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Essays on the nonlinear transmission of monetary policy

Doctoral Dissertation

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Any remaining errors are my own.

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Introduction

Monetary policy is one of the central instruments of macroeconomic stabilization. Through its influence on short- and long-term interest rates, financing conditions, asset prices, and expectations, it shapes aggregate demand and inflation dynamics and ultimately affects real activity. Because these channels operate through a complex macro-financial system, understanding the monetary transmission mechanism has long been a core objective of macroeconomics and an essential input into policy analysis.

The modern monetary policy environment is characterized by a fast-moving economic landscape, where shocks are frequent and the world economy has gone through many structural changes. The flow of information has sped up and central bankers need to process and respond to an ever-growing volume of data when making decisions about the conduct of monetary policy. In this setting, methods that discipline statistical inference and causal identification through observed time-series dynamics provide a particularly valuable perspective. Since the seminal work of Sims (1980), macroeconomics has been dominated by an empirical paradigm in which exactly such data-driven methods take center stage. A key premise of this dissertation is to follow this tradition, allowing the data to reveal the complex dynamics of the transmission mechanism.

A second premise is that monetary policy transmission may not be well described by a single, stable, linear mechanism. As Akerlof and Shiller (2010) emphasize the Keynesian “Animal Spirits”, macroeconomic reality is profoundly shaped by shifting human psychology—fluctuations in confidence, evolving perceptions of risk, and episodes of market exuberance. Because these underlying forces constantly alter the economic environment, there are strong reasons to expect that policy transmission is fundamentally nonlinear. Financial frictions can bind more tightly in environments of heightened fear, balance-sheet channels can become more powerful when exuberance leads to elevated leverage, and the reaction of expectations to policy communication can shift conditional on agents' beliefs about the economic outlook. These considerations imply that the same policy action may have different effects depending on the state of the economy. From a policy perspective, this matters because important decisions are made precisely when conditions are atypical. In such events, focusing on average effects may understate risks and tradeoffs, or potentially miss important channels of stabilization through policy. The remainder of this dissertation consists of three essays that examine these nonlinear transmission mechanisms from complementary angles: monetary policy under uncertainty and fragmentation, state dependence linked to housing market imbalances, and how forward guidance can transmit its effects through higher-order moments along the term structure.

The first paper examines the transmission of monetary policy in an environment characterized by heightened uncertainty and geoeconomic fragmentation. Motivated by recent episodes of elevated macroeconomic and geopolitical uncertainty, we study how this environment affects the transmission mechanism across a large panel of economies. We employ a bayesian threshold vector-autoregression that allows for economic dynamics to behave differently conditional on the level of uncertainty. Our results show that monetary policy is able to curb inflation considerably more when uncertainty is low, while the transmission to output remains largely unaffected. A key policy message to take away is that economic uncertainty raises the tradeoff central banks have to face in order to manage inflation.

The second paper investigates how nonlinearities may arise from housing market imbalances and financial frictions in the US. Housing markets play a key role for monetary policy transmission through its asset price, credit and wealth channels. The transmission channels may however be different, as pronounced housing imbalances can be a sign of fragility which may amplify the impact of shocks. I employ a factor-augmented threshold vector-autoregression to identify boom-bust periods in the housing market and trace out the impulse responses of the economy to monetary policy shocks. The results show that the response of the economy to a contractionary monetary policy shock is only slightly elevated in boom periods. However, the behavior of monetary policy differs sharply, as the adjustment of interest rates back to baseline takes a considerably longer time. A key message to take away is that monetary policy might require more patience and steady action to carefully manage deleveraging markets.

The third paper investigates the effects of monetary policy forward guidance shocks from a distributional perspective, that is, whether it operates through an additional channel affecting conditional volatility. While forward guidance is commonly understood as an unconventional tool that served to depress expectations about future yields and provide further monetary easing when interest rates were near zero, managing expectations may naturally carry a reduction in uncertainty about the future. By explicit commitments to future policy, forward guidance can alter not only the expected path of interest rates, but also reduce perceived risk in financial markets, subsequently offering a secondary channel that promotes macro-financial stability.

I investigate this along the US treasury yield curves using a dynamic location-scale model, so that I can explicitly model the response of the conditional standard deviation of treasury yields to high frequency monetary policy and forward guidance surprises. My paper delivers robust results that forward guidance can lower conditional volatility along the term structure of interest rates, while policy rate surprises tend to raise it. A key implication is that policy communication, beyond changing expectations, provides a secondary channel that can reduce volatility and subsequently can be effective at tackling uncertainty.

Chapter 1

Monetary transmission in a fragmented, uncertain world

Coauthored with Tohid Atashbar (IMF)

Abstract: This paper investigates how economic uncertainty affects monetary policy transmission using Bayesian Threshold VARs across 30 economies. We find that during high uncertainty, the inflation response to monetary policy shocks is markedly weaker, while the GDP response remains stable. Consequently, state-dependent sacrifice ratios show disinflation is significantly more costly when uncertainty is elevated. The asymmetry we find is primarily driven by policy uncertainty and suggests that this uncertainty disrupts transmission by weakening the pass-through from economic slack to inflation.
Keywords: Monetary transmission, Economic uncertainty, Threshold Vector Auto-Regression, Sign restrictions

JEL: E32, E44, E52, C32

1.1 Introduction

How monetary policy is transmitted to the real economy is one of the oldest and most consequential questions in macroeconomics. Understanding these transmission dynamics has taken on renewed importance in an environment marked by unusually frequent and persistent uncertainty. Importantly, this environment is best characterized not by calculable risk, but by what Dequech (2000) terms fundamental uncertainty: a state in which the future is inherently uncreated and unknowable, rather than merely obscured by missing information. Today, this fundamental uncertainty is especially pronounced against the backdrop of geoeconomic fragmentation (the reconfiguration of trade, investment, and technology relationships along geopolitical rather than purely economic lines), which, as Ilyina et al. (2023) point out, continually generates structural economic and policy shocks.

This reconfiguration has accelerated markedly since the COVID-19 pandemic first exposed the fragility of global supply chains. Russia's invasion of Ukraine in 2022 triggered a large-scale sanctions regime and a near-collapse of European gas imports from Russia, feeding directly into the surge in euro area inflation that followed and prompting one of the fastest monetary tightening cycles in the ECB's history. Export controls on semiconductors and critical minerals, alongside a broader push toward "friend-shoring" and reshoring of production, have reshaped US-China economic relations since 2022, while global tariffs rose sharply again in 2024–2025 amid a fresh round of trade-policy escalation. Measures of policy and trade uncertainty have surged in step with these developments, and by 2025 several indicators of geopolitical and trade fragmentation stood at or near multi-decade highs (see, e.g., the ECB/ESRB (2026) report).

These developments naturally interact with monetary policy transmission. As Andriantomanga et al. (2022) and Bolhuis et al. (2023) note, geoeconomic fragmentation carries substantial real economic costs and heightened inflationary pressures, both of which central banks must navigate. Crucially, when operating under deep fundamental uncertainty, economic agents may shift away from rational optimization toward the realm of Keynesian "animal spirits" — the gut feelings, emotions, and spontaneous optimism that drive human economic decisions when future outcomes cannot be mathematically calculated (Akerlof and Shiller (2010)). Understanding how monetary policy operates in this behavioral realm is vital, as conventional interest rate signals may become distorted. In order to accurately assess the efficacy of central bank policy in achieving its mandates under high uncertainty, models must account for these structural and behavioral shifts in the economy's underlying dynamics.

Given the extensive literature on uncertainty shocks and the broad consensus about their real effects, the immediate implications of heightened uncertainty are comparatively well understood and offer useful guidance for methodological choices. A small but growing literature has begun to address this question directly. This literature tends to find that monetary policy may be less effective in times of high uncertainty. These findings are attributed to the fact that high uncertainty already dampens investment demand and increases consumer precaution; as a result, the demand-pull effect of monetary policy is smaller.

Although these findings provide a consistent narrative across the existing literature, several methodological limitations offer room for extension. Some of the existing frameworks impose restrictive assumptions on how uncertainty alters macroeconomic dynamics, typically allowing only partial structural shifts. For instance, Aastveit et al. (2017) restrict regime dependence strictly to interest rate elasticities, while Aquino et al. (2022) assume that only the monetary policy reaction function shifts during uncertain times. Such constraints may fail to capture the full spectrum of state-dependent interactions across the economy.

Other empirical findings often rely on specific proxies or older samples that may not fully reflect contemporary, globalized fundamental uncertainty. While Castelnuovo and Pellegrino (2018) document a significantly milder real effect of unexpected policy moves when macroeconomic uncertainty is high, their sample concludes in 2008, predating the Global Financial Crisis (GFC). Furthermore, their analysis utilizes a forecast-error-based uncertainty measure (Jurado et al. (2015)), which is conceptually distinct from the modern text- and narrative-based measures widely employed today to capture perceived fundamental uncertainty. Finally, the overwhelming majority of these studies are heavily US-centric; as such, they do not capture whether varying structural characteristics of the economy produce any changes in how uncertainty and monetary policy interact.

Motivated by these considerations, we develop a parsimonious econometric framework to study the relationship between uncertainty and monetary transmission across a broad panel of countries. Rather than relying on a theory-consistent structural model that is calibrated to match the results of earlier work, we follow the data-driven VAR tradition initiated by Sims (1980) and let the reduced-form dynamics of the data speak. Specifically, we employ a two-regime Threshold Vector Autoregression (TVAR) capable of flexibly capturing state-dependent transmission mechanisms and varying shock impacts across high- and low-uncertainty regimes.

To limit the number of parameters and keep the computational workload in check, the model is deliberately parsimonious, containing only a compact information set intended to capture open-economy dynamics amid uncertainty shocks. Accordingly, our endogenous variables include the policy interest rate, GDP growth, CPI inflation, the real effective exchange rate, and a measure of economic uncertainty. We identify monetary policy shocks using sign restrictions, as this approach does not rely on external high-frequency instruments, which are unavailable for many of the economies included in our broad sample of advanced and emerging markets.

Our results diverge from much of this literature in an important respect. Rather than finding that monetary policy loses its grip on real activity under high uncertainty, as Aastveit et al. (2017), Aquino et al. (2022), and Castelnuovo and Pellegrino (2018) variously do, we find that the response of GDP growth to a policy shock is broadly unchanged across uncertainty regimes. What changes rather, is how much of that contraction shows up as disinflation. Inflation responds less persistently to a monetary tightening when uncertainty is high, so that the sacrifice ratio (the amount of output that must be forgone per unit of disinflation) rises sharply in high-uncertainty periods relative to low-uncertainty ones. This pattern is stable across our broad country panel, across advanced and emerging economies alike, and across alternative definitions of the uncertainty threshold, though it is considerably more pronounced for narrative measures of economic policy uncertainty than for a model-based uncertainty index or a measure of geopolitical risk specifically. We interpret this as evidence that uncertainty disrupts monetary transmission primarily on the inflation side of the mechanism, rather than by weakening the real effects of a policy shock as much of the existing single-country evidence suggests.

The remainder of the paper is organized as follows. The next section reviews the relevant literature. Section three describes the data used in the estimations, with particular emphasis on measures of uncertainty. Section four outlines the methods, including the estimation of the TVAR with Bayesian methods, the identification strategy as well as further calculations and aggregating assumptions. Section five discusses the results in detail, and section six concludes.

1.2 Literature review

We identify three strands of literature that guide our investigation: (i) the real economic effects of uncertainty shocks, (ii) the state-dependence of macroeconomic dynamics (particularly concerning uncertainty), and (iii) how monetary transmission itself varies conditional on the state of the economy. We highlight key contributions from each strand below.

Real effects of uncertainty shocks. A substantial literature finds that uncertainty shocks act much like negative demand shocks, primarily by depressing investment as firms adopt a more precautionary stance (Bloom et al. (2007); Bloom (2009); Bloom (2014); Gilchrist et al. (2014)). Caldara et al. (2016) emphasize the joint role of financial and uncertainty shocks in driving business-cycle fluctuations and argue that the Great Recession likely reflected the interaction of both. Bonciani and Ricci (2020) use local projections to estimate the impact of global financial uncertainty on small open economies and find contractionary effects that are stronger in more open economies and during downturns. Colombo (2013) shows that US uncertainty shocks spill over substantially to the euro area business cycle, with US shocks generally mattering more than euro-area shocks for that spillover.

The real effects of uncertainty also appear to differ systematically between advanced and emerging economies. Carrière-Swallow and Céspedes (2013) show that uncertainty shocks exert greater influence in emerging economies owing to tighter credit constraints, a finding echoed by Ahir et al. (2019). Cheng and Chiu (2018) show that geopolitical risk shocks are important drivers of business cycles in emerging markets specifically, while Jung et al. (2021) use Korean data to show that geopolitical risk triggers sharp declines in stock prices, particularly for large, domestically owned, or asset-heavy firms.

Caggiano and Castelnuovo (2021) estimate a global financial uncertainty factor from volatility data spanning 42 countries and find that a meaningful share of the world output loss during the Great Recession would have been avoided in the absence of global uncertainty shocks. Bobasu et al. (2024) build on the measurement approach of Jurado et al. (2015) to construct a global uncertainty measure for the euro area's main trading partners and show, using a proxy-SVAR instrumented with gold-price movements, that global uncertainty shocks have historically been an important driver of euro area industrial production.

State-dependence in economic dynamics and uncertainty. Another strand of literature investigates whether the dynamics governing the economy's evolution vary with the state of the economy. Using a smooth-transition VAR, Paccagnini and Colombo (2020) find uncertainty shocks to be significantly more severe in recessions than in normal times, and that central bank balance sheet tools are particularly helpful in mitigating their impact. Alessandri and Mumtaz (2019), using a Threshold VAR, find a similar pattern tied to financial conditions. Uncertainty shocks are inflationary in normal times but deflationary, and more contractionary for output, during periods of financial stress. De Santis and Cardamone (2026) show that the parameters of the Phillips curve, the dynamic IS equation, and the Taylor rule are themselves regime-dependent across joint states of inflation and the output gap, with the size of monetary policy shocks significantly larger when inflation exceeds target.

State-dependence in the transmission of monetary policy. Monetary policy studies using nonlinear models offer some relevant findings as well. Kakes (1998) uses a Markov-switching model and finds monetary policy to be more effective in recessions in both the US and Germany, while Avdjiev and Zeng (2014) find that the impact of monetary shocks is amplified during periods of low growth, even as policy itself tends to be more aggressive during booms. Pellegrino et al. (2023) document, with a nonlinear proxy-VAR, that a large financial uncertainty shock can account for a substantial share of the US output loss during the Great Recession, while systematic monetary policy played a powerful role in limiting that loss. Caggiano et al. (2017) find that the Federal Reserve's systematic response to uncertainty shocks is considerably more effective at stabilizing real activity in expansions than in recessions.

Discussed more thoroughly in the introduction, Aastveit et al. (2017) and Aquino et al. (2022), using interacted VARs, provide evidence that the effect of monetary policy is dampened by high uncertainty. Using a full TVAR, Castelnuovo and Pellegrino (2018) also find that high macro-uncertainty dampens the transmission, a finding they also rationalize via a New Keynesian model.

Taken together, these findings reinforce that economic uncertainty is a primary driver of global business cycles, with considerable spillovers from global or systemically important economies to smaller ones. The literature also clearly establishes that high financial stress and uncertainty fundamentally alter macroeconomic dynamics. This structural shift affects both the systematic reaction function of monetary policy and the real economy's responsiveness to policy shocks. For instance, central banks may react directly to uncertainty proxies, or their response to inflation and demand shocks may change conditional on the prevailing level of uncertainty. Concurrently, the state of the economy can dictate the risk appetite and price-setting behavior of agents, subsequently steepening or flattening the slopes of the Phillips and IS curves.

Finally, the empirical definition of "good" versus "bad" times can drastically alter conclusions: as highlighted above, "bad times" defined by one metric (e.g., low growth) may amplify monetary policy effectiveness, whereas "bad times" defined by another (e.g., high uncertainty) may dampen it. We aim to contribute to this literature by systematically testing how high uncertainty measured across several distinct indicators interacts with the transmission of interest rate shocks across a large cross-section of economies.

1.3 Data

Macro aggregates. Our empirical analysis relies on a compact set of four core macroeconomic variables[1]: real GDP, consumer price inflation, the real effective exchange rate and the policy interest rate. The data is sampled at a quarterly frequency covering the period from 1995Q1 to 2026Q1. The resulting panel is unbalanced, as data for certain emerging economies only becomes available in the early 2000s. We view this compact set of variables as the necessary minimum to adequately capture open-economy macroeconomic dynamics. We choose to keep the model parsimonious in order to be able to include a relatively large panel of economies in our analysis. Further, maintaining a parsimonious model mitigates the substantial computational workload of estimating regime-switching models with Bayesian methods over a large cross-section of countries.

The estimation is carried out individually across a diverse panel of 30 economies, encompassing a wide range of large, small, advanced, and emerging markets.[2] Notably, rather than modeling individual member states of the European Monetary Union, we incorporate them via a single Euro Area[3] aggregate. Since all member states are subject to a common monetary policy stance, this aggregation choice is consistent with our core objective of analyzing the transmission of monetary policy shocks. Additionally, replacing individual members of the Euro Area with a single aggregate substantially reduces overall estimation time. Whether ECB monetary policy impacts individual member countries differently in high- versus low-uncertainty times is left for future research.

In order to account for structural change across the decades, we apply two essential transformations to the data to ensure robust structural identification. First, to

[1] All macro aggregates except the policy interest rate are expressed in year-over-year growth rates. Data for real GDP is retrieved from the IMF's database, while the rest of the series are retrieved from BIS data. Inflation and GDP data for the Euro Area are retrieved from Eurostat, while data for the effective exchange rate is retrieved from the ECB's data portal, and the Euro Area policy interest rate and shadow rate come from the database of Krippner (2013).

[2] The sample includes Australia, Brazil, Canada, Switzerland, Chile, Colombia, the Czech Republic, Denmark, the Euro Area, the United Kingdom, Hungary, Indonesia, India, Iceland, Israel, Japan, South Korea, Mexico, North Macedonia, Norway, New Zealand, the Philippines, Poland, Romania, Singapore, Serbia, Sweden, Thailand, the United States, and South Africa.

[3] We use the "Euro Area (changing composition)" definition of Eurostat and the ECB to account for new entrants over the decades.

account for low-frequency shifts in inflation targets and evolving monetary policy regimes over our three-decade sample, we detrend both the inflation and interest rate series using the regression-based filter proposed by Hamilton (2018). Second, to accurately capture the unconstrained stance of monetary policy during episodes when nominal rates hit the zero lower bound (ZLB), we substitute the observed policy rates with shadow short rates wherever applicable. Specifically, we utilize the shadow rate framework developed by Krippner (2013)[4], supplemented by the shadow rate estimates of De Rezende and Ristiniemi (2023) for Sweden.

Uncertainty measures. Because economic uncertainty is inherently unobservable, quantifying it requires proxy indicators. The macroeconomic literature has traditionally relied on financial market metrics, such as implied volatility indices (most commonly the VIX), equity market volatility (such as the EMV tracker from Baker et al. (2026)), or broader financial stress indicators (such as the Chicago Fed's NFCI or the ECB's CLIFS). While highly responsive, these market-based metrics primarily capture the risk premia and volatility expectations of financial market participants. Consequently, they often conflate true macroeconomic uncertainty with financial stress and asset price imbalances which may not accurately reflect broader uncertainty that households and firms face. Following the work of Baker et al. (2016), text query-based indices have emerged as a robust alternative to gauging macro-level uncertainty instead of proxying it via financial market-based measures. By scraping news archives and policy reports for specific keywords, these narrative-based measures capture a more direct, qualitative reflection of uncertainty as it is actually perceived and articulated by economic agents, policymakers, and journalists in real time.

Under such considerations, we also choose to use such an index for the bulk of our analysis. Namely, we use the World Uncertainty Index (WUI) developed by Ahir et al. (2022). We select the WUI as our baseline for several reasons. First, it is based on IMF Economist Intelligence Unit quarterly reports which are compiled by IMF staff. As such, the underlying text from which the index is built is created by a highly reliable source and it has global coverage. Second, the search terms used to

[4]The dataset covers Australia, Canada, Switzerland, the Euro Area, the United Kingdom, Japan, New Zealand, Singapore and the United States.

compile the index offer a very broad definition of economic uncertainty, as the index merely counts the number of times the word "uncertainty" and its variants occur in each report.

In order to ensure our findings are not driven by the idiosyncrasies of a single indicator, we employ several alternative metrics as sensitivity checks. These include the US Economic Policy Uncertainty (EPU) index of Baker et al. (2016), the 1-month ahead macroeconomic uncertainty index (JLN1M) of Jurado et al. (2015), and the global Geopolitical Risk (GPR) index of Caldara and Iacoviello (2022). Although the EPU and the JLN1M are derived from US data rather than global data, we choose the original US-specific versions, as many economic policy and macrofinancial uncertainty episodes (and the global spillovers that follow) frequently originate from the United States. As such, while these may not be truly global measures of uncertainty, they serve as close proxies of global uncertainty processes.

It is also important to note the conceptual nuances among these proxies. The index proposed by Jurado et al. (2015) is derived econometrically from the unforecastable components of a broad set of macroeconomic indicators. As such, it conceptually lies somewhat closer to volatility and financial stress measures than to the text-based uncertainty measure counterparts. On the other hand, while the GPR index of Caldara and Iacoviello (2022) follows the text-based measurement of the other indices, its search terms focus more on geopolitical tension rather than strictly economic (policy) uncertainty. We still choose to include this index in our analysis because empirical evidence overwhelmingly demonstrates that geopolitical shocks trigger macroeconomic contractions that closely mirror pure uncertainty shocks.

Finally, we apply necessary transformations to these indices prior to estimation. Due to the apparent upward sloping trends in the narrative series, we detrend both the WUI and the EPU indices also using the regression-based filter of Hamilton (2018). In contrast, the GPR and JLN1M indices exhibit stable long-run means and are therefore simply demeaned. In our baseline specification, we define a "high uncertainty" regime as any period where the chosen index lies above its historical median. We also conduct two sensitivity exercises regarding this threshold. We raise the cutoff to the 70th percentile of the historical distribution to investigate whether more extreme levels of uncertainty distort transmission dynamics further, and we also classify regimes based on "cyclical" uncertainty, where a high regime is strictly defined as periods when the indicator sits above its trend (mean). The uncertainty indices and their respective baseline regime classifications are plotted in detrended (demeaned) levels in Figure 1.1. In all VAR specifications, the chosen uncertainty measure enters as the fifth endogenous variable and is scaled to a unit standard deviation.

