A Unified Measure of ECB Monetary Policy Shocks[†]

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Abstract

This paper extends Bu, Rogers and Wu (2021) paper , to the Euro area. The methodology leverages a heteroskedasticity-based partial least squares approach and Fama-MacBeth style regressions to create a comprehensive monetary policy shock series. Unlike prior measures, this series is effectively devoid of the central bank information effect, making it more robust for analyzing the macroeconomic transmission of monetary policy. The Proxy-SVAR approach reveals that these monetary policy shocks present impulse response functions aligned with the literature. Splitting the sample into policy-effect days and information-effect days, following Jarocinski and Karadi (2020), yields consistent results. Further analysis has been performed using a measure of uncertainty derived from the estimated volatility of the monetary policy shock series. Uncertainty delivers negative effects on the real economy. These findings underscore the robustness and relevance of the proposed methodology for understanding monetary policy dynamics in the Euro area.

Key Words: Monetary Policy, Proxy SVAR, Event-Study, Identification with external instruments

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Overview

1 Introduction

Monetary policy (MP) has lead the charge of cyclical policymaking in the last twenty years. Following the Great Financial Crisis and the sovereign debt crisis, unconventional measures were adopted. The measurement of MP shocks and the estimation of their effects was a new challenge for researchers. For instance, in the USA, distinct policymaking regimes were adopted before, during and after the Zero Lower Bound (ZLB) period. Great scholars thought about exploiting MP shocks from the European Central Bank (ECB) announcements, in the Euro Area, and the FOMC meetings[1], in the USA. These occasions provide an opportunity to isolate unexpected variation in policy and can be utilized to access MP impact on real activities (Gertler and Karadi, 2015). Recent literature (see section 2) exploited interest rate futures/options price changes in sufficiently narrow windows around the announcements and used this as an external instrument identifying monetary surprises.

Miranda-Agrippino (2016) explain the two assumptions that need to hold in order to ensure identification in these types of approach: (*i*) markets efficiently incorporate all the relevant information as it becomes available, and the underlying risk premium of these contracts takes longer than the measurement window to change; (*ii*) the set of economic forecasts upon which central banks' decisions are taken, are the same as those of market participants, implying the equivalence between price updates and MP shocks. The adoption of these assumptions translate price movements into updates in market-implied policy-rate expectations. Therefore, we can treat those announcement-driven updates as the monetary policy shock. Miranda and Agrippino, in the same paper, show why both assumptions do not hold. Monetary surprises capture more than just the MP shock. They incorporate anticipatory effects if market participants are not able to correctly account for the systematic component of the policy when they are surprised by a policy announcement. The fact that private sector forecasts are generally not equal to central banks' forecast means that what is unexpected to markets may be anticipated by central banks. Moreover, monetary surprises are dependent on forecasts of macroeconomic fundamentals, creating an effect on risk premium change within the measurement window. In parallel to Gertler and Karadi (2015), they found that by

[1] The Federal Open Market Committee is the key part of the Federal Reserve System in charge of setting monetary policy.

leveraging data available prior to the policy announcements, high-frequency monetary surprises are predictable. Time-varying risk premia change within the interval of analysis because the uncertainty about the future policy path is gradually resolved. These evidences show the existence of an information effect that undermines the theoretical MP nonneutrality. Christiano et al. (2005) were the first to question this topic. In simpler terms, the central bank reveals, in its meeting day announcements, not only pure monetary policy news but also its private information on the state of the economy, its own preferences, or the model it uses to analyze the economy. In conclusion, conventionally-measured monetary policy surprises are correlated with developments in non-monetary policy economic fundamentals, making the external instrument utilized endogenous.

Central banks information shocks have been shown to have significant macroeconomic effects, hence ignoring them could lead to biased measurements of monetary nonneutrality. For instance, if we look at what happened on March 20, 2001, the FED surprised the market by cutting federal funds rate by 50 basis points. However, the S&P stock market index showed a sizeable decline, contrary to what the theory would predict. This was arguably caused by a specific statement in the announcement: "substantial risks that demand and production could remain soft." The contractionary market response after a monetary easing occurs frequently in the post-90 era in the USA. At the same time in the Euro area, in the episodes of 3 March 2011 and 5 June 2008, Altavilla et al. (2019) found strong evidence of information effect following statements such as "strong vigilance" in one episode, and "state of heightened alertness" and readiness to act "in a firm and timely manner" in the other episode. Theory that information effect may lead to monetary transmission responses with sign that differ from traditional theory are reported in section 2.

Recent literature showed that MP shocks devoid of the information effect display conventionally signed impulse responses of output and inflation, while the information effect contributes in the opposite direction. Leaving the traditional approach of Christiano et al. (1996) and the narrative approach of Romer and Romer (2004), other identification approaches have been proposed in order to overcome these issues. One of them is proposed in this paper. I expand Bu, Rogers and Wu (2021) method to compute a unified measure for monetary policy shock to the Euro area. This novel econometric approach develops a heteroskedasticity-based partial least square (PLS) technique to identify shocks to ECB monetary policy announcements. The idea is to use the Fama and MacBeth (1973) two-step regressions to estimate the unobserved MP shock. In the first step, I compute sensitivity coefficients of the outcome variables (Zero-Coupon Yields) with respect to the policy variable (Overnight Index Swaps at 2 year maturity). Specifically, I first run time-series regressions to estimate the sensitivity of yields at different maturities to ECB announcements. In order to filter out non-monetary policy news, I employ the heteroskedasticity-based estimator of Rigobon and Sack (2003, 2004), implemented with instrumental variables (IV), into this step. In the second step, I regress all outcome variables onto the corresponding estimated sensitivity index from step one, for each time t. In this way, I derive the new monetary policy shock.

The authors argue that the approach has many comparative advantages over other modern methods. The first is that the data utilized are easily available for the US. The second one is that intra-day data may be costly and hard to obtain over a long period of time. Moreover, the lack of EU literature is due to the lack of a systematic database of high-frequency, intra-day data for a broad class of asset prices in the Euro area of the kind that has been employed in the US for about fifteen years.

Anyway, the policy variable used for the Euro area is not easy to obtain over the last 25 years[2]. Additionally, this method is useful for longer periods and for multi-country analysis.

The series I obtain is compared to the ones of Altavilla et al. (2019) and Jarocinski and Karadi (2020) in order to capture common features and evaluate the main differences. My shock can be seen as an "average" of the Altavilla et al's factors, since it is able to capture their largest spikes. By filtering out non-policy noise and minimizing the influence of the information effect, this method produces a clean series of shocks and allows for a detailed analysis of their macroeconomic impacts. Therefore, the exogenous instrument derived is utilized in a Proxy SVAR method in order to access the macroeconomic transmission effects of the policies. The result is that my shock displays conventionally signed impulse response functions, hence a monetary policy easing pushes the industrial production, the stock market and the prices up.

The paper includes estimation of shocks volatility, modeling their dynamics using volatility

[2] Further discussion on this point is left to section 4.

frameworks such as EGARCH and GARCH-t. The best volatility model (Garch-t 3,3) is used as an instrument in the structural analysis. This measure captures the uncertainty of the monetary policies and helps identify alternative monetary policy shocks transmission channels.

The debate, after these findings, centers on whether staff models should be constructed to feature the information effect associated with MP announcements. If so, what is the appropriate foundation stone? Should the impulse responses that the staff's quantitative models attempt to match be the signs predicted by traditional monetary theory, or of the unconventional signs consistent with recent evidence? This question is of primarily importance to central banks.

In the next section, I will review the literature for a better context of the subject. In section 3, I will describe how to obtain the MP shock series. In section 4, I will describe the data structure. Section 5 will display the volatility analysis and compare my series with relevant ones from the literature. In section 6, I will show the econometric approaches to infer causality on macroeconomic transmission channels. In section 7, I will show the transmission effects of the shocks. Finally, I will show the robustness of the approach and conclude respectively in sections 8 and 9.

2 Literature Review

This piece of paper builds its literature foundation from pre-crisis papers. Relevant contributions are Kuttner (2001) early work extracting monetary surprises via interest-rate futures, Cochrane and Piazzesi (2002) bond-market factor models, Rigobon and Sack (2003) event-study innovations and Gürkaynak et al. (2005) daily data analyses. Following the Global Financial Crisis (GFC), unconventional monetary policies were expanded. Since then, researchers have refined how we measure both conventional rate shocks and the novel dimensions of forward guidance (FG) and large-scale asset purchases (LSAPs). The availability of high-frequency financial data made possible to exploit price changes within narrow windows around FOMC announcements (e.g., (Wright, 2012; Gertler and Karadi, 2015; Rogers et al., 2018; Swanson, 2018; Jarocinski and Karadi, 2018)), sharply isolating policy surprises from other news, departing from recursive VAR innovations (Christiano et al.,

1996) and narrative shocks (Romer and Romer, 2004). This tight-window identification has been challenged by the "Fed information effect" (Romer and Romer, 2000; Campbell et al., 2012, 2016; Nakamura and Steinsson, 2018; Miranda-Agrippino, 2016; Jarocinski and Karadi, 2018), which shows that central bank announcements also carry private economic insights that shift expectations in ways inconsistent with pure policy shocks and raise concerns of biased estimates. The methodology of the construction of the MP shock series reported in this paper is built on Fama and MacBeth (1973) two-steps regressions, here used to estimate the unobservable monetary policy shock. The application of Rigobon and Sack (2003) heteroskedasticity-based estimator is implemented to filter out all non-monetary policy news. Bu et al. (2021) were the first one to develop this new unified approach to extrapolate MP shock series without the use of intra-daily data.

Early applications of these surprises focused on financial markets transmission. For instance, Nakamura and Steinsson (2018) document sizable effects on real rates, expected inflation and output growth, while Swanson (2018) demonstrates that FG and LSAP shocks move treasuries, corporate bonds, equities, exchange rates, and option-implied interest rate uncertainty. Miranda-Agrippino (2016) enforce this literature by noting that monetary surprises are predictable. Its predictability can be interpreted as indicating the presence of time-varying risk premium. Rudebusch (1998) was the first to suggest the inclusion of futures on interest rates in monetary VARs to overcome the potentially misspecified reaction function implicitly estimated in these models. Gertler and Karadi (2015) were the first ones to use monetary surprises as external instrument in a Proxy SVAR (Stock and Watson, 2012; Mertens and Ravn, 2013). Jarocinski and Karadi (2018) advance the narrative by jointly using interest-rate and stock-price surprises to disentangle pure policy shocks from concurrent information shocks, confirming that central-bank communication indeed reveals actionable private information that materializes on average.

Finally, this paper utilizes Plagborg Moller codes to compute the pointwise (Cushman and Zha, 1997) and plug-in sup-t (Montiel Olea and Plagborg-Møller, 2019) bands in the Proxy SVAR.

