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A statistical approach to identifying ECB monetary policy

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Abstract

We construct monetary policy indicators from high-frequency asset price changes following policy announcements, emphasising the concentration of asset price responses along specific dimensions and their leptokurtic distribution. Traditionally, these dimensions are identified by rotating principal components based on economic assumptions that overlook information in excess kurtosis. We employ Varimax rotation, leveraging excess kurtosis without using economic restrictions. Within a set of euro-area risk-free assets Varimax validates policy news along dimensions previously derived from structural identification approaches and rejects evidence of macro-information shocks. Yet, once adding risky assets Varimax identifies only one risk-free factor in medium- to long-term yields and instead points to additional risk-shift factors.

JEL code: E43, E52, E58, C46, G14.

Keywords: Monetary policy instruments, Varimax, fat tails, event study, high-frequency identification.

Non-technical summary

In the wake of the global financial crisis (GFC) and the economic challenges arising from it central banks have deployed novel policy tools, impacting asset prices in ways different from the traditional short-term interest rate instrument. The European Central Bank (ECB) has employed various strategies such as forward guidance on interest rates and asset purchases to lower long-term interest rates and reduce fragmentation in the sovereign debt market. These measures have attenuated risk aversion and eased financing conditions across the board. Conversely, as inflation surged in the post-pandemic environment, central banks have begun to unwind asset purchase programmes and tightened monetary policy, while at the same time continuing to guide financial market expectations about future policy action. This approach has helped manage short-term policy expectations but has also led to significant responses in long-term yields to policy news. These developments have shown how different monetary policy instruments can affect specific asset price segments, suggesting that monetary policy operates along multiple dimensions.

This paper introduces a new, agnostic approach to measure the multi-dimensional effects of monetary policy using high-frequency asset price movements around ECB policy announcements. Traditional methods often solely rely on economic assumptions, but our approach utilises statistical properties of the data to identify different monetary policy factors without imposing economic restrictions. This approach is named Varimax rotation of principal components.

When applying Varimax rotation to risk-free yields, we identify the same policy factors (*target*, *path*, and *QE* i.e. quantitative easing) as those found in previous studies and we do not find evidence of macro-economic information news in ECB policy announcements. This validation shows that our method can statistically support the conventional approach to identifying these factors. Yet, adding risky assets blurs the previously identified separation between the forward guidance and the QE dimension in favour of risk-shift factors. Specifically, when considering yields on various sovereign bonds, our approach confirms an additional *sovereign risk* factors. Including more data from risky assets, such as corporate bond spreads, stock prices, stock market volatility, interest rate uncertainty, and the EUR/USD exchange rate, uncover further risk dimensions that segment into *sovereign risk*, *policy uncertainty*, and *corporate risk*. We subsequently model the financial propagation of these factors.

The sample period (spanning from 2002 until late 2023) covers different phases of monetary policy including the quiescent pre-GFC period, the GFC, the sovereign debt crisis, the subsequent period in which policy interest rates were constrained by their effective lower bound, the Covid-19 pandemic, and the post-pandemic inflation surge. We find that different ECB policy instruments have consistently impacted medium-to-long-term maturities, both before and after the GFC and before the formal adoption of forward guidance in 2013. However, the influence of monetary policy on risky assets, particularly sovereign bond yield spreads and risk appetite, became more prominent since the GFC.

Our approach departs from traditional methods of using economic assumptions by employing the Varimax rotation technique. This method leverages excess kurtosis, a statistical property indicating the presence of strong outliers in the distribution of asset price responses to policy announcements, and that each policy instrument influences a distinct subset of assets, thus ensuring interpretability and sparsity. In this context, outliers are a feature, not a drawback. While most monetary policy surprises are small and centred around zero, large announcement effects are especially informative for identification.

These findings have significant implications for central bank policy decisions. By demonstrating that traditional monetary policy factors can be identified using a purely statistical approach, we provide a robust method for policymakers to gain deeper insights into how policy instruments work and how to deploy them most effectively.

Additionally, the prominence of the detected risk-shift dimension for the euro area enriches the understanding of how monetary policy instruments work. It suggests that central banks need to account for broader market conditions, beyond traditional risk-free assets, to fully understand the transmission of monetary policy.