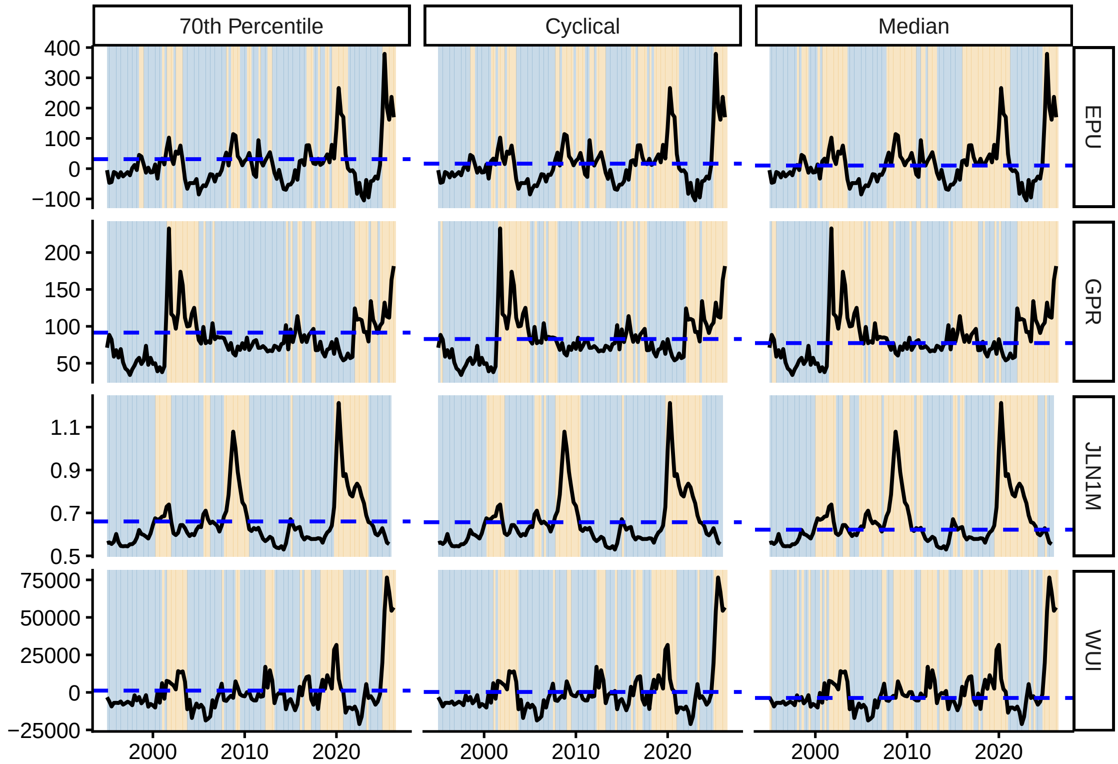

Figure 1.1: Uncertainty measures and regime classifications.

Notes: The dashed blue lines indicate the threshold levels. Blue shading and yellow shading along the series indicates the low uncertainty and high uncertainty regimes respectively.

1.4 Empirical framework

Bayesian Threshold VAR estimation. Our analysis is based on a compact structural threshold vector autoregression (TVAR) with five endogenous variables: GDP growth, inflation, the effective exchange rate, the nominal interest rate, and a measure of global uncertainty. In all cases, the TVAR is estimated with two regimes, corresponding to periods of high and low uncertainty. Mathematically, the model is specified as:

$$Y_t = \sum_{k=1}^{4} \Theta_{high,k} I(X_{t-1} \geq \mu) Y_{t-k} + \sum_{k=1}^{4} \Theta_{low,k} I(X_{t-1} < \mu) Y_{t-k} + u_t \tag{1.1}$$

where Y_t is the vector of endogenous variables, $\Theta_{low,k}$ and $\Theta_{high,k}$ are the coefficient matrices for each regime, $I(.)$ is the regime indicator function, X_{t-1} is the (one-quarter lag of the) threshold variable, μ is the threshold value and u_t is the error term.

We estimate these models for each country in the sample individually and subsequently aggregate the resulting impulse responses post estimation. All models are estimated using Bayesian methods following Giannone et al. (2015). While the VAR coefficients (and contemporaneous structural responses) are allowed to be regime-specific, we simplify the prior specification by setting the overall degree of shrinkage equal to that of a linear VAR estimated on the full sample. This strategy ensures that any differences between impulse responses of the two states are caused by differences in dynamics and not by asymmetric or uneven priors. This simplification is done in order to streamline the interpretation of the results, though it leaves the question of whether prior shrinkage should be regime-specific to future research. All models are estimated using 4 lags and 5,000 posterior draws.

Impulse responses and aggregation. To synthesize our findings and evaluate representative structural dynamics across the panel, we implement a posterior pooling strategy. For our baseline results, we assume that the country-specific distributions of IRFs are independent draws from the global (representative) IRFs. Under this assumption, we calculate the median and 68% credibility sets from a distribution that stacks draws across all countries in our sample. By aggregating the posterior distributions in this manner, we capture the central tendency of the global transmission mechanisms while fully preserving the underlying estimation uncertainty from the individual country models.

Importantly, we report purely regime-specific rather than generalized impulse response functions. These impulse responses reflect the dynamics as if the economy remained in the regime where the shock originated. We view this assumption as economically acceptable for two primary reasons. First, the core objective of our investigation is precisely to isolate and evaluate how a shock propagates within a specific state of uncertainty. Second, these uncertainty regimes are relatively stable over time, as demonstrated in Figure 1.1, which minimizes the likelihood of rapid regime-switching during the transmission horizon. In this spirit, our methodological approach closely aligns with the regime-specific transmission analysis recently employed by De Santis and Cardamone (2026).

Beyond the baseline global aggregation, we also check for heterogeneity across different country groups to ascertain whether there are systematic differences in how uncertainty influences the transmission of monetary policy along various structural characteristics. When evaluating these subsets (such as advanced versus emerging market economies), we apply similar aggregating assumptions. For example, when separating the panel by development level, we assume that the country-specific distributions are independent draws from the global advanced economy IRFs and the global emerging market economy IRFs, respectively. As such, we stack the posterior draws within each subgroup and extract the representative set of IRFs. Repeating this approach along several structural characteristics allows us to check which ones improve or deteriorate the efficacy of monetary policy in high-uncertainty times. We provide an extensive list of these characteristics and related country groupings in the Appendix.

Identification. We identify shocks using sign restrictions, following the methodology of Arias et al. (2018). To properly isolate the monetary policy shock, we identify four additional structural shocks in the model: a domestic demand shock, a cost-push supply shock, a global uncertainty shock, and a risk premium (exchange rate appreciation) shock. Additionally, we leverage the well-documented transmission lags of monetary policy (see, e.g., Friedman (1961) and Batini and Nelson (2001)) and place restrictions for this shock to horizons $h = 1, 2$ quarters ahead as well. This is implemented as an extra precaution in isolating the monetary policy shock from any other possible structural shocks that the small variable set may not cover. The sign restrictions used for the identification are summarized in Tables 1.1 and 1.2 below.

Forni and Gambetti (2014) show that a VAR model can fail to recover the true

	UIP	Demand	Cost-push	Monetary Policy	Global uncertainty
EER	+			+	
GDP	-	+	-	-	-
π	-	+	+	-	-
R	-	+	+	+	
U					+

Table 1.1: Sign restrictions, $h = 0$

	UIP	Demand	Cost-push	Monetary Policy	Global uncertainty
EER					
GDP				-	
π				-	
R				+	
U					

Table 1.2: Sign restrictions, $h = 1, 2$

structural shocks if it does not adequately span the economy's relevant information set. Due to the large cross-section of countries in our panel, we do not formally test for informational sufficiency, although such a test could, in principle, be conducted on a country-by-country basis. We believe that our five endogenous variables provide adequate coverage to capture the primary shocks faced by an average open economy. Namely, domestic demand, cost-push, monetary policy, external risk premium, and global uncertainty[5] shocks. We acknowledge that a richer dataset incorporating factors such as detailed commodity price dynamics, credit constraints, financial frictions, technological innovations, and fiscal variables could certainly sharpen the identification. Doing so, however, would necessitate dropping several countries from the sample due to data availability and would impose a significantly heavier computational burden. As such, we leave these expanded specifications for future research. Nevertheless, to ensure the reliability of our baseline findings, we do relax the persistence assumption on monetary policy shocks in our robustness exercises.

The economic reasoning behind these identification restrictions is grounded in standard macroeconomic theory. First, we leave global uncertainty unconstrained across

[5]Caldara and Herbst (2019) for instance show that correctly identifying monetary shocks requires explicitly modelling the systematic reaction of policy to credit spreads. Failing to do so induces an attenuation bias that can itself masquerade as weak transmission. While we do not possess credit spread data, adding the endogenous (and regime-specific) reaction to uncertainty should help sharpen the identification of monetary policy shocks.

all domestic shocks. This reflects the standard small open economy assumption: it remains ambiguous whether individual countries of the sample carry sufficient weight in international dynamics to significantly impact global uncertainty.

Second, we separate domestic demand shocks from global uncertainty shocks. A positive domestic demand shock simultaneously raises output, inflation ($GDP \uparrow, \pi \uparrow$) and induces an endogenous monetary policy tightening ($R \uparrow$). A global uncertainty shock similarly acts as an aggregate demand contraction on domestic real activity ($GDP \downarrow, \pi \downarrow$), but it is uniquely identified by an exogenous spike in global uncertainty ($U \uparrow$) and an ambiguous response of interest rates. Leaving R unconstrained accounts for the ambiguity in how monetary policy might respond to uncertainty. Following the Knightian uncertainty narrative, it might trigger a "wait-and-see" type response. Alternatively, global uncertainty spikes might lead to capital flight-to-safety or currency depreciation, which might force the central bank to balance domestic easing against defensive rate hikes.

Third, the cost-push supply shock captures standard stagflationary dynamics, driving output down while pushing inflation up ($GDP \downarrow, \pi \uparrow$). Monetary authorities are assumed to react systematically by raising policy rates ($R \uparrow$) to control the inflationary pressure. Finally, the UIP shock isolates exogenous currency appreciation ($EER \uparrow$) driven by risk premium shifts (or international capital flows). The resulting loss of price competitiveness and cheaper imported inputs subsequently compress domestic output and consumer prices ($GDP \downarrow, \pi \downarrow$). To cleanly disentangle this from a monetary policy contraction, we impose that the central bank leans against the appreciating exchange rate and eases interest rates ($R \downarrow$).

Measuring monetary policy efficacy. When monetary policy intervenes to curb inflation, it inherently comes with a cost in terms of real output losses because it pulls back aggregate demand. Traditionally, the sacrifice ratio serves as a measure to gauge how much cumulative loss in output the economy must endure to achieve a given reduction in inflation. In the context of our VAR framework, we construct this metric at each horizon h by taking the ratio of the cumulative impulse response of GDP growth to the cumulative impulse response of inflation. Mathematically, the sacrifice ratio IRFs are defined as

$$SR_h = \frac{\sum_{h=0}^{H} IRF_h^{GDP}}{\sum_{h=0}^{H} IRF_h^{\pi}} \tag{1.2}$$

where IRF_h^{GDP} and IRF_h^{π} denote the orthogonalized impulse responses of GDP growth and inflation to a contractionary monetary policy shock at horizon h. As such, this measure provides a standardized measure of how much real growth needs to be sacrificed per unit of disinflation. Besides standardizing the results (i.e. independent of the size of the monetary policy shock), reporting sacrifice ratio IRFs helps us compress information into a few easily interpretable graphs that describe how the efficiency of the transmission changes when uncertainty is high.

To properly account for estimation uncertainty, the sacrifice ratio is not calculated simply by dividing the median impulse responses. Instead, the ratio in Equation 1.2 is computed dynamically at each individual posterior draw. From this resulting posterior distribution of the sacrifice ratios, we extract the posterior medians to be presented in the main figures. Aggregation of the sacrifice ratio IRFs follows the same aggregation logic outlined before.

It should be noted that while the sacrifice ratio IRFs help streamline the interpretation of the results, using them as the main visual tool has a downside. Because the sacrifice ratio requires dividing two estimated, normally distributed random variables, the resulting ratio-distribution is heavy tailed and can produce highly variable, possibly extreme and asymmetric density functions (see, e.g., Yang and Gui (2023)). Subsequently, wide 68% credibility sets would obscure the central tendencies and visual interpretation of the results. As such, for all sacrifice ratio IRFs in the main text, we report the medians exclusively. We report some of the sacrifice ratio IRFs with the 68% credibility set in the Appendix in order to fully account for the estimation uncertainty of these impulse responses as well.

1.5 Results

Figure 1.2 reports the central result of the paper. While the impulse responses of GDP growth, the policy rate, and the exchange rate to a monetary policy shock are broadly similar across uncertainty regimes, the response of inflation is not, as it is less persistent in the high-uncertainty regime than in the low-uncertainty regime. The implied sacrifice ratio (Panel B) makes this concrete. After the initial transition, roughly one unit of cumulative output loss is needed per unit of disinflation in the high-uncertainty regime, versus a small fraction of a unit in the low-uncertainty regime. High uncertainty does not so much prevent monetary policy from contracting the economy as it prevents that contraction from translating into disinflation.

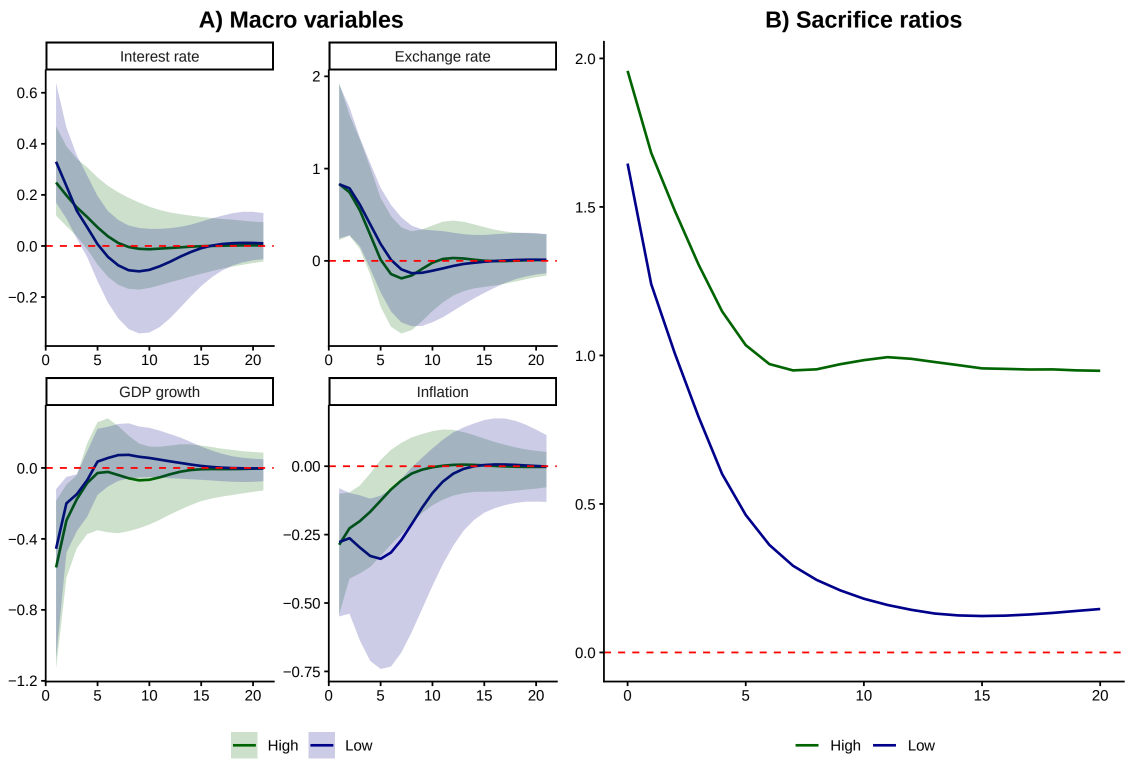

Figure 1.2: State-dependent impulse responses to a monetary policy shock.

Notes: Green (High) and blue (Low) lines show posterior median impulse responses in the high- and low-uncertainty regimes, respectively, pooled across all sample countries; shaded bands show 68% credibility sets. Panel B reports the implied sacrifice ratio, defined as the ratio of the cumulative impulse response of GDP growth to that of inflation (Equation 1.2).

This differs from the mechanism emphasized in much of the earlier literature, where uncertainty dampens transmission primarily by muting the real response to a policy shock (e.g., Castelnuovo and Pellegrino (2018)). In our setting, GDP contracts by a broadly comparable amount in both regimes. What changes is how much of that contraction shows up as disinflation. Read together with Figures 1.8 and 1.9 in the Appendix, the pattern is consistent across both the full sample and the shadow-rate subsample. The nonlinearity is primarily reflected in how inflation responds to the policy shock.

While the individual impulse responses (taking all shocks into account in Figures 1.8 and 1.9 in the Appendix) look broadly similar in both regimes, this does not invalidate the use of the threshold model. A modest, consistent gap in the cumulative inflation response compounds over the horizon into a large gap in the sacrifice ratio (as seen before in Panel B of Figure 1.2 before). A linear model that pooled both regimes would report a single blended inflation response that correctly describes neither one, and would misstate the sacrifice ratio in both states[6]. The fact that this separation survives across a barrage of sensitivity tests further suggests a stable underlying feature of the data rather than an artifact of any one specification.

The stark divergence in price dynamics across uncertainty regimes could suggest a flattening of the Phillips Curve under high economic policy uncertainty. In the presence of nominal rigidities, elevated policy uncertainty increases the real option value of waiting, prompting the "wait-and-see" type response widely documented in uncertainty literature as well. As forecasting future marginal costs and aggregate demand becomes increasingly difficult, firms systematically opt against costly nominal price markdowns. Consequently, less of a given change in economic slack passes through into prices. This accounts for both the shallower inflation trough and its faster reversion in the high-uncertainty regime.

Alternatively, the pattern could be driven by how economic agents form inflation expectations during volatile periods. Under high uncertainty, agents face a harder signal-extraction problem; with more disturbances in play, it is rational to attribute less of any given inflation surprise to a persistent shift, and thus they revise their expectations by less. This mechanically flattens the backward-looking empirical Phillips curve without requiring any structural change in firms' underlying price-setting behavior. Furthermore, if agents perceive severe policy uncertainty as a precursor to adverse supply shocks or eventual fiscal dominance, their inflation expecta-

[6] Figure 1.7 reports the linear BVAR impulse responses pooled across our panel. By inspecting the impulse responses to a monetary policy shock, we can visually confirm that the linear impulse response of inflation appears indeed to be a blend of the two regimes' responses.

tions may retain an upward bias, stubbornly anchoring pricing behavior and directly counteracting the intended disinflationary pressures of the interest rate hike.

Because our reduced-form threshold VAR identifies shocks via sign restrictions rather than an explicit structural model, we cannot definitively distinguish between a change in price-setting behavior and a shift in the anchoring of expectations. We present both as plausible, non-competing candidates. We leave the direct more precise identification between these channels to future research utilizing structural models. We however do also observe a "wait-and-see" type reaction in the policy rate path as well, as under low uncertainty the stance appears to normalize more aggressively. This, as well as the consensus of the uncertainty literature on "wait-and-see" motives prompts us to slightly favor this narrative.

How much do country characteristics influence the results? While Figure 1.2 establishes the average pattern, Figure 1.3 asks whether structural country characteristics[7] (factors outside the estimated system itself) help explain which economies bear a larger or smaller uncertainty penalty. The results established in Figure 1.2 are remarkably stable. Across every partition we consider, the high-uncertainty sacrifice ratio remains well above the low-uncertainty one, so none of these characteristics overturns the headline result. Where characteristics matter, they matter mostly at the margin, and mostly within the high-uncertainty regime.

Advanced economies face a somewhat worse sacrifice ratio than emerging markets under high uncertainty, the opposite of what a standard credit-constraint story for emerging-market vulnerability would predict. This at face value is a surprising result, however we attribute this to other factors being highly correlated with the EME classification. For instance, Panel E reports that economies with high trade openness face a more favorable sacrifice ratio compared to the global one, possibly due to international diversification and risk sharing. Net commodity exporters likewise fare worse than net importers under high uncertainty, consistent with commodity-driven inflation being less responsive to domestic demand conditions specifically when uncertainty is elevated. This is a pattern that falls in line with the aggregate-supply interpretation of the main result above, since commodity-price pass-through

[7] We provide details on how countries assigned into each subgroup along each of the structural characteristics in the Appendix.

operates largely outside the domestic output gap altogether.