3 Derivation of the MP shock series

In this section, I detail the methodology employed to derive the monetary policy shock series. The process is rooted in the identification of MP shocks using a heteroskedasticity-based instrumental variable (IV) regression framework, inspired by Rigobon and Sack (2003), and extends this with the Fama and MacBeth (1973) two-step procedure for constructing sensitivity coefficients across the yield curve.

The main policy indicator is the change in the 2-year EUR overnight indexed swap (OIS) rate[3]. These market-based curves embed both actual and expected central-bank actions in a continuously available measure. OIS rates trade over the counter on actual transactions and are tied to nearly risk-free overnight benchmarks (e.g.,€STR) , so they closely track the true cost of overnight funding and market expectations of future policy moves. By using the fixed leg of a tenor-specific IRS (e.g., 2 years), researchers capture the term structure of anticipated policy over different horizons, which is useful for detaching pure expectation shocks from term-premium effects in the identification process. Finally, these swap rates are nearly free of bank-credit risk; they provide a clean, more reliable proxy for the pure monetary stance.

At the core of the methodology proposed is the identification of monetary policy shocks (e_t), which are unobservable. Extracted changes in OIS around policy announcement days are assumed to result from both monetary policy shocks (e_t) and non-policy disturbances (η_t), with the monetary policy shock normalized to have a one-to-one relationship with the 2-year policy variable.

$$\Delta OIS_{2,t} = \alpha_0 + e_t + \eta_t \tag{1}$$

[3]It was chosen because this maturity captures the medium-term impact of monetary policy changes, especially during periods of unconventional policymaking.

3.1 Fama-MacBeth: Sensitivity Estimation

By employing the Fama and MacBeth (1973) two-step procedure, we first estimate the sensitivity of bond yields to policy shocks and then isolate the common component across maturities.

$$\Delta R_{i,t} = \alpha_i + \beta_i e_t + \varepsilon_{i,t} \tag{2}$$

Let's assume that the outcome of monetary policy decisions is reflected in the movements of zero-coupon yields ($\Delta R_{i,t}$) with maturities i of 3 months to 30 years and also that the unobserved monetary shock e_t is uncorrelated to $\varepsilon_{i,t}$.

We can now replace our policy variable so that:

$$\Delta R_{i,t} = \theta_i + \beta_i \Delta OIS_{2,t} + \xi_{i,t} \tag{3}$$

where

$$\xi_{i,t} = -\beta_i\, \eta_t + \varepsilon_{i,t},$$

and θ_i is a constant. Recalling that η_t is the error term in the policy indicator (see equation (1)), we see that the regressor $\Delta OIS_{2,t}$ is correlated with the error term $\xi_{i,t}$ due to the component "$-\beta_i\eta_t$". The OLS estimate of β_i is thus biased.

3.2 Heteroskedasticity-Based IV Regression

I now employ the Rigobon and Sack (2003) heteroskedasticity-based estimator, utilizing an instrumental variable (IV) to address endogeneity.

Specifically, I create a matrix combining the 2-year yield changes ($\Delta OIS_{2,t}$) with the same change a week prior the ECB announcement ($\Delta OIS^{*}_{2,t}$)[4]. As demonstrated by Bu et al. (2021) (also reported in Appendix A), β_i can be consistently estimated using

$$[\Delta R_{i,t}] \;=\; \alpha_i \;+\; \beta_i\,[\Delta IV_{2,t}] \;+\; \mu_{i,t}, \quad i = 1, 2, \ldots, 30 \tag{4}$$

[4]Note that the window of the starred change in the OIS has the same lenght of the non-starred change (i.e. 1 day).

where $[\Delta R_{i,t}]$ is a matrix constructed such as $(\Delta R_{i,t}, \Delta R^*_{i,t})$ and $[\Delta IV_{2,t}]$ is built such as $(\Delta OIS_{2,t}, -\Delta OIS^*_{2,t})$, in rigorous chronological order. The instrumental variable is constructed to isolate the policy-induced component of the 2-year swap changes. With their negative counterpart from the starred returns $(\Delta OIS^*_{2,t})$[5], this matrix captures the heteroskedasticity inherent in ECB announcement days, where the assumption is that monetary policy shocks cause an identifiable variance shift while non-policy noise remains relatively stable. β_i is the coefficient vector estimated using ordinary least squares (OLS) on the IV-transformed data. The fitted values from this regression represent the policy-driven component of the 2-year OIS changes. By leveraging the variance shift during ECB announcement days, it isolates policy-induced movements from background noise.

3.3 Final Step: Monetary Policy Shock series

The final step of the procedure allows us to derive the aligned monetary policy shock from cross-sectional regressions of ΔR_{it} on the estimated sensitivity index $\hat{\beta}_i$ for each time t.

$$\Delta R_{it} = \alpha_i + e_{\text{aligned},t}\hat{\beta}_i + v_{it}$$

This iterative process, implemented via a loop in MATLAB and STATA, generates a shock series that reflects the policy-induced changes at each time step.

3.4 An Approach that is robust over time

In this subsection, I am going to verify the consistency of the approach over time and check the validity of my code. I take the last updated original series from Bu et al. (2021) and I replicate it for the USA using data through the end of 2024.

[5] $\Delta OIS_{2,t}$ represents the change at the 2-year maturity between the day of the announcement and the day before. $-\Delta OIS^*_{2,t}$ denotes the change at the same maturity one week prior, with its sign inverted to construct the IV

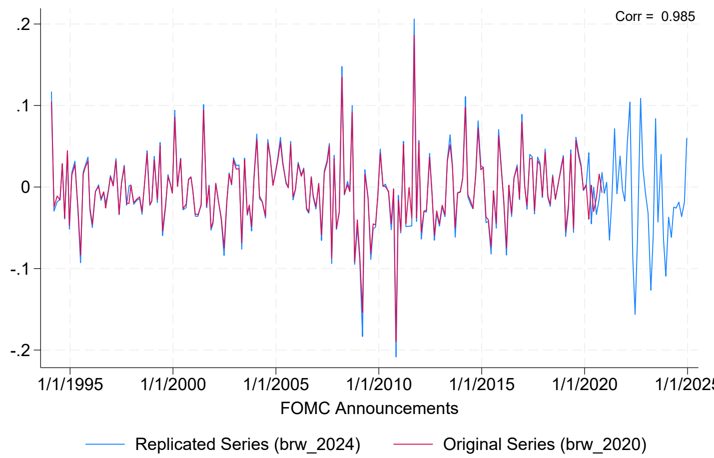


Figure 1: Comparison of the replicated series (brw_2024) and the original series (brw_2020) over 1994–2024. The x-axis marks FOMC announcements while the y-axis shows the shock in units. The correlation between the two series is 0.985.

The correlation between the two series is 0.985, suggesting that the extraction procedure remains stable even after adding the more volatile post-2020 period. Slightly higher spikes in the replicated series can be due to the re-estimation with the new sample. Higher volatility in the OIS series, present in my 2024 sample, does not affect the final result, thanks to the heteroskedasticity-based procedure that is able to cancel out any non-monetary noise (if the assumptions hold). This paragraph also enforces the belief that the code used to extend the approach to the Euro area is correct.

4 Data

In this section, I describe the construction of my dataset[6] with daily yield curves spot rate at different horizons. I used the entire yield curve from 3 months up to 30 years. To provide full scope, I considered the Euro area changing composition spot rates, issued by all ratings governments. The curves are interpolated in order to manage weekend missing values. All the single series can be found on the ECB YC Database. I also created a list of ECB announcements of the last 25 years in order to identify the changes of the policy variable around the meetings days to complement the list made by Altavilla et al. (2019).

The policy variables are alternatively the 2 and 5-years Overnight Index Swaps (OIS) curve,

[6] All files to replicate the series are on my GitHub Repository.

which represents the fixed rate one pays (or receives) to swap against the Euro Short-Term Rate (€STR) over T years. While in the USA the OIS is readily available, in the Euro area the data collection changed methodology in 2019. Prior to 2019, the EONIA was utilized. EONIA (Euro Overnight Index Average) was an unsecured interbank-survey rate. This index has been fully replaced by the €STR. €STR is a transaction-based, volume-weighted average of unsecured overnight deposits across a broad set of counterparties. On the Bloomberg service, adjusted and merged series were available from 2007. Therefore, I manually adjusted the EONIA rates prior to 2007, following the instructions of the ECB, in order to make them completely comparable to the €STR[7].

The analysis is constraint from October 2004 until October 2024. The central bank shock instrument have been transformed into monthly series in order to proceed with Macro-application. The second dataset, comprising macroeconomic variables, was built using data from Eurostat and the ECB Data Warehouse. All series are monthly, seasonally adjusted, and constructed with a changing composition reflecting the Euro area up to date. Relevant macroeconomic indicators are: the Harmonized Index of Consumer Prices (HICP), unemployment rate, industrial production and intermediate goods value. Other financial indicators added to the dataset are: Euro STOXX 50 Equity Index and €/$ exchange rate. For the sake of interpretation, all these variables are transformed using the function 100*In(.).

Finally, in order to benchmark my measure against relevant ones from the literature, I have downloaded Jarocinski and Karadi (2020) series from their github repository, and I have used the replication files of Altavilla et al. (2019) in order to obtain their rotated factors[8].

5 Empirical Analysis

This section serves as a baseline to choose the proper uncertainty measure to analyze how variability in monetary policies can effect the real economy. I analyze the MP surprises' statistical properties and I compare the series to established proxies for monetary policy shocks.

[7]'EESWE2 Curncy' is the Bloomberg's ticker for 2-year EUR interest-rate swap rate (ESTR-referenced).
[8]See Section 5.3

5.1 Analysis of Shocks' volatility

A diagnostic exploration of the MP shocks, using autocorrelation functions (ACF), reveals relevant evidence of volatility clustering. This observation suggests the presence of conditional heteroskedasticity, warranting further investigation. I implemented an automated grid search over an ARMA(p,q) in order to control linear dynamics and then test for unexplained volatility clustering of the residuals. The model selection is guided by the Akaike Information Criterion (AIC)(Akaike, 1974), ensuring parsimony while accounting for goodness of fit[9]. To formally test for ARCH effects, the McLeod and Li (1983) test is conducted. This is a Lagrange multiplier test, where the fitted errors from the linear model are squared and regressed on past q lagged values. With this simple specification, the errors proved to have autoregressive conditional heteroskedasticity.