We show that communication, even if not considered an explicit element of forward guidance, has a powerful and persistent financial impact. In addition, communication and asset purchases transmit strongly along a risk dimension, a channel that in the euro area appears to dominate a ‘central-bank information’ impact (a strong financial impact from the central bank’s public assessment of the state of the economy), rather than communication about policy instruments.

In conclusion, our novel approach offers a statistically validated, comprehensive view of the multi-dimensional effects of monetary policy. It underscores the importance of considering a wide range of asset price responses and provides valuable insights for designing monetary policy and monetary policy communication.

1 Introduction

In the wake of the global financial crisis (GFC), central banks have deployed novel policy instruments, which have been affecting asset prices in ways different from the traditional short-term interest rate instrument. In the euro area, the European Central Bank (ECB) used different forms of forward guidance on interest rates and asset purchases to lower long-term interest rates and attenuate sovereign bond market fragmentation, thereby easing financing conditions more broadly. Conversely, central banks tightened monetary policy in response to the post-pandemic inflation surge, while seeking to guide expectations about the pace and extent of increases in policy rates. This communication effort has contributed to contain expectation errors about the near-term course of monetary policy decisions, but at the same time also generated historically large adjustments in longer-term yields. These examples show that the impact of different monetary policy instruments can be concentrated in specific asset price segments, pointing to monetary policy working along multiple and distinct dimensions.

Measuring such multi-dimensional effects of monetary policy at different maturity horizons from high-frequency asset price movements around policy announcements has been prominently proposed by Gürkaynak et al. (2005), following the seminal paper by Kuttner (2001) who focused on single-dimension measures of monetary policy using short-term yields.

In this paper we adopt a novel, agnostic approach constructing multi-dimensional monetary policy indicators from high-frequency asset price changes following ECB's monetary policy announcements, relying on statistical properties for identification. As opposed to the established literature, which relies on structural assumptions in rotating principal components in cross-asset-price adjustments, we employ Varimax rotation. This approach leverages excess kurtosis and sparsity in the impact of policy instruments without using economic restrictions.

Using Varimax to identify different dimensions of monetary policy is a natural choice, given that monetary announcements induce high-frequency changes in asset prices characterised by two key features. First, the impact of monetary policy instruments is usually concentrated within specific dimensions, meaning that certain asset segments experience more pronounced responses compared to others. Second, these high-frequency changes in asset prices do not follow a normal distribution. As can be seen in Figure 1, in most cases the responses are small, but in instances of significant monetary policy announcements, asset price responses are substantial, making their distribution fat-tailed (see Jarociński, 2024).

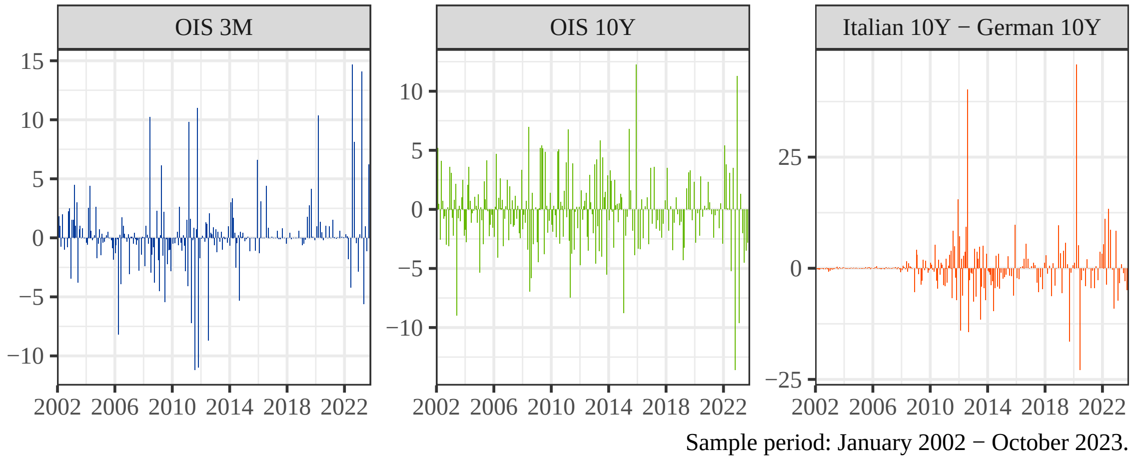
We show that applying Varimax rotation to risk-free yields uncovers the same policy factors – *target*, *path*, and *Quantitative easing (QE)* – as previously identified in Altavilla et al. (2019) and other studies, statistically validating their structural identification approach within this specific set of assets. However, when adding further information from risky assets, like sovereign bonds, corporate bond spreads, stock prices, stock market volatility, interest rate uncertainty, and the EUR/USD exchange rate, we find it more challenging to distinguish forward guidance and QE dimensions and instead identify a further *risk-shift* dimension that can be segmented into the *sovereign risk* factor and in addition a *policy uncertainty* and a *corporate risk* factors.

