretation of the monetary policy shocks components (level, slope, and curvature), where comovements are not sufficiently explicit to disentangle the underlying channels at play. In particular, these factors may *simultaneously* reflect movements in expectations about the future path of policy and variations in risk premia, without clearly distinguishing between the two. As a result, while the analysis highlights heterogeneous responses of uncertainty across asset classes, it does not allow us to attribute these dynamics to one channel or the other. Future research could build on this limitation by adopting a framework that more explicitly separates these effects, thereby providing a sharper interpretation of the sources of heterogeneity. Prior existing studies, such as Hanson and Stein (2015) or Rogers et al. (2018), could offer further insights regarding this.

5.3 Bayesian Model Averaging, New Policy Tools & Models: Implications for Policy Robustness

The comparative exercise conducted in Chapter 4 highlighted the merits of different simple interest rate rules across a range of structural macroeconomic models. Following the approach of Wieland et al. (2012) and motivated by Binder et al. (2019), particular attention was devoted to models featuring financial frictions, where we examined how these more recent frameworks affect the evaluation and robustness of five different monetary policy rules. Several remarks can be made that open avenues for extending this analysis.

First, our conclusions are derived from a finite set of models, based on fixed calibrations of structural parameters taken from the MMB. This approach does not account for uncertainty regarding the structural parameters themselves, which may affect the evaluation of policy rules. As emphasized by Cogley et al. (2011), parameter and model uncertainty can play a central role in shaping optimal monetary policy prescriptions. Extending the analysis to incorporate such uncertainty would allow us to assess the robustness of rule performance across different parameterizations and obtain a distributional perspective on the loss functions associated with each model.

A second point that could potentially impact the robustness of our results concerns the model averaging exercise. We have reduced the complexity by assigning weights to the model on an equiprobable basis. Another approach would be to perform Bayesian Model Averaging (BMA) and adjust the model weights (as well as the parameters) by confronting the models with the data. Assuming an equiprobable repartition of weights a priori, one could revise their belief about which model is the most likely to characterize the data a posteriori. This will involve estimating and assigning weights based on in-sample fit or based on their relative forecasting performance (Deák et al., 2025).

Lastly, future research on policy robustness could be fruitfully extended along several dimensions. First, following Bernanke (2020), robustness analysis should encompass not only conventional tools but also the new instruments, such as large-scale asset purchases and forward guidance, that have become integral parts of the monetary policy landscape. While these tools were initially evaluated in contexts of low interest rates, subdued inflation, and financial market disruptions, their continued use underscores the need to assess their effectiveness and robustness across a wider range of economic environments. Second, a promising avenue for future research is to connect the literature on uncertainty, business cycles, and monetary policy design. Building on theoretical contributions such as Bloom (2009); Fernández-Villaverde et al. (2011); Christiano et al. (2014); Basu and Bundick (2017), it would be valuable to assess the robustness of policy rules in DSGE models that explicitly incorporate different microfoundations for how agents respond to uncertainty. Such an extension would not only provide policymakers with clearer guidance on how to address economic uncertainty but also yield a richer understanding of its interaction with monetary policy. Taking Bloom's word, this would enable us to be more certain about how monetary policy should be designed in the face of various dimensions of economic uncertainty. Moreover, it would establish a natural bridge with the strand of literature discussed in Chapter 2.

Chapter 6

Conclusion

"Uncertainty is not just an important feature of the monetary policy landscape; it is the defining characteristic of that landscape"[1]
— Alan Greenspan, (2003).

Alan Greenspan's words resonate with particular force in today's economy—an environment in which uncertainty, multifaceted and pervasive, unfolds across multiple dimensions, and within which monetary policy must simultaneously operate and respond. It also returns to the central theme of the dissertation: the nexus between *monetary policy* and *higher-order uncertainty*. The thread that runs through the thesis is simple to state but difficult to tame empirically and theoretically: uncertainty is multifaceted, evolving, and consequential for policy, while policy itself is multidimensional, adaptive, and a driver of the very uncertainty it seeks to manage. There is no single, accepted taxonomy of uncertainty. Instead, macroeconomic, financial, and real-sided notions coexist (Jurado et al., 2015; Ludvigson et al., 2021); some are statistical (volatility, higher moments), others informational (disagreement, ambiguity), and still others structural (model misspecification). At the same time, the conduct of monetary policy has become more complex: the policy toolkit has broadened from conventional short-rate adjustments to forward guidance, balance-sheet policies, and a richer communication architecture; the financial landscape shapes its transmission and has proven crucial to macroeconomic dynamics. In such a context, understanding this nexus proves more crucial than ever and will remain so in the future.

These two forms of multiplicity—of uncertainty and of policy—interact in ways that complicate the research design. The dissertation's arc was built precisely to address that challenge: to understand how policy shapes financial uncertainty and to ask how policy can remain robust when the model of the economy is itself uncertain. The general research question was stated explicitly: *How does monetary policy interact with uncertainty from a higher-order perspective—by shaping financial uncertainty across markets, measures, and instruments, and by remaining robust under structural/model uncertainty in rule-based design?*

Against this backdrop, the dissertation pursued three questions that form a coherent progression along the different chapters: (i) *Does monetary policy endogenously affect financial uncertainty, and with what implications for business cycles?*; (ii) *Are the effects of monetary*

[1] Alan Greenspan, "Monetary Policy under Uncertainty," remarks at the Federal Reserve Bank of Kansas City's Jackson Hole Symposium, Jackson Hole, WY, August 29, 2003. Board of Governors of the Federal Reserve System. Available at: `https://www.federalreserve.gov/boarddocs/speeches/2003/20030829/default.htm` (accessed September 25, 2025).

policy on financial uncertainty heterogeneous across asset classes and yield-curve dimensions?; (iii) *Which simple interest-rate rules remain robust when the model of the economy is itself uncertain—especially in the presence of new-generation models with financial frictions?*

The first question asked whether financial uncertainty is itself *endogenous* to monetary policy. The second examined how the *composition* of policy along the yield curve—level, slope, and curvature components—maps into *heterogeneous uncertainty* response across financial markets. The third focused on *model uncertainty* and its implications for policy design, where we revisited the *robustness* of simple interest-rate rules when the model of the economy is itself uncertain, explicitly incorporating a new generation of DSGE models with financial frictions. Each of these questions is examined in the Euro Area, providing a coherent empirical focus that ties the chapters together. In addition, the questions are linked to and contribute to three distinct, yet interconnected, strands of the literature. Throughout the chapters, we have sought to provide answers to these questions.

In Chapter 2, we study whether monetary policy endogenously affects financial uncertainty and with what implications for business cycles. To do so, we build a non-Gaussian proxy-SVAR framework with a single external instrument, which allows a clean separation of conventional from unconventional policy shocks while avoiding the recursive (Cholesky) ordering limitations of earlier studies. We show that this framework is suitable for the problem at hand and can be extended to different economic applications. Our method has the merit of partially solving the shock-labeling issue often encountered in statistically identified SVARs. It also sharpens the identification of monetary policy shocks in certain empirical settings. This framework extends the one proposed by Schlaak et al. (2023) with an identification scheme based on ICA and for two policy shocks of interest. Using this framework, our results show that contractionary policy shocks consistently lead to higher financial uncertainty, with conventional shocks producing a sharper and more immediate rise, while unconventional shocks exert smaller but more persistent effects. These dynamics are tightly linked to the tightening of financial conditions through monetary policy has an influence. In particular, we find that financial uncertainty responds to monetary policy mainly through its indirect effects on financial conditions. Historical decomposition analyses confirm that monetary policy innovations have accounted for significant swings in financial uncertainty, especially in the run-up to the global financial crisis. The principal contribution of this chapter is to demonstrate empirically, and with a novel SVAR framework, that uncertainty is not an exogenous disturbance but a state variable influenced by policy actions, with direct implications for the literature on uncertainty and the business cycles as well as, to some extent, financial stability.

In Chapter 3, we reframe financial uncertainty as a *latent*, *asset-level* object and ask how different dimensions of monetary policy shape its response across markets. Methodologically, we make use of *high-frequency* monetary policy surprises (Altavilla et al., 2019) with a *functional* view: ECB policy-announcement movements are treated as shifts of the entire yield curve and then summarized, similarly to Inoue and Rossi (2021), into economically interpretable *level*, *slope*, and *curvature* components measured within the announcement window. These components of monetary policy shocks are integrated into a Bayesian stochastic-volatility framework that recovers latent uncertainty for a broad cross-section (sovereign and corporate bonds, country and sector equities, and major EUR exchange rates) of euro-area financial assets. The principal advantage of this specification lies in its capacity to attribute variations in uncertainty to distinct yield curve dimensions, as opposed to attributing them to a solitary reduced-form shock. Moreover, we show that this conceptualization and measurement of uncertainty from the data is very close to the one proposed by Jurado et al. (2015). Taken broadly, this design brings *second-order* transmission into focus and reveals pronounced *heterogeneity* in uncertainty responses across asset classes and shock dimensions. This heterogeneity about the effects of monetary policy on financial-market uncertainty manifests along several margins: impact and dynamic responses to shocks, contributions to the time variation in uncertainty, and behavior around key policy announcements. Heterogeneity appears to be particularly pronounced in curvature-related responses, and the ZLB period modifies the manner in which financial markets respond to monetary policy, owing to its influence on the yield curve. These results contribute to the macro-finance literature and offer insights for policymakers by demonstrating that the effects of monetary policy on financial markets extend beyond *first-order* impacts and vary significantly depending on how central banks, through their different instruments and dimensions, shape the yield curve.

Chapter 4 turns to design under *model uncertainty*, asking which simple interest-rate rules remain *robust* when the true model of the economy is unknown, especially once new-generation DSGEs with financial frictions are admitted. The chapter brings a common family of implementable rules into a harmonized comparison (Wieland et al., 2012) across a broad model set calibrated for the Euro Area and spanning pre- to post-crisis vintages. We evaluate both simple (fixed-coefficient) and optimized rules under a common welfare loss, draw policy frontiers and the sensitivity of reaction coefficients, and conduct a Bayesian model averaging to deliver robust-optimal coefficient profiles. Our analysis has revealed that financial frictions steepen the inflation–output volatility trade-off and erode the performance of legacy Taylor-type rules; a class of simple rules characterized by high inertia, moderate inflation response, and an explicit level-gap term seems to remain robust across models. Consequently, these findings (i) identify which type of simple rules preserve performance once financial amplification is present, (ii) quantify how optimal coefficients shift with policymakers' preferences and with the inclusion of frictions, and (iii) show that model-averaged rules yield implementable guidance rather than model-specific optima.

Taken together, the three chapters deepen the questions posed in the introduction and offer evidence-based answers grounded in our results and the relevant literature. They also shed new light on the overarching nexus between monetary policy and higher-order uncertainty. The conclusions depend on the methods used and the scope defined by the three main strands of literature anchoring the chapters. Chapter 5 outlines the principal limitations and sets out avenues for future research to extend and refine the dissertation's analyses. Finally, giving voice to Bloom's words, we hope that this dissertation leaves us a little more certain about how uncertainty and monetary policy jointly shape our understanding of the economic world.

Appendices

Appendix A

Appendix to Chapter 2: Supplementary Material

Section A.1 provides a concise description of the identification scheme proposed by Lanne et al. (2017). Section A.2 provides additional information and supplementary results concerning the simulation study performed in this paper. Section A.3 contains additional results of the empirical application.

A.1 Identification and Estimation in Non-Gaussian SVARs

This appendix summarizes the identification and estimation approach of Lanne et al. (2017) for SVARs with non-Gaussian shocks.

Identification problem in SVARs

Consider the structural VAR (SVAR) model

$$y_t = \gamma + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B\varepsilon_t, \tag{A.1}$$

where y_t is a n-dimensional time series of interest, B is nonsingular and ε_t contains the structural shocks. The reduced form is obtained by defining $u_t = B\varepsilon_t$:

$$y_t = \gamma + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t. \tag{A.2}$$

In the classical Gaussian case, the distribution of u_t is characterized solely by its covariance matrix $\Sigma_u = \mathbb{E}(u_t u_t')$. If the components of ε_t are mutually uncorrelated, Gaussian, and normalized to have unit variance, then for any orthogonal matrix Q the alternative matrix $B^* = BQ$ generates the same reduced-form representation, since $B^* B^{*\prime} = BB' = \Sigma_u$. Thus the structural matrix B is not uniquely identified: the model is observationally equivalent under infinitely many orthogonal rotations of the structural shocks.

Under stability, the reduced-form VAR in (A.2) admits an MA representation

$$y_t = \bar{y} + \sum_{j=0}^{\infty} \Psi_j u_{t-j}, \tag{A.3}$$

where $\bar{y} = \mathbb{E}(y_t) = \big(I_n - A_1 - \cdots - A_p\big)^{-1}\gamma$ denotes the unconditional mean of y_t and the matrices Ψ_j collect the reduced-form MA coefficients, with $\Psi_0 = I_n$. Substituting $u_t = B\varepsilon_t$

into (A.3) yields the structural MA representation

$$y_t = \bar{y} + \sum_{j=0}^{\infty} \Psi_j B \varepsilon_{t-j}. \tag{A.4}$$

The matrix of j-step-ahead structural impulse responses is therefore

$$\Theta_j \equiv \Psi_j B, \qquad j = 0, 1, 2, \ldots, \tag{A.5}$$

and is likewise not uniquely defined, since any admissible $B^* = BQ$ with orthogonal Q implies

$$\Theta_j^* = \Psi_j B^* = \Psi_j BQ. \tag{A.6}$$

Identification under non-Gaussianity

Lanne et al. (2017) show that this indeterminacy disappears if one imposes a mild non-Gaussianity assumption on the shocks:

Assumption 1. (i) The structural shocks $\varepsilon_{1,t}, \ldots, \varepsilon_{n,t}$ are mutually independent, (ii) at most one of them is Gaussian, (iii) all have finite, positive variances.

Under this assumption, independence and non-Gaussianity severely restrict the allowable transformations of B. Their key identification result (high-level version of their Proposition 1) states:

Identification Result. If two SVARs of the form (A.1) generate the same distribution for $\{y_t\}$ under Assumption 1, then their impact matrices B and B^* satisfy

$$B^* = BDP, \tag{A.7}$$

where D is diagonal with nonzero entries and P is a permutation matrix.

Hence, the SVAR is identified up to

- column permutations (relabeling shocks), and
- rescaling of each column (changes in shock units),

but no longer up to arbitrary rotations. This corresponds to the fundamental "Independent Component Analysis" (ICA) identification.

Selecting a unique representative among the set of equivalent classes

For estimation and inference, we need B to be uniquely specified. Lanne et al. (2017) therefore introduce a normalization mapping (so-called the *Identification Scheme* in their paper) that maps every matrix in the equivalence class (A.7) into a unique representative.