Monetary policy shocks often exhibit time-varying volatility and asymmetry that a constant variance model cannot capture. An EGARCH (Nelson, 1991) specification models the log of conditional variance directly. In this way volatility clustering without imposing non-negativity constraints is taken into account and "leverage" parameters are estimated (γ_k) to see whether, let say, contractionary shocks have a larger or more persistent impact on future volatility than expansionary ones. Incorporating these considerations, and minimizing the AIC, an AR(1) model with an EGARCH(5,4) volatility specification has been fitted:

$$y_t = \phi\, y_{t-1} + \varepsilon_t, \qquad \varepsilon_t = \sigma_t\, z_t, \qquad z_t \sim \mathcal{N}(0,1)$$

$$\log(\sigma^2_{t|t-1}) = \omega + \sum_{i=1}^{5} \beta_i \log(\sigma^2_{t-i|t-i-1}) + \sum_{j=1}^{4} \alpha_j [|z_{t-j}| - \mathbb{E}(|z_{t-j}|)] + \sum_{k=1}^{4} \gamma_j\, z_{t-k}$$

where $\mathbb{E}(|z_{t-j}|) = \sqrt{(}2/\pi)$ when z_{t-i} is Gaussian. This model is estimated using maximum likelihood, with the optimization constrained to ensure parameter stability. The McLeod and Li test applied to the standardized residuals confirms the model's validity in capturing the data's dynamic structure.

To explore alternative specifications, a GARCH-t model is implemented since it combines time-varying volatility with heavy-tailed error distributions. The GARCH component allows the condi-

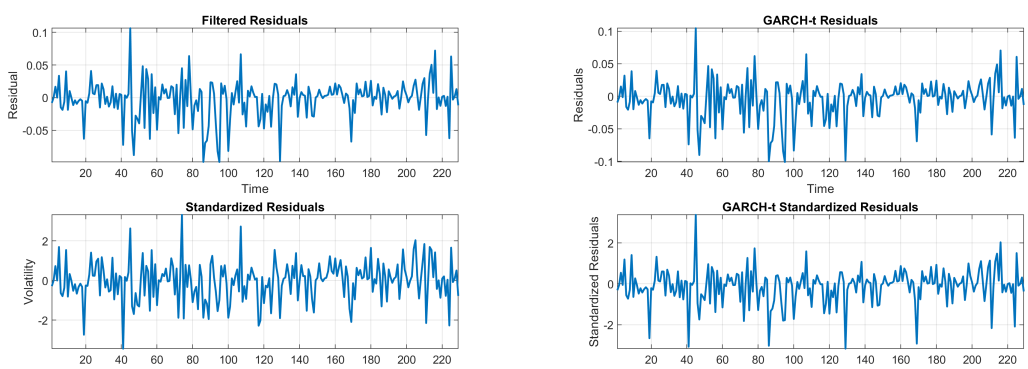
[9] AIC is generally preferred in small timeseries like the one of this paper. For more details, see Hurvich and Tsai (1989).

tional variance to respond to past shocks, reflecting the clustering of high- and low-volatility regimes often seen around major policy announcements. Meanwhile, the Student-t errors accommodate extreme surprise movements giving greater probability to outlier events than a normal distribution would. This robustness to fat tails makes this model an ideal proxy for measuring uncertainty (see section 7.2). The lag selection for the GARCH components is based on minimizing AIC across multiple candidate models and the optimal GARCH(3,3)-t framework is estimated. Also this model provides a robust fit, capturing volatility persistence effectively[10].

For comparative purposes, a Dynamic Conditional Score model with Student-t innovations (DCS-t), is estimated, leveraging its adaptability in handling heavy-tailed distributions. Parameter estimation is conducted by maximizing the t-likelihood via constrained nonlinear optimization. Starting from a small-noise initial vector, the model update uses the likelihood score each period to recalibrate volatility in real time, ensuring the model learns efficiently from every new surprise. In addition, as previously discussed, the Student-t error distribution guards against the distorting influence of extreme rate moves.

5.2 Findings

In this subsection, the main results of this empirical analysis are shown, illustrating distinct aspects of volatility and residual dynamics across different models. Figure 2a presents the residuals and standardized residuals from the EGARCH(5,4) model, while figure 2b shows the ones from the GARCH-t(3,3).



(a) EGARCH residuals

(b) GARCH-t residuals

Figure 2: Diagnostics of residuals (top) and standardized residuals (bottom) for EGARCH vs. GARCH-t models. Expressed in units over time.

[10]see the Findings section for more

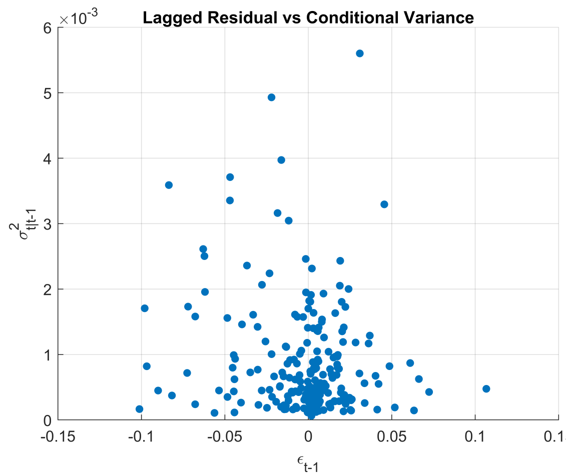
Visually, the standardized residuals appear to be centered around zero and roughly i.i.d. distributed. Most importantly, they both capture volatility clustering that was present in the original series. These two models look alike, but the EGARCH is able to capture the asymmetry better.

EGARCH(5,4) Conditional Variance Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	-1.2534	0.64171	-1.9532	0.050795
GARCH{1}	0.71467	0.043154	16.561	1.3401e-61
GARCH{2}	0.57254	0.050792	11.272	1.7991e-29
GARCH{3}	-0.55179	0.050687	-10.886	1.3412e-27
GARCH{4}	-0.8026	0.04724	-16.99	9.7514e-65
GARCH{5}	0.89366	0.053869	16.59	8.292e-62
ARCH{1}	0.28347	0.14217	1.9939	0.046168
ARCH{2}	0.13437	0.16359	0.8214	0.41142
ARCH{3}	-0.17888	0.16233	-1.1019	0.27049
ARCH{4}	0.41838	0.16816	2.4881	0.012844
Leverage{1}	0.12817	0.049149	2.6078	0.0091137
Leverage{2}	-0.059607	0.027802	-2.144	0.032031
Leverage{3}	-0.11977	0.047987	-2.4959	0.012565
Leverage{4}	-0.051548	0.042237	-1.2204	0.2223

No significant ARCH effects detected (p-value = 0.9033).
Model1: AIC=-1040.15, BIC=-985.21

(a) EGARCH(5,4) conditional variance model parameter estimates (Gaussian distribution). Parameters include Constant, GARCH (1–5), ARCH (1–4) and Leverage (1–4); columns report Estimate, Standard Error, t-Statistic and p-Value. Bottom rows show the ARCH LM test p-value and model selection criteria (AIC, BIC).



(b) Scatter plot of lagged residuals vs. conditional variance for the EGARCH model over the sample period.

Figure 3

It is really interesting to note significant leverage effects for the first 3 lags (coherent with comparable shocks in the literature). Specifically, the first lag shows a positive asymmetry, meaning that contractionary shocks last month will effect today's variance more than expansionary ones. The opposite happens with innovations lagged 2 and 3 months. In figure 3b, we can also observe how negative innovations have larger impact on the conditional variance, compared to positive ones.

A key pattern that is common to both estimations is that the monetary policy shocks have high persistency. Past variance (i.e., GARCH coefficients) strongly drives current variance, while past shocks have weaker evidence of impacting volatility.

Figure 4 demonstrates that the DCS-t model (blue line) captures smoother and more persistent volatility dynamics compared to the more volatile GARCH-t model (red dashed line). This indicates that the DCS-t model provides a more stable representation of the underlying volatility structure since it is less sensitive to outliers.

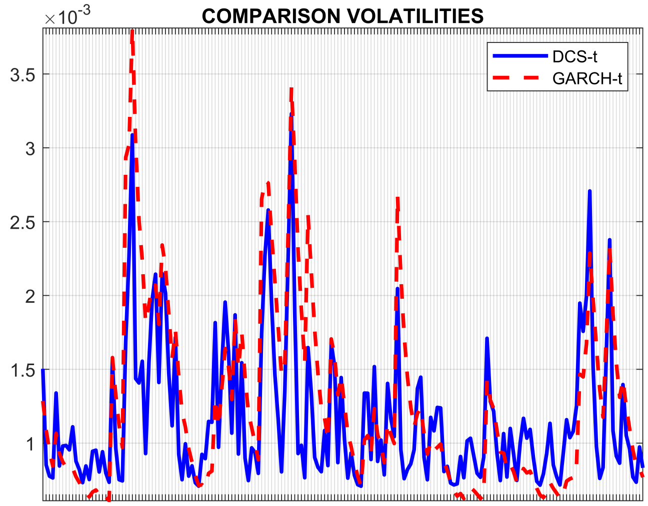


Figure 4: Comparison of volatilities from the DCS-t model (blue line) and the GARCH-t model (red dashed line) over the sample period.

The ability of the DCS-t model to adjust weights for outliers, while maintaining robustness, is clearly visible in figure 5. It shows a parabolic relationship between standardized prediction errors (ϵ/σ) and their associated weights, meaning the framework assign to outliers almost zero weight.

However, this is the reason I view GARCH-t as a more reliable proxy for monetary policy uncertainty. The DCS-t model can underestimate uncertainty in certain periods, especially around the sovereign-debt crisis.

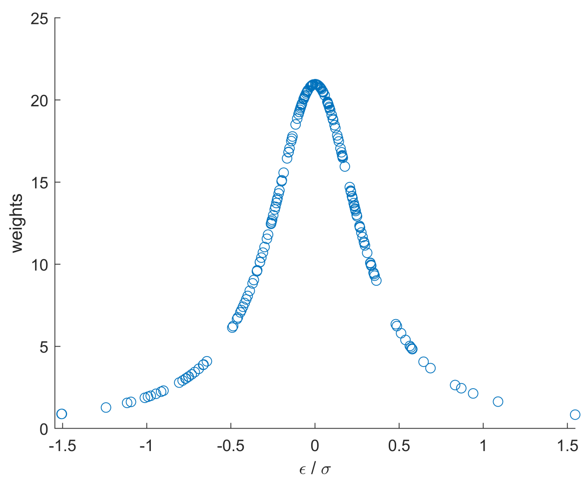


Figure 5: Scatter plot of weights versus standardized prediction errors (ϵ/σ).

Finally, figure 6 reveals the standardized residuals of the DCS-t model and the corresponding probabilities of observing outliers. The high spikes in outlier probabilities align with periods of significant shocks, emphasizing the DCS-t model's ability to identify and handle extreme values effectively. More than 75% of the observations have a probability of being outliers below 0.3. The highest spikes, considered as ouliers, occur in Feb. 2008, June 2008, Nov. 2011, Jan. 2013, Aug. 2013 and June 2015.