Our sample, spanning from 2002 until late 2023, captures distinct periods in the use of monetary policy instruments. We show that the ECB's monetary policy affected medium-to-longer term maturities in the period before the GFC as much as it did since the formal adoption of forward guidance as of 2013, and also measurably before the deployment of asset purchase programmes. At the same time, the impact of monetary policy instruments on risky assets, in particular sovereign bond yields, has gained prominence in the context of the GFC and until very recently. Across all instrument dimensions, monetary policy effects have been significant during the recent inflation surge. During this period, the ECB tightened monetary policy by raising interest rates and gradually reducing its asset portfolio through quantitative tightening.

Surprisingly, despite being a conspicuous aspect of the data, excess kurtosis has been largely overlooked in the extensive literature identifying monetary policy from asset prices. The literature extensively relies on structural assumptions in rotating principal components to extract the key dimensions in surprises observed from financial asset price responses surrounding monetary policy events.[1] Principal components are effective in explaining most of the variance in asset prices around policy announcements, but they are essentially statistical and do not directly represent the underlying structural economic shocks responsible for the variations in asset prices around monetary policy announcements. Similar to reduced-form shocks in vector autoregression (VAR) literature, they

[1] See e.g., Brand et al. (2010); Altavilla et al. (2019); Motto and Özen (2022) for the euro area, originating from Gürkaynak et al. (2005) for the US. The same applies to the single-dimension indicator originating from Kuttner (2001).

Figure 1: Value of the high frequency change in basis points in selected assets around ECB Governing Council meetings, based on data from Altavilla et al. (2019).



embody a combination of underlying structural shocks.

To provide a structural interpretation of the principal components, studies exploring the multiple dimensions of monetary policy surprises have typically imposed identifying restrictions based on economic theory for rotating the principal components. However, since any rotation of the principal components is observationally equivalent in the data, the credibility of the results depends fully on how believable the a-priori economic assumptions are.

By using Varimax, we employ a straightforward statistical approach, capitalising on excess kurtosis in asset price data to estimate monetary policy indicators without relying on a-priori economic assumptions. As conventional in the literature, we first extract principal components from high-frequency asset price changes to policy news. In a second step, instead of using structural assumptions to rotate principal components, we utilise the Varimax rotation of principal components, a technique introduced by Kaiser (1958) and widely applied across various academic fields (with the paper accumulating more than ten thousand citations on Google Scholar). We reconstruct structural factors, based on economic assumptions, to demonstrate that conventional monetary policy factors based on economic restrictions can emerge from an approach that solely considers the presence of significant tails in the reactions of numerous asset prices, without imposing any economic restrictions linked to specific policy instruments.

The Varimax rotation distinguishes itself by rotating factors to achieve sparsity and interpretability. It takes advantage of the leptokurtic distribution and concentration of responses in specific asset segments. In our context, the objective of the rotation is to uncover monetary policy factors without imposing economic assumptions on its structure. It aims to maximise the variance of the squared loadings of factors across assets while maintaining orthogonality. The goal is to attribute each factor to as small a subset of assets as possible, having in mind the idea of sparsity, meaning that each factor primarily influences a subset of the variables. In our specific setting, this objective implies that each policy instrument affects a distinct part of the asset price spectrum. The higher kurtosis in the data, the better it enhances the identification of the most crucial and interpretable factors.