The scheme (i) rescales each column of B to unit length, (ii) permutes columns to impose a triangular ordering condition, and (iii) applies a final rescaling to set all diagonal elements to one. When this sequence of operations is well-defined, which holds except for a set of measure zero, the resulting matrix lies in a set

$$\mathcal{B} = \{\Pi(B) : B \in M_n\},$$

and each observationally equivalent SVAR corresponds to exactly one element of $\mathcal{B}$. Thus the SVAR becomes fully identified once B is restricted to $\mathcal{B}$.

Likelihood and estimation

To estimate the model, the marginal distributions of the shocks are parametrized as

$$f_{i,\sigma_i}(x; \lambda_i) = \sigma_i^{-1} f_i(\sigma_i^{-1} x; \lambda_i),$$

where $\sigma_i > 0$ is the scale and λ_i governs the shape (e.g. degrees of freedom in a Student-t). Let θ collect all structural and reduced-form parameters, and let $\varepsilon_t(\theta) = B(\tilde{\beta})^{-1} u_t(\pi)$ denote the structural shocks implied by parameter vector θ.

The log-likelihood for a sample $\{y_t\}_{t=1}^{T}$ takes the form

$$L_T(\theta) = \frac{1}{T} \sum_{t=1}^{T} \left[\sum_{i=1}^{n} \log f_i\big(\sigma_i^{-1} \varepsilon_{i,t}(\theta);\ \lambda_i\big) - \log|\det B(\tilde{\beta})| - \sum_{i=1}^{n} \log \sigma_i \right].$$

Two practical estimation strategies arise: (1) Full ML (one-step); i.e., jointly maximize $L_T(\theta)$ over all parameters and (2) Multi-step ML; estimate the reduced-form VAR by OLS, then maximize the likelihood with respect to the structural parameters using the OLS residuals, and (optionally) update the VAR parameters in a final ML step.

Asymptotic properties

Under regularity and smoothness assumptions on the densities f_i (high-level versions of their Assumptions 2–5), Lanne et al. (2017) establish:
Asymptotic Normality (Theorem 1). Let θ_0 denote the true parameter vector and $\hat{\theta}_T$ any sequence of local maximizers of the likelihood. Then

$$\sqrt{T}\,(\hat{\theta}_T - \theta_0) \ \xrightarrow{d}\ \mathcal{N}\big(0,\, I(\theta_0)^{-1}\big)\,,$$

where $I(\theta_0)$ is the Fisher information matrix. The multi-step estimator has the same limit distribution.

A.2 Simulation Results for Gaussian Cases

Here we report simulation results for structural shocks with a standard Gaussian distribution. The performance criteria match those in Section 2.3.4 of Chapter 2. For each DGP, we compare the labeling performance of our method with a sign-restriction approach and also present MSE results in Figure A.1.

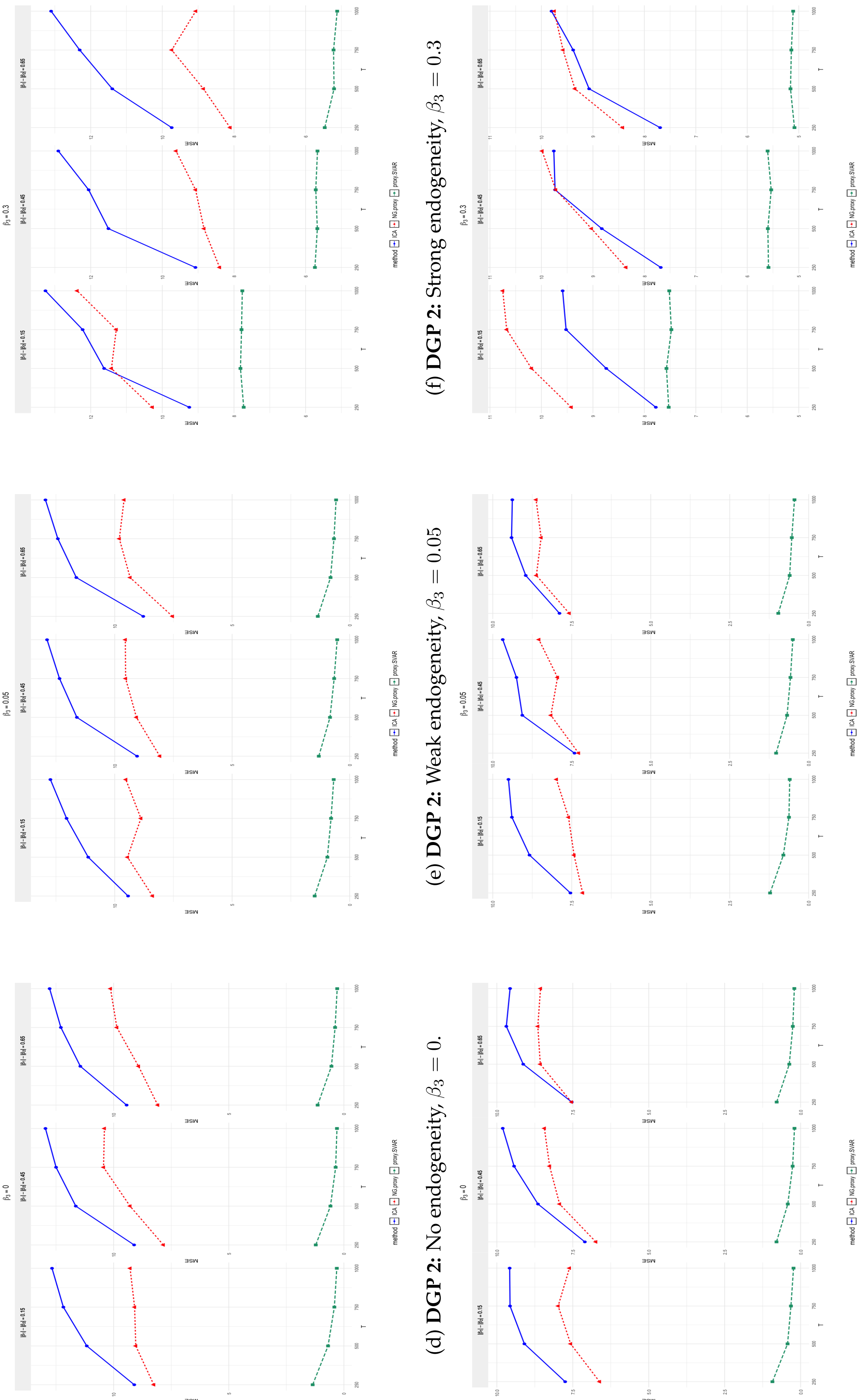
Table A.1: Comparison of labeling performance for DGP1 (sign pattern vs NG proxy).

	$\beta_3 = 0$		$\beta_3 = 0.05$		$\beta_3 = 0.3$	
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.15$	$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.248	0.486	0.248	0.508	0.282	0.390
500	0.236	0.534	0.194	0.510	0.220	0.370
750	0.236	0.538	0.222	0.504	0.244	0.420
1000	0.196	0.554	0.194	0.502	0.244	0.330
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.45$	$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.250	0.668	0.234	0.606	0.216	0.524
500	0.234	0.642	0.230	0.640	0.208	0.442
750	0.202	0.620	0.200	0.632	0.196	0.436
1000	0.240	0.584	0.210	0.624	0.222	0.368
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.65$	$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.222	0.730	0.248	0.712	0.226	0.510
500	0.246	0.692	0.232	0.672	0.242	0.498
750	0.234	0.674	0.216	0.682	0.238	0.478
1000	0.218	0.680	0.194	0.660	0.206	0.496

Table A.2: Comparison of labeling performance for DGP2 (sign pattern vs NG proxy).

	$\beta_3 = 0$		$\beta_3 = 0.05$		$\beta_3 = 0.3$	
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.15$	$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.958	0.518	0.958	0.516	0.968	0.712
500	0.974	0.456	0.972	0.500	0.962	0.712
750	0.976	0.428	0.976	0.454	0.984	0.710
1000	0.976	0.444	0.980	0.444	0.968	0.702
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.45$	$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.950	0.552	0.958	0.482	0.966	0.550
500	0.976	0.428	0.960	0.416	0.962	0.508
750	0.980	0.412	0.978	0.418	0.984	0.456
1000	0.972	0.392	0.968	0.394	0.982	0.438
$\lvert\beta_1\rvert - \lvert\beta_2\rvert = 0.65$	$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$		$\mathcal{N}(0,1)$	
T	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**	**Sign pattern**	**NG proxy**
250	0.972	0.476	0.962	0.460	0.968	0.522
500	0.978	0.390	0.968	0.400	0.974	0.416
750	0.974	0.374	0.976	0.402	0.980	0.386
1000	0.984	0.358	0.980	0.374	0.980	0.356

Figure A.1: Evolution of MSEs across methods and simulation settings in Gaussian cases.



(a) **DGP 1:** No endogeneity, $\beta_3 = 0$.

(b) **DGP 1:** Weak endogeneity, $\beta_3 = 0.05$.

(c) **DGP 1:** Strong endogeneity, $\beta_3 = 0.3$.

(d) **DGP 2:** No endogeneity, $\beta_3 = 0$.

(e) **DGP 2:** Weak endogeneity, $\beta_3 = 0.05$

(f) **DGP 2:** Strong endogeneity, $\beta_3 = 0.3$

A.3 Additional Empirical Results

The procedure we described for labeling the two shocks of interest requires testing the instrument's relevance and exogeneity conditions w_t. This requires imposing zero restrictions on certain elements of β and comparing the likelihood of two models, i.e., models with(out) restrictions. Given that we do not know, a priori, the ordering of structural shocks in the system, and therefore that of monetary policy shocks, it is necessary to specify those tests for each permutation of β to detect the space of shocks that can be labeled as potential monetary policy shock candidates. The table A.3 below shows the permutations and specifications of β which satisfy the relevance condition for p-value less than 0.01. We additionally report results for the exogeneity of w_t, along with AIC and BIC information criteria.

Table A.3: Labeling space satisfying LR tests procedure (DE20Y as w_t).

β specification	Exo	Relevance	AIC	BIC
$\beta = (0, 0, 0, \beta_4, 0, 0, \beta_7)$	1	0.0002	3594.158	4200.536
$\beta = (\beta_1, 0, 0, 0, 0, 0, \beta_7)$	1	0.0008	3597.253	4203.631
$\beta = (0, \beta_2, 0, \beta_4, 0, 0, 0)$	1	0.0008	3597.360	4203.737
$\beta = (0, 0, 0, \beta_4, \beta_5, 0, 0)$	1	0.0015	3598.576	4204.954
$\beta = (0, 0, 0, \beta_4, 0, \beta_6, 0)$	1	0.0047	3600.794	4207.171

A.3.1 Testing for the non-Gaussianity of the errors

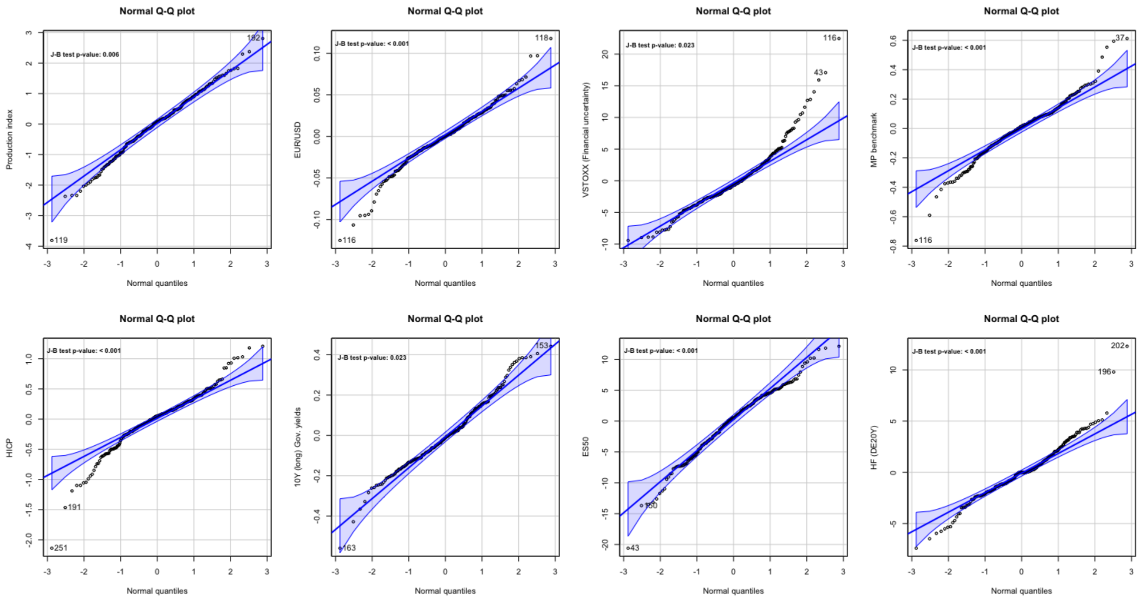


Figure A.2: Normal Q-Q plots of VAR residuals. The figure shows Normal Q-Q plots of the residuals (u_t) for all variables entering the baseline VAR. Each sub-graph also indicates the associated p-value of the Jarque-Bera tests. Given the very low p-values, this leads us to support the hypothesis of non-Gaussianity underlying the identification of shocks.

A.3.2 Historical decomposition and FEVD of stock prices and long yields

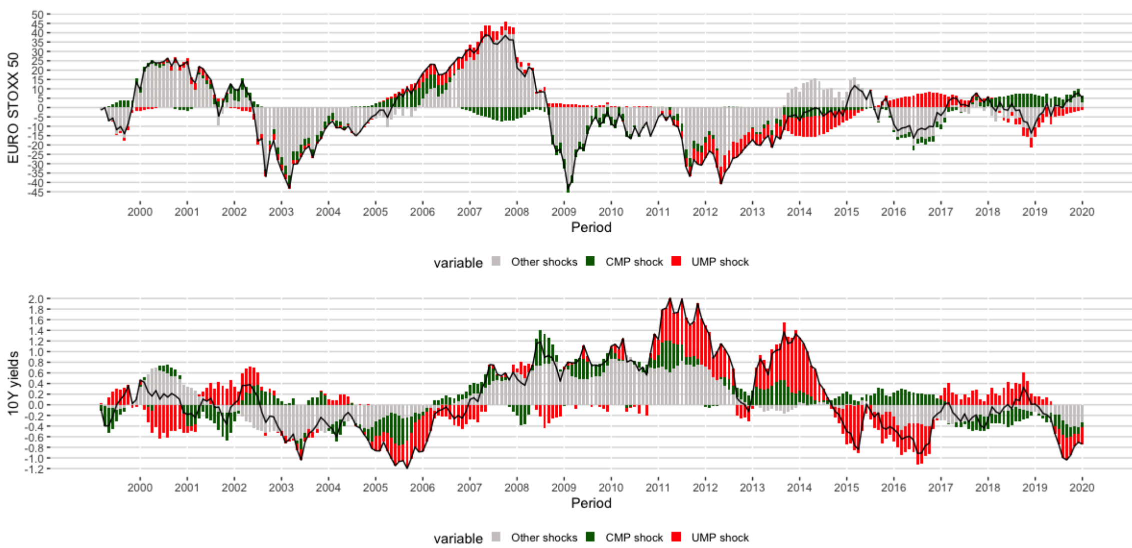


Figure A.3: Historical decomposition of stock prices (EURO STOXX 50) and long-term yields. The legend and the construction of the series plotted are the same as Figure 4 shown in the empirical part of the paper (Section 4.2.2).