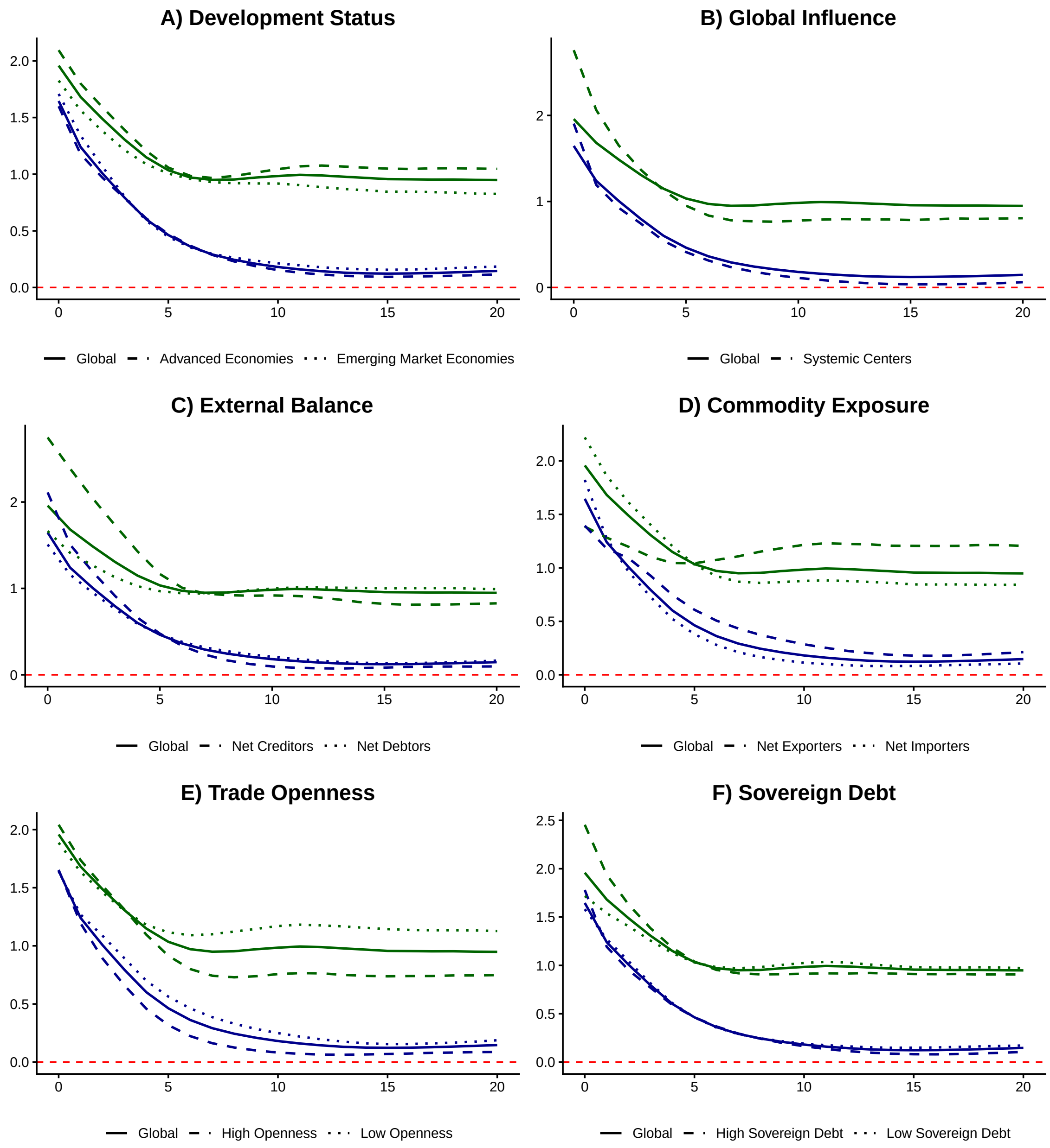

Figure 1.3: The impact of structural characteristics on the state-dependent sacrifice ratios.

Notes: Solid lines reproduce the global median sacrifice ratio from Figure 1.2B for the high- (green) and low- (blue) uncertainty regimes; dashed and dotted lines show the corresponding median sacrifice ratios for each country subgroup, obtained by pooling posterior draws within the subgroup rather than across the full sample. Country groupings are defined in the Appendix.

Does the level of uncertainty matter? Figure 1.4 checks whether the result is an artifact of the specific threshold used to separate high- from low-uncertainty periods. Apparent from the sacrifice ratios reported here, it is not. The median, 70th-percentile, and cyclical (above-trend) classifications produce sacrifice ratio paths where high uncertainty pushes the sacrifice ratio up. The level at which high uncertainty is defined only appears to matter at the margin. Pushing the threshold level up from the median to the 70th percentile, for instance, somewhat raises the sacrifice ratio at almost all horizons, indicating that possibly the higher the level of uncertainty is, the worse the inflation-output tradeoff becomes for the central bank.

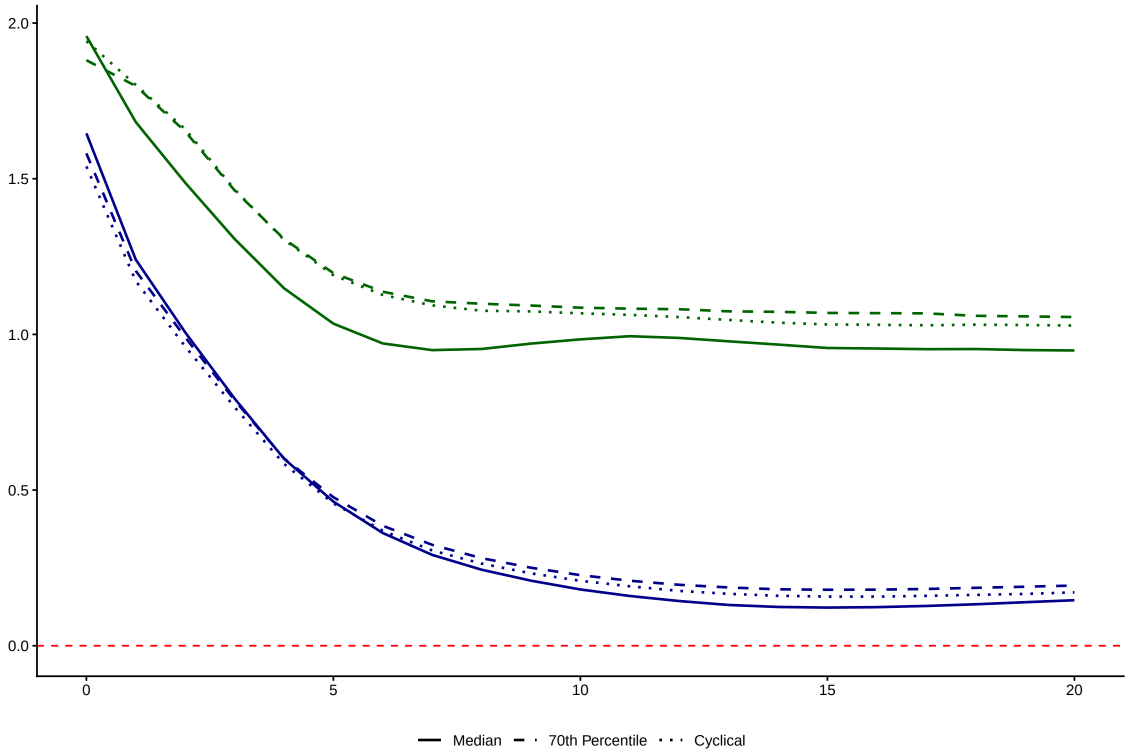

Figure 1.4: State-dependent sacrifice ratios under alternative threshold definitions.

Notes: Solid lines show the baseline median-threshold classification from Figure 1.2B; dashed and dotted lines show the corresponding sacrifice ratios when the high-uncertainty regime is instead defined as periods above the 70th percentile, or as periods above trend ("cyclical"), of the relevant uncertainty index.

How sensitive are the results to the uncertainty measurement? The result is not uniform across uncertainty measures. Figure 1.5 shows that the headline pattern is clearest for the two narrative, text-based measures of policy-type uncertainty, the WUI and the EPU. It is considerably weaker under the JLN1M index, and reverses under the GPR index, where the low-uncertainty regime shows the higher sacrifice ratio instead.

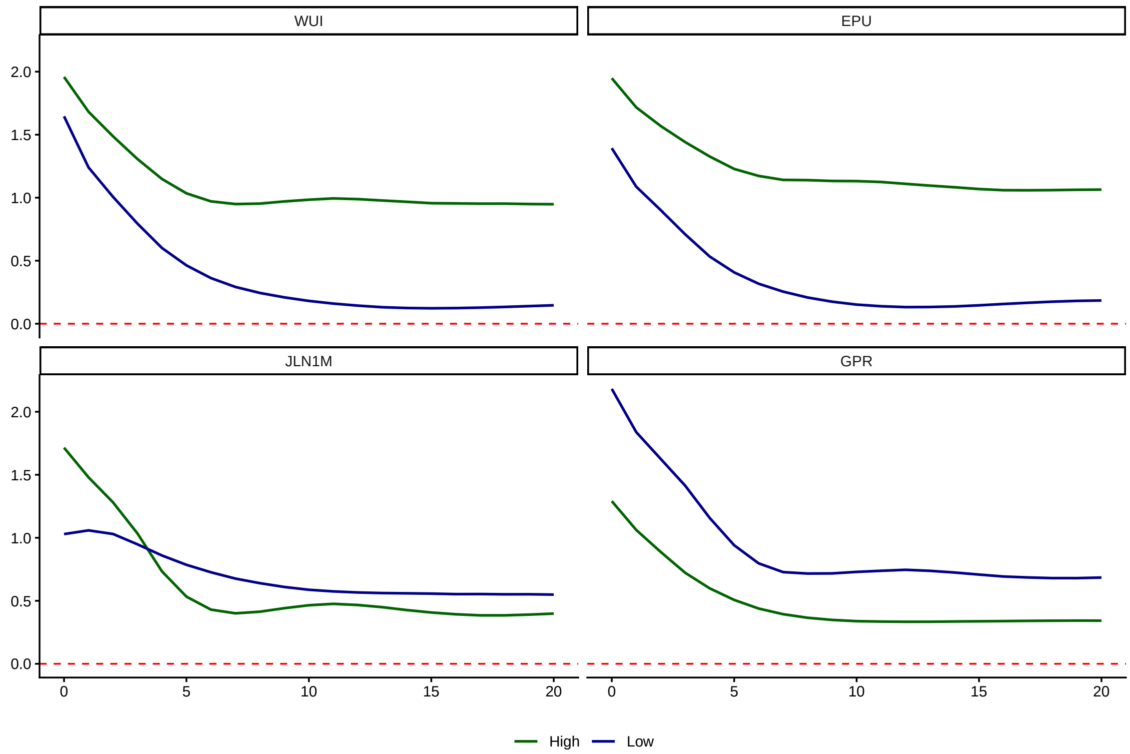

Figure 1.5: State-dependent sacrifice ratios under alternative uncertainty measures.

Notes: Each panel replaces the baseline WUI-based regime classification with the indicated alternative uncertainty measure (EPU, JLN1M, or GPR; see Data section) and re-estimates the model accordingly. Green and blue lines denote the high- and low-uncertainty regimes as defined by that measure.

Figure 1.11 in the Appendix points to where this divergence comes from. Under WUI and EPU in the low-uncertainty regime, the inflation responses' deep and persistent drop is what drives the low sacrifice ratio seen in Figure 1.2. Under JLN1M and GPR, the low-uncertainty inflation response closes markedly faster, practically the relationship here swaps. Under these two indices, there appears to be more of a difference between output responses too. For the GPR index, in low uncertainty times, the real contraction is largest out of all specifications and considerably larger relative to the high uncertainty counterpart with the same index. Regarding the JLN1M index, while the initial drop is larger in high uncertainty, output adjusts quicker, whereas the transmission to real output in low uncertainty times indicates a slightly more prolonged response. With respect to output, these results resonate more with the findings of earlier papers.

This is consistent with the conceptual distinctions already drawn in the Data section. JLN1M is derived from realized macro-financial forecast-error volatility rather than perceived policy uncertainty, and GPR captures geopolitical tension specifically rather than economic-policy uncertainty. Read together, the result may be better understood as a finding about policy-type uncertainty in particular. While the results may not hold under all sources of uncertainty, hesitancy in price-setting driven by unresolved questions about the future policy and regulatory environment does appear to hinder the effectiveness of monetary policy in achieving disinflation.

Robustness to the identifying restrictions. In order to test the robustness of our results, we drop the identifying restrictions imposed on horizons $h = 1, 2$ and rely only on the $h = 0$ restrictions to identify the monetary policy shock. Figure 1.6 shows that the implications of the results hold even when relaxing the identifying restrictions. While on shorter horizons the sacrifice ratios coincide, they stabilize such that the high-uncertainty ones are consistently above the low-uncertainty ratios. Figure 1.12 in the Appendix shows where the sensitivity that does exist is concentrated. Relaxing the restriction primarily changes the GDP responses, while the inflation impulse response patterns stay largely unchanged regardless of identifying restrictions. Since inflation has been the primary driver of our results, this reassures us that the core conclusions are unchanged.

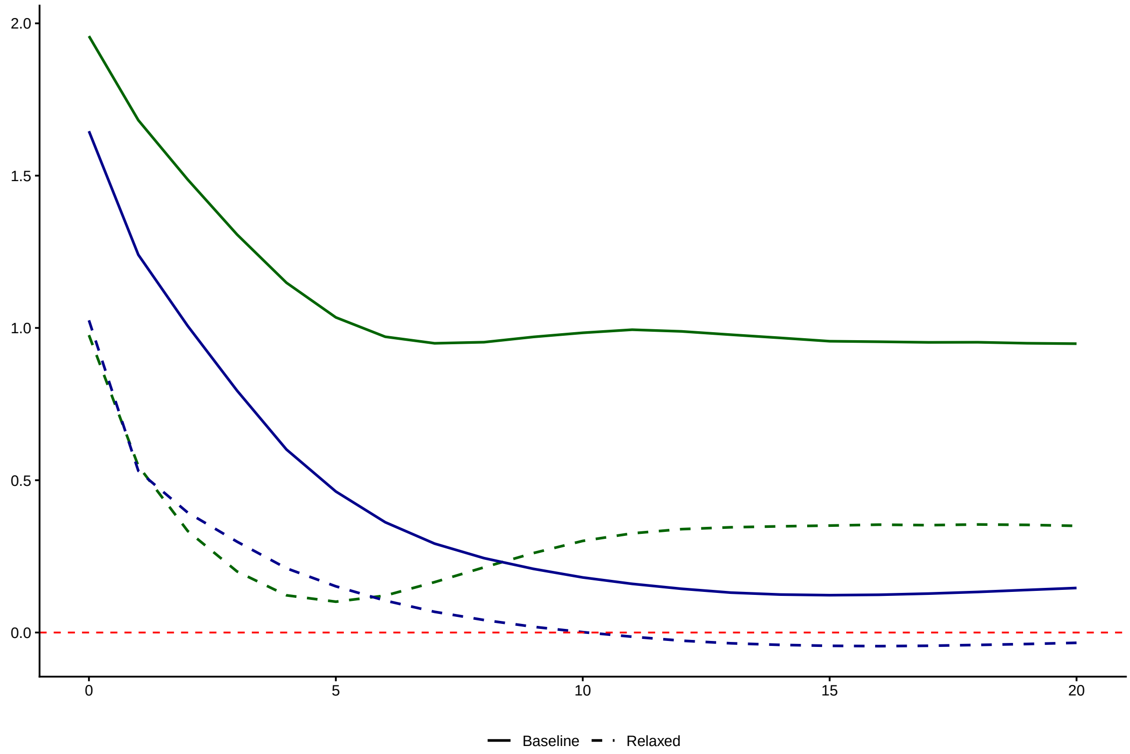

Figure 1.6: Robustness check: relaxing the persistence restriction on the monetary policy shock.

Notes: "Baseline" imposes the sign restrictions in Tables 1.1 and 1.2, including persistence of the monetary policy shock through $h = 1, 2$; "Relaxed" drops the horizon-1–2 persistence restriction on the monetary policy shock while retaining the contemporaneous ($h = 0$) restrictions.

1.6 Conclusion

This paper set out to ask whether, and how, economic uncertainty alters the transmission of monetary policy. Using Bayesian Threshold VARs estimated across a broad panel of 30 advanced and emerging market economies, with monetary shocks identified via sign restrictions and the full system allowed to vary by uncertainty regime, we find a clear answer. Transmission is state dependent, but not through the channel most of the existing literature emphasizes. The response of GDP growth to a monetary policy shock is broadly similar whether uncertainty is high or low. What differs sharply is the response of inflation, which is shallower and closes faster in the high-uncertainty regime than in the low-uncertainty regime. The resulting sacrifice ratio is several times larger under high uncertainty, making disinflation a considerably more expensive undertaking for central banks precisely when uncertainty is elevated.

Two features of the result stand out on closer inspection. First, it is inflation, not output, that carries the state dependence, which reframes the policy problem. Uncertainty does not so much prevent a central bank from contracting the economy as it prevents that contraction from buying disinflation. We interpret this, tentatively, as most consistent with an aggregate-supply channel (a flattening Phillips Curve) though a reduced-form, sign-restricted framework cannot distinguish this from an observationally similar story in which less-anchored or harder-to-update inflation expectations play the same role, and we present both as candidate explanations rather than adjudicate between them. The modest state dependence we also find in the policy rate response itself suggests that the systematic conduct of policy, not only the private-sector side of transmission, may adjust under uncertainty as well.

Second, the result is not uniform across uncertainty measures: it is strongest for narrative, text-based indicators of economic policy uncertainty specifically, and weaker or reversed for a model-based macro-uncertainty index and a geopolitical risk index. This suggests the finding is less about uncertainty in a universal sense than about economic policy-related uncertainty interacting with how prices and expectations respond to demand conditions.

Policy implications. Three implications follow. First, and most directly, central banks may need to expect a materially worse inflation-output tradeoff during episodes of elevated policy uncertainty. A given monetary tightening buys less disinflation, so achieving a given inflation objective may require either a larger or a more sustained policy response than the same objective would require in calmer times. Following the logic of the sacrifice ratios we computed, the real economic cost associated with achieving disinflation rises significantly.

Second, because the effect we document is considerably stronger for measures of economic policy uncertainty than for uncertainty in general, our results point to a complementarity between monetary policy effectiveness and the predictability of the broader policy environment (not only monetary policy, but fiscal, regulatory, and trade policy as well). To the extent that episodes of geoeconomic fragmentation of the kind discussed in the introduction generate exactly this type of policy uncertainty, they may impose a cost on inflation control that falls on central banks even when the underlying disturbance originates well outside their mandate. This is, in effect, an argument for policy coordination and clear communication across government as a complement to monetary policy, not only a matter for central banks acting alone.

Third, if the anchoring-based interpretation of our results has merit, central bank communication and credibility take on added importance precisely when uncertainty is high, since well-anchored expectations are what would prevent a given shock from propagating further into future inflation. This reinforces a familiar prescription that investing in credibility matters. With our results in mind, there is a measurable cost of failing to do so.

1.7 References

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1.8 Appendix

1.8.1 Supplementary graphs for Figure 1.2

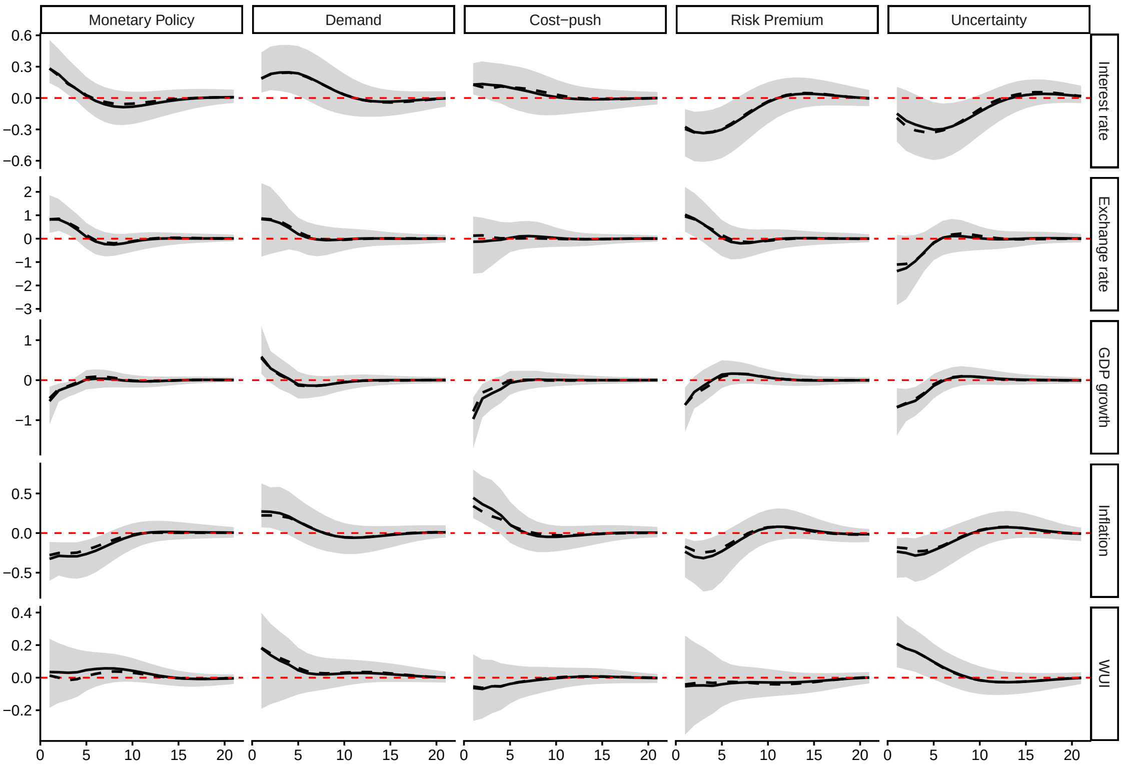

Figure 1.7: Linear VAR impulse responses to the five identified shocks.

Notes: Solid lines show the median impulse response for the full country panel; dashed lines indicate the median impulse response computed from the subset of economies where estimated shadow short rates are used.

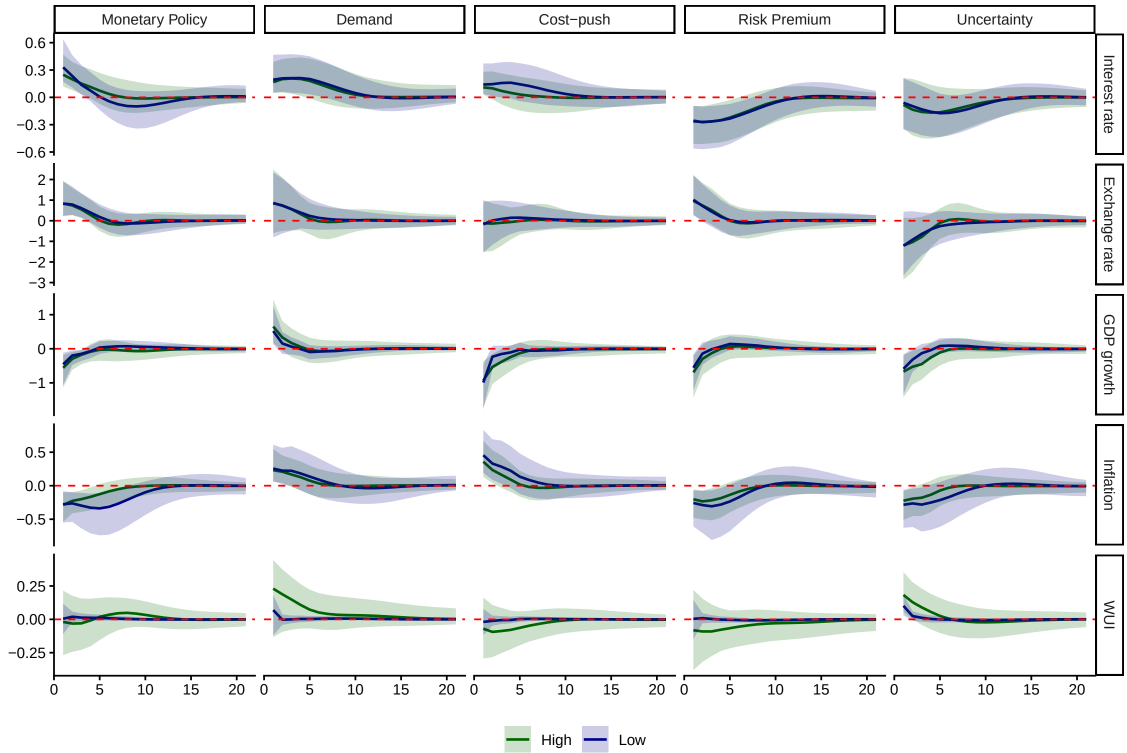

Figure 1.8: State-dependent impulse responses to the five identified shocks - full sample.