Jarociński (2024) was the first to exploit these crucial statistical features, estimating independent and interpretable student-t-distributed factors that drive asset price responses to monetary policy announcements by the Federal Reserve in the US. Jarociński (2024) shows that his results align with those obtained identifying four factors based on economic assumptions. Unlike the approach taken by Jarociński (2024), Varimax does not depend on distributional assumptions. It aligns more closely with the traditional method of obtaining principal components from a large set of asset prices and rotating them. However, there is an analogy between Jarociński (2024)'s approach and Varimax: in the absence of fat tails, as is the case when data are normally distributed, the likelihood function becomes flat. In such cases, the Varimax approach also lacks statistical power to identify underlying rotation of the principal component that generates the data.

The main contribution of our paper is the following: First, focussing on high-frequency changes in risk-free assets our alternative statistical approach substantially confirms the presence and characteristics of monetary policy indicators commonly identified through structural methods. In the euro area, using a baseline model with seven risk-free rates (1-month to 10-year) and 10-year sovereign yields from the four largest economies, four factors naturally emerge. These factors support evidence of ECB policy dimensions via the interest rate 'target', 'path' forward guidance, 'QE', and 'sovereign risk' (similar to Altavilla et al., 2019; Motto and Özen, 2022). However, we do not find statistical support for central bank macro-information shocks in the euro area (identified by Nakamura and Steinsson, 2018; Jarociński and Karadi, 2022; Miranda-Agrippino and Ricco, 2021, among others, for the US). Second, expanding the set of asset prices with variables capturing uncertainty about monetary policy and risk appetite reveals evidence of a risk-shift factor (as recently documented by Cieslak and Schrimpf, 2019; Cieslak and Pang, 2021; Kroencke et al., 2021; Bauer et al., 2023, for the US). In this dataset Varimax no longer produces evidence of separate forward-guidance and QE dimensions, but only one corresponding factor loading into medium- to longer-term risk-free yields. Thirdly, we investigate the financial transmission of policy indicators identified both with the baseline and with a risk-extended set of factors. We show that there is significant evidence of monetary policy transmitting through risk-taking when considering the extended set of asset price responses to policy announcements.

The reminder of the paper is organised as follows. Section 2 provides an overview of the methodologies for inferring multi-dimensional monetary policy indicators by using high-frequency asset price movements. Section 3 outlines the conventional approach in the literature, while Section 4 introduces the Varimax approach for identifying monetary policy indicators. Section 5 introduces additional dimensions of monetary policy surprises using Varimax based on an extended set of assets. Section 6 presents evidence on the transmission of both baseline and extended monetary policy dimensions to selected asset classes and the persistence of their effects. Finally, Section 7 concludes.

2 Identifying multi-dimensional indicators of monetary policy surprises from high-frequency asset price movements

In this section, we provide an overview of the methodologies used to infer the dimensions of monetary policy surprises embedded in high-frequency asset price movements around policy decisions. We collect high-frequency changes in n series of asset prices around T monetary policy meetings of the ECB's Governing Council in a matrix $\underset{T\times n}{X}$. We standardise each column to have mean 0 and standard deviation 1.[2] We then use principal components to decompose X into k factors as $\underset{T\times n}{X} = \underset{T\times k}{F}\underset{k\times n}{\Lambda} + \underset{T\times n}{\eta}$, where η is a residual, and the columns of F are orthogonal to each other, as well as the rows of Λ. For now, this procedure is purely statistical, and it maximises how much each principal component

[2] In this, we also deviate from papers such as Altavilla et al. (2019) and Motto and Özen (2022) for the euro area, but not from Swanson (2021) for the US. Choosing whether to standardise the input data affects the results. Since the first step is to extract principal components from X, standardising all the columns is equivalent to giving each column the same importance. Not standardising implies that the principal components attempt to explain more of the systematic variation in the assets with more volatility in their unit of measure. This aspect becomes more important once a broader set of assets is considered. For example, in Altavilla et al. (2019), only risk-free yields are included. In our paper, we also include sovereign yields, some of which are significantly more volatile than risk-free rates (see Table 2), as well as other assets which are measured in different scales (e.g., equity returns and equity market volatility). In this case, standardising the changes becomes a natural approach also to avoid comparing movements in assets with different units.

can explain of the variance of the columns of matrix X.