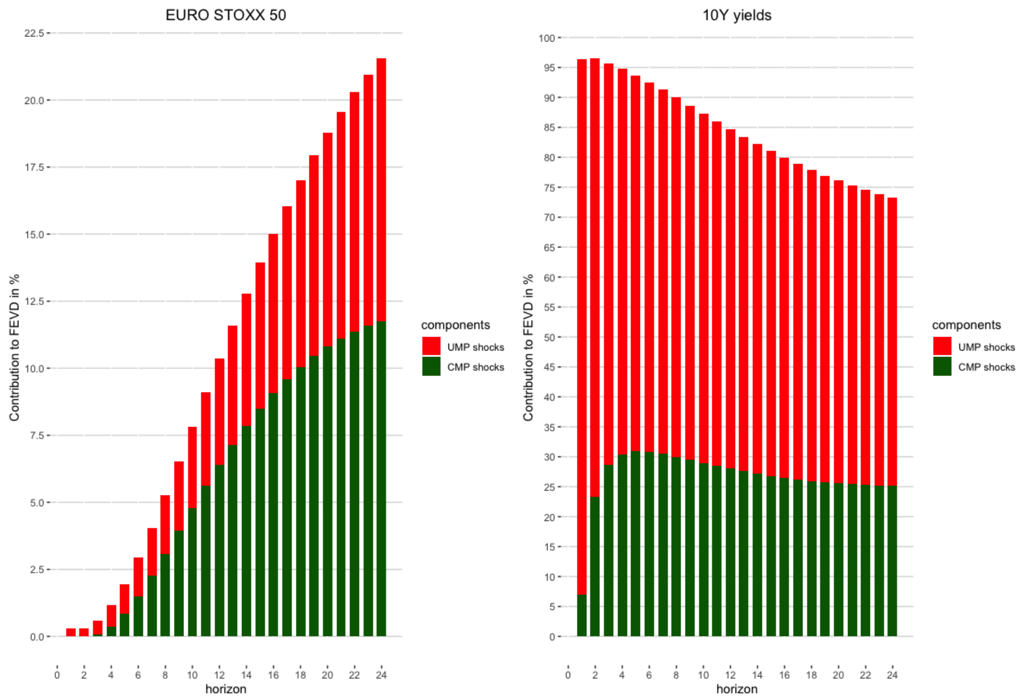


Figure A.4: FEVD of stock prices (top) and long-term yields (bottom). The legend is similar to Figure 5 discussed in the empirical part of the paper (Section 4.2.2).

A.3.3 Robustness analysis

In this section, we stress the robustness of our baseline results for both the impulse responses and the labeling of the shocks. First, we apply the same framework as before while changing the instrument in the model. The dataset of Altavilla et al. (2019) enables us to take surprises in the German yield for different maturities. Thus, we consider two other instruments by taking high-frequency reactions in the German yield with a thirty-year maturity (DE30Y) and a ten-year maturity (DE10Y).

As before, we set the order[1] of the VAR to $p = 2$ and specify D according to the LR tests. It leads us to select the same columns as before for both alternative instruments considered. In the following, we examine the impact of changing the instrument on both the impulse responses and the shock labeling.

Longer maturity instrument (DE30Y)

Figure A.5 depicts the impulse responses associated with the two monetary policy shocks identified in our framework. Overall, the responses are similar to the ones observed earlier. Indeed, we observe the same kind of dynamics in the responses to the shocks. However, note that we find some differences in the magnitude of certain responses. Focusing first on the instrument, we observe a higher sensitivity of the instrument to unconventional shocks. The associated reactions at impact are now respectively 0.6 and 0.125, making the

[1]Note that this lag order is higher than suggested by the AIC. The optimal lag length according to the AIC is $p = 1$ for both instruments. We also perform the analysis with this lag order and obtain similar results concerning impulse responses and the labeling of shocks.

difference more pronounced than in the baseline specification (0.5 and 0.2). Moreover, we also observe a change in the magnitude of interest rate responses. While the reaction of the German rate to conventional shocks remains similar, the reaction to unconventional shocks is now higher and significant in the very first periods. Also, the magnitude of the response in long yields is reduced. The impact response is 0.025, and the response peaks below 0.1, while for the baseline model, we observed an impact response of 0.05 and a peak above 0.1. Finally, focusing on the reaction of the VSTOXX, we again observe similar dynamics as before. Monetary policy tightening results in an increase in the level of uncertainty perceived by investors in the months following the impact. Although the VSTOXX impulse response peaks at a higher level (0.5) for unconventional shocks than before, it remains more affected by conventional shocks. Financial uncertainty tends to be more affected by conventional monetary policy shocks than unconventional shocks.

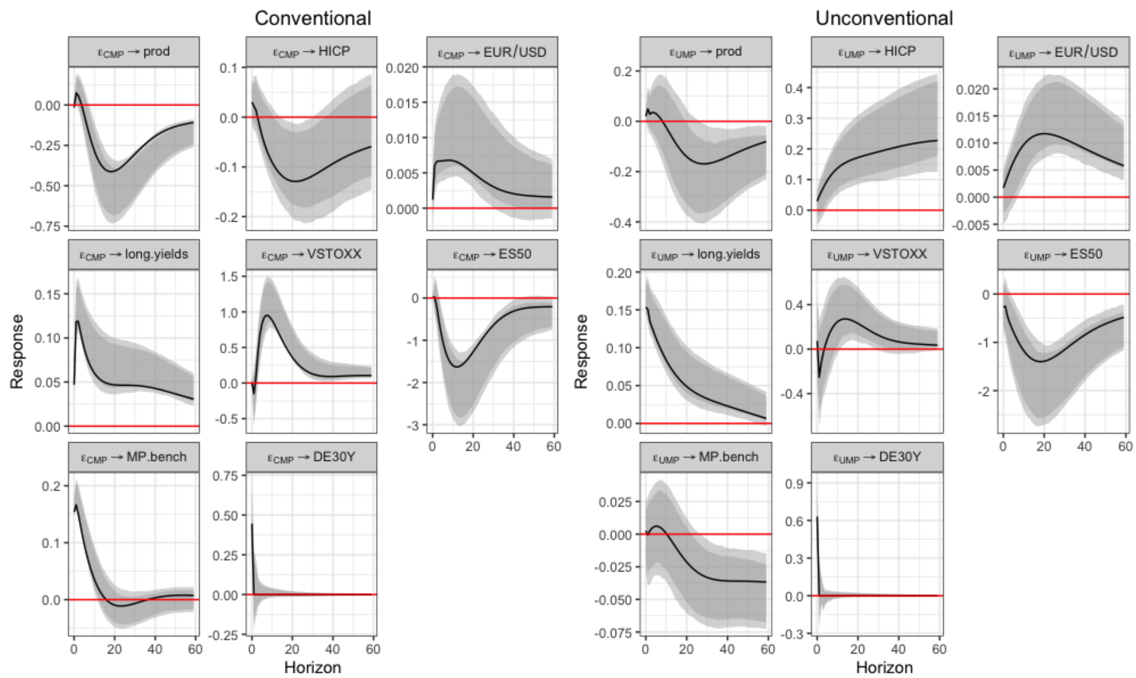


Figure A.5: Impulse responses to conventional (left) and unconventional (right) monetary policy shocks for a longer maturity instrument (DE30Y). Confidence bands are obtained by moving block bootstrap (block length = $T^{1/3}$) with 16-84 (darker band) and 10-90 (lighter band) Hall's percentiles.

Finally, to complete the interpretation of the results with this instrument, we also observe, as with the baseline model, that the magnitude of the responses is consistent with the labeling of the shocks. The change in variance of the shocks is now more pronounced, with the variance of the unconventional shocks increasing from 0.83 to 1.1 while the unconventional shocks decrease from 1.09 to 0.78. As shown in Figure **??** and Figure A.7, the properties of the considered shocks over time (time series and time-varying estimates of the variance) remain also similar to what was observed earlier.

Shorter maturity instrument (DE10Y)

We now turn to the case where the instrument has a shorter maturity. Figure A.6 summarizes the impulse responses of the model to the shocks. We notice as before that the responses match the ones observed for the baseline specification, as well as those discussed for the longer maturity instrument (DE30Y). The major difference lies in the instrument's reaction to the shocks. The reactions of high-frequency surprises to unconventional and conventional shocks are now respectively 0.56 and 0.41, making the difference less pronounced than before. Nevertheless, the conclusions regarding uncertainty and other impulse responses remain identical. The evolution of shocks' time series and rolling variances is depicted in Figure A.7. As before, the shocks exhibit similar properties as previously observed[2].

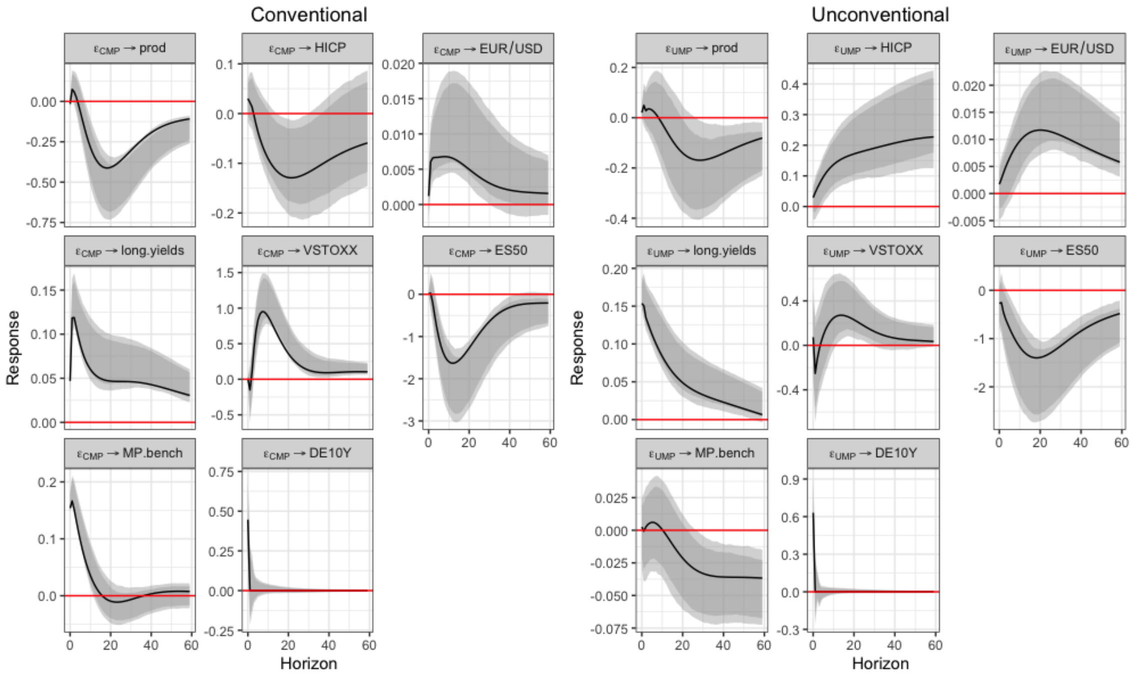


Figure A.6: Impulse responses to conventional (left) and unconventional (right) monetary policy shocks for a shorter maturity instrument (DE10Y). Confidence bands are obtained by moving block bootstrap (block length = $T^{1/3}$) with 16-84 (darker band) and 10-90 (lighter band) Hall's percentiles.

[2]Note that the evolution of the variance is somewhat different. Indeed, we only observe a decrease in the variance of "conventional" shocks, and no longer an increase in the variance of "non-conventional" shocks as this was previously the case.

Time series of the shocks

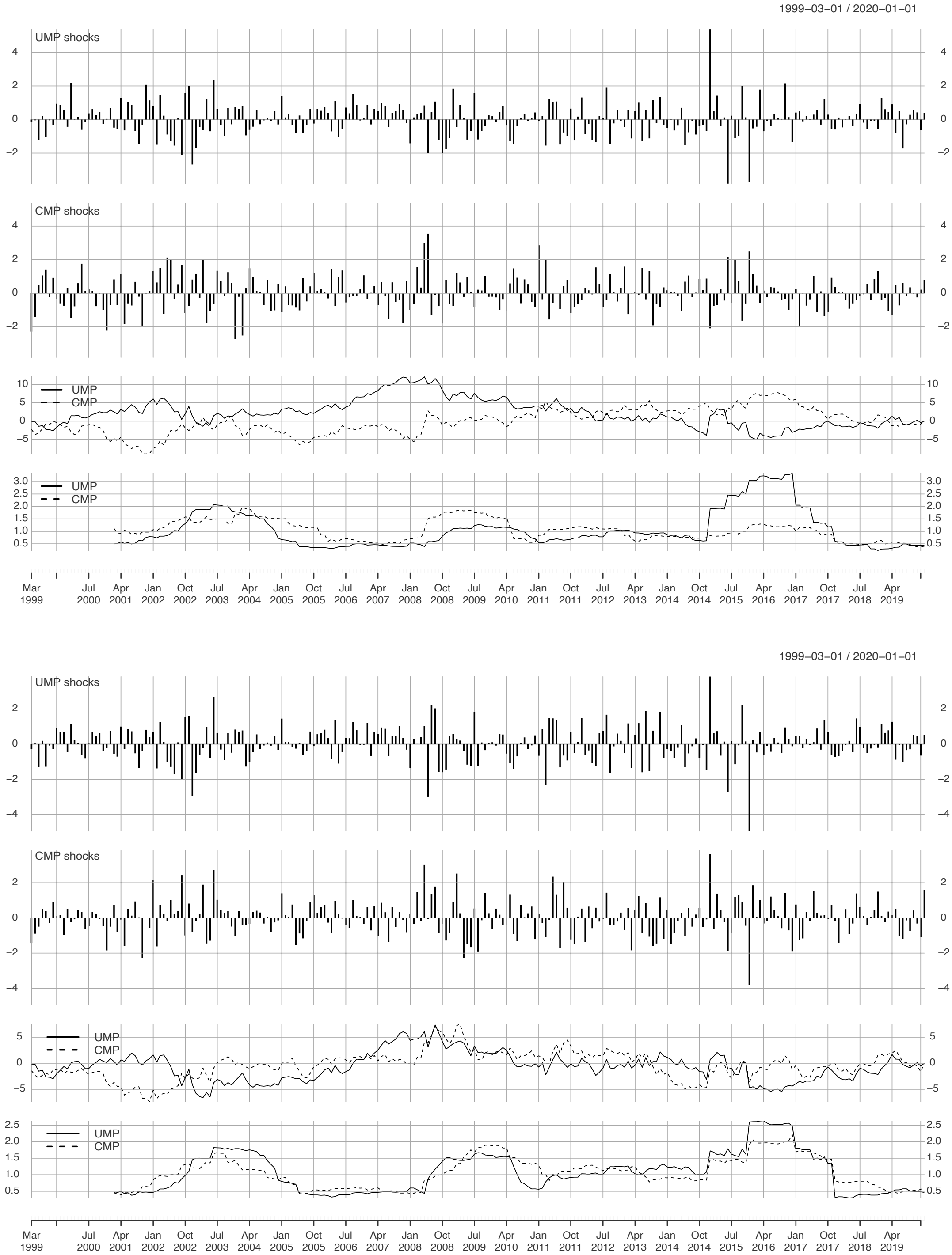


Figure A.7: Time series properties of monetary policy shocks under a longer (top,DE30Y) maturity instrument and shorter (bottom, DE10Y) one. Each figure is composed of four panels: the first two panels exhibit respectively the time series of unconventional (UMP) and conventional (CMP) monetary policy shocks, the third panel shows the cumulative sum of shocks (dashed: conventional, plain: unconventional), and the last panel plots the evolution of the variance of the shocks with a 24-month rolling window (dashed: conventional, plain: unconventional).