Notes: Green (High) and blue (Low) lines denote posterior median impulse responses in the high- and low-uncertainty regimes; shaded bands show 68% credibility sets. Estimated on the full country panel.

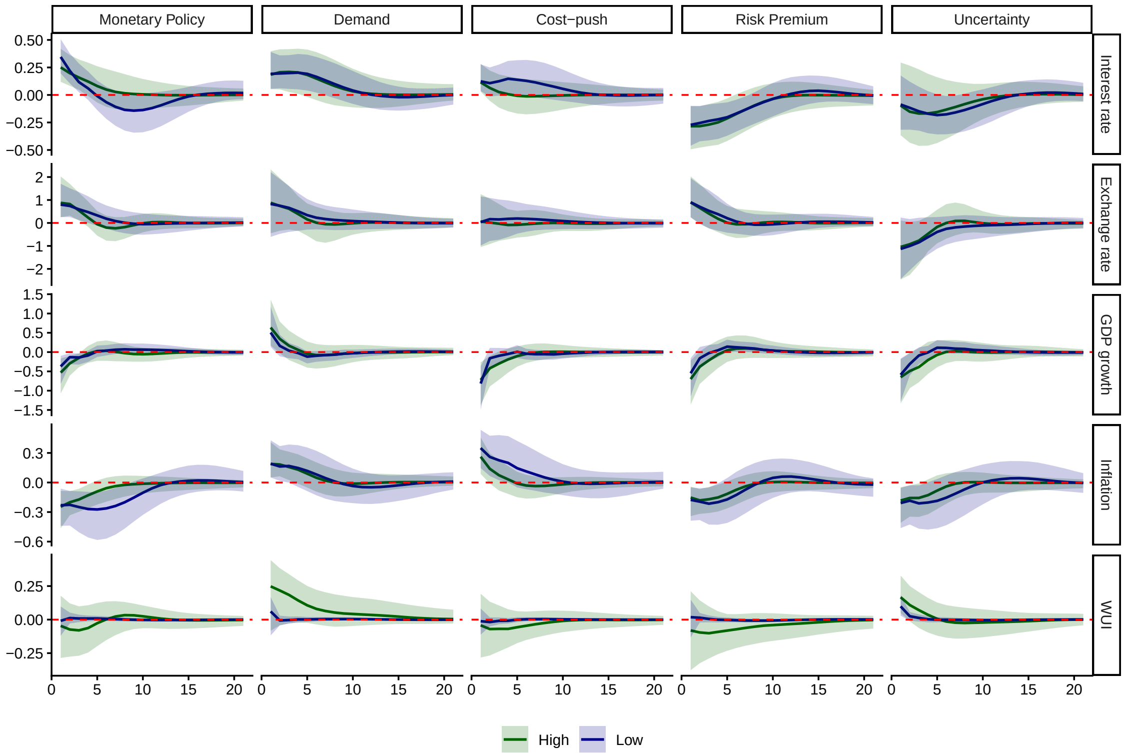

Figure 1.9: State-dependent impulse responses to the five identified shocks - shadow-rate subsample.

Notes: As Figure 1.8, restricted to the subset of economies for which estimated shadow short rates are used in place of the observed policy rate (see Data section).

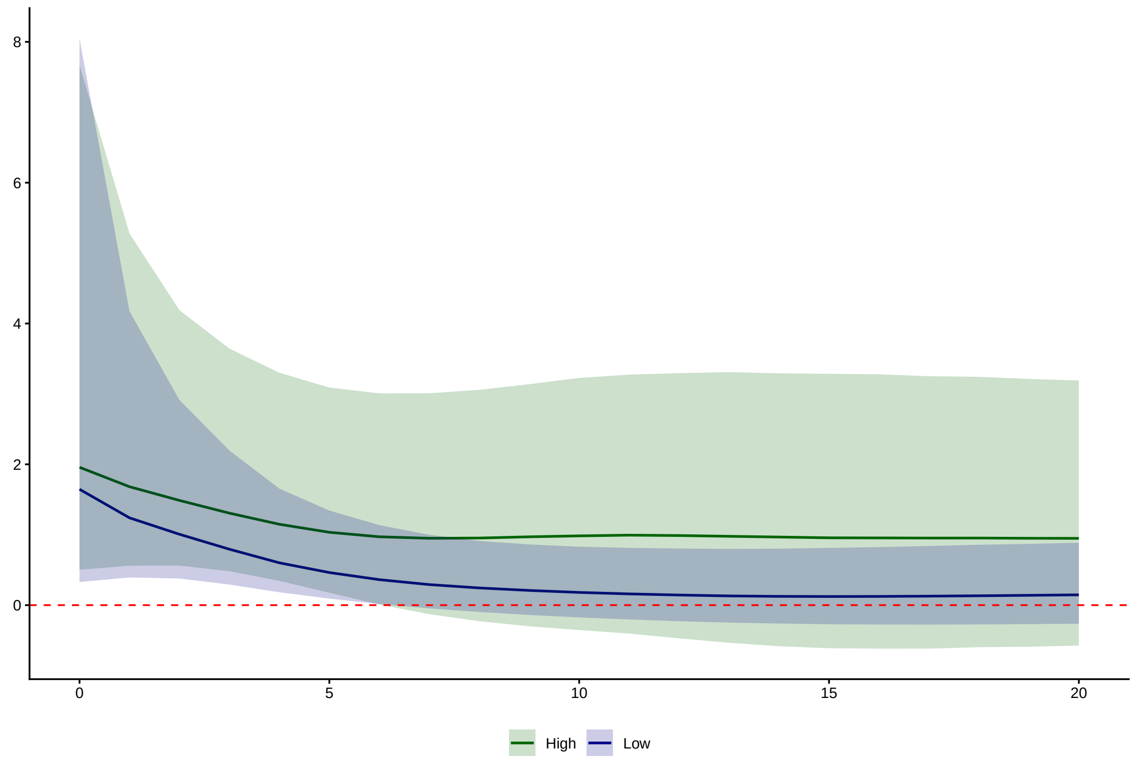

Figure 1.10: Sacrifice ratios with 68% credibility sets.

Notes: As Figure 1.2B, but showing the posterior 68% credibility set (shaded) around the median sacrifice ratio (solid line) for each regime.

1.8.2 Classification of country groups in Figure 1.3

This subsection of the Appendix details the macroeconomic classifications used to partition the sample of 30 economies into the structural groupings presented in Figure 1.3. The assignments rely on standard institutional databases and established empirical thresholds to ensure consistent cross-country comparisons.

Development Status: Economies are classified as Advanced Economies (AEs) or Emerging Market Economies (EMEs) in accordance with the IMF World Economic Outlook taxonomy. The AE subsample comprises AUS, CAN, CHE, DNK, EA, GBR, ISL, ISR, JPN, KOR, NOR, NZL, SGP, SWE, and USA. The remaining economies are designated as EMEs (BRA, CHL, COL, CZE, HUN, IDN, IND, MEX, MKD, PHL, POL, ROU, SRB, THA, ZAF).

Global Influence: We select a handful of “Systemic Centers” based on gross economic footprint and global financial influence. Systemic Centers include major reserve currency issuers and exceptionally large domestic markets (BRA, EA, GBR, IND, JPN, USA).

Commodity Exposure: Economies are grouped by their structural net trade position in primary commodities. Net Commodity Exporters (AUS, BRA, CAN, CHL, COL, IDN, NOR, NZL, ZAF) are defined as those generating positive net exports of raw materials and energy products. All remaining economies are classified as Net Importers.

External Balance: This classification hinges on the Net International Investment Position (NIIP) to separate Creditor and Debtor economies. Net Creditors possess a structurally positive NIIP (CHE, DNK, EA, ISR, JPN, KOR, NOR, SGP, SWE). The designated Net Debtors operate with a negative NIIP (AUS, BRA, CAN, CHL, COL, CZE, GBR, HUN, IDN, IND, ISL, MEX, MKD, NZL, PHL, POL, ROU, SRB, USA, ZAF).

Trade Openness: Economies are partitioned based on their gross trade-to-GDP ratios utilizing standard trade metrics $\frac{Exports+Imports}{GDP}$. Economies exceeding a high structural openness threshold are classified as High Openness (CHE, CZE, DNK, HUN, ISL, KOR, MKD, POL, ROU, SGP, SRB, SWE, THA), with the remaining economies categorized as having Low to Moderate Openness.

Sovereign Debt: Sovereign debt groupings are determined by general government gross debt-to-GDP ratios. Economies exhibiting elevated structural debt levels are assigned to the High Debt category (BRA, CAN, EA, GBR, HUN, IND, ISR, JPN, USA, ZAF). All remaining economies are classified as having Low to Moderate Sovereign Debt.

1.8.3 Supplementary graphs for the uncertainty measure variation

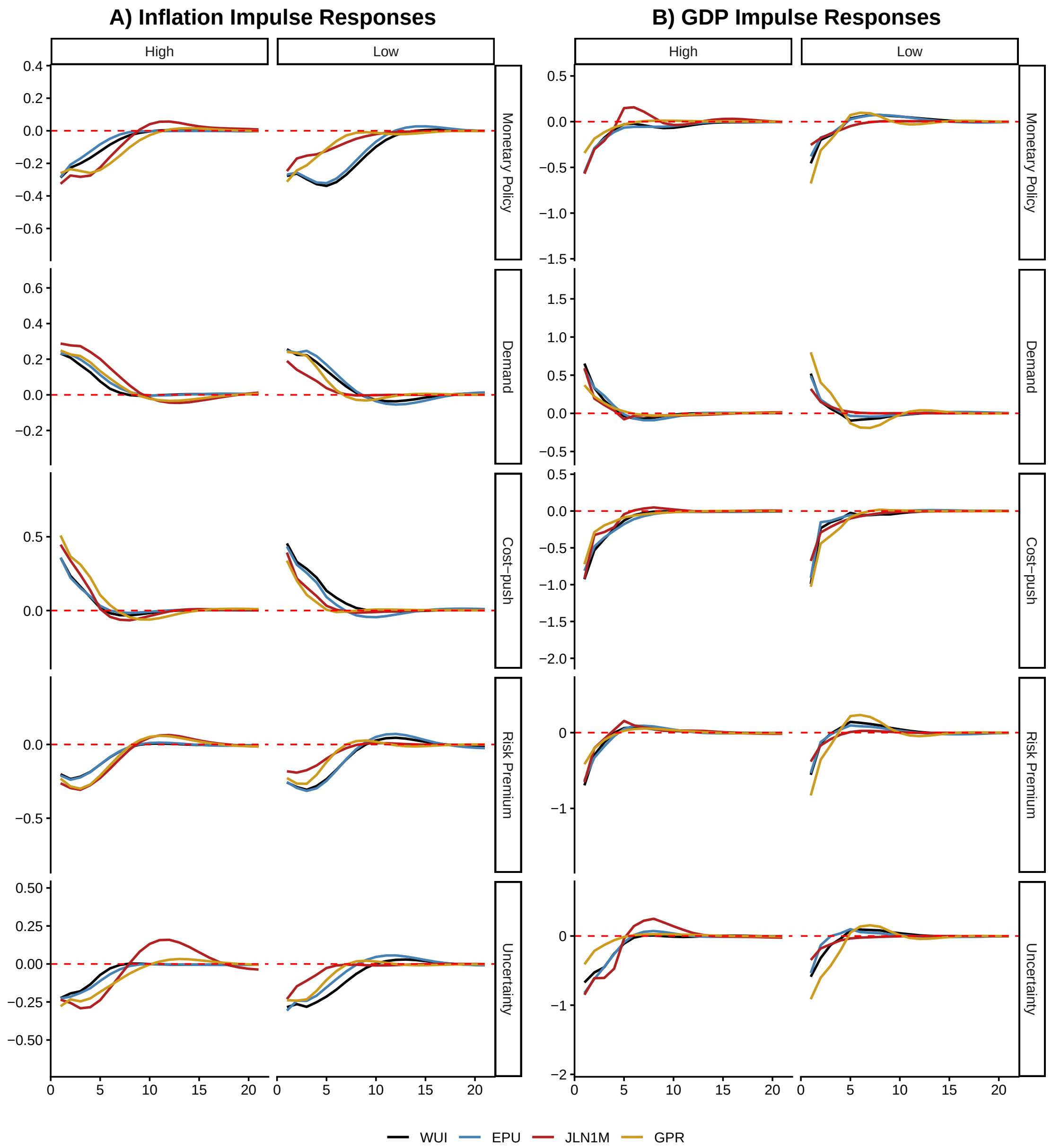

Figure 1.11: State-dependent GDP and inflation impulse responses under alternative uncertainty measures.

Notes: Each colored line shows the posterior median impulse response under the indicated uncertainty measure (WUI, EPU, JLN1M, or GPR), separately for the high- and low-uncertainty regimes as classified by that measure.

1.8.4 Supplementary graphs for testing the identifying restrictions

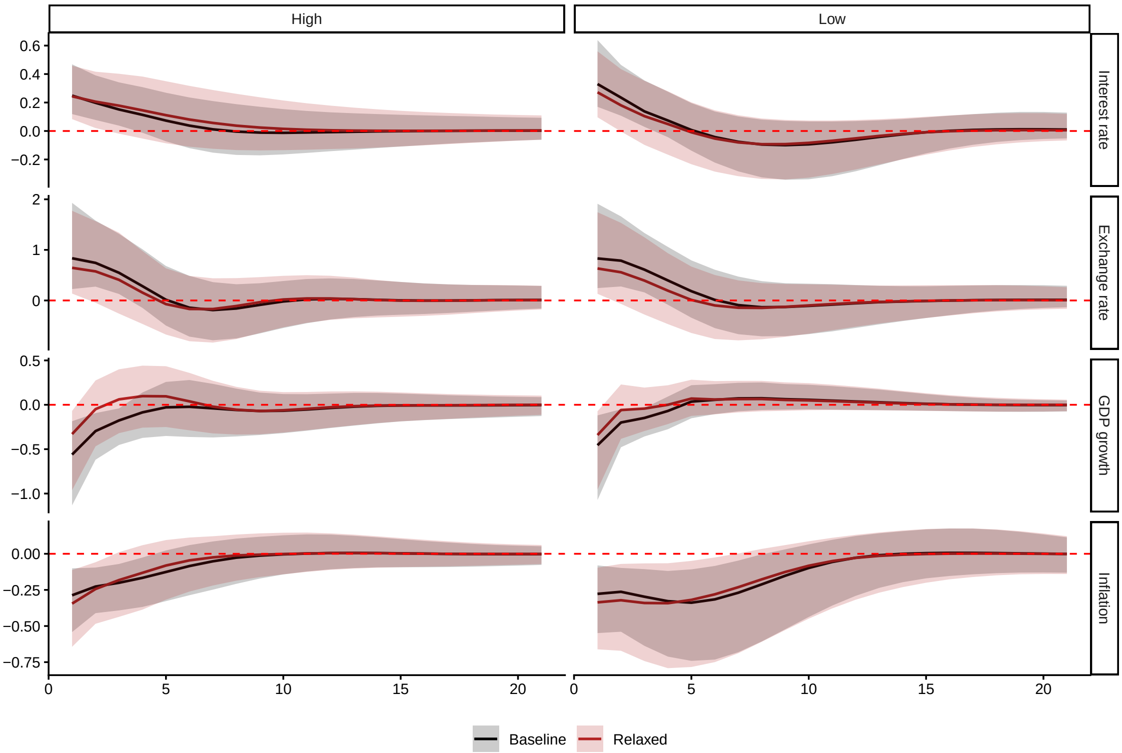

Figure 1.12: State-dependent impulse responses under the relaxed identifying restriction.

Notes: "Baseline" and "Relaxed" correspond to the two specifications in Figure 1.6; shaded bands show 68% credibility sets. High- and low-uncertainty regime results are shown in separate columns rather than overlaid, unlike Figures 1.8 and 1.9.

Chapter 2

Nonlinear Transmission of Monetary Policy and Housing Market Imbalances: Evidence from a Factor-Augmented Threshold VAR Analysis

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Abstract: In recent decades, persistently low rates have driven housing booms and prompted questions on how market imbalances interact with monetary policy. In this paper, I investigate how such imbalances affect the monetary transmission in the United States. I create a boom-bust cycle indicator from the rent-price ratio and credit-to-GDP gap, then embed it in a factor-augmented threshold VAR with two regimes to isolate the two parts of the cycle. Impulse responses show that monetary policy itself behaves differently conditional on the state of the housing market. Interest rates are eased much more gradually around booms, which suggests that broader macro-financial signals are incorporated into the policy framework in order to effectively manage deleveraging in the market. The transmission channel appears to be less affected, as real and financial aggregates show only somewhat larger contractions in response to a monetary policy shock in a booming market.
Keywords: Housing market, Monetary policy, Threshold Vector Auto-Regression, Latent factors, Generalized Impulse Responses

JEL: E32, E44, E52, C32

2.1 Introduction

Housing is a central driver of business cycles. Residential investment makes up a sizable share of demand, and the housing market amplifies shocks through credit and monetary channels. After the Global Financial Crisis, prolonged low rates produced a large expansion in mortgage lending and a sharp rise in property prices, raising bubble concerns. As inflation rose sharply in 2022 and remained persistently high, central banks entered prolonged tightening cycles. Although many have since concluded these cycles and begun easing monetary conditions, reassessing the relationship between the housing market and monetary policy remains a pressing issue for researchers and policymakers.

The motivation for this study stems from both empirical and policy-related challenges. First, a deeper understanding of the interaction between housing markets and monetary policy is essential, as housing is a leading indicator of broader economic imbalances. Historical episodes, such as the housing price bubble identified by Case and Shiller (2003) and subsequent market corrections illustrate how sustained deviations from fundamental values can lead to severe economic downturns. Kydland et al. (2016) provides empirical evidence that residential investment is not only a leading indicator, but also a critical driver of business cycle fluctuations. Adelino et al. (2018) surveys the role that mortgages and inflated house prices played in the GFC, and the literature review by Duca et al. (2021) compiles evidence that housing cycles are closely linked to broader business cycle dynamics at the international level.

Second, there remains considerable ambiguity regarding the nonlinear transmission mechanisms through which monetary policy shocks affect the economy. Li and St-Amant (2010) investigate Canadian monetary transmission and find strong state-dependent dynamics in the presence of financial stress. Fry-Mckibbin and Zheng (2016) report similar findings for U.S. monetary transmission during crises. Schmidt (2020) examines nonlinear monetary transmission in European asset markets and also finds stronger responses during periods of high stress. Traditional linear models may overlook important regime-dependent dynamics, particularly how shocks interact with underlying market vulnerabilities.

Third, the study is motivated by the three-way interaction between housing markets, monetary policy, and financial conditions. The seminal work of Bernanke et al. (1999) on the financial accelerator illustrates how credit market imperfections can magnify the effects of monetary shocks. Papers by Iacoviello (2005), Iacoviello and Minetti (2008), and Mian and Sufi (2011) examine the interaction between housing, monetary policy, and borrowing constraints. These studies show that house price fluctuations can amplify aggregate demand via collateral effects that influence borrowing capacity.

Although the low interest rate environment post-2008 encouraged lending and inflated asset prices, the subsequent rise in inflation forced a reversal in monetary policy. This tightening may have implications for speculative pressures in housing markets. When central banks raise rates in a highly leveraged and credit-sensitive economy, prior research suggests that the impact may be amplified under high-stress conditions. By introducing a state-dependent Threshold Vector Autoregressive (TVAR) framework, this study aims to identify and quantify such nonlinearities. In doing so, it contributes to the literature on the heterogeneous effects of policy interventions in overheated versus stable market conditions, as well as on the evolution of housing market imbalances. Rising home prices, in turn, have been shown to be closely linked to financial stress and to serve as early warning indicators of broader economic downturns.

This paper presents a natural continuation of the existing literature. Using the rent-price ratio and the credit-to-GDP gap as measures of real estate and credit market imbalances, I construct a synthetic index of to track the boom-bust cycle in the housing market using principal component analysis (PCA). This composite indicator is embedded into a Factor-Augmented TVAR (TFAVAR) model to identify forming bubbles in the real estate market and to trace regime-specific impulse responses to monetary shocks across a carefully selected set of variables. These impulse responses are estimated using Generalized Impulse Responses that account for regime switches. The results indicate some regime-dependent effects of monetary policy shocks, although the differences across regimes are relatively minor. Importantly, the behavior of monetary policy appears to shift significantly depending on the state of the economy. During housing booms, the policy stance remains tighter for longer, and interest rates adjust more gradually, reflecting the Federal Reserve's cautious approach to navigating financial and housing market imbalances. These findings suggest that monetary policy responds to broader economic conditions than those captured by the standard Taylor rule, particularly when managing deleveraging during housing booms.

The remainder of this paper is structured as follows. Section 2 describes the dataset, which comprises quarterly U.S. data from 1970Q2 to 2024Q3 and includes real aggregates, financial stress measures, and housing market variables. Section 3 outlines the methodological framework, including the construction of the composite housing stress indicator and the estimation of the TVAR model. Section 4 presents the empirical results, focusing on the nonlinear transmission of monetary policy shocks. Section 5 concludes with a discussion of the implications and directions for future research.

2.2 Data

To fully capture complex macro-financial dynamics, I construct a quarterly dataset consisting of real aggregates, financial stress indicators, and housing market variables for the United States from 1970Q2 to 2024Q3. The dataset contains 10 variables: Real GDP (Y), Consumer Prices (P), Real Property Prices (HP), Rent-price ratio (RP), Real Estate Loans (HL), Mortgage Rate (MR), Federal Funds Rate (R), Term Spread (TS), Credit Spread (CS), and Credit-to-GDP Gap (CGG).