Beyond simply providing a statistical summary of the asset price responses to monetary policy news, we are interested in rotating factors to make them interpretable in terms of the type of news associated to specific monetary policy instruments or key dimensions of monetary policy transmission. Notice that, for any orthonormal matrix (i.e. a square matrix where all the columns have unit length and are orthogonal) $\underset{k\times k}{U}$, we can rotate principal components by rewriting $F\Lambda$ as $FUU'\Lambda = \tilde{F}\tilde{\Lambda}$ while maintaining the same fit and residuals.[3] Multiplying the principal components by a rotation matrix U is observationally equivalent to doing it with any other orthonormal matrix, i.e., there is an infinite number of data generating processes that are equally compatible with the observed data. To identify the underlying structural drivers of the data and their economic interpretation, we need to impose additional assumptions to restrict or, more commonly, uniquely identify a rotation matrix that characterises the structural data generating process. This challenge is analogous to the difficulty of identifying structural shocks from reduced form residuals in vector autoregressions.

3 Conventional approach: structural identification based on economic assumptions

So far, the literature has largely measured different dimensions of monetary policy by relying on identifying assumptions to explain cross-asset price movements around monetary policy events. The most common approach in the monetary policy factors literature (e.g., Gürkaynak et al., 2005; Brand et al., 2010; Altavilla et al., 2019; Swanson, 2021; Motto and Özen, 2022) is to find a matrix U that imposes identifying restrictions based on economic theory. Common approaches include imposing zero restrictions (indicating that a rotated principal component, representing a structural shock, does not affect a specific asset), sign restrictions (e.g., indicating that certain assets must move in a specific direction in response to a shock), and applying variance minimisation (e.g., ensuring that factors representing the effects of asset purchases have low variance before their official

[3] Note that if U is orthonormal, then $U^{-1} = U'$. When extracting principal components from a dataset, the solution yields a set of orthogonal principal components F, and a set of orthogonal loadings Λ. However, at most only one of these properties can be retained after rotation, as explained by Jolliffe (1995). In economic terms, this result implies we must assume that either the underlying drivers of monetary policy surprises have orthogonal impacts on the yield curve, but their activation is correlated, or that they are activated independently but have correlated impacts on financial assets. In this paper, we have chosen the latter, in line with the usual assumption that structural shocks should be orthogonal.

introduction).

We intend to extract and identify multi-dimensional indicators of monetary policy surprises for the euro area based on high-frequency cross-asset price movements. Thereby, the identification strategy follows economic reasoning how different policy instruments affect specific asset prices, taking into consideration the specific role of sovereign risk in a currency union, as discussed in Motto and Özen (2022), Mira Godinho (2021), Wright (2019).

We use the Euro Area Monetary Policy Database (EA-MPD) of Altavilla et al. (2019), updated until October 2023. The database contains the change in a cross-section of asset prices around ECB Governing Council meetings in three windows: around the press release, around the press conference, and a full event window covering the period from before the press release to after the press conference. While until 2016 the ECB would announce non-standard measures only in the press conference, it is now a common practice to announce changes in forward guidance and asset purchases already in the press release.[4] For this reason, we depart from other papers in the euro area monetary policy surprises literature, such as Altavilla et al. (2019) and Motto and Özen (2022), and use the full event window.

We use a baseline set of assets covering interest rates from 1-month to 10-years based on overnight index swap (OIS) rates for the euro area, and 10-year sovereign bond yields for Germany, France, Italy, and Spain, the four largest economies in the euro area. We estimate four principal components, as these account for 94% of the variance in the standardised data, as shown in Table 1. The marginal fifth principal component would only explain around 1% of the variation.