Comparing and identifying monetary policy shocks via sign restrictions

To compare the properties of our two main shocks of interest, we also conduct a complementary analysis in which we identify monetary policy and information shocks by imposing sign restrictions on the movement of policy surprises taken from the Euro Area Monetary Policy Event-Study Database (EA-MPD, Altavilla et al. 2019). The sign restrictions imposed are directly taken from those of Goodhead (2024) to isolate three sources of disturbances: a forward guidance (FG) shock, a yield curve compression shock, and an information shock. Following Jarociński and Karadi (2020), we identify an information (communication) shock as a shock that raises both short-term rates and equity prices. This shock reflects revisions in investors' beliefs about future macroeconomic conditions rather than a pure change in the monetary policy stance. We assume that FG shocks affect the expected path of short rates and hence move both the 2-year yield and the long end, with a modest steepening of the yield curve. By contrast, policy shocks like QE compress long-term yields relatively more than short-term ones, leading to a flattening of the 10Y–2Y slope. Table A.4 below summarizes the sign restrictions imposed on the set of surprises taken from Altavilla et al. (2019). Structural shocks are obtained following Rubio-Ramirez et al. (2010), a QR-rotation algorithm with allows sign and zero restrictions for achieving identification. Out of 500,000 random orthonormal rotations, we retain the first 500 matrices satisfying all restrictions and use their element-wise median as the point estimate of the impact matrix among the set of admissible rotations.

Table A.4: Sign restrictions imposed as Goodhead (2024).

	Forward Guidance	Yield Curve Compression	Information
2Y DE Yield	$+$	$+$	$+$
10Y - 2Y DE Yield (Slope)	$+$	$-$	(unrestricted)
STOXX50	$-$	$-$	$+$

Table A.5: Correlation between shocks (NG-Proxy vs. sign restrictions).

NG-Proxy	**SR-based**	**Correlation**	**t-statistic**	**Signif.**
CMP	FG	0.260	4.25	***
CMP	YComp	-0.244	-3.97	***
CMP	INFO	-0.162	-2.60	**
UMP	FG	0.096	1.52	
UMP	YComp	-0.619	-12.44	***
UMP	INFO	-0.254	-4.15	***

Notes: All shocks are standardized. Two-sided tests of $H_0 : \rho = 0$.
Significance levels: * $p < 0.10, * * p < 0.05, * * * p < 0.01$.

A.3.4 Bias-corrected impulses responses (Kilian, 1998)

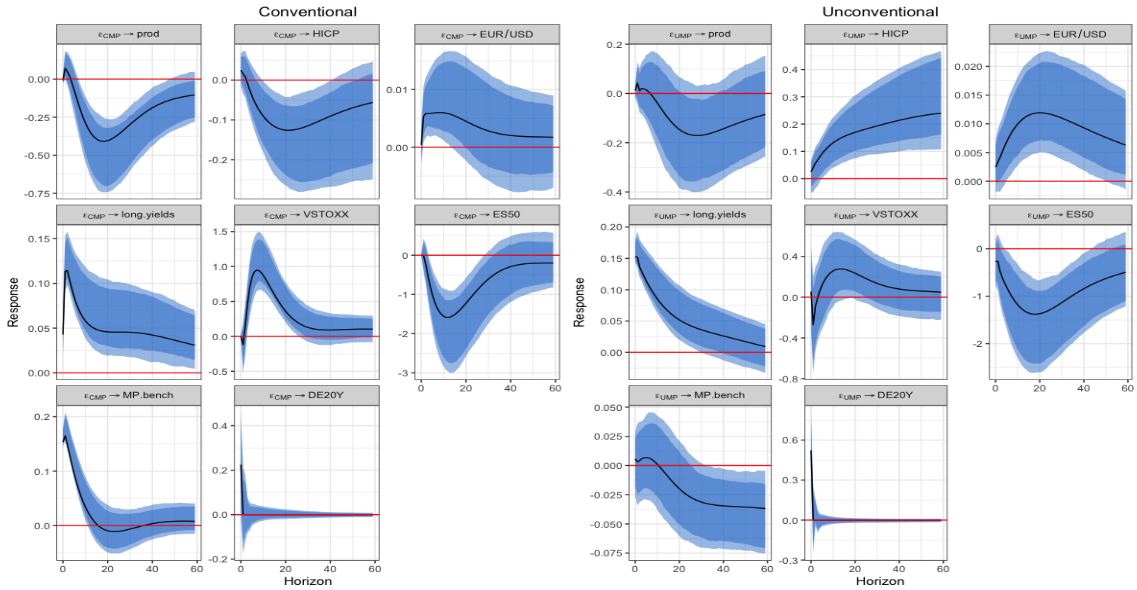


Figure A.8: Bootstrap-after-bootrap impulse responses (baseline specification, DE20Y) to conventional (left column) and unconventional (right column) monetary policy shocks. Confidence bands are obtained by using the bias-corrected bootstrap procedure of Kilian (1998) to account for any potential small sample biases with 16-84 (darker band) and 10-90 (lighter band) Hall's percentiles.

Appendix B

Appendix to Chapter 3

This document provides additional details regarding the methods and results discussed in the paper. Appendix B.1 complements Section 2.2 of the paper for the identification of monetary policy shocks. Appendix B.2 documents the Bayesian estimation framework, including the stochastic volatility specification, prior choices, and the MCMC procedure used for posterior inference.

B.1 Identification of Monetary Policy Shocks

We analyze two complementary identification strategies. First, a daily approach à la Inoue and Rossi (2021), in which monetary policy shocks components are defined as the factor changes from a daily Nelson and Siegel (1987); Diebold and Li (2006) yield curve model estimated on the grid

$$\boldsymbol{\tau}^{\text{daily}} = (12, 24, 36, 48, 60, 72, 84, 96, 108, 120, 240, 360) \text{ months.}$$

Second, a high-frequency (HF) approach that projects intra-day German yield surprises from Altavilla et al. (2019) onto the NS space using

$$\boldsymbol{\tau}^{\text{HF}} = (24, 36, 48, 60, 72, 84, 96, 108, 120, 240, 360) \text{ months.}$$

The figures below introduce each step and object used in the identification and provide visual checks of fit and interpretation. Sections B.1.1 and B.1.2 respectively present monetary policy shocks and their components identified as (Inoue and Rossi, 2021) and those captured from HF surprises. Finally, Section B.1.3 compares the properties of the shock components under each approach. We also connect our shocks with those captured during the conference window (Timing, FG, QE) by Altavilla et al. (2019)

B.1.1 Daily-based identification

Figure B.1 summarizes the cross-sectional evolution of the German zero-coupon curve at $\boldsymbol{\tau}^{\text{daily}}$ over 1999–2020, providing the raw object used for daily NS estimation. Figures B.4 and B.5 then report the estimated factors and their loading functions, clarifying the interpretation of level, slope, and curvature across maturities. Finally, Figure B.6 illustrates an announcement-day shock as a maturity profile $\Delta y(\tau)$ implied by factor changes $(\Delta\beta_1, \Delta\beta_2, \Delta\beta_3)$.

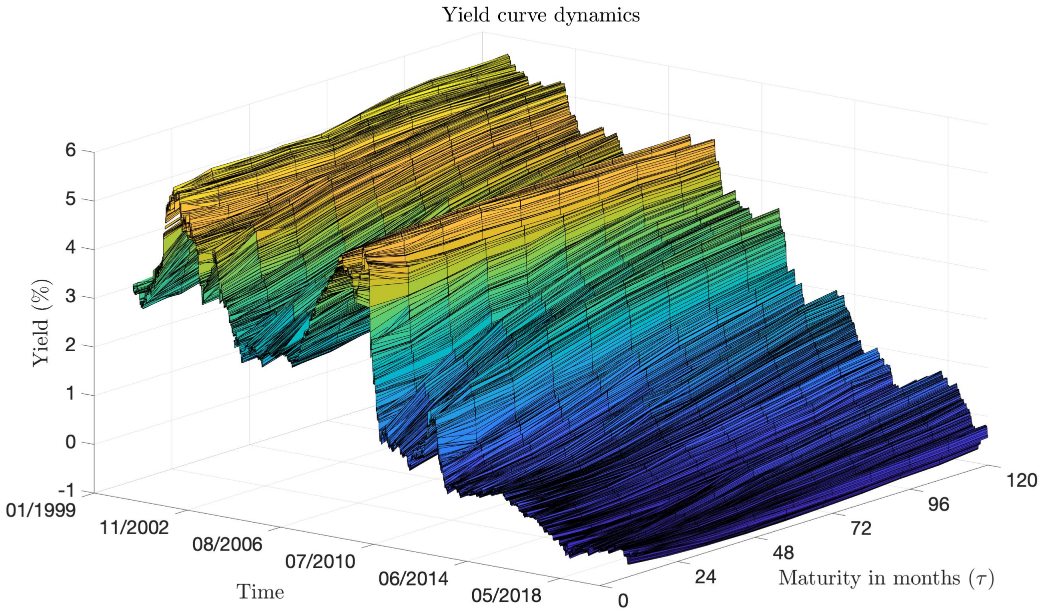


Figure B.1: German yields over time (daily). Cross-sections of $y_t(\tau)$ at $\boldsymbol{\tau}^{\text{daily}} = (12, \ldots, 120, 240, 360)$ months, 1999–2020. This panel provides the raw input for the daily Nelson–Siegel estimation used to construct announcement-day factor changes.

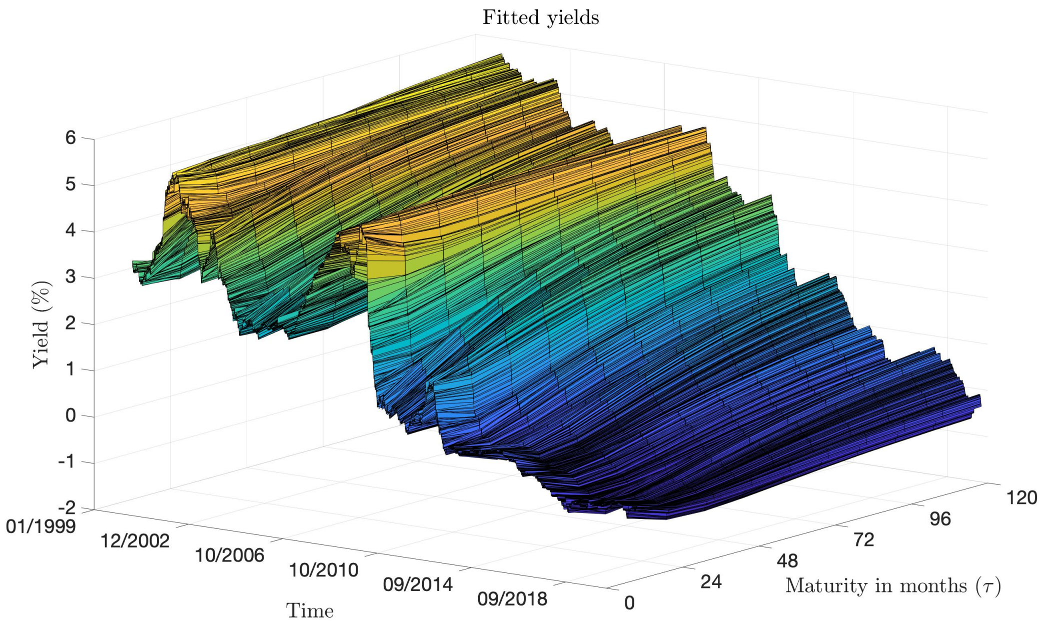


Figure B.2: Fitted German yields over time (daily). Cfr Figure B.1.

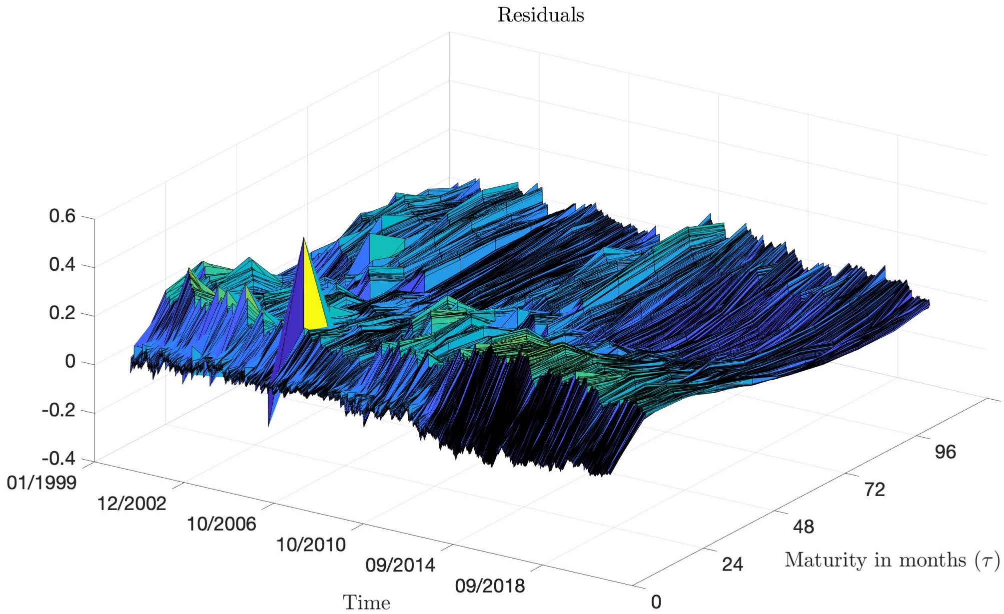


Figure B.3: Residuals after estimation of the NS model on daily yields. Cfr Figure B.1.