Specifically, on January 10, 2013, my shock registers a negative spike even if nothing really occurred that day. Draghi simply reported that the economy was going through a normalization phase of certain conditions. The Eurobonds increased due to external causes, biasing my measure[11]. On 3 June 2015, the ECB president announced that high volatility was about to come and that the ECB had to mantain a steady monetary stance. This tightening communication of future policies was correctly captured by other relevant series in the literature but not by mine. As reported by the Financial Times, a few hours after the GC announcement, new positive forecasts were published by the ECB, generating positive movements in the market. This confounding effect clearly biases my result. Other two episodes happened in February and June 2008, when markets already knew the ECB strategy and no main surprise appeared.

In the next paragraph, I will analyze what occurred in other relevant days that result as a spike in my MP shock series. The estimated outliers, corroborated by commentaries, are set equal to zero in my proxy in order to have cleaner impulse response functions.

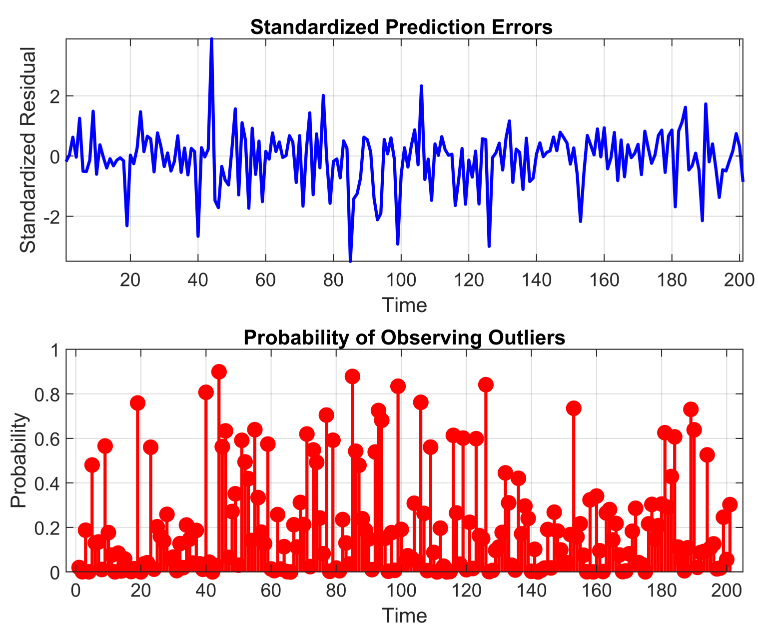


Figure 6: Standardized prediction errors (top panel) and corresponding outlier probabilities (bottom panel) from the DCS-t model.

[11]In those days The Economist published the article 'Has anyone seen the ECB?'. The ECB was neutral in that period and no shock could have occurred, enhancing the argument that on that day I registered an outlier.

5.3 Comparison with shocks in the literature

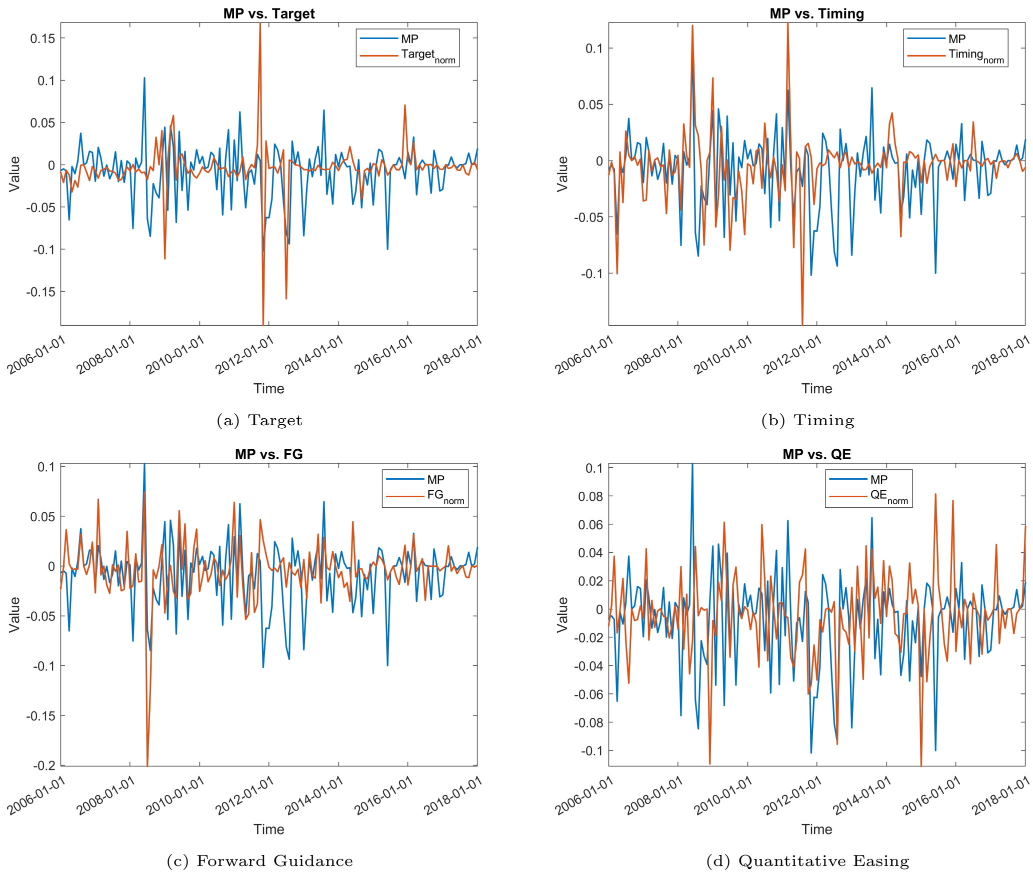
In this subsection, I will present an important comparison of my series against other relevant series such as those of Jarocinski and Karadi (2020) and the Altavilla et al. (2019). In order to better understand the comparison, it is adequate to explain the meaning of when my unified shock[12] is aligned with one or more of Altavilla et al's factors (see Fig. 7).

Their target surprise reflects unanticipated changes in the ECB's short-term rate decision. This factor is completely uncorrelated with the press-conference window OIS movements. It is interesting to note that this factor shares important key features with my shock, such as the same leverage effects in the EGARCH variance modelling for the first 3 lags. My shock lines up with its peaks on 3 November 2011 and 5 July 2012. The former meeting was the absolute first one chaired by Mario Draghi and nobody was expecting a 25 basis points cut. This day shock is clearly present also in the Jarocinski's series (Fig. 9). On the latter date, the deposit facility rate was surprisingly brought down to zero. Comovements with this target factor show the pure policy-rate surprise that drives immediate front-end yield moves. However, from this date onward, this factor rarely appeared in the ZLB period and understandably was not present in my unified shock series as well.

The timing factor captures the shifts in market expectations over the next few meetings that leaves longer-term interest rates essentially unchanged. The two largest spikes of this factor are captured by my series and they are respectively on 5 June 2008 and 3 March 2011. At both meetings, the interest rates were left unchanged, but the communication in the introductory statement of the press conference was key. Expressions like "strong vigilance", "state of heightened alertness" and "ready to act in a firm and timely manner" signalled potential action in the following meetings. As a matter of fact, in the month following those announcements, the interest rates were raised as correctly predicted by the market through the Governing Council communication. The co-spikes with this factor indicate the series also pick up sudden re-phasing of future rate dates. On 15 January 2009, the policy rate was unexpectedly cut by 50 basis points, as correctly captured by the target surprise, but the overall effect caught by my series is dominated by the timing factor. In fact, on the same day the deposit interest rate was cut by 100 basis points, forcing banks to withdraw

[12] My series can be seen as an 'average' of Altavilla's factors.

liquidity, flooding the overnight market with lendable cash, pushing down the policy variable used to build the unified series (i.e., the Euro OverNight Index Swap)[13].



(a) Target

(b) Timing

(c) Forward Guidance

(d) Quantitative Easing

Figure 7: Comparison of my monetary-policy shock ("MP") with Altavilla et al.'s four surprise factors.

Forward Guidance (FG), in fig. 7c, captures revisions to the medium-term policy path (from 1 to 3 years). My shock spikes in tandem with this guidance shock and Jarocinski series on 3 July 2008. The negative spike records the announcement of not having further hikes in the rates. This spike was preceded by a contractionary shock the previous month, making the new comments by Jean-Claude Trichet widely unexpected (Economist and Financial Time say).

Finally, the Quantitative Easing (QE) surprise isolates unexpected changes in asset-purchase scale. The disalignment of my shock with the QE factor underlines that my series is not able to pick up unconventional policy surprises that predominantly affect long maturities. A spurious comovement occurred on the first day of August 2013, when, following what The Economist and Morgan Stanley reported, the markets were expecting an implementation of a QE, since the pro-

[13]This dynamic is easily explainable: the opportunity cost of depositing money relatively increased since the deposit rate was cut more than the policy rate.

longed period of 'lowflation'. To enforce the argument that the procedure proposed in this paper cancels out the information effect, when the Asset Purchase Program was announced, my shock was not responsive.

My proxy seems to be a 'summary' of the Altavilla et al's factors. In fact, regressing my series on these variables, it is clear that they can explain part of the variance of my dependent variable. It is relevant to note that the QE factor is not significant, signaling that my shock does not truly capture long-term maturities movements.

Figure 8 displays the plot of the fitted values of the four surprises against my main series. Five spikes appear in my series and are unexplained by this unified measure of their factors. Specifically Jan. 2013 and June 2015 are outliers as previously explained, while Nov. 2011, July 2012 and Aug. 2013, are captured by single factors but not by the fitted values. This shows an example of how my shock could be interpreted as a good average of the four variables, since it captures the main relevant episodes that would have been lost with a simple average of the four factors. The other advantage is that my series is not affected by the information effect (see Section 8.2).

VARIABLES	ecb_2yr	ecb_5yr
Target Factor	0.210***	0.159**
	(0.079)	(0.064)
Timing Factor	0.387***	0.215***
	(0.078)	(0.063)
Forward Guidance Factor	0.343***	0.293***
	(0.079)	(0.063)
Quantitative Easing Factor	–0.004	0.049
	(0.078)	(0.063)
Observations	151	151
R-squared	0.263	0.223
Mean dep. var.	–0.00761	–0.00619

Table 1: Regression of my shock proxies, computed using 2-years OIS and 5-years OIS, on the 4 factors estimated by Altavilla et al. (2019).
Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Standard errors in parentheses.