To account for the continuity of monetary policy action during periods when nominal rates are constrained by the Zero-Lower-Bound, the Wu and Xia (2016) shadow rate is used in place of the observed Federal Funds Rate values. The term spread, calculated as the yield on 10-year minus the yield on 1-year Treasury bills, serves as a measure of expectations about future interest rate fluctuations. The credit spread is calculated as the return on BAA minus AAA-rated corporate bonds and is useful for tracking episodes of financial stress or tight financial conditions.

The rent-price ratio serves as a valuation metric of the housing market aimed at capturing potential misalignments between property prices and economic fundamentals.

I calculate the rent-price ratio as $\ln(\text{Real Rental Index}) - \ln(\text{Real Property Prices Index})$, where the Real Rental Index is $\frac{\text{CPI: Rent of primary residence}}{\text{CPI: All items less shelter}}$. The Credit-to-GDP gap serves as an indicator of credit cycle imbalances and helps detect periods of excessive lending relative to long-run trends. CGG is defined as the deviation of $\frac{\text{Credit}_t}{\text{GDP}_t}$ from its long-run trend and is calculated using an HP filter.

All data except the CGG series are downloaded from the FRED database. The CGG series is downloaded from the BIS data portal. Variables Y, P, HP, and HL are log-normalized. All variables except R are scaled to zero mean and unit standard deviation. Table 2.1 below summarizes the variables and transformation steps:

Variable	**Symbol**	**Definition / Calculation**	**Transformation**	**Data Source**
Real GDP	Y	Real Gross Domestic Product	Log-level, scaled to zero mean and unit std.	FRED
Consumer Prices	P	Consumer Price Index	Log-level, scaled to zero mean and unit std.	FRED
Real Property Prices	HP	Real Property Prices Index	Log-level, scaled to zero mean and unit std.	FRED
Rent-Price Ratio	RP	$\ln(HP) - \ln\left(\frac{\text{CPI: Rent of primary residence}}{\text{CPI: All items less shelter}}\right)$	Scaled to zero mean and unit std. dev.	FRED
Real Estate Loans	HL	Total Real Estate Loans	Log-level, scaled to zero mean and unit std.	FRED
Mortgage Rate	MR	Mortgage interest rate	Levels, scaled to zero mean and unit std.	FRED
Federal Funds / Shadow Rate	R	Nominal Federal Funds Rate; replaced with shadow rate during ZLB periods	Entered in levels	FRED
Term Spread	TS	Difference between 10-year and 1-year Treasury yields	Levels, scaled to zero mean and unit std.	FRED
Credit Spread	CS	Difference between BAA and AAA corporate bond yields	Levels, scaled to zero mean and unit std.	FRED
Credit-to-GDP Gap	CGG	Deviation of $\frac{\text{Credit}_t}{\text{GDP}_t}$ from trend (HP filter)	Scaled to zero mean and unit std. dev.	BIS

Table 2.1: Variable definitions and transformations

2.3 Methodology

This section outlines the analytical framework used in the paper. The methodological challenges are threefold: (i) credibly identifying periods of booms and busts in the housing market; (ii) modeling nonlinear dynamics; and (iii) correctly capturing the propagation of monetary policy shocks in a nonlinear system. Threshold-type models are well-established for handling nonlinearities in empirical macroeconomics (see B. Hansen (1999), B. E. Hansen (2000), Lo and Zivot (2001), Caner and Hansen (2001), B. E. Hansen and Seo (2002), B. E. Hansen (2011)). Generalized impulse response functions (GIRFs), introduced by Koop et al. (1996), offer a way to analyze dynamic responses in such settings. I closely follow the GIRF implementation methods of Andreasen et al. (2021). Lastly, composite indicators are widely used in empirical macro for tracking financial stress or business cycle conditions (see Estrella and Mishkin (1998), Stock and Watson (1989), Bai and Ng (2002), Union and Centre (2008), Hatzius et al. (2010), Koop and Korobilis (2014)).

2.3.1 Identifying the boom-bust cycle in the Housing Market

Speculative pressures in housing markets tend to arise from the interaction of credit expansion and housing overvaluation. I propose a framework that captures this joint dynamic using two core measures: the credit-to-GDP gap (CGG), which signals excessive credit growth, and the rent–price ratio (RP), which reflects deviations of housing prices from rental fundamentals. While each measure is informative on its own, they are susceptible to measurement error and idiosyncratic variation. To synthesize their shared signal and reduce noise, I construct a composite indicator using principal component analysis (PCA).

The use of such composite indicators is well grounded in the literature. For example, Borio and Drehmann (2009) and Drehmann and Juselius (2014) aggregate various imbalance indicators into early warning measures for financial crises. Similarly, Alessandri and Mumtaz (2019) employ a nonlinear VAR framework centered around a composite financial stress index, and Auerbach and Gorodnichenko (2012) use a smooth transition VAR based on a composite business cycle indicator.

Construction of the housing boom-bust cycle indicator begins with standardized series (as seen in the Data section): both the CGG and RP series are scaled to have zero mean and unit variance, since PCA is scale-sensitive. The standard PCA procedure involves decomposing the covariance matrix of these inputs. The eigenvector corresponding to the largest eigenvalue provides the linear combination that maximizes shared variance:

$$PC1 = w_1 CGG + w_2 RP \tag{2.1}$$

where w_1 and w_2 are the weights from the leading eigenvector. This first principal component (PC1) thus captures the joint variation in credit and housing price signals, functioning as a latent factor that represents the simultaneous emergence of credit excess and housing overvaluation. The resulting time series is shown in Figure 2.1.

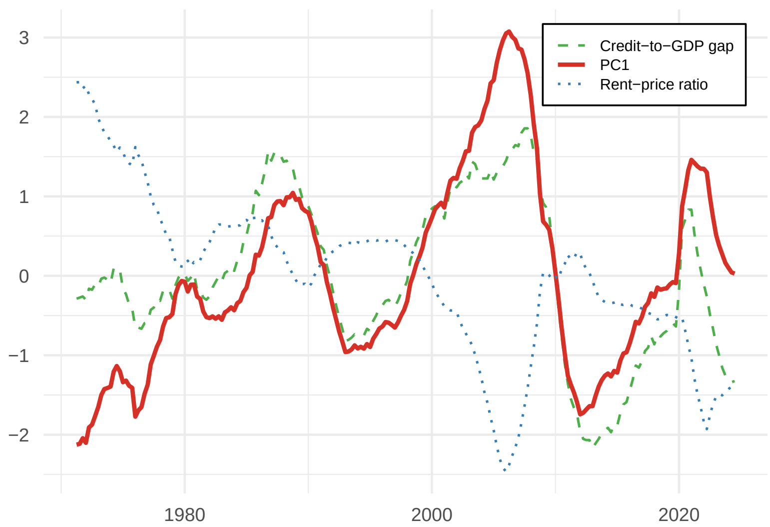

Figure 2.1: An indicator of the boom-bust cycle in the housing market.

PC1 explains roughly 61% of the shared variance. This leaves 39% of the variation unexplained, which may raise concerns about missing relevant dynamics. However, a visual inspection suggests that the index rises precisely when credit expansion accelerates and house prices decouple from fundamentals. It therefore provides a theoretically grounded and practically useful indicator of boom-bust cycles in the housing market.

2.3.2 Threshold VAR Estimation and Identification

Nonlinear models are becoming staples in empirical macroeconomics, especially when assessing how aggregate dynamics shift during episodes of financial strain, heightened uncertainty, or outright recessions. For example, Schüler (2014) and Lhuissier et al. (2016) show that uncertainty shocks matter far more when the banking sector is already under pressure. Likewise, Chiu and Hacioglu Hoke (2016) finds that financial shocks in downturns spark disproportionately larger contractions, while Ferraresi et al. (2015) and Afonso et al. (2018) use TVAR frameworks to uncover that fiscal multipliers are larger when credit conditions tighten. More recently, Kole and Dijk (2023) finds that financial stress shocks have stronger impacts in bearish markets and during recessionary times, and Mittnik and Semmler (2018) document how leverage cycles can destabilize macro dynamics.

Across these studies, scholars have adopted a variety of empirical models to capture nonlinear behavior. The threshold VAR (TVAR) stands out for its transparency and modest computational demands. Unlike Markov-switching VAR (MSVAR) and Time-Varying Parameter VAR (TVP-VAR) models, which capture regime changes via latent processes or gradually evolving coefficients, the TVAR explicitly splits the sample based on an observed variable. The explicit regime separation makes the interpretations very clear, as the differing propagation of shocks can be directly attributed to the state of the economy as identified by the regimes. The straight forward interpretation as well as the relative computational ease makes the TVAR and ideal choice for modeling the nonlinear transmission of monetary policy across the housing cycle.

Naturally, no empirical method is without its drawbacks. Firstly, the state of the economy is more accurately represented by a smooth spectrum, rather than black and white worldview of the binary regime indicator suggested by the TVAR. Secondly, the TVAR substantially reduces degrees of freedom, as it essentially doubles the number of estimated parameters (assuming there are two regimes).

As shown in the Results Section, the regime switches are not at all abrupt, and the regimes do indeed have a clear interpretation, as such I see no reason to address the first shortcoming of the TVAR model by introducing smoother transitions. As for the issue of over-parametrization, I adopt a dimensionality-reduction strategy using Factor-Augmented VARs (FAVAR), originally proposed in Bernanke et al. (2005).

A standard FAVAR can be estimated using two steps. First, a small number of latent factors are extracted (typically) from a large panel of observed variables. These factors can be extracted using different techniques, such as principal components or dynamic factor models. For the purposes of this paper I rely on PCA to extract the factors. Second, a VAR model is fit on variables (typically) excluded from the factor extraction step and the extracted latent factors. This two stage approach has the benefit significantly reducing dimensionalty, while retaining the majority of the shared variance across a number of variables. As the second step suggests, the FAVAR at its core is a standard VAR estimated using latent factors, which makes its combination with the TVAR estimation steps straight forward.

Although FAVARs often draw on hundreds of series, my threshold FAVAR (TFAVAR) relies on just seven indicators (Y, P, HP, HL, MR, TS, and CS) in the factor extraction process. While unusual, this streamlined setup remains consistent with the original motivation behind the FAVAR model: overcoming the standard VAR's curse of dimensionality without sacrificing informational richness. By focusing on these seven series, I preserve a relatively parsimonious framework that captures the main transmission channels of monetary policy while also incorporating aggregates relevant for the housing market.

I extract three principal components, which jointly explain around 93% of the variance across the seven variables, as shown in Table 2.2. These three factors, together with the interest rate and housing stress indicator, form a 5-variable TFAVAR. I define the list of endogenous variables y_t as the interest rate as well as the Housing Stress Indicator, and the list of factors $f_t = [F1, F2, F3]$ as the first three principal components extracted.

	F1	F2	F3
% of Variance	63.936%	15.589%	13.990%
Cumulative %	63.936%	79.524%	93.515%

Table 2.2: Variance Explained by Principal Components

Factor loadings in Table 2.3 help interpret each component. F1 loads positively on real GDP, prices, real estate loans, and house prices, and negatively on mortgage rates. It captures broad real economy and housing market conditions. F2 loads heavily on the term spread and, to a lesser extent, on credit spreads, as such it can be interpreted as a yield-curve and risk sentiment factor. F3 emphasizes credit spreads and also reflects term spreads and mortgage rates, capturing broader financial stress and borrowing conditions.

	Loadings			Contributions (%)		
Variable	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
MR	-0.806	-0.077	0.366	14.51	0.54	13.68
CS	-0.357	0.464	0.781	2.85	19.74	62.23
TS	0.179	0.910	-0.340	0.71	75.90	11.81
HL	0.981	0.058	0.140	21.52	0.30	2.01
HP	0.906	-0.186	0.234	18.36	3.16	5.61
P	0.950	0.063	0.181	20.18	0.36	3.36
Y	0.989	-0.006	0.113	21.87	0.00	1.31

Table 2.3: Loadings and Contributions for Factors 1–3

With the above derived factors and the remaining variables in mind, we can write the reduced form TFAVAR as seen in Equation 2.2 below:

$$\begin{bmatrix} y_t \\ f_t \end{bmatrix} = \sum_{k=1}^{4} \Theta_{1,k}\, I(x_{t-1} \geq \gamma) \begin{bmatrix} y_{t-k} \\ f_{t-k} \end{bmatrix} + \sum_{k=1}^{4} \Theta_{2,k}\, I(x_{t-1} < \gamma) \begin{bmatrix} y_{t-k} \\ f_{t-k} \end{bmatrix} + u_t, \quad (2.2)$$

where $\Theta_{i,k}$ are the matrices of regime specific coefficients, $I(.)$ is the regime indicator, γ is the threshold value and u_t are the reduced form residuals. x_t is the threshold variable which in our case is the housing stress indicator. This specification defines a two-regime TVAR, where we can interpret one of the regimes as boom and bust periods of the housing market cycle respectively. The TVAR model is linear in parameters for a fixed threshold value γ and fixed threshold variable x_t and can be estimated using Conditional Least Squares. The threshold value is set to $\gamma = \gamma^*$, where γ^* is the optimal threshold value obtained using a grid search that minimizes the residual sum of squares.

Shocks are identified using the state-of-the-art sign restriction methodology of Arias et al. (2018). After estimating the reduced-form TFAVAR and obtaining the Cholesky factor Σ of the residual covariance matrix, I construct an orthonormal rotation matrix Q in the five-dimensional factor space. I then impose the following zero-horizon sign restrictions on the observed variables: $[R : +,\ TS : -,\ CS : +,\ MR : +,\ HL : -,\ CGG : -,\ P : -,\ HP : -,\ RP : +,\ Y : \text{no restriction}]$.[1] The structural impact matrix ΣQ is mapped back to the space of observed variables using the factor loadings, allowing for verification that the imposed signs hold. As permitted by the TVAR framework, this identification procedure is implemented on a regime-specific basis, allowing the initial Cholesky factor Σ to vary across regimes. In practice, the IRFs at the zero horizon however turn out to be near identical for most of the observed variables.

2.3.3 Generalized Impulse Response Analysis

A challenge in nonlinear VAR modeling is a good representation of the impulse responses. While the regime-wise orthogonalized impulse responses are relatively informative in showcasing the different dynamics across the two regimes, they do not account for the regime switches themselves. Following the work of Koop et al. (1996), GIRFs are an appropriate tool to fully account for the dynamics of TVAR models. To construct the set of GIRFs, I closely follow algorithm outlined for the Interacted-VAR model of Andreasen et al. (2021). Specifically, the GIRFs for y_t at horizon h to a monetary policy shock ϵ_{monpol} can be defined as

[1] Note that a standard FAVAR with recursive ordering already resolves the price puzzle and produces plausible responses for GDP and inflation. Here, additional sign restrictions are imposed to ensure that the contemporaneous effects on financial variables align with theoretical expectations.

$$GIRF_y(h, \epsilon_{monpol}, x_{t-1}) \equiv E_t(y_{t+h}|\epsilon_{monpol}, x_{t-1}) - E_t(y_{t+h}|x_{t-1}) \tag{2.3}$$

With the above definition in mind, the GIRFs depend on the regime which is defined using the relation of x_{t-1} to the threshold value γ. I construct a set of GIRFs for both regimes using the following algorithm:

- I randomly sample $K = 100$ realizations of the residuals u_t from regime 1.
- For each random draw K, I simulate the h period ahead forecast $y_{t+h}|x_{t-1}$ for $h = 0 : 20$.
- For each random draw K, I simulate the h period ahead forecast $y_{t+h}|\epsilon_{monpol}, x_{t-1}$ for $h = 0 : 20$ by adding ϵ_{monpol} to the randomly sampled realization of residual u_t, then I calculate $GIRF_y$ using Equation 2.3.
- I repeat steps 1-3 for $H = 100$ randomly sampled histories (starting points) from regime 1 and take the average of the obtained GIRFs $\overline{GIRF_y}(h, \epsilon_{monpol}, x_{t-1}) = \sum_1^H \sum_1^K \frac{1}{H}\frac{1}{K} GIRF_y(h, \epsilon_{monpol}, x_{t-1})$.
- I repeat the process for regime 2.

As this procedure is executed in the dimensions of the five-equation TFAVAR, I first compute the GIRFs for the latent factors, then use the estimated factor loadings (weights) to recover the responses of the original series. Using this same approach, I disaggregate the housing boom-bust cycle indicator into its two components (RP and CGG) yielding ten GIRF sets per regime. These are presented in the Results section. All variables except the policy rate (R) are shown in standardized units, reflecting the data normalization prior to factor extraction. The policy rate, which remains in levels, is displayed in percentage points. Confidence bands are constructed from 2000 bootstrap replications using the Maximum Entropy Bootstrap procedure of Vinod (2006) in order to handle non-stationary series.

2.4 Results

Is the monetary transmission truly state-dependent? A growing body of empirical work shows that both the conduct and effects of monetary policy vary with macro-financial conditions. The generalized impulse response functions (GIRFs) in

Figure 2.2 show that (i) the Fed holds interest rates higher for longer during periods of housing booms, and (ii) credit aggregates, real activity, and prices fall somewhat more sharply in those periods. Still, for most variables, regime differences are smaller than one might expect, especially considering the relatively wide confidence bands. Strikingly, house-price responses are nearly identical across regimes, suggesting that there is no major change in the asset price channel across the two regimes.

Nevertheless, as the financial accelerator mechanism of Bernanke et al. (1999) suggests, adverse financial market conditions amplify shocks to macroeconomic aggregates. Output, prices and credit volume appear to contract more in a booming real estate market following the monetary policy shock. Similarly to the findings of Fry-Mckibbin and Zheng (2016), the larger contraction in credit volumes is not accompanied by widening credit spreads, which respond almost identically in both regimes, suggesting no significant change in the pricing of risk across the two regimes.

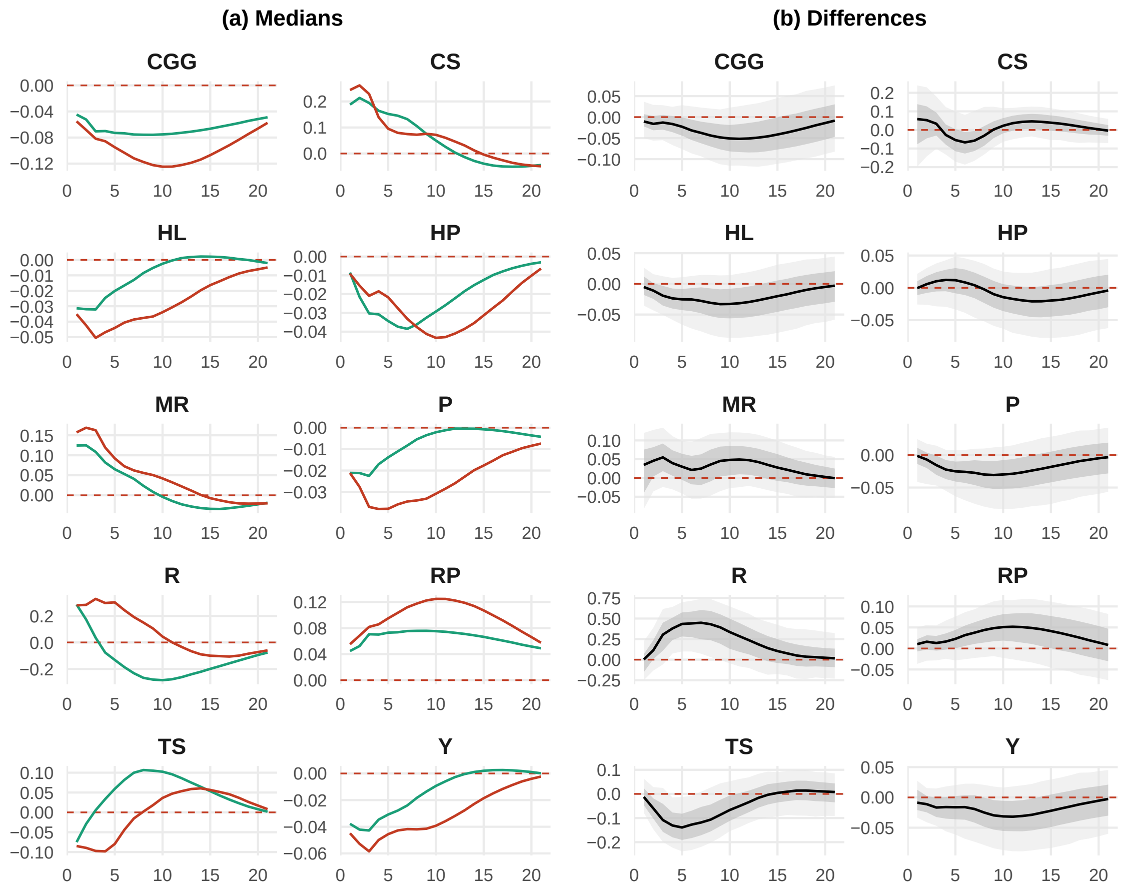

Figure 2.2: Generalized Impulse Responses.

Notes: Panel (a) shows the median impulse repsonses estimated from the bootstrap exercise. The color green indicates busts, while the color red indicates booms in the housing market. Panel (b) shows the differences between the regime specific impulse responses along with the 68% and 95% confidence bands in darker and lighter grey respectively.

The most substantial regime difference lies in the policy rate path (and by extension, the term spread) following a monetary tightening. In the boom regime, the Fed maintains elevated rates for several quarters before easing. By contrast, during times of housing busts, the Fed begins to reverse course more quickly. These results support Fry-Mckibbin and Zheng (2016), who argue that monetary easing is delayed when financial conditions are fragile. Similarly, Adrian and Liang (2018) argue that a looser stance during boom phases can fuel excessive leverage and risk-taking, prompting central banks to maintain tighter policy during potential housing bubbles. More recent work of Kiley and Mishkin (2024) suggests that this cautious rate adjustment reflects an explicit weighting of financial-stability objectives in the Fed's framework.