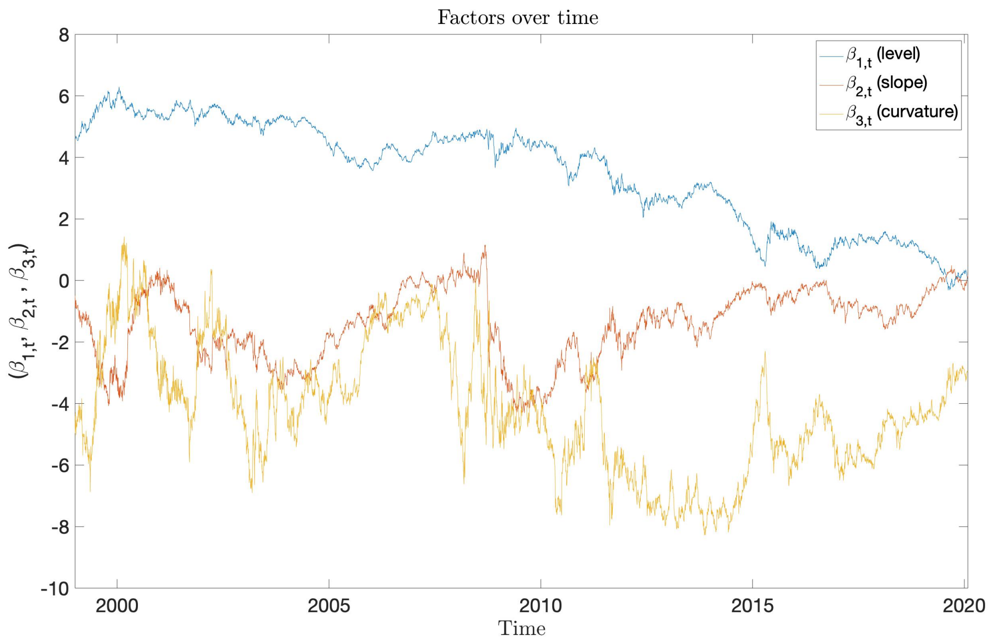


Figure B.4: Daily Nelson–Siegel factors. Time series of level ($\beta_{1,t}$), slope ($\beta_{2,t}$), and curvature ($\beta_{3,t}$) estimated from $y_t(\tau)$ on $\boldsymbol{\tau}^{\text{daily}}$. These factors summarize parallel shifts (level), steepening/flattening (slope), and hump-shaped movements (curvature) of the term structure.

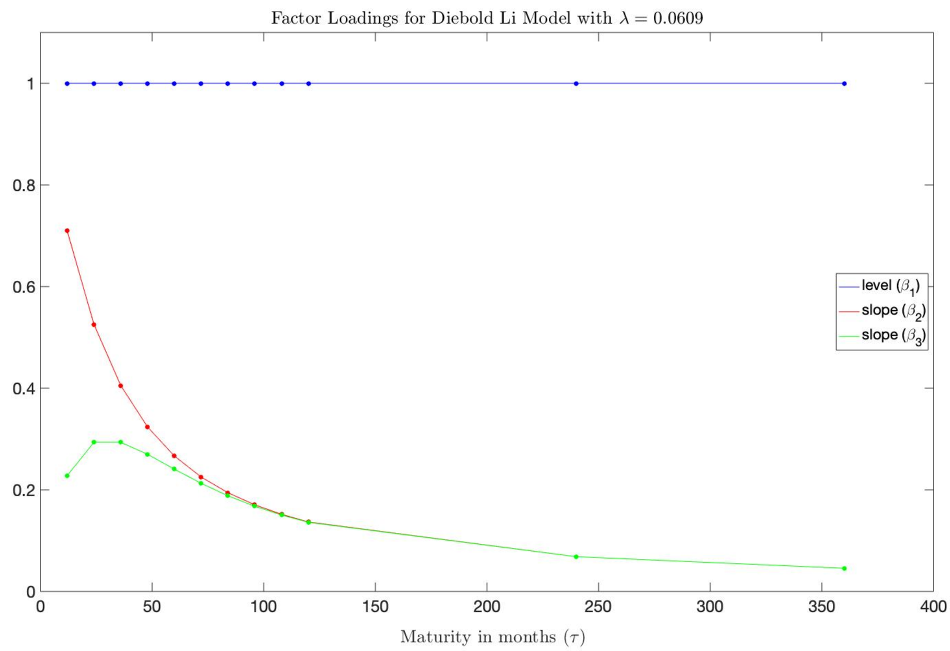


Figure B.5: Nelson and Siegel (1987); Diebold and Li (2006) loading functions across maturities. Factor loadings evaluated over $\boldsymbol{\tau}^{\text{daily}}$ show (i) uniform loading for level, (ii) decaying short-end sensitivity for slope, and (iii) a hump for curvature, guiding the interpretation of factor changes on announcement days.

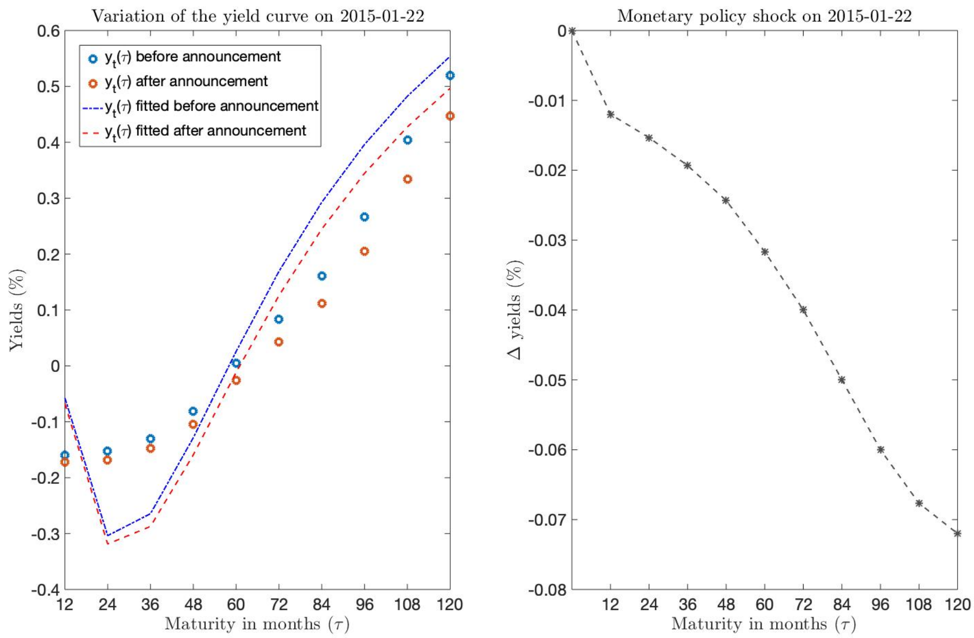


Figure B.6: Example announcement-day shock profile (daily identification). Fitted change in the curve $\Delta y(\tau)$ as a function of maturity τ implied by $(\Delta\beta_1, \Delta\beta_2, \Delta\beta_3)$ on the selected event date.

B.1.2 High-frequency identification

We next project intra-day yield surprises from Altavilla et al. (2019) onto the NS space at $\boldsymbol{\tau}^{\text{HF}}$. Figure B.7 reports the observed surprises (top) and their NS fit (bottom) across monetary policy announcements, confirming that the NS basis captures the cross-sectional pattern of policy shocks within the tight announcement window. Figure B.8 plots the shocks and is a replication of Figure 1 of the paper. Figure B.9 plots a representative shock profile captured within an HF window, alongside the three components.

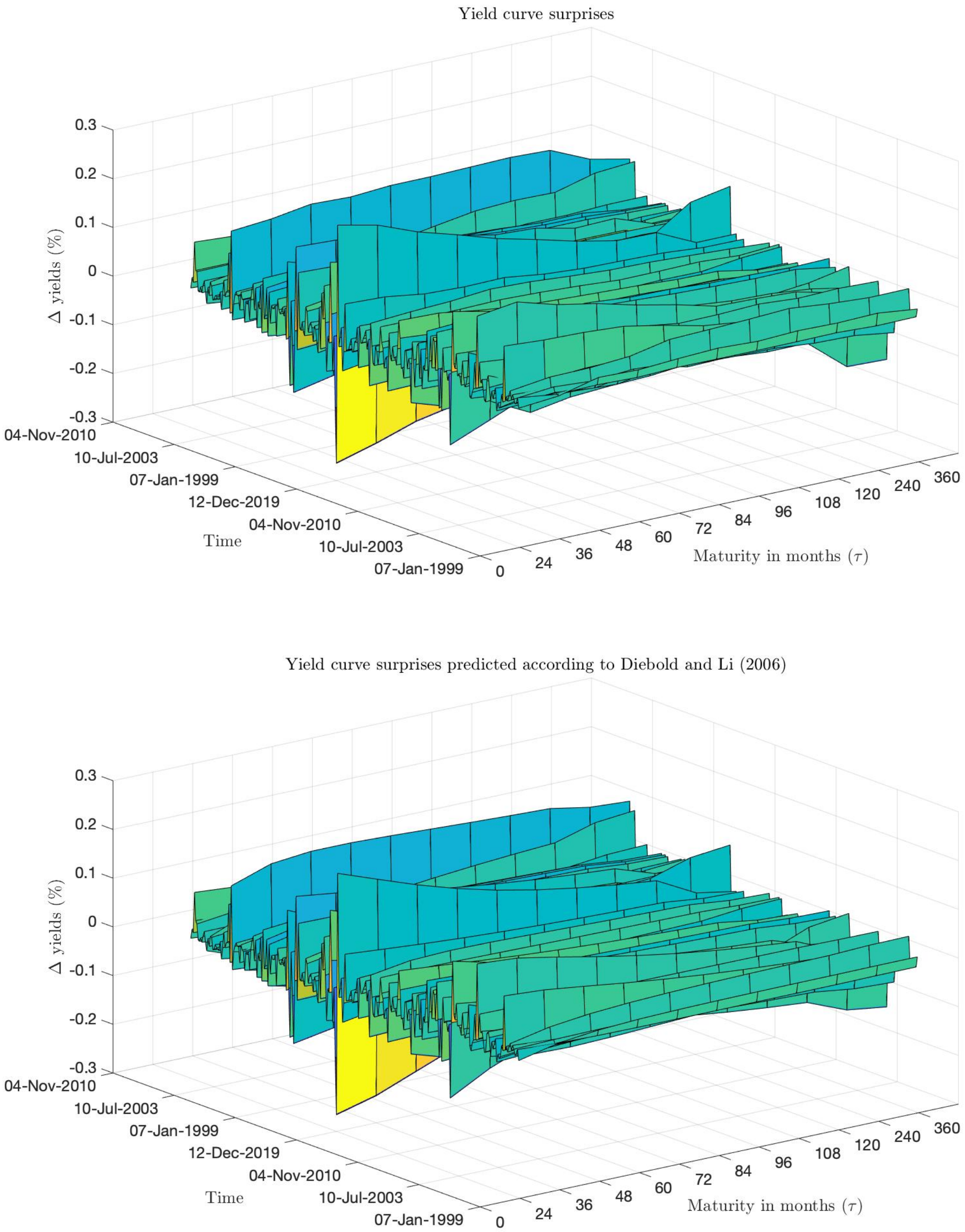


Figure B.7: Observed and NS-fitted yield surprises (HF identification). Top: raw intra-day German surprises (DExxY) from Altavilla et al. (2019) at $\boldsymbol{\tau}^{\mathrm{HF}} = (24, \ldots, 120, 240, 360)$ months over ECB announcements. Bottom: Nelson–Siegel fit, used to recover HF factor movements $(\Delta\beta^{\mathrm{HF}}_{1,t}, \Delta\beta^{\mathrm{HF}}_{2,t}, \Delta\beta^{\mathrm{HF}}_{3,t})$.

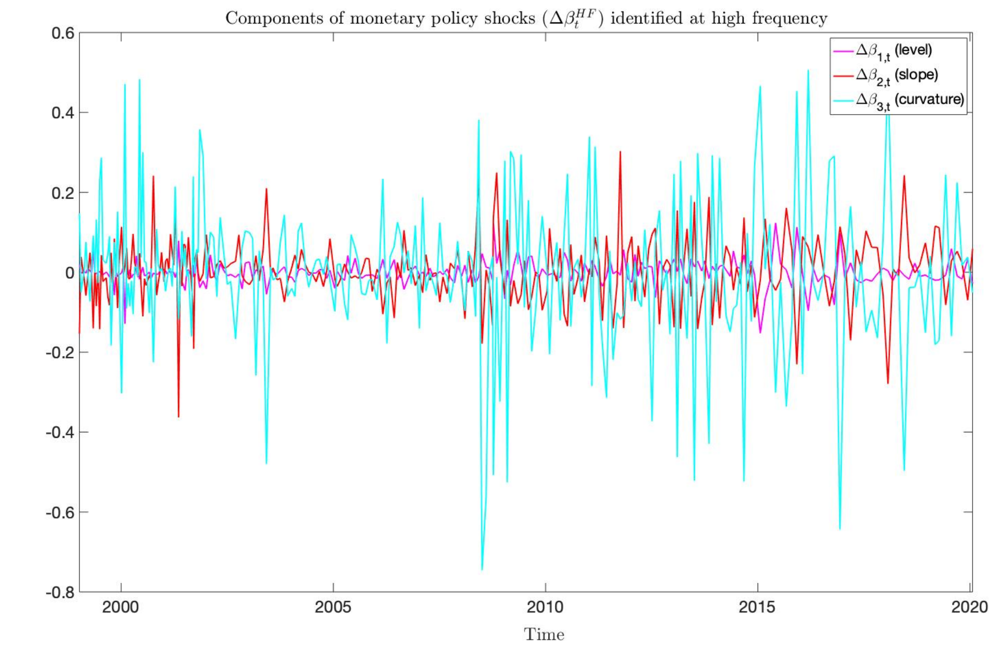


Figure B.8: HF factor components of policy shocks. Time series across announcements of $(\Delta\beta_{1,t}^{\mathrm{HF}}, \Delta\beta_{2,t}^{\mathrm{HF}}, \Delta\beta_{3,t}^{\mathrm{HF}})$ obtained from projecting intra-day surprises onto the NS basis on $\boldsymbol{\tau}^{\mathrm{HF}}$.