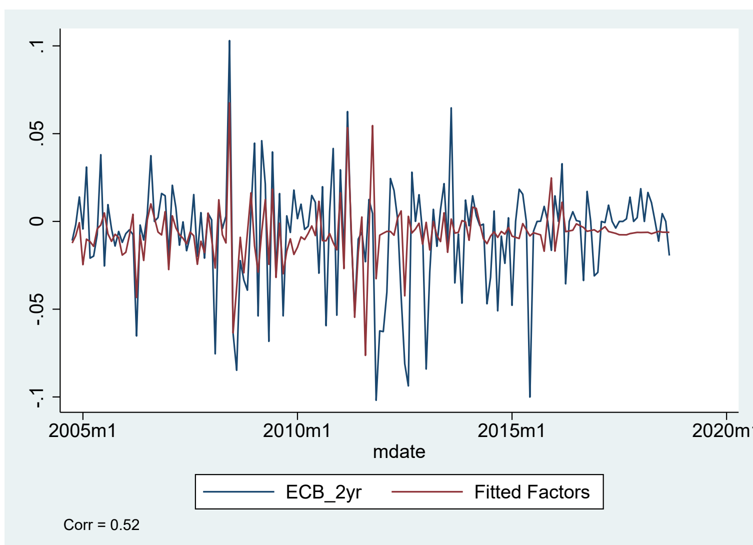


Figure 8: Plot of my main policy shock against the fitted values of the regression displayed in Table 1. The correlation of 0.52 is displayed on the bottom.

Comparing my series to the one of Jarocinki and Karadi (see Fig. 9), two synchronous movements are relevant. On April 2006, the President announced that raise in the interest rates would have been postponed, generating a positive reaction in the market. The second episode is on March

2020, when President Lagarde commented on italian spread during the press-conference and she added "We are not here to close spreads, this is not the function or the mission of the ECB... There are other tools for that and other actors to deal with those issues". She later apologized, because, without realizing it, this type of communication caused a financial shock captured by any other competitive measure of MP shocks. My series, for better or worse, captured a pure monetary policy easing, due to the rate cuts made to face the upcoming pandemic crisis.

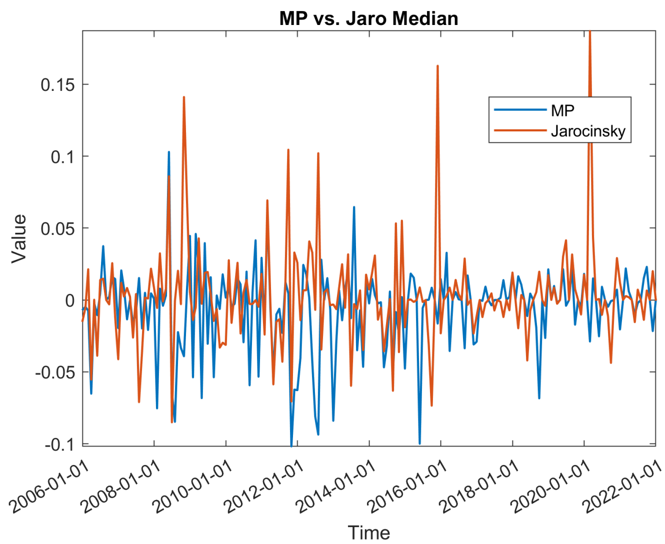


Figure 9: Comparison between my MP proxy and Jarocinski and Karadi one, over the sample period.

In order to show a potential limitation on the choice of my policy variables, it is useful to understand what happened in December 2015. The ECB announced the extension of asset purchases. Altavilla and Jarocinski's shocks correctly capture a monetary tightening that day. It is trivial, but key, to understand the reason behind the dynamic, because it shows off a weakness of my procedure. The Economist and the Financial Times reported bad reaction from the markets because the main interest rates had been cut by 10 basis points, from -0.2 to -0.3, but the market was discounting higher cuts. Goldman Sachs confirmed that futures were pricing larger rate reductions. Additionally, in the press-conference, a further negative shock was registered since the extension of the QE arrived without an enlargement of the total amount collected. The ECB action had been simply diluted over time. Traders had reckoned that the ECB would have increased the scale of its regular purchases. While the whole market crumpled, the eurobonds reacted in the opposite direction, and as a final result my MP shock signals a monetary easing for that day.

6 A Proxy SVAR approach

The analysis proceeds with the implementation of the Proxy-SVAR econometric approach to estimate impulse response functions (IRFs) evaluating the effects of the shock on the real economy. Proxy-SVAR estimates a VAR model where an external instrumental variable (proxy) identifies the structural shocks. Economically, this assumes a valid instrument that isolates the shock of interest, enabling the decomposition of reduced-form residuals into structural components. In the VAR estimation I utilize 6 variables: Industrial Production, Harmonized Index of Consumption Price (HICP), Intermediate Good values, Euro STOXX 50 returns, $/€ exchange rate and finally the cumulative function of my MP surprise proxy. First, I fit the reduced-form VAR(p) by ordinary least squares and obtain ε_t. The underlying assumption is that

$$\varepsilon_t = Bu_t,$$

where

$$u_t$$

are the structural shocks. We solve the endogeneity issue of the structural shocks via the instrumental variable (Z) satisfying $\text{Cov}(Z_t, u_{6,t}) \neq 0$ and $\text{Cov}(Z_t, u_{j,t}) = 0$ for $j \neq 6$. Hence, the structural loadings are identified by regressing the residuals onto the instrument, computed as:

$$b = (Z'Z)^{-1}Z' \times \widehat{\varepsilon}_{i,t}$$

and normalizing the coefficient vector by scaling it with respect to the identifying variable of the policy (i.e., the cumulative function of my cleaned ecb surprises). This normalized vector is then used to compute the structural IRFs by multiplying it with the respective Wold representation coefficient of the VAR:

$$\theta(h) = A^h \times b$$

where A is the companion-form VAR coefficient matrix.

To quantify uncertainty, I construct simultaneous confidence bands for the impulse response function $\theta(h)$. Pointwise bands are given by

$$\theta(h) \pm z_{1-\alpha/2}\,\mathrm{se}\big[\widehat{\theta}(h)\big],$$

where $z_{1-\alpha/2}$ is the standard normal quantile ($\alpha = 0.10$) and $\mathrm{se}[\widehat{\theta}(h)]$ its standard error. These bands guarantee coverage at each fixed h, but do not control the probability of simultaneous coverage over all h. To address this, the plug-in sup-t band uses the estimated covariance matrix Σ of $\widehat{\theta} = [\widehat{\theta}(0), \ldots, \widehat{\theta}(H)]'$. I draw 10000 samples $t^{(i)} \sim N(0, \Sigma)$, computes the studentized maxima $M^{(i)} = \max_h |t_h^{(i)}/\sqrt{\Sigma_{hh}}|$, and sets the critical value $c_{\mathrm{sup}-t}$ as the 90th percentile of $\{M^{(i)}\}$. The sup-t band is then

$$\widehat{\theta}(h) \ \pm \ c_{\mathrm{sup}-t}\,\mathrm{se}\big[\widehat{\theta}(h)\big],$$

ensuring simultaneous coverage $\Pr\{\forall h : \theta(h) \in \text{band}\} \geq 0.9$.

Proxy-SVAR relies on the dynamic consistency of the VAR structure to estimate IRFs, which embeds the entire dynamic system of equations.

The Proxy-SVAR procedure ensures that the IRFs represent the dynamic effects of the structural shocks on the system's variables over the specified horizon.

7 Evidence on the ECB shock series

In this section, I will display my main results regarding the effects of my main proxy obtained using the 2-year OIS to derive the MP shock. The Impulse Response Functions (IRFs) present the 90% pointwise bands and the 90% plug-in Sup-t bands described in the previous paragraph. The shock is expressed in units and the macro variables are all 100*In(.) transformed for the sake of a better interpretation. The IRFs using the 5-year OIS are relegated to paragraph 8.

7.1 Impulse response Functions

In figure 10, I plot the dynamic responses to a one-percent monetary policy easing. Industrial production jumps by roughly 1.5 % at impact and then decays gradually, returning to baseline after about one year. HICP, by contrast, rises more slowly, peaking around month 20 at about 0.3 percent before narrowing down, consistent with Calvo-pricing frameworks in which output gaps feed into prices with a lag. The value of intermediate goods exhibits an even larger peak response and more persistence, while equity returns (EURO STOXX 50) surge nearly 2 % on impact, retracing all the gain by month 3. The euro depreciates modestly—about 0.5-0.7 % and lasts about 2-3 months, coherent with Peersman and Smets (2005) and De Santis and Zimic (2006). Finally, the cumulative monetary-policy proxy shows a negative impact (as a pure monetary policy easing should display) over the first year and then plateaus. The results yield textbook behaviors, confirming the argument of this piece of paper: this procedure is robust in canceling out the information effect.

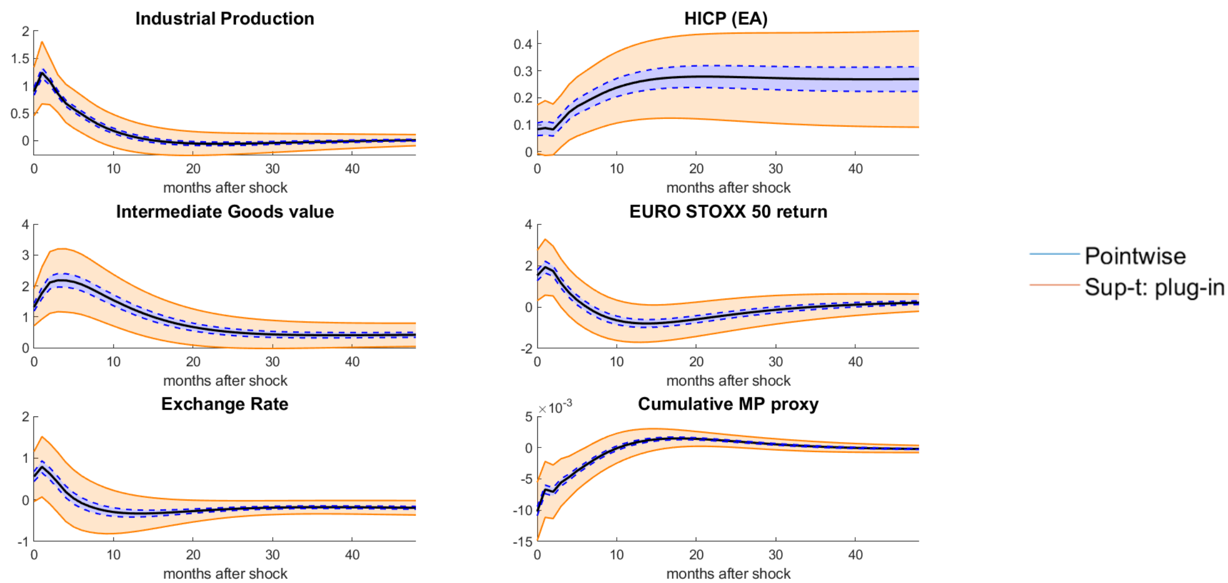


Figure 10: Proxy SVAR using the 2-year OIS Monetary Policy Shock expressed in units. The IRF reflects a one percent monetary policy easing over a 48-month horizon. Solid black lines: point estimates; dashed blue lines: 90% pointwise confidence bands; shaded orange areas: 90% plug-in Sup-t bands. Sample period: Oct 2004–Oct 2024. (Legend on the right)

7.2 A proxy for uncertainty

This paper not only proves the robustness of the Bu et al. (2021) approach, but wants to analyze also the effects of uncertainty of monetary polices. In recent literature, researchers have utilized various indexes and proxies to isolate the exogenous component of monetary policy (MP) uncertainty and evaluate its impact on the economy. For example, Husted et al. (2020) developed an MP uncertainty index, Bekaert et al. (2013) used the VIX index alongside high-frequency data, and Baker et al.