Why use the composite index instead of either RP or CGG? As discussed in the Identifying the boom-bust cycle in the Housing Market subsection, in order to successfully identify emerging bubbles in the housing market, correctly identifying high leverage along real estate market misalignments is key. Figure 2.3 shows the regime classifications using purely RP, purely CGG and lastly the composite index as threshold variables holding all else constant. Using purely RP as the threshold variable incorrectly identifies essentially two periods. Firstly it fails to identify the late 80s / early 90s Savings and Loans (S&L) crisis, as the excessive credit buildup preceding the real estate market adjustment was not taken into account. Secondly, it classifies essentially all of the post 2000s time periods as a period of booming real estate market, even though home prices returned close to their fundamental value as well as excessive credit buildups have substantially moderated following the GFC up until early 2020.

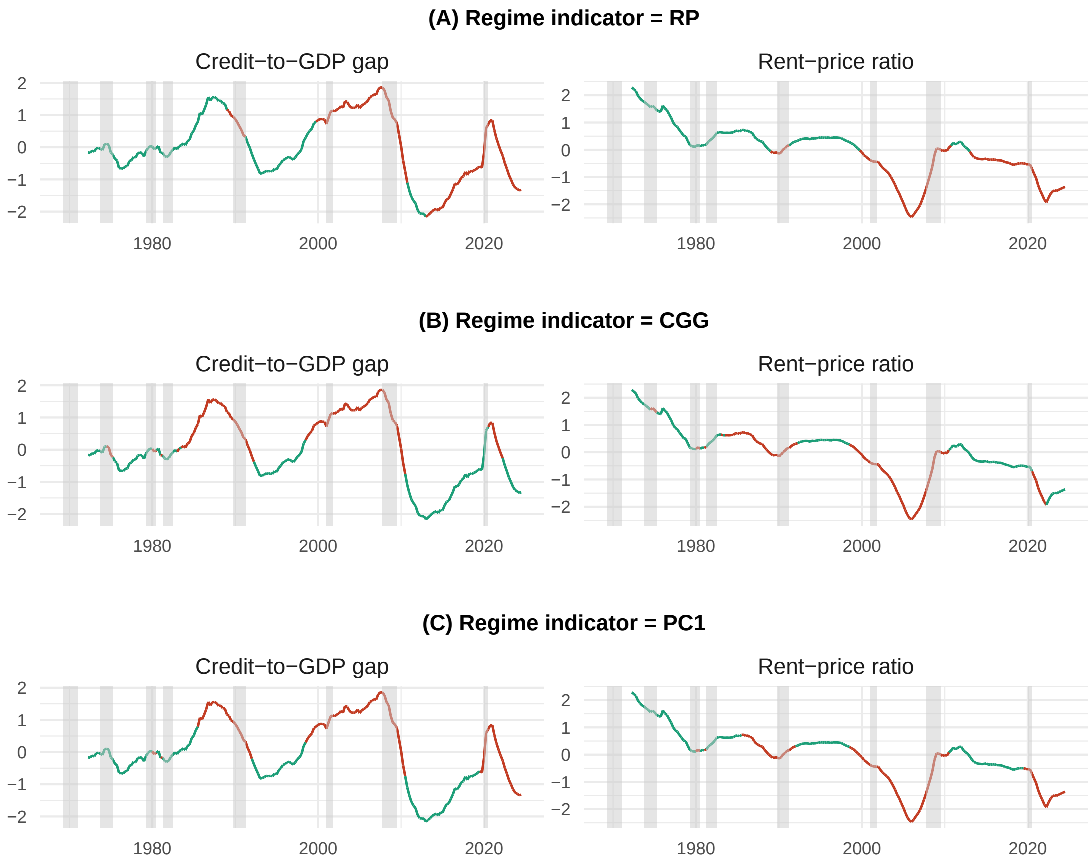

Figure 2.3: An indicator of housing market stress

Notes: The color green indicates busts, while the color red indicates booms in the housing market using the RP, CGG and their composite index (PC1) as regime indicators respectively. Shaded areas indicate US recessions using the Hamilton GDP-based recession indicator.

On the other hand, using purely the CGG as the threshold variable fails to take into account housing fundamentals. Around the S&L crisis, it gives "too early of a warning" along the credit cycle, way before home prices started becoming misaligned from their fundamental value. Moreover, it fails to identify housing market misalignments around the 2020s. Leveraging the linear combination of both aggregates as the threshold variable yields us regime classifications that seem to align with historical events when real estate market misalignments were likely fueled by excessive credits and overleveraging.

The model's definition of a forming housing bubble is also particularly elegant. Housing boom begins when rising credit gaps coincide with a sharp decline in rent-price ratios, and it persists until both metrics revert to their underlying trends or fundamentals. In other words, a bubble is identified whenever excessive leverage coincides with (and likely fuels) a misalignment of real estate prices from their fundamental values, ending only once the markets correct and cool off. Moreover, the regimes do not change abruptly, distinctly isolating phases of the housing cycle and yielding a continuous, timely indicator of boom-bust periods in the housing market.

2.5 Conclusion

This paper examines how U.S. monetary policy shocks propagate conditional on the state of the housing market. I construct a composite housing-stress indicator using principal component analysis on the rent–price ratio and the credit-to-GDP gap and embed it as the threshold variable in a two-regime threshold factor-augmented VAR (TFAVAR). This framework effectively identifies boom-bust cycles in the housing market. To trace the propagation of shocks, I estimate generalized impulse response functions (GIRFs) and regime-specific shocks. A bootstrap simulation exercise confirms that monetary policy itself is indeed state-dependent. What stands out most from the results is the Fed's conduct: during housing booms, the stance of monetary policy is adjusted much more carefully after an intervention. This caution reflects the central bank taking a broader set of macro-finantial variables into account when adjusting policy rates in order to avoid the possibility of a rapid resurgence in lending amid falling interest rates.

From a policy perspective, several key implications emerge. First, the response of real estate prices to monetary shocks does not differ substantially across regimes. This implies that the asset-price channel remains stable and monetary policy shocks alone are unlikely to cause a major crash. Second, while the financial accelerator appears to operate throughout the housing cycle, its amplification effects are somewhat muted. Still, this provides a rationale for pursuing active policy interventions during booms in order to restrain excessive credit growth. Third, the slower reversal of interest rates in the boom regime implies that policymakers proceed gradually when easing to avoid a resurgence of lending booms. In this sense, the results align with recent literature advocating for macro-financial considerations in monetary policymaking.

Looking ahead, several extensions could deepen this analysis. One important direction is to explore cross-sectional heterogeneity, as real estate dynamics may vary significantly across regions. This could be pursued either by extending the analysis to multiple countries or by examining state-level data within the U.S. Both approaches would pair well with a richer FAVAR framework that incorporates a broader set of variables in the factor extraction process. Finally, the composite housing-cycle indicator could be further refined by incorporating additional indicators such as loan-to-value or debt-to-income ratios. While such data are less widely available, the current index already provides a useful and interpretable signal of emerging housing bubbles.

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Chapter 3

A Distributional Perspective on Forward Guidance and Monetary Policy along the US Term Structure

Abstract: This paper investigates the impact of monetary policy and forward guidance on the U.S. term structure of interest rates with a focus on how it affects conditional volatility dynamics. Employing a dynamic location-scale model and several high-frequency surprises, I find that monetary policy announcements have a significant effect on the conditional volatility of the yield curve. While standard policy rate shocks generally increase volatility, forward guidance tends to compress it. However, these effects on conditional volatility are far smaller and less persistent than the conditional mean effects. The volatility channel is primarily driven by information signals and is asymmetric with respect to the sign of the shock. The results are robust to alternative specifications.
Keywords: Forward guidance, Term Structure, Conditional volatility
JEL: E43, E52, C32, G14

3.1 Introduction

Since the Global Financial Crisis, central banks have increasingly relied on communication as an active policy instrument. In the United States, forward guidance became a central tool once the policy rate approached its effective lower bound (ZLB). Because the current policy rate could no longer be lowered, communication about the future course of policy action provided further easing to the stance of monetary policy. The Federal Reserve's forward guidance evolved over time from relatively simple, less informative statements to state-contingent language that explicitly tied future policy action to macroeconomic variables like the unemployment rate. As forward guidance proved useful in managing expectations, it remained a permanent fixture in the monetary toolkit, helping to smooth the gradual rate increases that began in December 2015 and continuing to shape market expectations today.

Following the definitions of Campbell et al. (2012), central banks manage expectations through two distinct mechanisms. First, the central bank can make commitments regarding future policy action, referred to as Odyssean guidance. Second, it can communicate its own forecasts about the economic outlook, which inherently implies a future course of monetary policy, known as Delphic guidance. While the intentions behind these interventions are clear, their transmission mechanisms are theoretically complex. For example, Hanson and Stein (2015) show that guidance indicating persistently low interest rates can paradoxically raise long-term yields if markets interpret it as a signal of stronger future growth and inflation. Similarly, Andrade et al. (2019) argue that commitments to maintain low rates may be interpreted either as bad news about future economic conditions or as good news reflecting a more accommodative policy stance. Consequently, the effects of both Odyssean and Delphic guidance on broader economic uncertainty remain theoretically ambiguous—positive and negative signals may either reduce or amplify market volatility.

To study how different monetary policy tools affect financial markets and the economy, recent literature relies heavily on high-frequency identification (HFI) methods. Asset price movements in tight windows around FOMC meetings capture exogenous policy surprises. First established by Kuttner (2001) and Bernanke and Kuttner (2005), this approach was expanded by Gurkaynak et al. (2005) (GSS), who demonstrated that at least two factors are needed to explain the co-movement of yields at different maturities. A "Target" factor that captures current policy rate shocks from high-frequency changes in shorter term contracts and a "Path" factor that captures future policy (forward guidance) through high-frequency changes in medium-term contracts. Swanson (2021) extended this framework to show that forward guidance and large-scale asset purchases (LSAPs) operate primarily through a signaling channel, lowering the entire term structure of expected future short-term rates. The most active frontier of this HFI literature concerns central bank information effects (Nakamura and Steinsson (2018); Jarociński and Karadi (2020)). If a contractionary shock conveys superior central bank information about stronger future economic conditions, it can generate seemingly puzzling responses in macro-financial variables. Recent work has focused heavily on disentangling these "pure" policy shocks from central bank information and the Fed's response to incoming news (Bauer and Swanson (2023); Jarocinski and Karadi (2025)).

However, by primarily focusing on the conditional mean responses of yields and asset prices, the HFI literature risks overlooking a crucial second-order dynamic. Policy communication may shape expectations through two distinct channels: it can depress the expected path of future interest rates (moving the conditional mean), but it can also provide greater certainty to markets by clarifying the future course of policy (affecting higher-order moments, specifically conditional volatility). Policy communication is frequently described in practice as a way to reduce uncertainty and avoid "surprising" markets. Filardo and Hofmann (2014) explicitly note that forward guidance can reduce uncertainty and interest rate volatility, potentially lowering risk premia.

Addressing this conditional volatility channel is vital. The macro-uncertainty literature already demonstrates that uncertainty is a significant driver of economic downturns (see e.g.: Bloom (2009); Jurado et al. (2015); Baker et al. (2016)). More specifically, Husted et al. (2020) show that uncertainty about monetary policy itself causes economic contractions, implying that alleviating this uncertainty might offset the contractionary effects of rate hikes. Bundick et al. (2017) and Bundick et al.

(2024) provide direct evidence that forward guidance operates partly by changing the term structure of policy rate uncertainty, which helps explain yield movements beyond standard monetary policy shocks. If monetary policy can alleviate such uncertainty, this constitutes an important transmission mechanism in its own right. Conversely, if policy actions increase uncertainty, policymakers face a mean-variance trade-off where intended policy effects are partly offset by adverse volatility.

This paper studies forward guidance from a distributional perspective, asking whether forward guidance affects not only the location of the distribution of U.S. Treasury yields, but also its scale (i.e., the conditional volatility that investors face when pricing and hedging interest-rate risk). Even if average yield effects appear modest at certain maturities, systematic reductions in conditional volatility can materially affect term premia, portfolio allocation, and broader financial conditions.

This distributional view connects naturally to the growing "outlook-at-risk" literature in macro-finance (see e.g.: Adrian et al. (2019); Lopez-Salido and Loria (2024); Furceri et al. (2025)). This literature emphasizes that some factors (such as financial stress) impact macro aggregates asymmetrically across their distributions. Specifically, financial stress affects the left tail of GDP growth and the right tails of inflation and debt more adversely than it does the medians. However, Frangiamore et al. (2025) shows that fiscal consolidation also affects the tails asymmetrically. The paper derives the tail effects from how fiscal policy shocks affect the conditional location and the conditional scale of the debt distribution. Their dynamic model shows that a contractionary fiscal policy shock can reduce both the conditional location of future public debt and its conditional scale too (in other words reducing debt-uncertainty).

To provide this distributional view on monetary policy and forward guidance, I closely follow the methodologies of two papers, Hubert and Labondance (2018) and Frangiamore et al. (2025). I extend the framework of Hubert and Labondance (2018) in three key dimensions. First, rather than modeling conditional heteroskedasticity purely as an ARCH-type process, I estimate a location–scale specification in which forward guidance, monetary policy shocks, and macro-financial controls can independently shift both the conditional mean and the conditional volatility of yields across the term structure. Second, I embed this model in a local projections framework similar to the one used by Frangiamore et al. (2025) in order to trace the dynamic responses (both in terms of location and scale) of different maturity yields. Third, I use novel methods from the HFI literature to capture different components on monetary policy, namely: standard policy rate shocks, Odyssean forward guidance shocks and Delphic forward guidance shocks.

3.2 Data

The empirical analysis primarily uses daily zero-coupon U.S. Treasury yields across multiple maturities from the Gürkaynak et al. (2007) dataset. In order to capture the full shape of the yield curve, I use maturities ranging from 6 months to 10 years. This allows for investigating how different monetary policy shocks influence short-term instruments as well as longer term expectations about policy stance and the economy. The Affine Term Structure Model of Christensen et al. (2011) decomposes the nominal yields into Expected Short Rates (ESR) and Term Premia (TP), which allows for individual examination of how the conditional volatility of risks and expectations influence the overall response of nominal yields. Lastly, I retrieve daily instantaneous forward rates on Treasury Inflation Protected Securities (TIPS) and Breakeven Inflation rates to check if the volatility channel has any spillover to real economy expectations. Summary statistics of each yield curve are reported in Table 3.1 in the Appendix.[1]

In addition to the yield curve data, the specification includes a set of macro-financial control variables capturing global risk factors, the monetary policy stance, financial market stress and uncertainty, as well as proxies for real economic activity. A more detailed description of these variables, along with summary statistics, is provided in Table 3.3 in the Appendix. Since shocks in the HFI literature are constructed to be plausibly exogenous, the inclusion of these controls is not essential for the consistent estimation of the location effects. However, improving the fit of the location model is important for the precision of the scale estimates, as conditional volatility is proxied

[1] Data on Nominal Yields, Expected Short Rates and Term Premia are retrieved from the San Francisco Fed website and available at https://www.frbsf.org/research-and-insights/data-and-indicators/treasury-yield-premiums/. Data on real yields and breakeven rates are retrieved from the Fed Board through https://db.nomics.world/

by the absolute residuals from the mean model.

3.2.1 Monetary policy and forward guidance shocks

Monetary policy shocks are constructed by replicating alternative identification schemes using the U.S. Monetary Policy Data (USMPD) database introduced by Acosta et al. (2025).[2] All HFI shocks are computed using data from 30-minute event windows around FOMC statement releases. While the USMPD also allows for the construction of shocks for windows around press conferences and meeting minutes, these alternative event windows are not used in the baseline analysis and are left for future research.

As a baseline, I adopt the identification strategy of Jarociński (2024), which yields four distinct shocks: a target rate shock, an Odyssean forward guidance shock, a Delphic information shock, and a large-scale asset purchase (LSAP) shock. In this paper, I focus on the first three factors. To assess robustness, I also consider alternative HFI shock measures from Rogers et al. (2018) and Jarociński and Karadi (2020). The "path" factor from the former and the central bank information shock from the latter closely correspond to the Odyssean and Delphic factors respectively. All shock series are scaled to have unit standard deviation. The sample period runs from January 2004 to May 2026. Descriptives and further details for the shocks are available in Table 3.2 of the Appendix.

3.3 Methodology

The empirical framework builds on the location–scale model of Rigby and Stasinopoulos (2005), in which the conditional distribution of a dependent variable is characterized by separate equations for its location and scale parameters. In its general form,

[2]Retrieved from the San Francisco Fed website and available at https://www.frbsf.org/research-and-insights/data-and-indicators/us-monetary-policy-event-study-database/.

$$
\begin{aligned}
y \mid X &\sim \mathcal{D}(\mu, \sigma), \\
\mu &= \beta_0 + X\beta, \\
\log \sigma &= \gamma_0 + X\gamma.
\end{aligned}
$$

where μ governs the conditional mean and σ the conditional dispersion of the dependent. Applied to yield changes, this framework allows forward guidance and monetary policy shocks to influence not only the expected response of interest rates, but also the degree of uncertainty surrounding that response. Within this framework, the coefficient vector β captures the effects of a regressor on the level ("location") of the dependent variable and is directly comparable to coefficients estimated via OLS in standard event-study regressions. The coefficient vector γ captures how a regressor shifts the conditional volatility ("scale") of the dependent variable. A negative value implies a compression of the conditional distribution, i.e. a reduction in uncertainty, while a positive value indicates an expansion of the conditional distribution and higher uncertainty.

To trace out the dynamic responses, I estimate location-scale models using the local projections framework of Jordà (2005). This specification allows me to trace both the response of yields and the response of their conditional volatility at different forecast horizons h. At each horizon, the regressions are estimated using a two-step OLS approach, where conditional volatility is proxied by the absolute residuals from the location equation. This setup closely follows Frangiamore et al. (2025), who estimate the scale effects of fiscal shocks on public debt.

Daily financial market data are considerably noisier than annual macro aggregates, and volatility clustering is therefore a concern. Engle (1982) and Bollerslev (1986) provide the canonical framework for modeling time-varying conditional variance. Hubert and Labondance (2018) make a similar point and uses ARCH-augmented dynamic event-study regressions to study how ECB forward guidance affects the euro yield curve. Building on that approach, I therefore augment the scale equation with an additional ARCH term to capture volatility clustering[3] in yields, and estimate the following system of regressions:

$$\begin{aligned} r^m_{t+h} - r^m_{t-1} &= \beta^h_0 + \beta^h_1 x_t + \beta^h_2 z_t + \varepsilon^h_{t+h}, \\ |\varepsilon_{t+h}| &= \gamma^h_0 + \gamma^h_1 x_t + \gamma^h_2 z_t + \gamma^h_3 |\varepsilon_{t+h-1}| + u_{t+h}. \end{aligned}$$

In these regressions, x denotes the matrix of monetary policy and forward guidance shocks, z represents the set of control variables, and r^m denotes yields at maturity m. The models are estimated at horizons $h \in \{0, 1, 3, 5, 10, 15, 20, 25\}$, where $h = 0$ corresponds to the standard event-study specification and captures the response of yields and their conditional volatility on the announcement day, while $h = 25$ measures the response approximately one business month after the shock. All regressions are estimated using Newey–West heteroskedasticity and autocorrelation consistent standard errors. Results are reported with one standard deviation confidence bands.

Since the scale equation uses the absolute residuals from the location equation as a proxy for conditional volatility, both sets of impulse responses are expressed in the same units. Accordingly, the location coefficient, β^h, can be interpreted as: "A one standard deviation contractionary shock increases the yield by β^h percentage points at horizon h." Similarly, the scale coefficient, γ^h, can be interpreted as: "A one standard deviation contractionary shock changes the conditional volatility of the yield by γ^h percentage points at horizon h."

3.4 Results

This section presents the empirical results for the location and scale effects of monetary policy shocks on the term structure of interest rates in the US. I document the responses with respect to three shocks. A Target rate surprise which corresponds

[3]Introducing an ARCH term into the scale equation prevents the direct application of the Machado and Silva (2019) framework, which requires identical covariates in the location and scale equations to recover quantile-specific marginal effects. This does limit the investigation to some extent; however, this is of little consequence, as the focus of the analysis is on volatility responses themselves rather than on heterogeneous effects across quantiles of the yield distribution.

to a standard interest rate shock. An Odyssean forward guidance surprise which corresponds to unexpected changes in the expected future path of monetary policy arising from central bank commitment. Finally, a Delphic forward guidance surprise which corresponds to an information shock revealing private information of the Fed regarding economic outlook and its implications for future policy. The results are organized as follows. I first document the location and scale responses to contractionary realizations of each shock. I then examine whether the scale responses differ between contractionary and expansionary shocks. In order to better understand the scale effects of monetary policy on nominal rates, I run the location-scale regressions on Expected Short Rates and Term Premia separately. Lastly, I check for possible real expectation spillovers by running the regressions on instantaneous forward rates of TIPS yields and Breakeven Inflation.

Figure 3.1 reports the estimated location and scale impulse responses of Treasury yields to the three shocks. The location effects are consistent with the existing literature. Target rate shocks have the strongest effects at the short end of the yield curve; Odyssean forward guidance shocks raise yields across the entire term structure; Delphic information shocks increase short-term yields but lower yields at longer maturities. As these responses closely replicate the results of Jarociński (2024), they serve two primary purposes. First, they validate both the replicated shock series and the local projection framework. Second and more importantly, they provide a natural benchmark against which to assess the magnitude of the estimated scale responses.