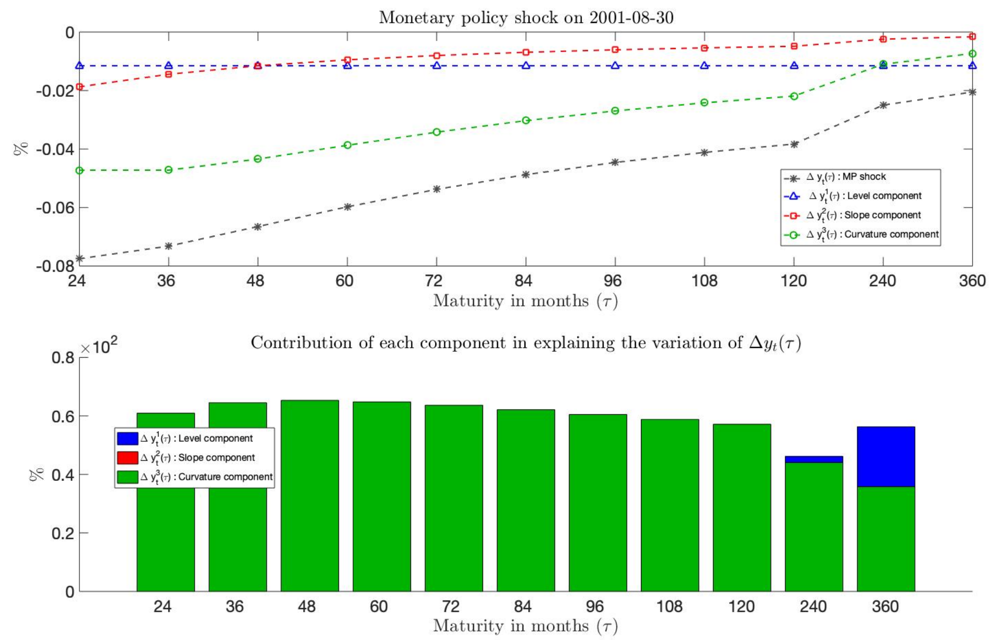


Figure B.9: Representative shock profile captured for a particular monetary policy announcement day. Fitted maturity pattern $\Delta y^{\mathrm{HF}}(\tau)$ across $\boldsymbol{\tau}^{\mathrm{HF}}$ for a single announcement (e.g., 2001-08-30). The plot visualizes how the HF surprise maps into level, slope, and curvature movements of the curve.

B.1.3 Shocks comparison

This section compares the structure and co-movement of components across identification schemes. Figure B.10 provides 3-D scatterplots among level, slope, and curvature components across both approaches. Figure B.12 aligns daily and HF factor changes one-for-one by component to gauge concordance.

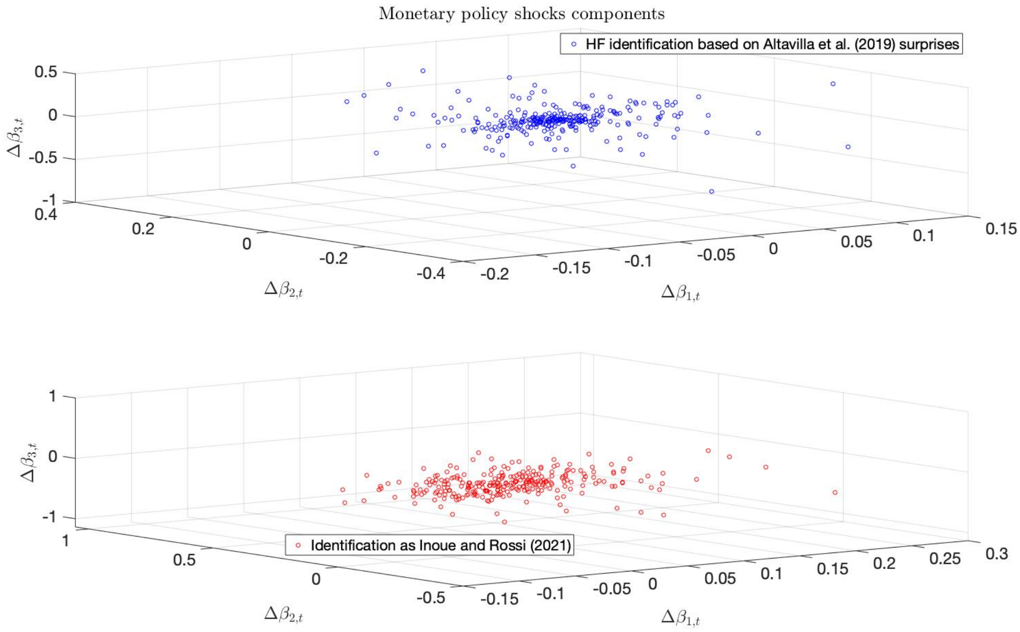


Figure B.10: 3-D scatterplots of MP shocks components. Daily vs HF window.

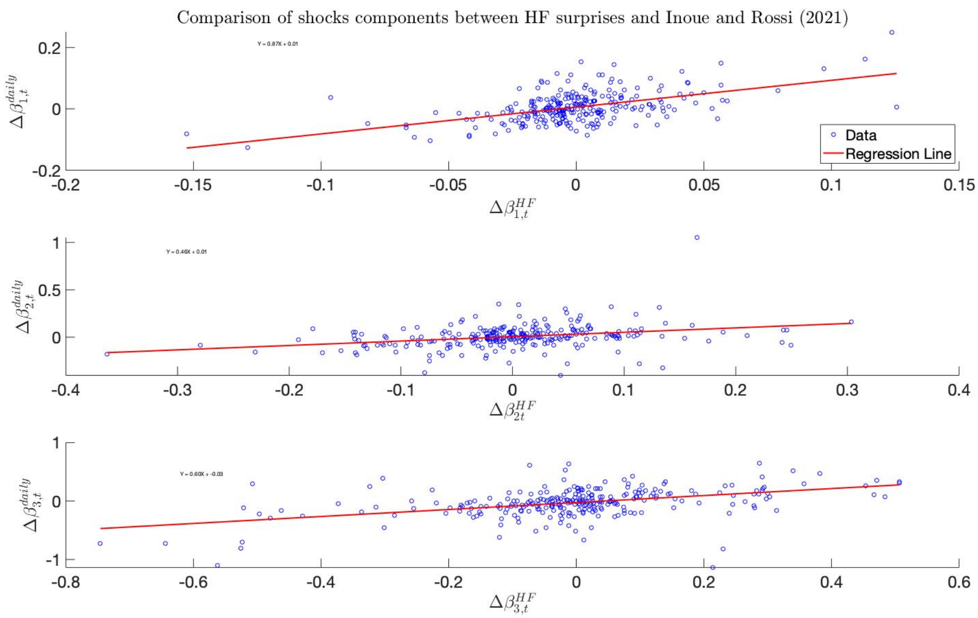


Figure B.11: $\Delta\beta_t^{daily}$ vs $\Delta\beta_t^{HF}$.

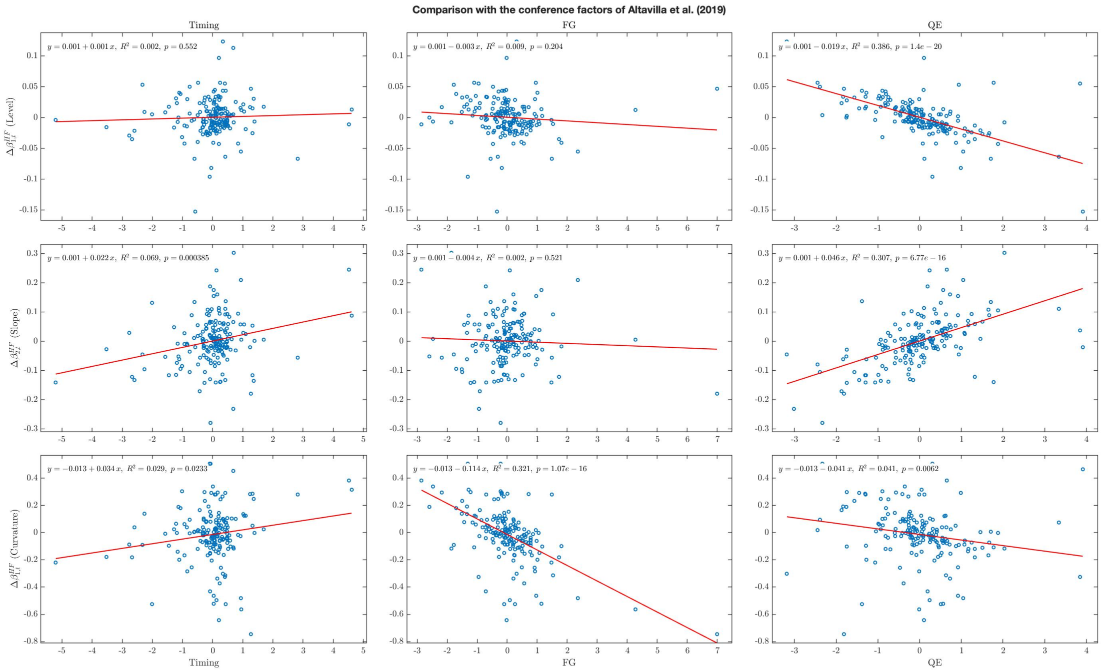


Figure B.12: $\Delta\beta_t^{HF}$ vs conference factors (Timing,FG,QE) by Altavilla et al. (2019).

Figure B.12 reports pairwise regressions of high-frequency yield curve factor changes ($\Delta\beta_{1,t}^{HF}, \Delta\beta_{2,t}^{HF}, \Delta\beta_{3,t}^{HF}$) on the conference-window monetary policy surprises of Altavilla et al. (2019). Before turning to the empirical correlations, it is useful to highlight the conceptual differences between our identification strategy and the approaches of Gürkaynak et al. (2005), Altavilla et al. (2019), and Swanson (2021), as emphasized by Inoue and Rossi (2021).

In the Gürkaynak et al. (2005) framework, policy surprises are extracted as a small number of orthogonal factors derived from high-frequency changes in a limited set of asset prices (and yields) around monetary policy announcements. These factors are subsequently rotated to obtain interpretable policy objects (instruments), such as a "current target" (policy-rate) shock and a "path" shock affecting expectations of future short rates. Altavilla et al. (2019) extend this methodology to separate forward-guidance and QE components.

By contrast, in the functional approach of Inoue and Rossi (2021), the shock is the entire high-frequency change in the yield curve. Rather than isolating a predetermined set of orthogonal policy instruments, monetary policy shocks correspond to potentially time-varying combinations of changes in level, slope, and curvature. The dimensionality of the shock is therefore not fixed, and different episodes may involve different maturities and different loadings. In this sense, the Nelson and Siegel (1987) (NS) factors do not aim to replicate GSS or Altavilla et al. (2019) shocks; instead, they summarize the shape of the yield curve's high-frequency response, providing a unified and real-time tractable representation of monetary policy disturbances.

These conceptual differences help explain why our shocks are only partially aligned with the Altavilla et al. (2019) factors. The Altavilla et al. (2019) components (Timing, FG, QE) are constructed to be mutually orthogonal and correspond to specific policy dimensions, while the NS factors capture broad features of the term-structure movement (parallel shifts, steepening, and curvature adjustments). A policy surprise that affects several maturities at once may therefore load on a combination of level, slope, and curvature even if, in the Altavilla et al. (2019) decomposition, it appears as a single FG or QE surprise.

Turning to the empirical correlations, three patterns emerge clearly from Figure B.12. First, the most pronounced relationships are obtained for QE surprises: the level factor displays the highest R^2 in the figure ($R^2 \approx 0.39$, $p < 10^{-20}$), followed by the slope factor ($R^2 \approx 0.31$, $p < 10^{-15}$). These correlations reflect that QE announcements tend to induce substantial movements at the long end of the curve, which the Nelson and Siegel (1987) representation decomposes into changes in the overall level and long-short differentials. Second, forward-guidance (FG) surprises exhibit the strongest association with the curvature component: the regression delivers an R^2 of about 0.32 (with a statistically significant negative coefficient). FG shocks typically affect medium-term maturities, regions where the curvature loadings are largest, and therefore naturally map into that dimension of the factor space. Third, Timing surprises show only weak explanatory power for any of the three factors (R^2 values below 0.03), which is consistent with the fact that Timing shocks primarily move very short-term rates (up to two years), while our factors are extracted from maturities starting at two years.

Overall, the correlations indicate that our high-frequency shocks exhibit economically meaningful co-movements with standard high-frequency monetary policy measures, particularly QE in terms of level and slope, and FG in terms of curvature. At the same time, differences in sign and magnitude are expected given the distinct conceptual foundations: Altavilla et al. (2019) shocks capture orthogonal policy instruments, whereas our NS factors summarize the functional form (geometry) of the yield-curve response. The observed correlations, therefore, validate that our shocks embed some information related to these policy dimensions, while also providing a complementary representation of the multidimensional effects of monetary policy on the term structure.

B.2 Bayesian Estimation and MCMC

B.2.1 Model specification

We estimate a stochastic volatility model augmented with shocks as exogenous covariates (SV-X), where the state of volatility of financial asset returns (h_t) is influenced by variations in level, slope, and curvature components. The observed return series is denoted $r_t = (r_1, \dots, r_T)'$, and $h = (h_1, \dots, h_T)'$ is the unobserved state of log-variance of returns.

The model is defined as follows:

$$r_t = \exp(h_t/2)\,\xi_t, \qquad \xi_t \sim \mathcal{N}(0,1), \tag{B.1}$$

$$h_1 \sim \mathcal{N}\left(\mu, \frac{\omega^2}{1-\phi^2}\right), \tag{B.2}$$

$$h_t = \mu + \phi(h_{t-1} - \mu) + \theta_1 x_{1,t} + \theta_2 x_{2,t} + \theta_3 x_{3,t} + \nu_t, \tag{B.3}$$

$$\nu_t \sim \mathcal{N}(0, \omega^2), \qquad \text{for } t = 2, \ldots, T. \tag{B.4}$$

The covariates $(x_{1,t}, x_{2,t}, x_{3,t})'$ denote, respectively, the components of shocks: level, slope, and curvature.

Prior distributions

The prior specifications are as follows:

- $\mu \sim \mathcal{N}(0, \sqrt{10})$
- $\phi \sim \mathcal{N}(0.9, 0.1)$ constrained to $[-1, 1]$
- $\omega^2 \sim$ Inverse-Gamma$(5, 0.16)$
- $\theta = (\theta_1, \theta_2, \theta_3)' \sim \mathcal{N}(\mathbf{0}, \mathbf{I_3})$

The initial state h_1 is drawn from its stationary distribution implied by the process in (B.4).

B.2.2 Posterior inference via MCMC

Posterior inference is conducted using Markov Chain Monte Carlo (MCMC) methods. We employ the No-U-Turn Sampler (NUTS) of Hoffman et al. (2014), an adaptive variant of Hamiltonian Monte Carlo (HMC), as implemented in Stan. NUTS automatically adjusts the path length in HMC to ensure efficient exploration of the posterior distribution, especially in high-dimensional models with latent variables.