(2016) created an Economic Policy Uncertainty (EPU) index based on newspaper frequency analysis.

In this study, I employ the GARCH(3,3)-t model to estimate the volatility of MP shocks as a proxy for MP uncertainty. Specifically, the procedure extracts the conditional variance of the MP shock. This approach assumes that the derived series is exogenous, allowing the variance to reflect the market's perceived uncertainty related specifically to MP shocks, providing a direct measure of their economic influence. The GARCH-t specification is preferred to other specifications (such as the DCS-t model; see par. 5) because its heavy-tailed error distribution makes it more sensitive to outliers, and thus better suited for capturing moments of extreme upside and downside uncertainty.

Figure 11, displays Sidak and Bonferroni bands for more robust results. The use of the Bonferroni bands offers a straightforward, assumption-free, way to guarantee joint coverage of the true IRF path at the nominal level by simply inflating each pointwise interval ($\alpha^* = \alpha/H$), but it tends to be overly conservative with wide bands and low power. Here it is useful to exhibit strong effects of uncertainty. Šidák bands, by contrast, adjust the per-horizon error rate via

$$\alpha^* = 1 - (1 - \alpha)^{1/(2H)},$$

producing tighter intervals under the assumption of independent or positively dependent IRF draws; Thus, Bonferroni's strength is robustness to any dependence structure, while Šidák's strength is efficiency under independence. Here are the IRFs:

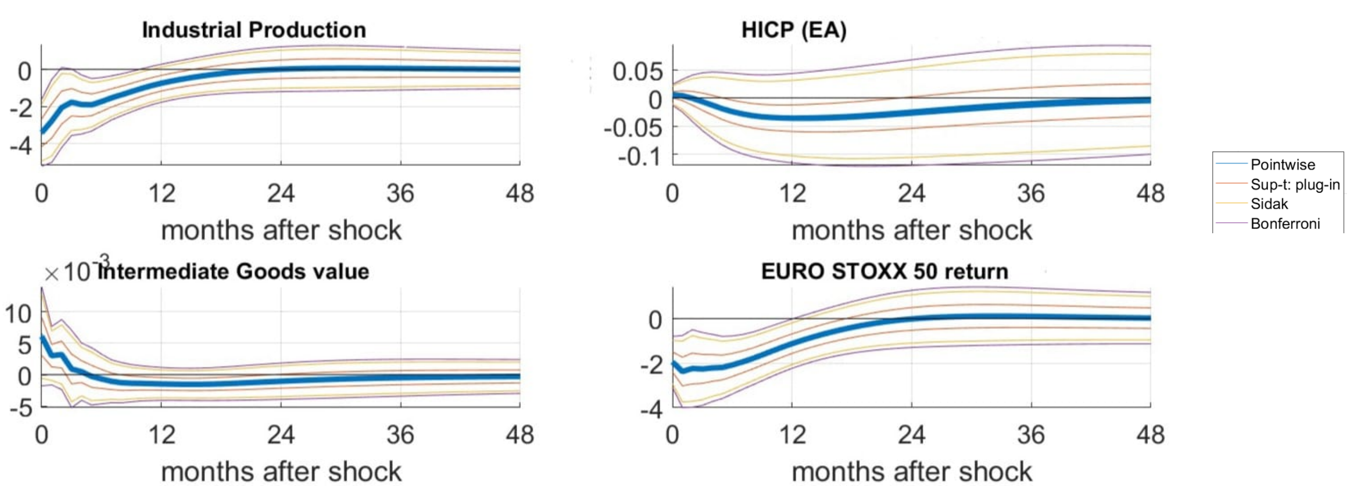


Figure 11: Proxy-SVAR using the Garch-t (3,3) as the proxy with all the confidence bands intervals (legend on the right). The responses are standardized to a 10% positive surprise in the volatility measure. All the Macro variables have been 100*log(.) transformed.

The uncertainty proxy shows significant effects only on Industrial production and market returns. A 10 percent increase in the uncertainty regarding ECB policies and its communication contracts by 3% the Industrial production and by 2% the European blue-chip equity index of the Euro Area. The significance fades after about 10 months in the first case and 12 in the second one, suggesting important policy implications for the European Central Bank. These results are in line with the literature above mentioned. ECB communication and actions can have significant negative impacts on the real economy.

8 Robustness Checks

In this section, I will present several robustness checks to prove consistency in the results exposed by the IRFs. The 5-years OIS monetary policy shock will be used as a proxy alongside alternative specifications of the 2 years-OIS proxy. Moreover, I will show how the information effects does not bias my procedure following the procedure proposed by Jarocinski and Karadi (2020).

8.1 Alternative Proxies

At first, looking at the MP shock computed using the differences of the 5-years OIS around the GC announcements, the results seem really consistent.

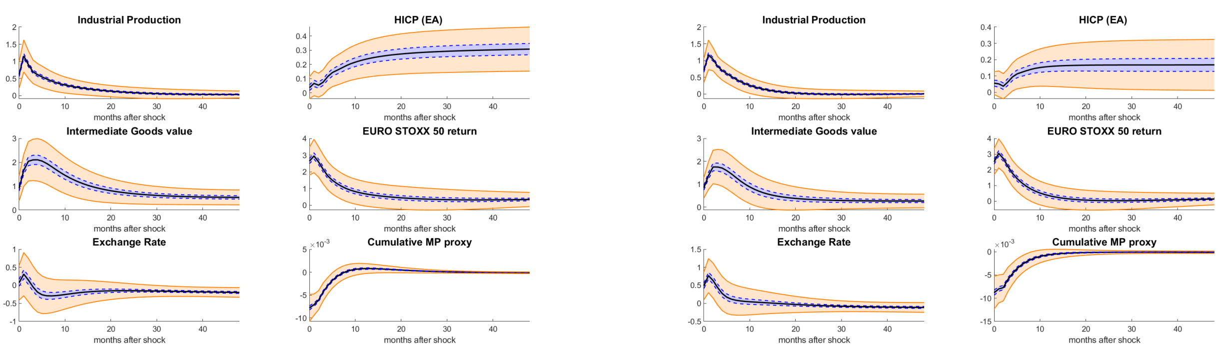


Figure 12: Left: Impulse Response Functions of the MP_5 proxy. Right: Impulse Response Functions of a new MP_2 proxy, where the 6mths, 9mths and 2-year yield curves have been removed. Both results are standardized to a 1% MP shock and all macro variables are in 100*log(.) form. The orange area is the 90% confidence Sup-t bands and the blue area is the 90% pointwise bands.

The results are quantitatively comparable to fig. 10. The same is true for the shock computed using the whole zero-coupon bonds yield returns, except the 6/9 months and the 2 years ones (exactly as the original procedure). This is not true when we use only key zero-coupon bond yields such as the 3 months, 1/2/5/7/10 years. As underlined by the authors, this approach needs the usage of the whole yields curve in order to be effective.

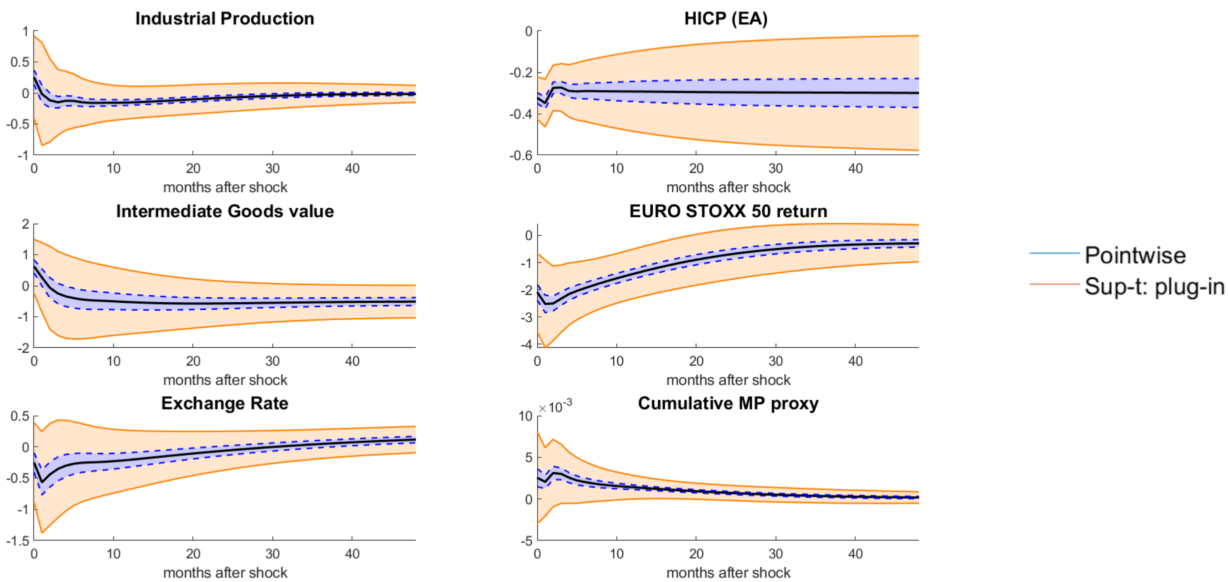


Figure 13: Impulse Response Functions of a the MP_2 proxy computed using only key yields. The IRFs are standardized to a 1% MP shock and all macro variables are in 100*log(.) form. Legend for the confidence bands is on the right.

8.2 Information Effect

The procedure I utilize to create the Euro Area MP proxy had removed the information effect in the US. However, the Euro Area is noted to have larger information effects that may be confounding. In this section, to prove the well-functioning of the procedure, I will compare the previous IRFs with those ones produced by removing information days from my sample. I am expecting to see no big changes in the responses. If the magnitude of the variation of the changes is large, information effect may bias the computed proxy. Therefore, I replicate the Jarocinski and Karadi (2018) procedure to isolate monetary policy from information shocks days by exploiting one day co-movements of the 2 years OIS rate and stock market around central bank announcements. The underlying intuition is that a pure monetary policy tightening shock should have a negative impact on the market and the other way around. I simply define

$$\sigma_t \;=\; \text{sign}(\Delta r_t) \times \text{sign}(\Delta s_t).$$

If $\sigma_t < 0$, I label t a pure *policy-effect* day; if $\sigma_t > 0$, I label t an *information-effect* day. This protocol cleanly separates Delphic (information) from Odyssean (pure policy) shocks, as firstly defined by Campbell et al. (2012). In the scatter plot (fig. 14), we have a visual representation of the surprises. The Delphic ones are in quadrant I and III, while Odyssean days are those one displayed in quadrant II and IV (about 45% of the total).