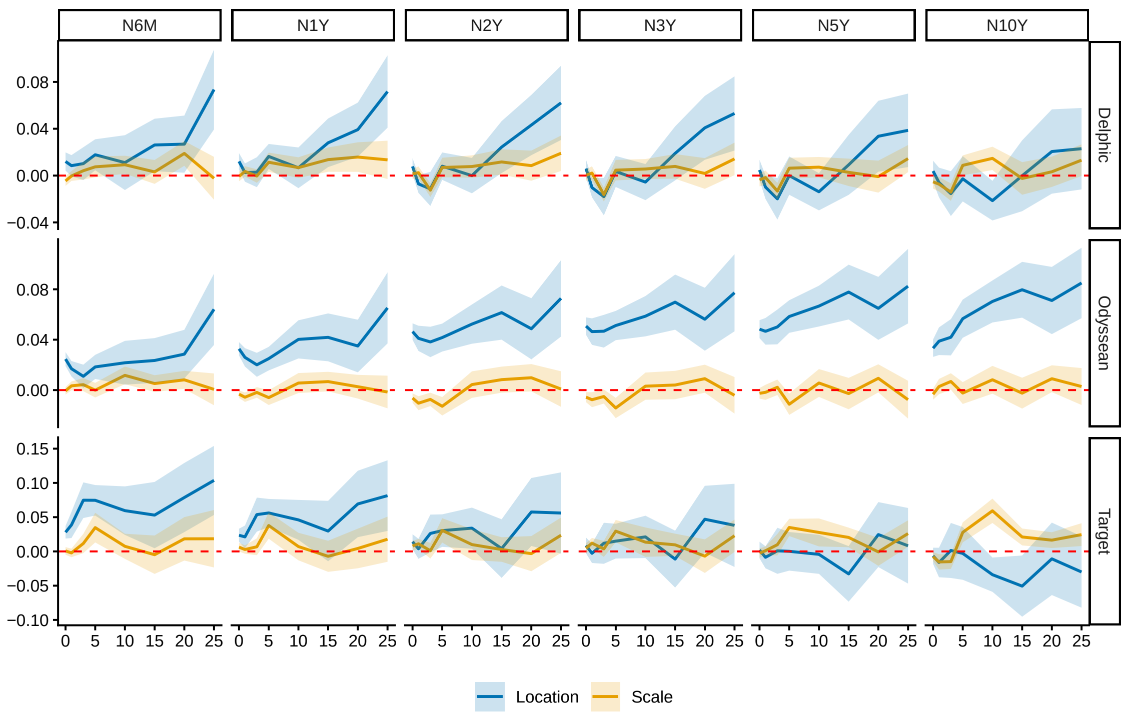

Figure 3.1: Dynamic responses of the nominal term structure to monetary policy shocks.

Relative to the location effects, the scale responses are considerably smaller in magnitude and substantially more short lived. The largest responses occur within the first few trading days following the announcement and dissipate rapidly thereafter. Subsequently, monetary policy announcements might influence uncertainty in Treasury markets only in the short term. However, despite the modest size and lack of persistence, the scale responses are systematically different across the three types of shocks. Target rate surprises generally increase conditional yield volatility across the term structure, with the largest response observed for the 10-year Treasury yield. In contrast, both forward guidance shocks tend to compress conditional volatility. The effects of Odyssean shocks are concentrated at medium maturities and are negligible at the short and long ends of the yield curve. Delphic information shocks also have negligible effects on shorter maturities, but impact both medium and long term yields.

This suggests two forces at play in the drivers of yield volatility around FOMC meetings: policy intervention causing uncertainty and communication mitigating it.

Unexpected changes in the current policy rate increase uncertainty regarding both the prevailing and expected future stance of monetary policy, leading to higher conditional volatility across the entire term structure. On the other hand, communication shocks (whether reflecting commitment about rates or information about economic outlook) tend to reduce uncertainty at medium maturities. Consequently, forward guidance offsets the uncertainty caused by shocks to the policy rate around the middle of the yield curve. While communication effects are negligible at the short end, the volatility response of 6-month and 1-year yields to a policy rate shock is small in magnitude and fades within a few trading days.

Unlike short to medium maturities, the scale response of the 10-year yield to a policy rate shock is relatively large, persistent and is not offset by either Odyssean or Delphic communication. One possible explanation is that policy rate interventions convey two opposing signals for longer-term interest rates. On the one hand, market participants may anticipate policy normalization some time after the Fed raises rates. This could be supported by the small (but mostly insignificant) negative location response as well. On the other hand, an unexpected policy tightening may increase uncertainty surrounding the longer-run macroeconomic outlook, which prompts market participants to reassess their outlook as well. Since these macro fundamentals are more influential for longer-term yields, communication about medium-term future policy may be insufficient to offset the increase in uncertainty over longer horizons.

The analysis thus far has imposed symmetry between contractionary and expansionary shocks, implying that both types of announcements affect conditional volatility to the same extent, differing only in sign. While this is a common simplification in most empirical models, there is substantial evidence on the asymmetric effects of opposing sign shocks (see e.g.: Cover (1992), Tenreyro and Thwaites (2016), Angrist et al. (2018)). While the simplification of symmetry is reasonable for the location estimates, it is particularly restrictive for the estimation of scale responses. For example, both good and bad macroeconomic news should help coordinate market expectations, whereas the symmetric assumption mathematically constrains one to increase and the other to decrease the conditional volatility. The local projections, however, can be easily adapted to accommodate the potentially asymmetric effect of opposing sign shocks. To investigate, the equations are re-estimated after decomposing each shock into separate contractionary and expansionary components.[4] The results in Figure 3.2 indicate that accounting for the sign of the shock matters for both the magnitude and the persistence in the scale responses.

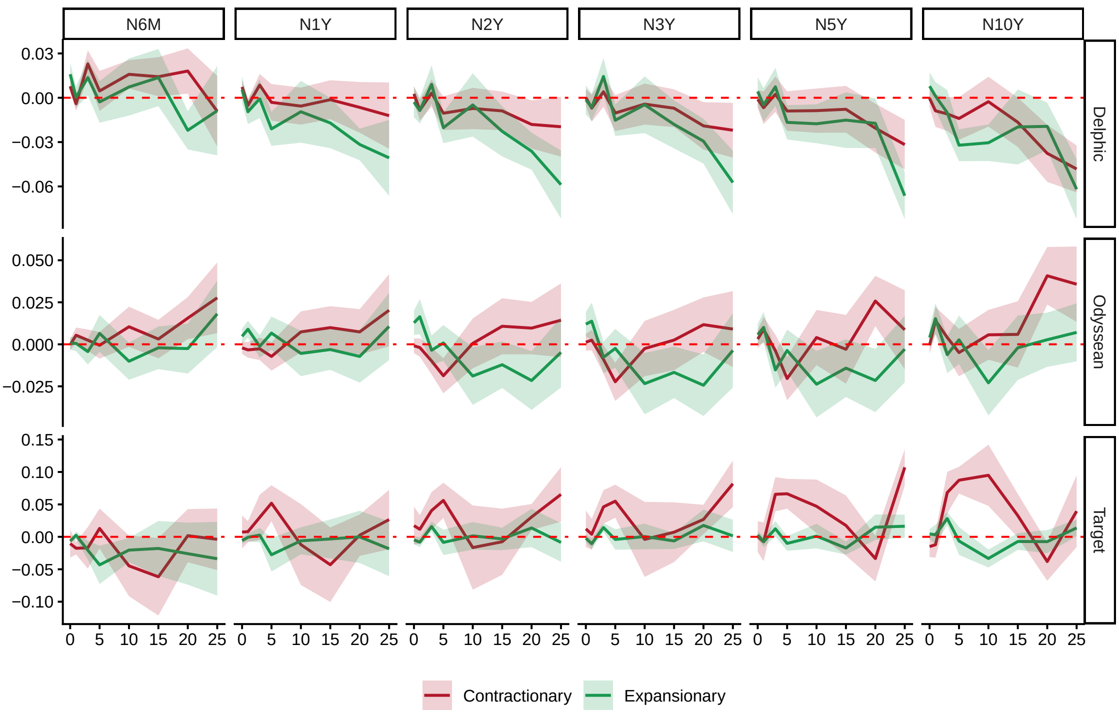

Figure 3.2: Sign-dependent scale effects across the nominal term structure of interest rates.

Asymmetry in the responses is present across all three shocks, though it manifests differently in each case. For Target shocks, contractionary surprises mirror symmetric estimates while expansionary ones barely affect volatility. Delphic shocks no longer yield an immediate volatility reduction. Instead, they generate a persistent compression at the long end, with positive signals slightly more effective than negative ones. Odyssean shocks exhibit a distinct temporal asymmetry. Contractionary forward guidance initially compresses volatility before the effect reverses, while accommodative commitments first increase, then lower volatility. These short-run effects are short-lived, however. At medium maturities, accommodative guidance suppresses

[4]Expansionary shocks are multiplied by -1 so that both shock series have a consistent interpretation when plotting the impulse responses. The sign-dependent shocks are not re-scaled using the standard deviations of the respective subsets.

volatility for about a month, yet at the long end, contractionary commitments raise volatility over the same horizon.

These results confirm that the volatility channel is primarily driven by information signals. This information can either be communicated directly, as in the case of Delphic forward guidance, or inferred by market participants from policy actions and commitments, as with Target and Odyssean shocks. Direct communication by the Fed regarding the economic outlook appears to be the most effective at reducing uncertainty irrespective of whether the news is good or bad. Odyssean guidance effectively coordinates medium-term expectations but fails to anchor the long run. Moreover, it may actually heighten long-term uncertainty, which reveals another policy trade-off.

3.4.1 Sources of the volatility response: Expected short rates versus term premia

The preceding analysis establishes that monetary policy announcements affect not only the expected level of Treasury yields but also their conditional volatility. A natural next question is which component of the yield curve drives these second-moment responses. Since nominal yields reflect both expectations about the future path of short-term interest rates and compensation for bearing interest rate risk, decomposing the yield curve provides additional insight into the economic channels through which monetary policy influences uncertainty. To this end, I run the location-scale regressions separately for expected short rates (ESR) and term premia (TP). The estimated scale impulse responses can be seen in Figure 3.3.

The nominal yields are decomposed into ESR and TP as in Christensen et al. (2011) such that $r^m = ESR^m + TP^m$. While this identity holds exactly for yield levels (and level responses), it does not generally extend to the estimated scale responses for two reasons. First, conditional volatility is proxied using the absolute residuals from the location equation, making the scale specification inherently nonlinear. Second, from a variance decomposition perspective $Var(r^m) = Var(ESR^m) + Var(TP^m) + 2 \cdot Cov(ESR^m, TP^m)$, where the covariance term is not separately identified in the present framework. Accordingly, the decomposition is intended to provide qualitative evidence on the economic sources of the volatility responses rather than an exact accounting identity.

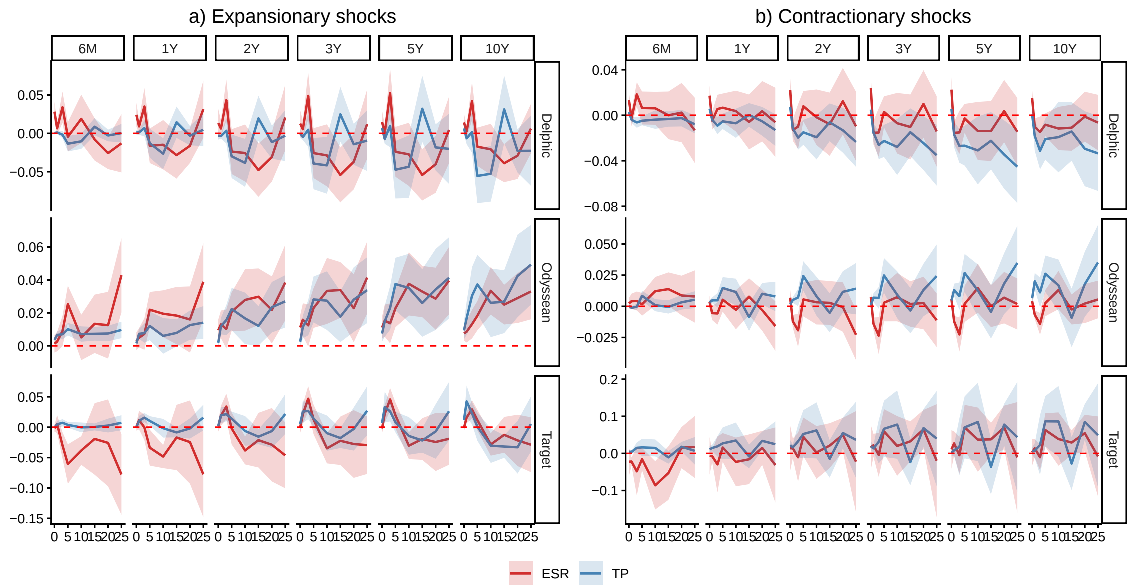

Figure 3.3: Scale responses of Expected Short Rates and Term Premia.

The transmission of Delphic shocks is clearest in the ESR-TP decomposition, as the scale responses of each component behave similarly to those of the nominal yields. This suggests that Federal Reserve communication about economic outlook simultaneously reduces uncertainty surrounding the future path of monetary policy and the compensation investors require for bearing interest rate risk. Since the responses of the individual components co-move with the total, there is little indication that Delphic shocks alter the covariance structure between the two components and the volatility decline is primarily driven by the uncertainty reduction of each component. Economically, this means that Fed information reduces uncertainty without altering the way markets think about how future policy expectations and longer-term risks are linked.

The decomposition of scale responses to Target shocks is relatively straightforward as well. Contractionary policy surprises generally increase the conditional volatility of both expected short rates and term premia, with the only notable exception being the 6-month expected short rate, whose scale response is slightly negative. This broadly matches the pattern of responses observed in nominal yields. However, the confidence bands around the component responses are noticeably wider than those for nominal yields, despite the latter displaying a relatively clear increase in conditional volatility. This suggests that part of the joint volatility arises from stronger co-movement between ESR and TP following a contractionary shock. A possible explanation for stronger co-movement along with rising uncertainty in both components is that unexpected policy tightening could lead to revisions in inflation expectations accompanied by higher inflation uncertainty. Expansionary policy rate shocks, by contrast, have little discernible effect on either expected short rate or term premium volatility. The corresponding responses of nominal yields are likewise close to zero, indicating only limited evidence of a volatility channel following unexpected policy easing.

The most puzzling component-wise responses come from Odyssean shocks. Expansionary commitments to maintain lower future policy rates increase the conditional volatility of both ESR and TP over approximately the first month following the announcement. During the first few trading days, these responses are consistent with the temporary increase in nominal yield volatility documented earlier. At longer horizons, however, the conditional volatility of nominal yields declines despite both underlying components exhibiting higher volatility. This pattern is consistent with a substantial decline in the covariance between ESR and TP. A plausible explanation is the inherently state-contingent nature of forward guidance. While such guidance may increase the sensitivity of both interest rate expectations and investors' assessment of long-term risks to incoming macroeconomic information, it may also strengthen the negative relationship between the two components. For example, favorable news may lead markets to expect a steeper policy path (raising ESR) while simultaneously reducing the compensation required for bearing duration risk (lowering TP), with the opposite occurring following adverse news. As a result, ESR and TP might move in opposite directions more strongly (decline in covariance) and consequently reduce the conditional volatility of nominal yields. For contractionary Odyssean shocks, the short-run decline in ESR volatility and the subsequent increase in TP volatility broadly match the patterns observed for nominal yields.

3.4.2 Spillover to real yields and breakeven inflation

Thus far, the analysis has focused exclusively on nominal Treasury yields, which jointly reflect expectations about future real interest rates and inflation compensation. While this establishes how monetary policy announcements affect the overall term structure, it does not reveal whether the documented volatility responses originate from changes in uncertainty surrounding real financing conditions or inflation expectations. To address this question, I repeat the location-scale regressions using instantaneous forward TIPS yields and breakeven inflation rates. Figure 3.4 documents these scale impulse responses to expansionary and contractionary shocks.

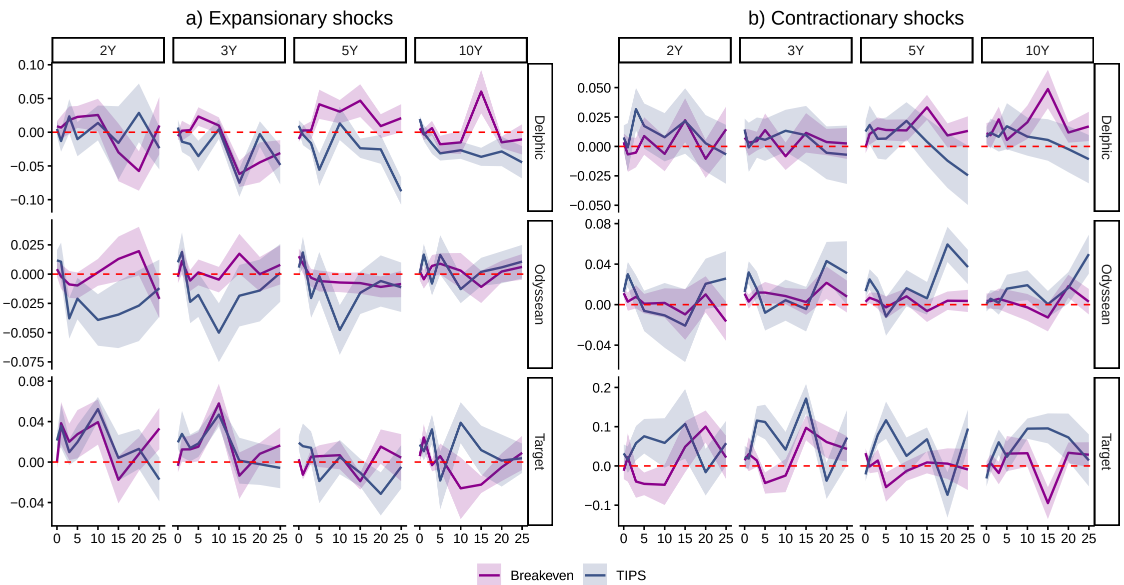

Figure 3.4: Scale responses of forward TIPS yields and breakeven inflation rates.

The scale impulse responses reveal that the volatility channel differs between real interest rates and inflation expectations. Policy rate shocks predominantly alter the conditional volatility of real rates, while the responses of expected inflation volatility are weaker and more heterogeneous. Both contractionary and expansionary Target shocks raise uncertainty surrounding future real interest rates, although the response is considerably stronger following policy tightening. Expansionary shocks primarily increase short-horizon inflation uncertainty, whereas contractionary shocks initially compress it before generating a modest increase at longer horizons.

Odyssean shocks have virtually no effect on inflation uncertainty. Instead, the response of real rates closely mirrors the patterns previously observed for nominal yields: commitments to a more accommodative future policy stance reduce uncertainty surrounding real financing conditions over the medium term, whereas commitments to tighter future policy increase it. By contrast, Delphic forward guidance has much more limited effects on the conditional volatility of TIPS yields and primarily affects the volatility of inflation expectations. Overall, these findings suggest that commitment-based communication operates mainly by increasing certainty regarding future real financing conditions, whereas information about the economic outlook primarily induces revisions in inflation expectations.

3.4.3 An illustrative counterfactual exercise

The location and scale impulse responses documented above quantify how monetary policy and forward guidance shocks move the conditional mean and volatility of yields, but they do not by themselves indicate how much of the observed path of any given yield is attributable to these shocks. This section constructs a simple counterfactual to address that question directly, isolating how much of the 2-year nominal yield's evolution over the sample is attributable to the location and scale effects of Odyssean forward guidance shocks specifically.

Unlike Vector-Autoregressions, local projections are inherently not forecasting models, where simulations are readily available by the system of equations. It is only at $h = 0$ where a genuine one-step-ahead forecast of $r_t - r_{t-1}$ is computed, whereas the remaining horizons $h > 0$ are separate non-nested regressions of h-day-ahead cumulative changes and cannot be spliced into a daily series in the same way the one-step-ahead forecast can. Subsequently, this counterfactual exercise is based on the $h = 0$ regressions alone. Given this regression, I reconstruct two counterfactual paths: one where the Odyssean shock is set to zero in the scale equation and one where it is set to zero in both equations.

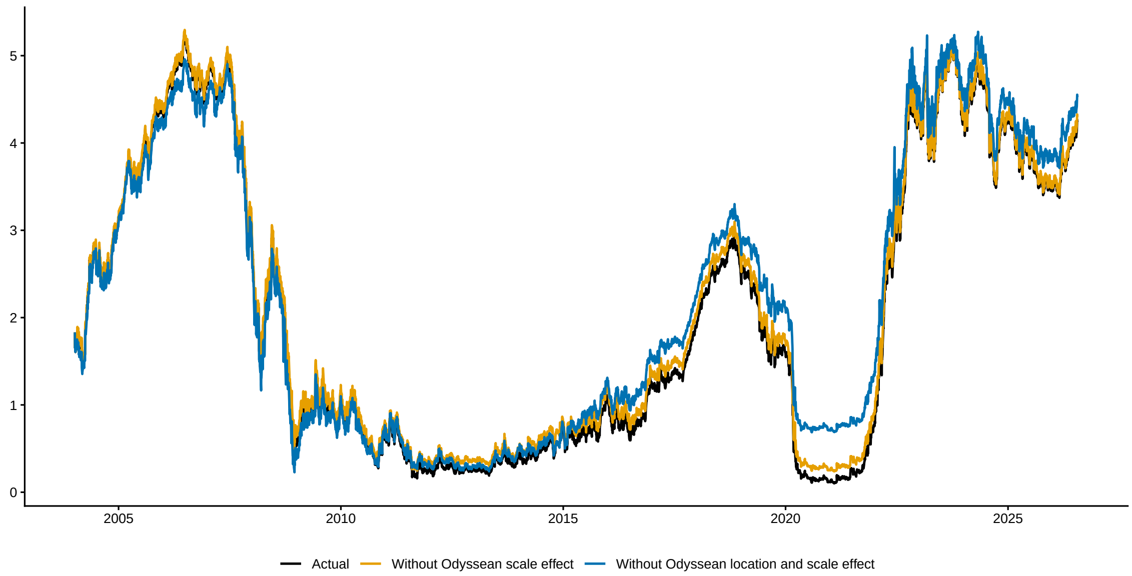

Figure 3.5: Actual and counterfactual 2-year nominal yield, absent the scale effect of Odyssean forward guidance and absent Odyssean forward guidance entirely.

Figure 3.5 reports the resulting three paths.[5] The counterfactual switching off the Odyssean shock entirely varies considerably over time. The difference between the actual and this counterfactual series is virtually non-existent during the acute phase of the Global Financial Crisis, when explicit forward guidance was not yet a standard element of the Federal Reserve's communication toolkit. It picks up slightly after 2015, when rates were coming off the ZLB, but the Fed was still maintaining communication that its stance is accommodative. The gap is largest over 2020-2022 when rates were again near the ZLB. Absent Odyssean guidance, the counterfactual 2-year yield runs consistently above its actual level throughout the acute phase of the pandemic and its immediate aftermath.

Consistent with the earlier findings, the scale effects are considerably smaller than that of the location. The majority of the differences between the actual and counterfactual series are driven by the location effects of the Odyssean shock. However,

[5]This exercise is reported for the Odyssean shock alone. This is done because, as Figure 3.1 showed earlier, the $h = 0$ impulse response coefficients are near zero for both the Target and Delphic shock and only build up gradually over the following days. Consequently, a counterfactual constructed purely from their $h = 0$ coefficients would mechanically show almost no divergence from the actual series. Conversely the coefficients are sizable at $h = 0$ for the Odyssean shock, which makes this exercise informative about this monetary policy instrument.

during some periods, particularly after rates lowered to the ZLB following the Covid pandemic, the scale channel accounts for a few basis points of difference too. These results are consistent with the Federal Reserve's explicit, outcome-based commitments to hold the policy rate near zero having been effective at anchoring near-term rate expectations during a period of exceptional uncertainty. As minor as the scale effects are, they do appear to materially translate to a reduction in the pricing of interest rate risk, at least during the period following the pandemic.