Sampling proceeds by drawing from the joint posterior distribution of the model parameters $\{\mu, \phi, \omega^2, \theta_1, \theta_2, \theta_3\}$ and the full latent state vector $\{h_1, \ldots, h_T\}$ conditional on the data. The sampler generates draws from the posterior distribution,

$$p(\mu, \phi, \omega^2, \theta_1, \theta_2, \theta_3, h_{1:T} \mid y),$$

which are then used to compute point estimates and credible intervals for inference. All results reported in the main text are based on posterior summaries obtained after running 4 different chains, each with a length of 5000 effective draws (burn-in = 2000).

B.3 Additional Figures and Tables

Table B.1: Summary statistics of log returns (r_t).

Variable name	Mean	Sd	Min	Max	Skewness	Kurtosis	Q1	Median	Q3
1. BD BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.01	0.34	-1.85	2.25	-0.21	1.92	-0.18	0.01	0.21
2. BG BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.01	0.42	-17.46	2.35	-13.28	548.95	-0.17	0.01	0.21
3. ES BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.00	0.77	-47.50	6.50	-42.02	2588.95	-0.21	0.01	0.23
4. FR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.02	0.73	-2.02	48.06	50.85	3324.97	-0.18	0.01	0.21
5. GR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.04	3.09	-29.19	198.54	48.76	3127.92	-0.27	0.00	0.27
6. IR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.02	1.02	-5.09	66.60	51.17	3349.00	-0.17	0.01	0.20
7. IT BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.03	1.77	-3.69	126.63	66.80	4781.20	-0.21	0.01	0.23
8. UK BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	0.04	2.42	-1.91	176.85	71.33	5218.94	-0.21	0.00	0.23
9. EMU BENCHMARK 10 YR. DS GOVT. INDEX - CLEAN PRICE INDEX	0.04	2.50	-1.85	183.81	72.07	5290.71	-0.18	0.01	0.21
10. IBOXX EURO CORPORATES - Cln Prc Indx Today	0.02	1.20	-1.08	88.42	71.81	5265.43	-0.09	0.00	0.10
11. IBOXX EURO OVERALL - Cln Prc Indx Today	0.02	1.12	-1.04	81.50	70.73	5160.70	-0.10	0.01	0.11
12. IBOXX EURO EUROZONE - Cln Prc Indx Today	0.02	1.13	-1.23	82.16	69.61	5051.92	-0.12	0.00	0.13
13. ICE BofA AAA Euro Corporate Index - Clean price	0.00	0.22	-5.17	3.32	-3.44	87.43	-0.10	0.00	0.11
14. ICE BofA BBB Euro Corporate Index - Clean price	0.00	0.18	-2.86	1.72	-0.51	21.24	-0.08	0.00	0.09
15. ICE BofA 1-3 Year BBB Euro Corporate Index - Clean price	0.00	0.13	-2.17	2.63	1.02	95.14	-0.03	0.00	0.03
16. ICE BofA 1-10 Year AAA Euro Corporate Index - Clean price	0.00	0.19	-4.09	4.33	0.07	134.53	-0.07	0.00	0.08
17. FTSE100PRICEINDEX	0.00	1.14	-9.27	9.38	-0.17	6.51	-0.52	0.00	0.57
18. FRANCECAC40PRICEINDEX	0.01	1.38	-9.47	10.59	-0.06	5.36	-0.64	0.01	0.70
19. IBEX35PRICEINDEX	0.00	1.41	-13.19	13.48	-0.10	6.45	-0.69	0.02	0.70
20. FTSEMIBINDEXPRICEINDEX	-0.01	1.47	-13.33	10.87	-0.22	5.31	-0.70	0.01	0.72
21. BEL20PRICEINDEX	0.00	1.20	-8.32	9.33	-0.03	6.31	-0.55	0.01	0.60
22. ISEQALLSHAREINDEXPRICEINDEX	0.01	1.31	-13.96	9.73	-0.64	8.77	-0.58	0.02	0.65
23. AEXINDEXAEXPRICEINDEX	0.00	1.36	-9.59	10.03	-0.14	6.98	-0.59	0.03	0.64
24. ATHEXCOMPOSITEPRICEINDEX	-0.02	1.82	-17.71	13.43	-0.32	6.67	-0.84	0.00	0.84
25. STOXXEUROPE600EPRICEINDEX	0.01	1.17	-7.93	9.41	-0.20	5.71	-0.53	0.03	0.58
26. EUROSTOXX50PRICEINDEX	0.00	1.40	-9.01	10.44	-0.08	4.98	-0.64	0.01	0.68
27. STOXXEUROPELARGE200PRICEINDEX	0.00	1.20	-8.18	9.82	-0.15	5.84	-0.55	0.03	0.58
28. STOXXEUROPESMALL200PRICEINDEX	0.02	1.09	-8.03	7.07	-0.48	5.04	-0.47	0.07	0.57
29. STOXXEUROPEMID200PRICEINDEX	0.02	1.11	-8.40	7.85	-0.42	5.35	-0.49	0.07	0.58
30. STOXXEUROPE600BASICMATSEPRICEINDEX	0.02	1.53	-12.42	13.29	-0.16	7.58	-0.69	0.03	0.78
31. STOXXEUROPE600INDUSTRIALSEPRICEINDEX	0.02	1.28	-9.61	9.98	-0.21	5.95	-0.57	0.04	0.68
32. STOXXEUROPE600TECHNOLOGYEPRICEINDEX	0.01	1.86	-12.22	10.76	-0.09	4.03	-0.83	0.06	0.90
33. STOXXEUROPE600UTILITIESEPRICEINDEX	0.00	1.13	-8.69	14.86	-0.03	11.68	-0.53	0.01	0.60
34. STOXXEUROPE600FINANCIALSEPRICEINDEX	-0.01	1.55	-13.59	14.67	-0.03	8.67	-0.68	0.00	0.68
35. STOXXEUROPE600HEALTHCAREEPRICEINDEX	0.02	1.07	-6.82	8.60	-0.09	4.82	-0.52	0.02	0.56
36. STOXXEUROPE600TELECOMEPRICEINDEX	-0.01	1.45	-9.44	9.66	0.05	4.12	-0.71	0.00	0.68
37. EUROSTOXXFINANCIALSVSEPRICEINDEX	0.01	1.40	-10.39	12.25	-0.22	6.66	-0.59	0.04	0.67
38. EUROSTOXXFINANCIALSEPRICEINDEX	-0.01	1.67	-14.71	15.36	0.00	7.62	-0.74	0.00	0.75
39. EUROSTOXXHEALTHCAREEPRICEINDEX	0.01	1.30	-8.71	9.67	-0.08	3.68	-0.66	0.02	0.71
40. EUROSTOXXINDSGDSSVSEPRICEINDEX	0.02	1.39	-10.36	11.58	-0.17	5.88	-0.66	0.02	0.74
41. EUROSTOXXINDUSTRIALSEPRICEINDEX	0.02	1.36	-10.47	11.05	-0.16	6.39	-0.62	0.03	0.71
42. EUROSTOXXTECHNOLOGYEPRICEINDEX	0.01	1.87	-14.02	11.22	-0.09	4.19	-0.84	0.03	0.91
43. EUROSTOXXTELECOMEPRICEINDEX	-0.01	1.49	-9.97	10.47	0.06	4.18	-0.72	0.00	0.69
44. USTOEURORFVEXCHANGERATE	0.00	0.61	-2.78	3.73	0.06	1.71	-0.35	0.00	0.33
45. SWISSFRANCTOEUROWMREXCHANGERATE	-0.01	0.41	-13.13	7.92	-5.20	241.71	-0.14	0.00	0.13
46. GBPTOEURBOEEXCHANGERATE	0.00	0.51	-2.93	6.22	0.46	6.51	-0.27	0.00	0.27
47. JAPANESEYENTOEUROWMREXCHANGERATE	0.00	0.73	-6.79	4.84	-0.30	5.37	-0.38	0.02	0.38

Table B.2: Contributions of shock components in explaining h_t^* across assets.

Name	Group	Region	Level (%)	Slope (%)	Curvature (%)	Noise (%)
1. BD BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Germany	10.07	24.82	24.71	40.40
2. BG BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Belgium	6.39	25.08	16.93	51.59
3. ES BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Spain	5.75	16.60	18.89	58.76
4. FR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	France	5.25	24.04	16.41	54.30
5. GR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Greece	0.27	14.13	10.48	75.12
6. IR BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Ireland	5.60	7.66	11.48	75.26
7. IT BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	Italy	1.41	9.70	31.01	57.88
8. UK BENCHMARK 10 YEAR DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	UK	1.98	25.66	19.33	53.02
9. EMU BENCHMARK 10 YR. DS GOVT. INDEX - CLEAN PRICE INDEX	Government bonds	EMU	0.36	8.63	28.71	62.30
10. IBOXX EURO CORPORATES - Cln Prc Indx Today	Corporate bonds	Europe	1.96	16.42	28.97	52.64
11. IBOXX EURO OVERALL - Cln Prc Indx Today	Corporate bonds	Europe	4.22	11.65	27.46	56.66
12. IBOXX EURO EUROZONE - Cln Prc Indx Today	Corporate bonds	Europe	5.29	7.41	28.86	58.44
13. ICE BofA AAA Euro Corporate Index - Clean price	Corporate bonds	Europe	3.83	12.75	23.72	59.70
14. ICE BofA BBB Euro Corporate Index - Clean price	Corporate bonds	Europe	10.96	15.48	11.51	62.06
15. ICE BofA 1-3 Year BBB Euro Corporate Index - Clean price	Corporate bonds	Europe	3.90	2.23	8.08	85.80
16. ICE BofA 1-10 Year AAA Euro Corporate Index - Clean price	Corporate bonds	Europe	5.24	10.80	13.92	70.04
17. FTSE100PRICEINDEX	Stocks (countries)	UK	2.31	21.51	34.81	41.36
18. FRANCECAC40PRICEINDEX	Stocks (countries)	France	2.46	15.92	42.83	38.78
19. IBEX35PRICEINDEX	Stocks (countries)	Spain	4.81	19.22	38.48	37.49
20. FTSEMIBINDEXPRICEINDEX	Stocks (countries)	Italy	2.66	21.17	37.71	38.46
21. BEL20PRICEINDEX	Stocks (countries)	Belgium	2.96	29.67	19.24	48.13
22. ISEQALLSHAREINDEXPRICEINDEX	Stocks (countries)	Ireland	1.69	24.86	38.04	35.41
23. AEXINDEXAEXPRICEINDEX	Stocks (countries)	Netherlands	1.08	29.69	30.19	39.04
24. ATHEXCOMPOSITEPRICEINDEX	Stocks (countries)	Greece	10.87	25.79	8.78	54.56
25. STOXXEUROPE600EPRICEINDEX	Stocks (sectors and market cap)	Europe	4.04	22.05	38.68	35.23
26. EUROSTOXX50PRICEINDEX	Stocks (sectors and market cap)	Europe	1.01	15.72	40.15	43.11
27. STOXXEUROPELARGE200PRICEINDEX	Stocks (sectors and market cap)	Europe	4.85	20.89	38.84	35.42
28. STOXXEUROPESMALL200PRICEINDEX	Stocks (sectors and market cap)	Europe	0.73	14.76	42.92	41.58
29. STOXXEUROPEMID200PRICEINDEX	Stocks (sectors and market cap)	Europe	0.38	18.80	38.78	42.05
30. STOXXEUROPE600BASICMATSEPRICEINDEX	Stocks (sectors and market cap)	Europe	4.77	26.31	38.30	30.61
31. STOXXEUROPE600INDUSTRIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	9.34	12.87	40.52	37.28
32. STOXXEUROPE600TECHNOLOGYEPRICEINDEX	Stocks (sectors and market cap)	Europe	13.34	6.98	40.34	39.33
33. STOXXEUROPE600UTILITIESEPRICEINDEX	Stocks (sectors and market cap)	Europe	0.58	25.06	43.88	30.48
34. STOXXEUROPE600FINANCIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	3.71	27.97	28.66	39.66
35. STOXXEUROPE600HEALTHCAREEPRICEINDEX	Stocks (sectors and market cap)	Europe	4.95	32.41	30.06	32.58
36. STOXXEUROPE600TELECOMEPRICEINDE	Stocks (sectors and market cap)	Europe	15.83	4.27	26.65	53.26
37. EUROSTOXXFINANCIALSVSEPRICEINDEX	Stocks (sectors and market cap)	Europe	1.97	32.88	29.53	35.62
38. EUROSTOXXFINANCIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	2.62	31.13	28.73	37.52
39. EUROSTOXXHEALTHCAREEPRICEINDEX	Stocks (sectors and market cap)	Europe	1.26	25.30	36.47	36.97
40. EUROSTOXXINDSGDSSVSEPRICEINDEX	Stocks (sectors and market cap)	Europe	19.57	1.40	37.11	41.93
41. EUROSTOXXINDUSTRIALSEPRICEINDEX	Stocks (sectors and market cap)	Europe	15.72	6.83	35.64	41.82
42. EUROSTOXXTECHNOLOGYEPRICEINDEX	Stocks (sectors and market cap)	Europe	13.03	5.37	39.17	42.44
43. EUROSTOXXTELECOMEPRICEINDEX	Stocks (sectors and market cap)	Europe	6.88	26.89	7.11	59.12
44. USTOEURORFVEXCHANGERATE	Exchange rates	EUR/USD	17.39	17.98	38.69	25.94
45. SWISSFRANCTOEUROWMREXCHANGERATE	Exchange rates	EUR/CHF	0.42	28.56	31.36	39.66
46. GBPTOEURBOEEXCHANGERATE	Exchange rates	EUR/GBP	15.51	13.67	25.80	45.02
47. JAPANESEYENTOEUROWMREXCHANGERATE	Exchange rates	EUR/JPY	4.05	24.37	24.07	47.52

Table B.3: Examples of key ECB monetary policy announcements (conventional vs. unconventional episodes).