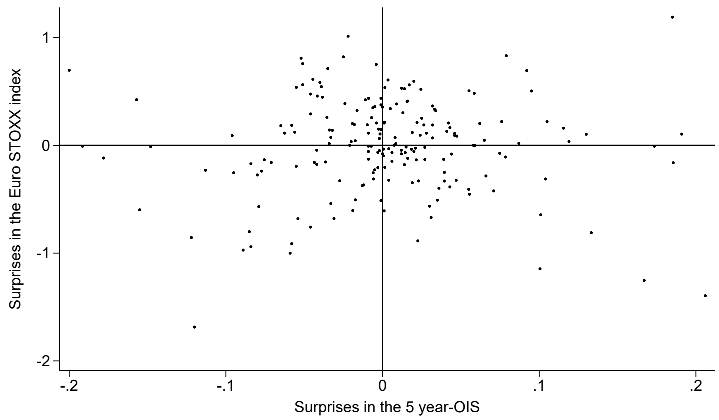


Figure 14: Scatterplot of the surprises in the 5-year OIS rate and EURO STOXX 50 index

In the last figure, we can clearly see how the IRFs are qualitatively and quantitatively close to the ones obtained using the original procedure. I can conclude that this procedure correctly cancels out the information effect from the series also in the Euro Area.

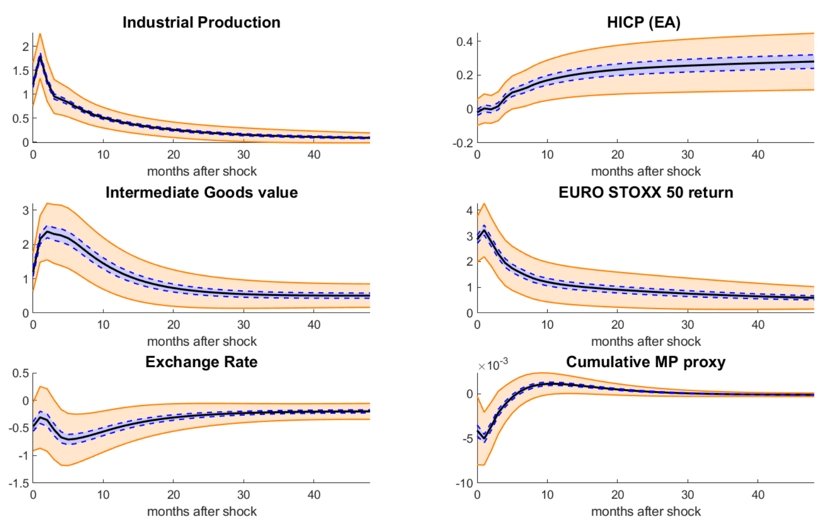


Figure 15: Impulse response function considering only policy-effect days. The IRFs are standardized to a 1% MP easing.

9 Conclusion

In this paper, I have replicated and validated a unified measure of ECB monetary policy shocks that strips away central-bank information effects to reveal the pure, unexpected stance shifts that drive euro-area dynamics. By marrying a heteroskedasticity-based IV filter with a Fama–MacBeth two-step estimation, I've shown that even without high-frequency data it is possible to extract a clean shock series whose impulse responses to output, prices and financial variables closely mirror textbook theory.

Using a Proxy-SVAR approach, I conclude that a one-percent surprise easing by the ECB, raises industrial production by 1.5 percent at impact and inflation with a +0.3 percent lift, often responding with 1 or 2 months of delay. Equities surge by 2 percent on impact, and the euro depreciates by 0.6 percent.

My volatility analysis further underscores the richness of this series. A score-driven framework helped me cleaning my series from outliers. Finally, by using the GARCH-t conditional variance as an uncertainty proxy, I demonstrate that moments of heightened policy ambiguity sharply dent industrial activity and equity returns. This finding speaks directly to the ECB's communication strategy: clarity not only stabilizes expectations but sustains growth.

In an era where every word from Frankfurt can reverberate through global markets, having a robust, transparent measure of ECB shocks is not just an academic exercise, it is a practical necessity.

Building on Gebauer et al's working paper, future research could explore the spillover effects of pure monetary policy on international economies. For instance, utilizing the proxies proposed in this paper, it would be possible to study how the FED pure monetary policy shock affects the European economy.

References

Akaike, H. (1974), 'A new look at the statistical model identification', *IEEE Transactions on Automatic Control* **19**(6), 716–723.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R. and Ragusa, G. (2019), 'Measuring euro area monetary policy', *Journal of Monetary Economics* **108**, 162–179.

Baker, S. R., Bloom, N. and Davis, S. J. (2016), 'Measuring economic policy uncertainty', *Quarterly Journal of Economics* **131**(4), 1593–1636.

Bekaert, G., Hoerova, M. and Lo Duca, M. (2013), 'Risk, uncertainty and monetary policy', *Journal of Monetary Economics* **60**(7), 771–788.

Bu, C., Rogers, J. and Wu, W. (2021), 'A unified measure of fed monetary policy shocks', *Journal of Monetary Economics* **118**(C), 331–349.

Campbell, J. Y., Ammer, J., Lopez, J. A. and Ramcharan, R. (2016), 'Real-time macroeconomic data and the prediction of stock returns', *Review of Finance* **20**(3), 1459–1496.

Campbell, J. Y., Evans, C. L., Fisher, J. D. M. and Justiniano, A. (2012), 'Macroeconomic surprises and bond returns', *Journal of Financial Economics* **110**(1), 182–205.

Christiano, L. J., Eichenbaum, M. and Evans, C. L. (1996), 'The effects of monetary policy shocks: Evidence from the flow of funds', *Review of Economics and Statistics* **78**(1), 16–34.

Christiano, L. J., Eichenbaum, M. and Evans, C. L. (2005), 'Nominal rigidities and the dynamic effects of a shock to monetary policy', *Journal of Political Economy* **113**(1), 1–45.

Cochrane, J. H. and Piazzesi, M. (2002), 'The fed and interest rates: A test of forecast efficiency', *Journal of Monetary Economics* **49**(6), 1105–1135.

Cushman, D. O. and Zha, T. (1997), 'Identifying monetary policy in a small open economy under flexible exchange rates', *Journal of Monetary Economics* **39**(3), 433–448.

De Santis, R. A. and Zimic, S. (2006), 'The effects of monetary policy on the euro–dollar exchange rate: Evidence from a structural var', *Journal of Money, Credit and Banking* **38**(4), 987–1008.

Fama, E. F. and MacBeth, J. D. (1973), 'Risk, return, and equilibrium: Empirical test', *Journal of Political Economy* **81**(3), 607–636.

Gertler, M. and Karadi, P. (2015), 'Monetary policy surprises, credit costs, and economic activity', *American Economic Journal: Macroeconomics* **7**(1), 44–76.

Gürkaynak, R. S., Sack, B. and Swanson, E. T. (2005), 'The sensitivity of long-term interest rates to economic news: Evidence and implications for macro models', *American Economic Review* **95**(1), 425–436.

Hurvich, C. M. and Tsai, C.-L. (1989), 'Regression and time series model selection in small samples', *Biometrika* **76**(2), 297–307.

Husted, L., Rogers, J. H. and Sun, B. (2020), 'Monetary policy uncertainty', *Journal of Monetary Economics* **115**, 20–36.

Jarocinski, M. and Karadi, P. (2018), 'Deconstructing monetary policy surprises—the role of information shocks', *American Economic Journal: Macroeconomics* **10**(2), 66–99.

Jarocinski, M. and Karadi, P. (2020), 'Monetary policy and information frictions: The impact of surprise announcements', *Journal of Monetary Economics* **112**, 42–58.

Kuttner, K. N. (2001), 'Monetary policy surprises and interest rates: Evidence from the fed funds futures market', *Journal of Monetary Economics* **47**(3), 523–544.

McLeod, A. I. and Li, W. K. (1983), 'Diagnostic checking arma time series models using squared-residual autocorrelations', *Journal of Time Series Analysis* **4**(4), 269–273.

Mertens, K. and Ravn, M. O. (2013), 'The dynamic effects of personal and corporate income tax changes in the united states', *American Economic Review* **103**(4), 1212–1247.

Miranda-Agrippino, S. (2016), 'The transmission of monetary policy shocks under information frictions', *Journal of Monetary Economics* **80**, 68–85.

Montiel Olea, J. L. and Plagborg-Møller, M. (2019), 'Simultaneous confidence bands: Theory, implementation, and an application to svars', *Journal of Applied Econometrics* **34**(1), 1–17.

Nakamura, E. and Steinsson, J. (2018), 'High-frequency identification of monetary non-neutrality: The information effect', *The Quarterly Journal of Economics* **133**(3), 1283–1330.

Nelson, D. B. (1991), 'Conditional heteroskedasticity in asset returns: A new approach', *Econometrica* **59**(2), 347–370.

Peersman, G. and Smets, F. (2005), 'Are ecb monetary policy actions effective? a structural var analysis', *Journal of Monetary Economics* **52**(6), 1247–1277.

Rigobon, R. and Sack, B. (2003), 'Measuring the reaction of monetary policy to the stock market', *The Quarterly Journal of Economics* **118**(2), 639–669.

Rogers, J. H., Scotti, C. and Wright, J. H. (2018), 'Unconventional monetary policy and international risk premia', *Journal of Money, Credit and Banking* **50**(8), 1747–1775.

Romer, C. D. and Romer, D. H. (2000), 'Federal reserve information and the behavior of interest rates', *American Economic Review* **90**(3), 429–457.

Romer, C. D. and Romer, D. H. (2004), 'A new measure of monetary shocks: Derivation and implications', *American Economic Review* **94**(4), 1055–1084.

Rudebusch, G. D. (1998), 'Do measures of monetary policy in a var make sense?', *International Economic Review* **39**(4), 907–931.

Stock, J. H. and Watson, M. W. (2012), 'Disentangling the channels of the 2007–2009 recession', *Brookings Papers on Economic Activity* **2012**(1), 81–135.

Swanson, E. T. (2018), 'Measuring the effects of federal reserve forward guidance and asset purchases on financial markets', *NBER Working Paper* .

Wright, J. H. (2012), 'What does monetary policy do to long-term interest rates at the zero lower bound?', *Econometrica* **80**(3), 1113–1151.

Appendix A: Implementation of Identification through Heteroskedasticity – IV approach

This demonstration was shown in Bu, Rogers, Wu's paper. Here it is reported for completeness.