3.5 Conclusions

This paper provides a comprehensive distributional perspective on how monetary policy and forward guidance shape the U.S. term structure of interest rates. By integrating high-frequency identification into a dynamic location-scale model, the analysis demonstrates that FOMC announcements do more than shift the expected path of future interest rates, they also affect the conditional volatility that investors face when pricing and hedging interest-rate risk. Standard policy rate interventions tend to heighten market uncertainty across the yield curve, whereas central bank communication—both in the form of Odyssean commitments and Delphic information signals—serves as a vital tool for compressing volatility and coordinating market expectations.

The findings highlight that the transmission mechanisms of these shocks are distinct and complex. Delphic guidance effectively reduces uncertainty across both expected short rates and term premia, and its effects spill over primarily into the volatility of inflation expectations. Conversely, Odyssean guidance coordinates medium-term expectations regarding real rates but can inadvertently increase long-term uncertainty. The results reveal that managing the volatility of expectations requires the central bank to release superior information directly in order to "calm down" the markets. The results also reveal two trade-offs. In the short run, policy rate shocks that are needed to cool the economy seem to raise uncertainty. In the medium-run, commitments to keep rates low requires giving up some certainty in the evolution of longer run yields. The results explicitly measure these in financial markets, however, implicitly this might spill over to the real economy.

Ultimately, focusing solely on the conditional mean risks missing a critical part of the monetary policy transmission mechanism. Because fixed-income markets price both risk and expectations, the systematic reductions in conditional volatility achieved through effective forward guidance can materially influence term premia, portfolio allocation, and broader financial conditions. Future research could extend this distributional framework to analyze alternative event windows, such as press conferences and meeting minutes, to further disentangle how various modes of central bank communication shape macroeconomic risks. Additionally, future research could address if the volatility channel exists beyond financial market data, and as such whether monetary policy can impact forecasters' uncertainty with respect to key macro aggregates.

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3.7 Appendix

3.7.1 Data and descriptives

Table 3.2 summarizes the monetary policy shocks identified using the alternative HFI approaches considered in this paper. All shock series are replicated using the USMPD database of Acosta et al. (2025), specifically the high-frequency changes observed in 30-minute windows around FOMC statement releases. For each identification scheme, I closely follow the original paper together with its accompanying replication files in selecting the relevant financial variables and implementing the estimation procedure. To facilitate comparisons across both shock series and identification methods, all shocks are scaled to have unit standard deviation. The identification procedures of Rogers et al. (2018) and Jarociński (2024) additionally recover an LSAP factor, which is included as a control variable in the empirical analysis. Since the focus of this paper is primarily on forward guidance, the responses to the

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Nominal Yields						
N6M	3.217	2.468	0.05	9.702	0.285	1.997
N1Y	3.31	2.482	0.055	9.802	0.279	2.015
N2Y	3.498	2.442	0.102	9.733	0.284	2.057
N3Y	3.682	2.38	0.127	9.659	0.303	2.102
N5Y	4.018	2.271	0.222	9.541	0.338	2.18
N10Y	4.63	2.132	0.52	9.43	0.304	2.26
Expected Short Rates						
ESR6M	2.312	2.039	-0.224	6.569	0.451	1.673
ESR1Y	2.324	1.979	-1.227	6.582	0.398	1.698
ESR2Y	2.397	1.842	-2.482	6.479	0.315	1.821
ESR3Y	2.489	1.696	-2.832	6.336	0.292	1.978
ESR5Y	2.654	1.446	-2.443	6.085	0.36	2.258
ESR10Y	2.889	1.139	-0.625	5.754	0.578	2.645
Term Premia						
TP6M	0.006	0.224	-0.402	1.298	1.114	4.662
TP1Y	0.036	0.369	-0.68	2.338	0.941	4.823
TP2Y	0.1	0.571	-1.124	3.649	0.923	4.811
TP3Y	0.172	0.688	-1.428	4.364	0.873	4.739
TP5Y	0.34	0.812	-1.723	5.017	0.723	4.392
TP10Y	0.753	0.915	-1.576	5.222	0.559	3.453
TIPS Yields						
T2Y	0.942	1.722	-2.274	7.304	0.583	3.271
T3Y	1.191	1.601	-1.907	6.095	0.398	2.758
T5Y	1.57	1.381	-1.161	4.62	0.182	2.449
T10Y	2.077	1.101	-0.417	4.352	-0.137	2.166
Breakeven Inflation						
B2Y	1.783	0.757	-2.515	4.084	-1.71	7.158
B3Y	1.901	0.571	-1.109	2.912	-1.599	6.093
B5Y	2.168	0.365	0.694	3.03	-0.581	2.896
B10Y	2.487	0.523	0.887	3.876	-0.166	2.399

Table 3.1: Descriptive Statistics: Yield Curve Components

LSAP shock are not reported.

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Jarociński (2024)						
Target	-0.152	1	-7.477	1.987	-3.961	26.314
Odyssean	-0.034	1	-4.32	3.462	-0.2	5.866
LSAP	-0.017	1	-13.031	2.517	-8.55	112.356
Delphic	-0.067	1	-4.077	6.815	0.701	12.498
Rogers et al. (2018)						
Target	-0.155	1	-6.883	2.418	-3.338	21.287
Path	-0.066	1	-3.692	4.134	-0.12	5.614
LSAP	-0.022	1	-13.307	2.358	-8.558	114.328
Jarociński and Karadi (2020)						
MP	-0.019	1	-6.512	2.342	-2.212	14.585
CBI	0.012	1	-3.771	4.734	-0.351	6.408

Table 3.2: Descriptive Statistics: Monetary Policy Shocks

For the identification strategy of Rogers et al. (2018), the information set consists of the first federal funds futures contract (MP1), the fourth Eurodollar futures contract (ED4), and the 10-year Treasury yield (ONRUN10). MP1 serves as the Target factor, ED4 orthogonalized with respect to MP1 serves as the Path factor, and the LSAP factor is ONRUN10 orthogonalized to Target and Path surprises and is set to 0 prior to October of 2008. Following Jarociński and Karadi (2020), the first principal component (PC1) of the first and fourth federal funds futures contracts (MP1 and FF4) together with the second through fourth Eurodollar futures contracts (ED2, ED3 and ED4) capture market responses to FOMC announcements. Along PC1, high-frequency changes in the S&P 500 (SP500) are used to recover the MP and CBI shocks such that MP raises interest rates and depresses stock returns, while CBI raises rates and stock returns. The shock series are recovered using the median-rotation algorithm. Finally, the identification scheme of Jarociński (2024) uses the first federal funds futures contract (MP1), the 2-year and 10-year Treasury yields (ONRUN2 and ONRUN10), and high-frequency changes in the S&P 500 returns (SP500). These variables are used to recover four structural shocks corresponding to Target rate surprises, Odyssean forward guidance, Delphic information, and an LSAP factor.

Given that the monetary policy shocks are identified using state-of-the-art HFI methods, additional control variables are not required for the consistent estimation of the average effects of monetary policy and forward guidance on the yield curve.[6] Nevertheless, I include a broad set of macro-financial controls to account for co-movements that may contribute to yield dynamics. In the location-scale models, these controls help isolate the residual variation used to construct the volatility proxy. In practice, however, their inclusion has only a negligible effect on both the estimated location and scale responses.

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Controls						
CISS	0.092	0.139	0	0.896	2.875	12.909
WTI	0	0.027	-0.424	0.426	-0.245	34.242
SP500	0	0.012	-0.128	0.11	-0.382	13.753
USD	4.526	0.114	4.267	4.789	-0.019	2.297
VIX	19.901	8.057	9.14	82.69	2.169	11.301
EPU	116.914	98.118	3.32	1026.38	2.479	11.756
NSI	0.023	0.188	-0.666	0.454	-0.57	3.21
SSR	2.008	2.859	-4.169	6.872	-0.234	1.911

Table 3.3: Descriptive Statistics: Control Variables

The choice of control variables closely follows the specification of Hubert and Labondance (2018), with some extensions and adapted to the U.S. economy and financial markets. These variables capture monetary policy stance, financial market conditions, uncertainty, and economic sentiment. Specifically, the Shadow Short Rate (SSR) of Krippner (2013) captures the stance of monetary policy, particularly during periods in which the federal funds rate is constrained by the effective lower bound. The ECB's Composite Indicator of Systemic Stress (CISS) provides a broad measure of systemic stress in the financial system. Changes in the S&P 500 index and WTI crude oil prices proxy for stock market sentiment and inflation shocks. The News Sentiment Index of Buckman et al. (2020) provides a broad, news based economic sentiment measure. The VIX index and the Economic Policy Uncertainty (EPU) of Baker et al. (2016) provide uncertainty measures. Lastly, the NYSE US Dollar Index (USD) is included to account for the international valuation of the US Dollar.

[6]For example, the long-run daily local projections in Jarociński (2024) are estimated without additional controls.

3.7.2 Robustness and sensitivity checks

To assess the robustness of the results, I consider three modifications to the baseline specification: first, I estimate the model without the ARCH term in the scale equation;[7] second, I drop the control variables that capture macro-financial fluctuations; third, I replace the baseline shocks identified using the methodology of Jarociński (2024) with alternative high-frequency identification schemes from the literature. Specifically, the path factor of Rogers et al. (2018) serves as an alternative measure of Odyssean forward guidance, while the central bank information shock of Jarociński and Karadi (2020) provides an alternative proxy for the Delphic component. To ensure comparability across specifications, these alternative shock series are also reconstructed using the USMPD database, thereby preserving the same sample period throughout the analysis.

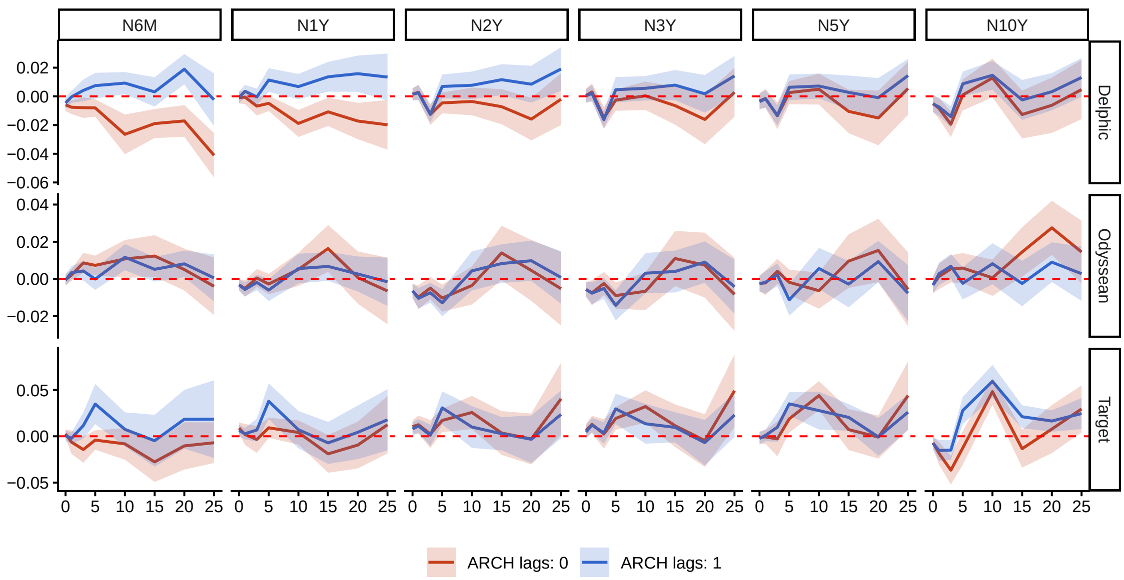

Figure 3.6: Sensitivity of the scale estimates to controlling for volatility clustering.

Figures 3.6 and 3.7 compare the estimated scale impulse responses obtained with and without the ARCH term in the scale equation and with dropping the macro-

[7]In principle, this robustness exercise could also consider higher-order ARCH specifications. However, including additional lags yields impulse responses that are virtually identical to those obtained with a single lag. These specifications are therefore omitted, as they provide little additional insight into the sensitivity of the results to volatility clustering.

financial controls respectively. Overall, the results are highly robust to accounting for volatility clustering. In particular, the responses at longer maturities and shorter impulse response horizons remain largely unchanged, while the contemporaneous ($h = 0$) responses are identical under both specifications. The main difference arises for the Delphic (central bank information) shock, particularly at the short end of the yield curve, where omitting the ARCH term leads to somewhat larger estimated reductions in conditional volatility. Regarding the use of control variables, the results are robust to specifications with or without using them. This further reinforces the ARCH specification, as it alone absorbs most of the variation of absolute residuals that would otherwise be captured by other variables.

The sensitivity of the results to accounting for volatility clustering is economically intuitive. As reported in Table 3.1, the unconditional standard deviation is substantially higher at the short end of the yield curve than at longer maturities. While long-term yields are driven to a greater extent by macroeconomic fundamentals, short-term yields are more susceptible to short-run fluctuations in expectations and financial market conditions. Consequently, failing to account for volatility clustering causes part of the persistence in short-term yield volatility to be attributed to the Delphic (information) shock. At longer maturities, this bias is smaller and the qualitative conclusions remain unchanged. At the short end of the yield curve, however, omitting the ARCH term leads to a noticeable overstatement of the estimated volatility-compressing effect.

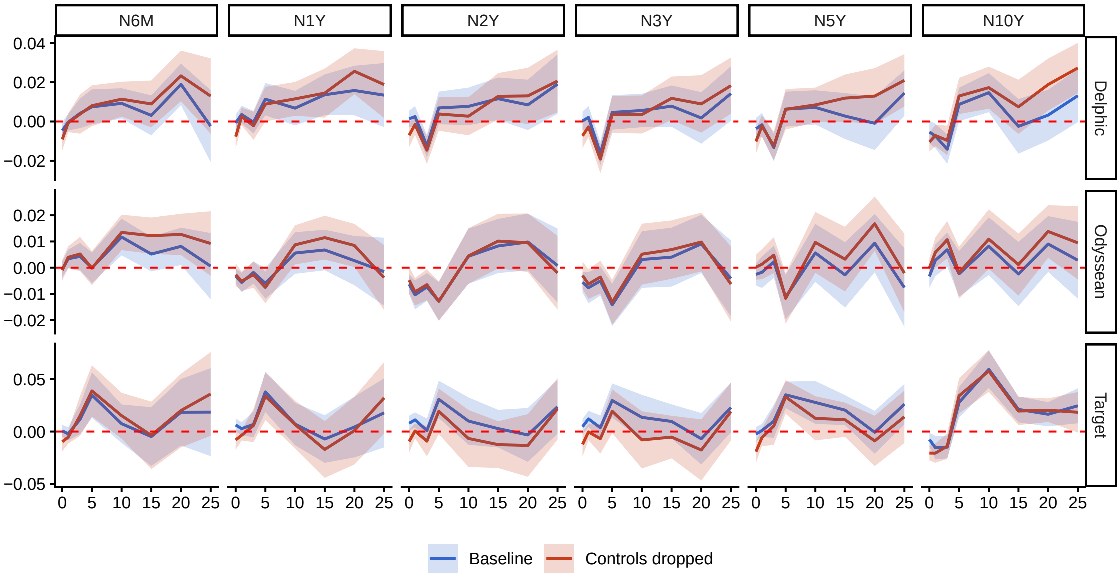

Figure 3.7: Sensitivity of the scale estimates to dropping control variables.

Figures 3.8 and 3.9 show the dynamic location and scale responses obtained using the identification schemes of Rogers et al. (2018) and Jarociński and Karadi (2020) respectively. In the former, both the location and scale responses of the Target and Path factors are virtually identical to those of the Target and Odyssean shocks reported earlier in Figure 3.1. In the latter, the location and scale responses of the term structure to a CBI shock match closely to those obtained with the Delphic shock. On the other hand, responses to the MP shock appear to reflect signals from Target, Odyssean (and possibly LSAP) surprises. Consequently, the results appear to be robust to the choice of orthogonalization and high-frequency series used to construct the surprises.

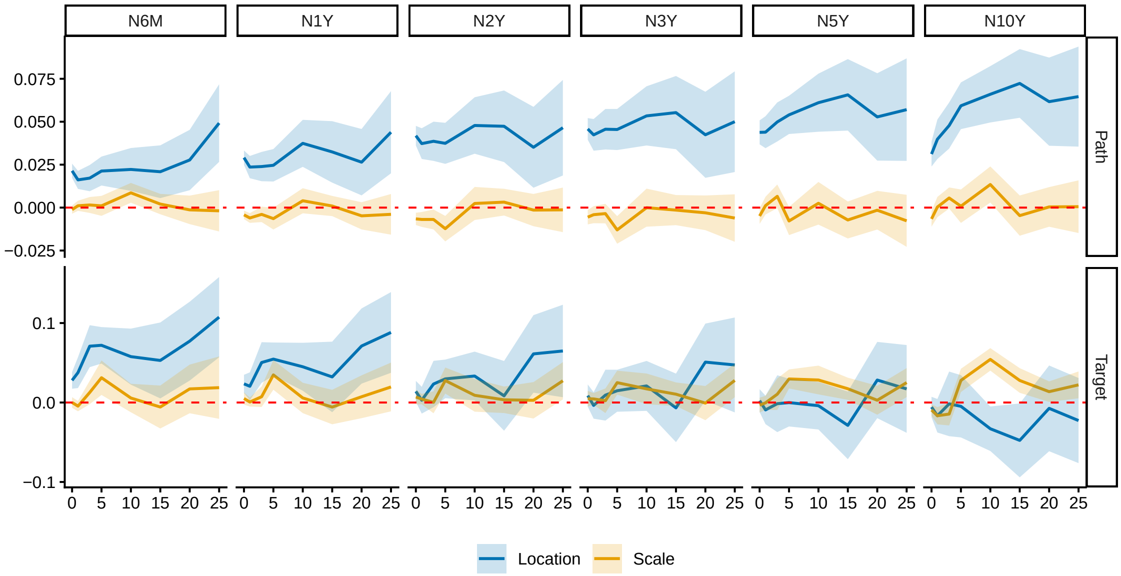

Figure 3.8: Dynamic responses of the nominal term structure - using the shock identification of Rogers et al. (2018)

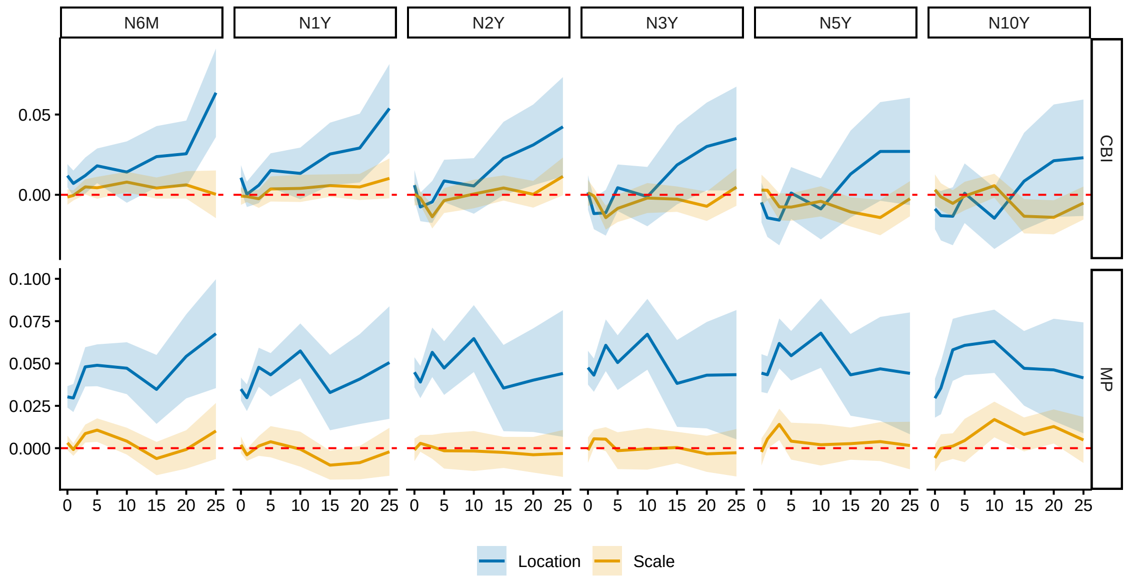

Figure 3.9: Dynamic responses of the nominal term structure - using the shock identification of Jarociński and Karadi (2020)

Conclusion

The papers in this dissertation examined the nonlinear nature of the monetary transmission mechanism. These essays were motivated by the limitation of standard linear frameworks in capturing more complex interactions in the modern-day macro-financial world. They provide complementary evidence that there is an interplay between uncertainty, financial frictions and imbalances and how monetary policy transmits its effects conditional on these factors. A common implication across the three essays is that evaluating monetary policy solely through average responses can provide an incomplete guide for policy design. State dependence, nonlinear dynamics, and higher-order moments play an important role in shaping both the effectiveness and the risks associated with policy actions. Incorporating these features into empirical analysis can improve policymakers' ability to assess tradeoffs, manage uncertainty, and communicate effectively in complex environments.

The first essay shows that heightened uncertainty fragmentation can materially alter the tradeoffs faced by central banks. While the transmission to the real economy remains largely intact, monetary policy is significantly less effective at curbing inflation during periods of elevated uncertainty. This finding emphasizes that uncertainty is a strong state variable that shapes the transmission mechanism and amplifies tradeoffs policymakers may face. The second essay demonstrates that housing market imbalances and financial fragility introduce additional nonlinearities into monetary transmission. Even when real effects appear modestly state dependent, the persistence and conduct of monetary policy itself can change substantially. This suggests that stabilization in deleveraging environments may require greater patience and sustained policy commitment. The third essay extends the analysis of monetary policy transmission to the domain of expectations and uncertainty. By showing that forward guidance systematically reduces conditional volatility along the US Treasury yield curve, the results suggest that policy communication influences not only expected policy paths but also the perceived risk surrounding future outcomes. This distributional perspective shows that there is an additional channel through which monetary policy can promote macro-financial stability, particularly when conventional policy instruments are constrained.