Date	Policy decision or key speech	Excerpt	Reference
Panel A: Conventional episodes			
08-Jun-2000	MRO rate raised by 50 bps to 4.25%	*"The interest rate on the main refinancing operations of the Eurosystem will be raised by 0.50 percentage point to 4.25% and applied in the two operations (which will be conducted as fixed rate tenders) to be settled on 15 and 21 June 2000."*	ECB Press Release, 8 June 2000
30-Aug-2001	MRO rate cut by 25 bps to 4.25%	*"The minimum bid rate on the main refinancing operations of the Eurosystem will be reduced by 0.25 percentage point to 4.25%, starting from the operation to be settled on 5 September 2001."*	ECB Press Release, 30 August 2001

Date	Policy Decision or Key Communication	Excerpt	Reference
05-Jun-2003	MRO rate cut by 50 bps to 2.00%	*"The Governing Council decided to lower the interest rate on the main refinancing operations of the Eurosystem by 0.50 percentage points to 2.00%."*	ECB Monthly Bulletin, June 2003, p. 9
08-Jun-2006	MRO rate raised by 25 bps to 2.75%	*"The Governing Council decided to increase the interest rate on the main refinancing operations of the Eurosystem by 0.25 percentage points to 2.75%."*	ECB Monthly Bulletin, June 2006, p. 6
02-Jul-2009	MRO rate held at 1.00% during crisis	*"The Governing Council decided to keep the interest rate on the main refinancing operations of the Eurosystem unchanged at 1.00%."*	ECB Monthly Bulletin, July 2009, p. 4
Panel B: Unconventional Episodes			
04-Aug-2011	Resumption of bond purchases under SMP	*"The Governing Council decided to conduct a liquidity-providing supplementary longer-term refinancing operation with a maturity of approximately six months."*	ECB Monthly Bulletin, August 2011, p. 3
08-Dec-2011	Launch of 3-year LTROs	*"The Governing Council decided to conduct two longer-term refinancing operations (LTROs) with a maturity of approximately three years."*	ECB Monthly Bulletin, December 2011, p. 4
04-Jul-2013	Introduction of forward guidance	*"The Governing Council expects the key ECB interest rates to remain at present or lower levels for an extended period of time."*	ECB Monthly Bulletin, July 2013, p. 6
22-Jan-2015	Launch of Expanded APP (including PSPP)	*"The Governing Council decided to launch an expanded asset purchase programme encompassing the existing purchase programmes for asset-backed securities and covered bonds."*	ECB Press Release, 22 January 2015
07-Mar-2019	Launch of TLTRO-III	*"A new series of quarterly targeted longer-term refinancing operations (TLTRO-III) will be launched, starting in September 2019 and ending in March 2021, each with a maturity of two years."*	ECB Press Release, 7 March 2019

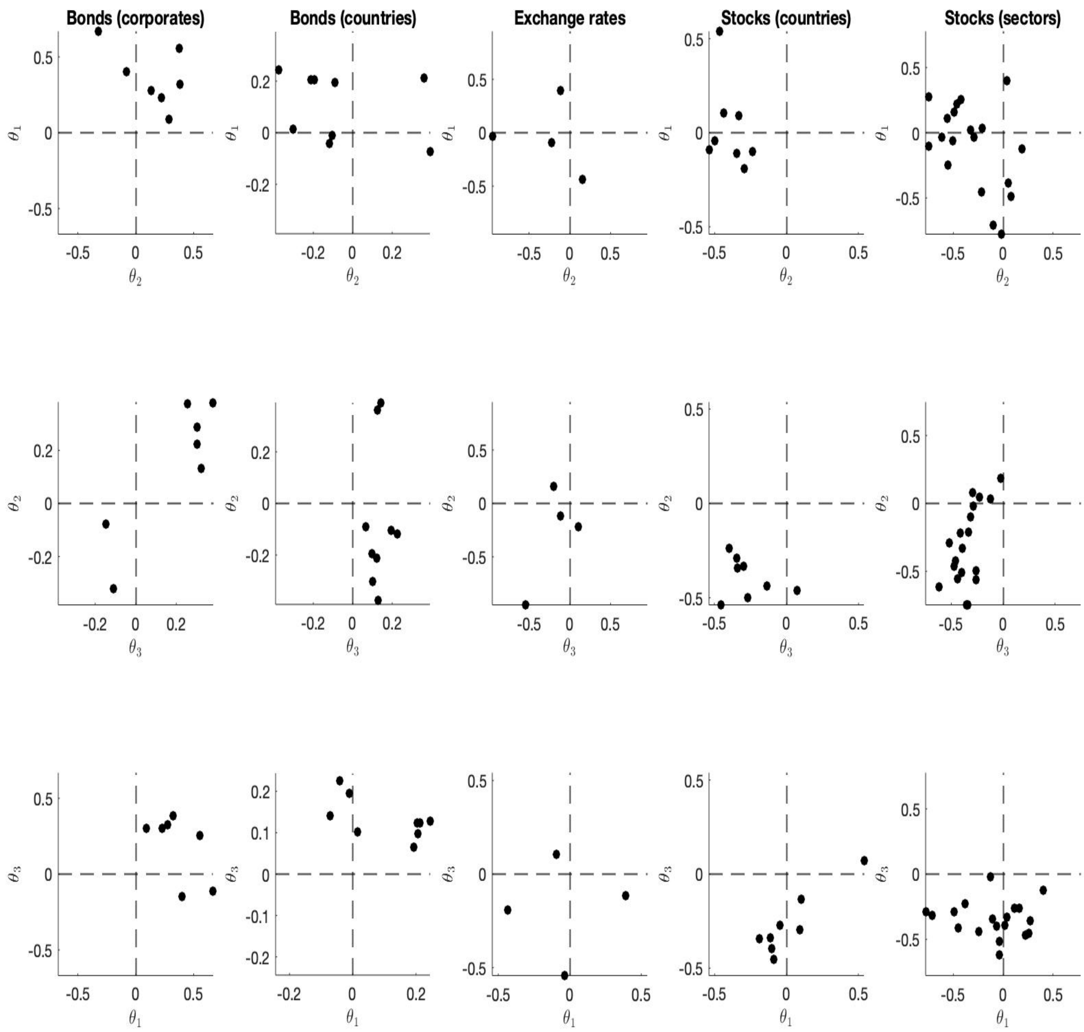


Figure B.13: Pairwise scatter plots of $\theta_1, \theta_2, \theta_3$, estimates by asset group.

Notes: Columns correspond to asset groups: bonds (corporates), bonds (countries), exchange rates, stocks (countries), stocks (sectors). Rows show the three pairwise combinations of coefficients: top (θ_1, θ_2), middle (θ_1, θ_3), bottom (θ_2, θ_3). Axes are centered at zero to highlight the sign of responses. This figure complements the main figure (see Figure 3.5) in Section 3.4.2 by visualizing joint patterns across components.

B.4 Robustness Analysis: First-Moment Effects of Monetary Policy Shocks

The specification used in the empirical analysis models daily log returns as

$$r_t = \exp\{h_t/2\}\,\xi_t, \qquad \xi_t \sim \mathcal{N}(0,1),$$

with log-variance dynamics

$$h_t = \mu_h + \phi(h_{t-1} - \mu_h) + \mathbf{x}_t^* \boldsymbol{\theta} + \nu_t, \qquad \nu_t \sim \mathcal{N}(0, \omega^2).$$

By construction, this implies a zero conditional mean, $\mathbb{E}[r_t \mid \mathcal{I}_{t-1}, \mathbf{x}_t^*] = 0$, so that daily expected returns are taken to be negligible and monetary policy shocks, $\mathbf{x}_t^* = (\Delta\beta_{1,t}^{hf}, \Delta\beta_{2,t}^{hf}, \Delta\beta_{3,t}^{hf})$, affect only the conditional variance (through $\boldsymbol{\theta}$), not the conditional mean. To assess whether this modelling choice is empirically holds for all assets considered, we estimate a set of auxiliary reduced-form regressions of returns on monetary policy shocks, outside the SV–X framework.

For each asset k, we first estimate a baseline regression with contemporaneous shocks,

$$r_{k,t} = \alpha_k^{(1)} + \mathbf{x}_t^* \boldsymbol{\gamma}_k^{(1)} + u_{k,t}^{(1)}, \tag{B.5}$$

where $\alpha_k^{(1)}$ absorbs any average drift in daily returns and $\boldsymbol{\gamma}_k^{(1)}$ (a column vector) captures contemporaneous first-moment effects of monetary policy shocks.

Second, we allow for lagged effects of shocks by estimating

$$r_{k,t} = \alpha_k^{(2)} + \mathbf{x}_t^* \boldsymbol{\gamma}_{k,0}^{(2)} + \mathbf{x}_{t-1}^* \boldsymbol{\gamma}_{k,1}^{(2)} + u_{k,t}^{(2)}, \tag{B.6}$$

where $\boldsymbol{\gamma}_{k,0}^{(2)}$ and $\boldsymbol{\gamma}_{k,1}^{(2)}$ measure, respectively, contemporaneous and one-day lagged mean responses to monetary policy shocks.

Third, we allow for simple autocorrelation in returns via an autoregressive term ρ,

$$r_{k,t} = \alpha_k^{(3)} + \rho_k^{(3)} r_{k,t-1} + \mathbf{x}_t^* \boldsymbol{\gamma}_k^{(3)} + u_{k,t}^{(3)}, \tag{B.7}$$

so that $\rho_k^{(3)}$ captures persistence in returns and $\boldsymbol{\gamma}_k^{(3)}$ captures contemporaneous mean effects of shocks conditional on $r_{k,t-1}$.

All specifications are estimated on the full daily sample using HAC (Newey and West, 1986) standard errors. For each asset and regression specification, we examine the estimated coefficients via their individual t-statistics and assess whether they are significantly different from zero at the 5% level.

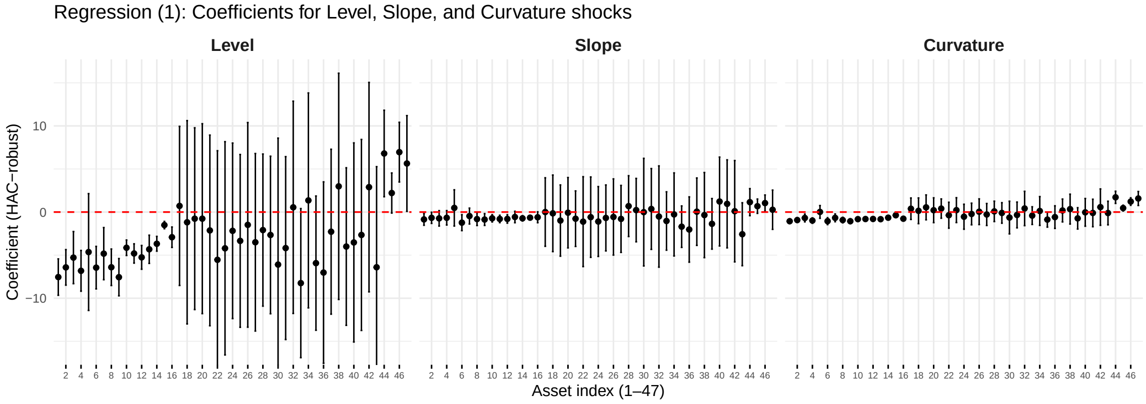


Figure B.14: Estimated regression coefficients of $\gamma_k^{(1)}$ with their 95% CIs. See equation (B.5) for more details.

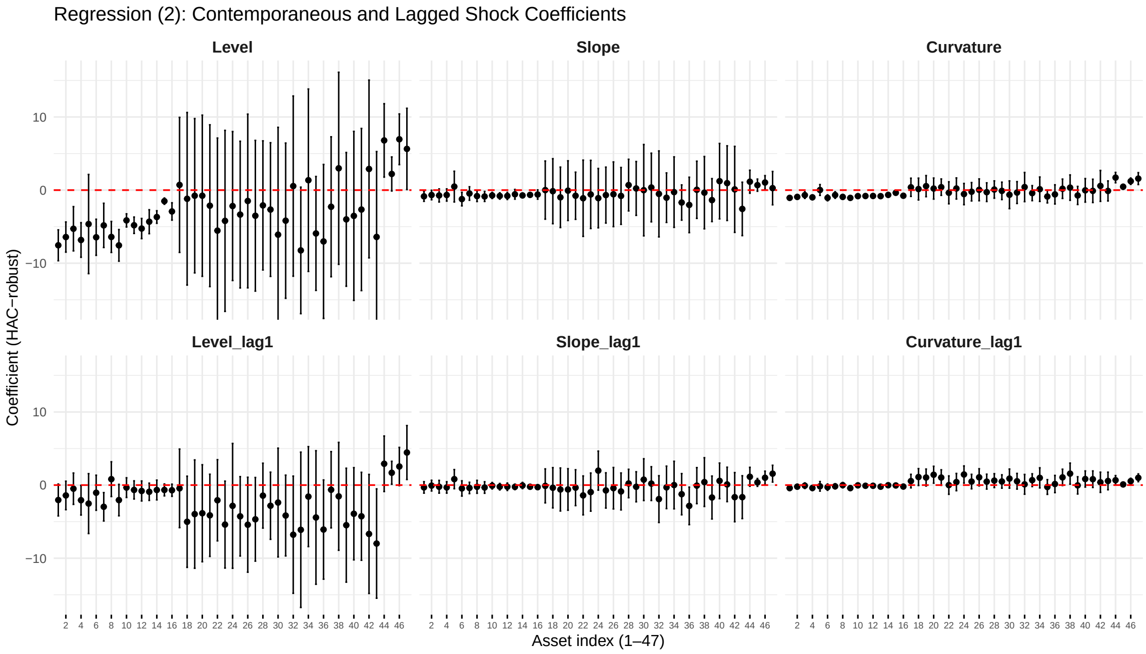


Figure B.15: Estimated regression coefficients of $\gamma_{k,0}^{(2)}$ and $\gamma_{k,1}^{(2)}$ with their 95% CIs. See equation (B.6) for more details.

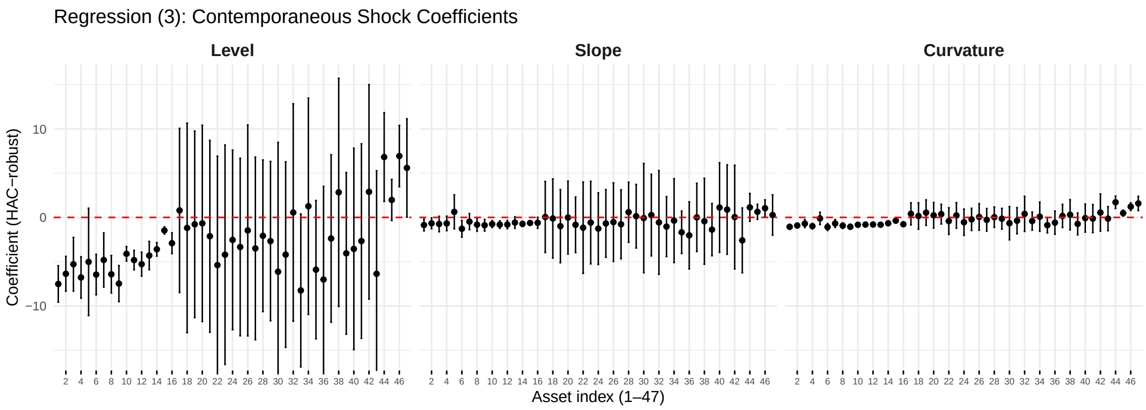


Figure B.16: Estimated regression coefficients of $\gamma_k^{(3)}$ with their 95% CIs. See equation (B.7) for more details.

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