We assume the monetary policy shock is unobservable. We normalize the shock to have 1–1 relationship with the changes in the 5 year interest rate,

$$\Delta R_{5,t} = \alpha_0 + e_t + \eta_t. \tag{7}$$

The equation of interest is

$$\Delta R_{i,t} = \theta_i + \beta_i \, \Delta R_{5,t} + \xi_{i,t}, \tag{8}$$

where $\xi_{i,t} = -\beta_i \, \eta_t + \epsilon_{i,t}$, where $\epsilon_{i,t}$ is the idiosyncratic error associated with $\Delta R_{i,t}$, $\epsilon_{i,t}$ is assumed not to correlate with the monetary policy shock e_t, and $\Delta R_{i,t}$ is the change in a year interest rate around FOMC announcements.

For simplicity and without loss of generality, we suppress the subscript i, and demean both $\Delta R_{i,t}$ and $\Delta R_{5,t}$,

$$\Delta R_t = \beta \, \Delta R_{5,t} + \xi_t. \tag{9}$$

Heteroskedasticity-based estimation By construction, the regressor $\Delta R_{5,t}$ is correlated with the error term $\xi_{i,t}$ due to the component $-\beta_i \eta_t$. The OLS estimation of β_i is biased due to the errors-in-variables problem.

To deal with this problem, we need to identify two subsamples, which are denoted as M and NM. M is the sample with event windows around FOMC announcements and NM represents the non-monetary windows, which are the corresponding event windows one week before. We also need two assumptions regarding the second moment of the shocks present in the model: on days of FOMC meetings, the variance of the 'true' monetary policy shock increases while that of the background noise remains unchanged.

Assumption 1: $\sigma_\eta^M > \sigma_\eta^{NM}, \quad \sigma_\xi^M = \sigma_\xi^{NM}$.
Assumption 2: $\mathbb{E}[\eta_t e_t] = \mathbb{E}[\xi_t e_t] = 0$.
The implementation is very similar to Rigobon and Sack (2004). Denote the variance-covariance matrix of each subsample as

$$\Omega^M = E\big[\, [\Delta R_{5,t}^M, \, \Delta R_t^M]' \, [\Delta R_{5,t}^M, \, \Delta R_t^M]\big] \tag{10}$$

$$\Omega^{NM} = E\big[\, [\Delta R_{5,t}^{NM}, \, \Delta R_t^{NM}]' \, [\Delta R_{5,t}^{NM}, \, \Delta R_t^{NM}]\big] \tag{5}$$

It is clear that

$$\begin{aligned} \Omega^M &= E \begin{pmatrix} (\Delta R_{5,t}^M)^2 & \Delta R_{5,t}^M \, \Delta R_t^M \\ . & (\Delta R_t^M)^2 \end{pmatrix} \\ &= \begin{pmatrix} (\sigma_e^M)^2 + (\sigma_\eta^M)^2 & \beta\big((\sigma_e^M)^2 + (\sigma_\eta^M)^2\big) \\ . & \beta^2\big((\sigma_e^M)^2 + (\sigma_\xi^M)^2\big) \end{pmatrix} \end{aligned} \tag{6}$$

The second equality follows from $E[\eta_t e_t] = E[\xi_t e_t] = 0$. Similarly, we can write Ω^{NM} out in terms of σ_η^{NM} and σ_ξ^{NM}. If we take the difference between these two covariance matrices and let $(\sigma_e^M)^2 - (\sigma_e^{NM})^2 = \lambda$, we have

$$\Delta\Omega = \Omega^M - \Omega^{NM} = \begin{pmatrix} \lambda & \beta\lambda \\ . & \beta^2\lambda \end{pmatrix}.$$

$$\Delta\Omega = \lambda \begin{bmatrix} 1 & \beta \\ . & \beta^2 \end{bmatrix}.$$

Then, it is clear that β can be estimated as follows,

$$\hat{\beta}_1 = \frac{\Delta\hat{\Omega}_{12}}{\Delta\hat{\Omega}_{11}} \tag{11}$$

Now,

$$\begin{aligned}
\hat{\beta}_1 &= \frac{\Delta\hat{\Omega}_{12}}{\Delta\hat{\Omega}_{11}} && (11) \\
&= \frac{\left(\Delta R^M_{5,t}, \Delta R^M_t\right) \; - \; \left(\Delta R^{NM}_{5,t}, \Delta R^{NM}_t\right)}{\left(\Delta R^M_{5,t}\right) \; - \; \left(\Delta R^{NM}_{5,t}\right)} && (12) \\
&= \frac{E_t\big[(\Delta R^M_{5,t} - \Delta R^{NM}_{5,t})\,(\Delta R^M_t, \Delta R^{NM}_t)'\big]}{E_t\big[(\Delta R^M_{5,t} - \Delta R^{NM}_{5,t})\,(\Delta R^M_{5,t} - \Delta R^{NM}_{5,t})'\big]} && (13)
\end{aligned}$$

According to (13), we may use an IV approach to implement this estimator. This approach rewrites (8) as:

$$[\Delta R_{i,t}] = \alpha_i + \beta_i\,[\Delta R_{5,t}] + \mu_{i,t}, \quad i = 1, 2, \ldots, 30 \tag{14}$$

where the independent variable $[\Delta R_{5,t}] = (\Delta R^M_{5,t}, \Delta R^{NM}_{5,t})'$, the event window of $[\Delta R_{i,t}]$ corresponds to $[\Delta R_{5,t}]$. β_i can be estimated using an instrumental variable

$$\Delta R^{IV}_t = (\Delta R^M_{5,t}, \, -\Delta R^{NM}_{5,t})'$$

for the independent variable. Intuitively, $(\Delta R^M_{5,t}, -\Delta R^{NM}_{5,t})'$ is able to instrument $(\Delta R^M_{5,t}, \Delta R^{NM}_{5,t})'$ because (1) they are correlated; (2) $(\Delta R^M_{5,t}, -\Delta R^{NM}_{5,t})'$ does not correlate with the error terms, which follows directly from Assumption 1 & 2.

Appendix B: Is the ECB a follower or a leader?

This Appendix explores the relation between USA shock and the European one. The intention is not to establish causality. However, it is interesting to see how the series linearly interacts with each other.

From Table 2, there is clear evidence that the ECB shock is not correlated with any lag of the American brw series.

Table 2: Does the ECB follow the Fed?

(a) Baseline specification

Does the ECB follow the FED?	(1) ecb	(2) ecb	(3) ecb	(4) ecb
brw_2024	0.006	0.006	0.009	0.008
	(0.041)	(0.041)	(0.042)	(0.042)
brw_lag1		-0.003	-0.003	0.000
		(0.041)	(0.041)	(0.042)
brw_lag2			-0.034	-0.035
			(0.042)	(0.042)
brw_lag3				-0.043
				(0.042)
Controls	No	No	No	No
Observations	241	240	239	238
R-squared	0.000	0.000	0.003	0.008
Mean dep. var	-0.00530	-0.00527	-0.00529	-0.00537

(b) With lagged BRW controls

Does the ECB follow the FED?	(1) ecb	(2) ecb	(3) ecb	(4) ecb
brw_2024	0.005	0.005	0.008	0.008
	(0.042)	(0.042)	(0.043)	(0.043)
brw_lag1		0.000	0.000	0.004
		(0.042)	(0.042)	(0.042)
brw_lag2			-0.036	-0.036
			(0.042)	(0.042)
brw_lag3				-0.045
				(0.042)
Controls	Yes	Yes	Yes	Yes
Observations	238	238	238	238
R-squared	0.003	0.003	0.007	0.012
Mean dep. var	-0.00537	-0.00537	-0.00537	-0.00537

On the other hand, looking at the Table 3, we can see that the second and third months lag of the EA shock are correlated. The F-test for the two lags is 5,56 with a pvalue of 0.005, therefore they are jointly significant and different from zero. In this non causal analysis, it seems that the FED monetary policy cycle follows with a 2/3 months delay the European one.

Table 3: Is it Vice-Versa?

(a) Baseline specification

Does the FED follow the ECB?	(1) brw_2024	(2) brw_2024	(3) brw_2024	(4) brw_2024
ecb	0.014	0.011	0.007	0.011
	(0.102)	(0.102)	(0.101)	(0.101)
ecb_lag1		-0.072	-0.061	-0.064
		(0.102)	(0.102)	(0.101)
ecb_lag2			0.241**	0.250**
			(0.102)	(0.101)
ecb_lag3				0.185*
				(0.101)
Controls	No	No	No	No
Observations	241	240	239	238
R-squared	0.000	0.002	0.026	0.039
Mean dep. var	-0.00408	-0.00410	-0.00413	-0.00420

(b) With lagged BRW controls

Does the FED follow the ECB?	(1) brw_2024	(2) brw_2024	(3) brw_2024	(4) brw_2024
ecb	0.019	0.016	0.012	0.019
	(0.103)	(0.103)	(0.102)	(0.102)
ecb_lag1		-0.071	-0.061	-0.063
		(0.103)	(0.102)	(0.102)
ecb_lag2			0.240**	0.248**
			(0.102)	(0.102)
ecb_lag3				0.196*
				(0.103)
Controls	Yes	Yes	Yes	Yes
Observations	238	238	238	238
R-squared	0.008	0.010	0.033	0.049
Mean dep. var	-0.00420	-0.00420	-0.00420	-0.00420

It is relevant to highlight, that this is just a linear correlation analysis and no causation is implied.

Appendix C: Descriptives

Table 4: Descriptive Statistics for the Macro-Dataset

Only variables used in the IRFs

Variable	Mean	SD	Min	Max
IP	96.2877	4.7516	71.30	105.30
HICP All EA	100.0579	11.3491	81.75	127.07
IntGoodsVal	9.25e+07	2.56e+07	4.75e+07	1.80e+08
STOXX50	3365.308	659.3884	1993.93	5022.56
ExcRate	1.2299	.1286	.9826	1.577
Unempl_Total	9.0238	1.7099	6.20	12.20

Notes: IP = Industrial Production index (2015=100); HICP = Harmonized Index of Consumer Prices for the Euro Area (2015=100), IntGoodsVal= Intermediate Goods Value, EuroSTOXX50= Euro STOXX 50 index, ExcRate= eur/dol exchange rate, Unempl_Total= Total Unemployment Rate in the Euro Area.

Table 5: Descriptive Statistics for OIS5 and OIS2

Main policy variables

stat	OIS5	OIS2
Mean	0.002	0.000
SD	0.065	0.067
Min	-0.200	-0.223
Date of Min	02 Feb 2023	27 Oct 2022
Max	0.206	0.266
Date of Max	15 Dec 2022	05 Jun 2008

Notes: OIS5= Overnight Index Swap at 5 years maturity. OIS2= Overnight Index Swap at 2-years maturity