To identify various dimensions of monetary policy, we impose a set of restrictions that identify a unique rotation matrix U, which contains 16 elements. First, U must be orthonormal, i.e., each of its columns has unit length (accounting for 4 restrictions) and each unique pair of columns is orthogonal (accounting for 6 restrictions). In addition, the rotated principal components $U'\Lambda$ must be such the 2^{nd} factor has a zero loading on the 1-month OIS, and the 3^{rd} and 4^{th} factors have zero loadings on 1-month and the 6-month OIS. These zero-restrictions impose that the first factor is free to capture variation across all assets; the second factor does not capture movements in very short-term maturities,

[4]See for example, the June 2020 meeting press release (https://www.ecb.europa.eu/press/pr/date/2020/html/ecb.mp200604~a307d3429c.en.html), which communicated the expansion of the envelope of asset purchases for the Pandemic Emergency Purchase Programme (PEPP).

Table 1: Summary statistics of principal components extracted from the baseline set of assets.

Variable	N obs.	Mean	St. Dev.	Skewness	Excess kurtosis	Contrib. Variance
PC1	226	0.0	2.6	-0.3	3.3	63%
		[0.0, 0.0]	[2.5, 2.7]	[-0.7, 0.9]	[1.9, 4.6]	[59%, 67%]
PC2		0.0	1.5	-0.7	6.6	21%
		[0.0, 0.0]	[1.4, 1.6]	[-1.5, 1.4]	[2.9, 10.0]	[18%, 25%]
PC3		0.0	1.0	2.4	17.2	9%
		[0.0, 0.0]	[0.8, 1.1]	[-3.0, 3.0]	[2.9, 22.6]	[6%, 12%]
PC4		0.0	0.7	0.2	2.6	4%
		[0.0, 0.0]	[0.6, 0.7]	[-0.7, 0.7]	[1.3, 4.6]	[3%, 5%]
PC5		0.0	0.4	-1.6	11.8	1%
		[0.0, 0.0]	[0.3, 0.4]	[-2.1, 2.1]	[3.6, 16.4]	[1%, 2%]

Notes: The components are extracted from the baseline set of 11 assets, comprising the OIS 1-month, 3-month, 6-month, 1-year, 2-year, 5-year, 10-year, and the 10-year German, French, Italian, and Spanish sovereign yields. Squared brackets indicate 90% intervals obtained with bootstrapping by resampling with replacement the dates of monetary policy surprises, obtaining new principal components from each new sample, and then computing the moments for each sample. Excess kurtosis refers to kurtosis in excess of the normal distribution, i.e., 3. 'Contrib. Variance' refers to the percentage that each principal component explains of the variance in the input data. Sample period is from January 2002 until October 2023.

and the third and fourth factors does not capture movement in short-term maturities.

These conditions are sufficient to pin down the first two factors up to a sign change, but not to uniquely identify factors 3 and 4. The final restriction is that, subject to the restrictions above, we minimise the variance of the sovereign loadings on the third factor. The intuition is that the third factor should capture movements as similar as possible across countries, while the fourth factor is free to capture heterogeneous movements across countries.

We do not impose negative comovements, nor do we minimise the variance of specific factors in certain historical periods as is common in the literature. This suggests that factors associated with a specific policy may be active even before the policy is enacted. That merely means that the yield curve reacted in a way consistent with the effect of that policy, sometimes representing expectations regarding the first use of such instrument, not necessarily that the policy instrument itself was already active. For example, we do not rule out the possibility that central bank communication may have affected medium-to-long term maturities before the ECB's more formal adoption of forward guidance as of 2013.

Finally, the factors are only identified up to a sign switch. Therefore, we normalise the signs on the loadings, by imposing that the four factors load positively on the OIS

1-month, OIS 1-year, OIS 10-year, and the Italian 10-year, respectively. A positive value represents a policy tightening.

The problem can be written more formally as follows.[5] Take $u_{i,j}$ to be the entry in row i and column j of matrix U with $u_{i,\cdot}$ and $u_{\cdot,j}$ representing row i and column j of a matrix U, respectively. Let $\underset{k\times n}{\Lambda}$ be the matrix of the first k principal components extracted from the data. Define $\tilde{\Lambda} = U'\Lambda$. In this particular problem, $k = 4$, and $n = 11$. We want to find:

$$\underset{4\times 4}{U}^* = \arg\min_U \operatorname{var}(\tilde{\Lambda}_{3,j\in\{DE10Y,FR10Y,ES10Y,IT10Y\}})$$

subject to:

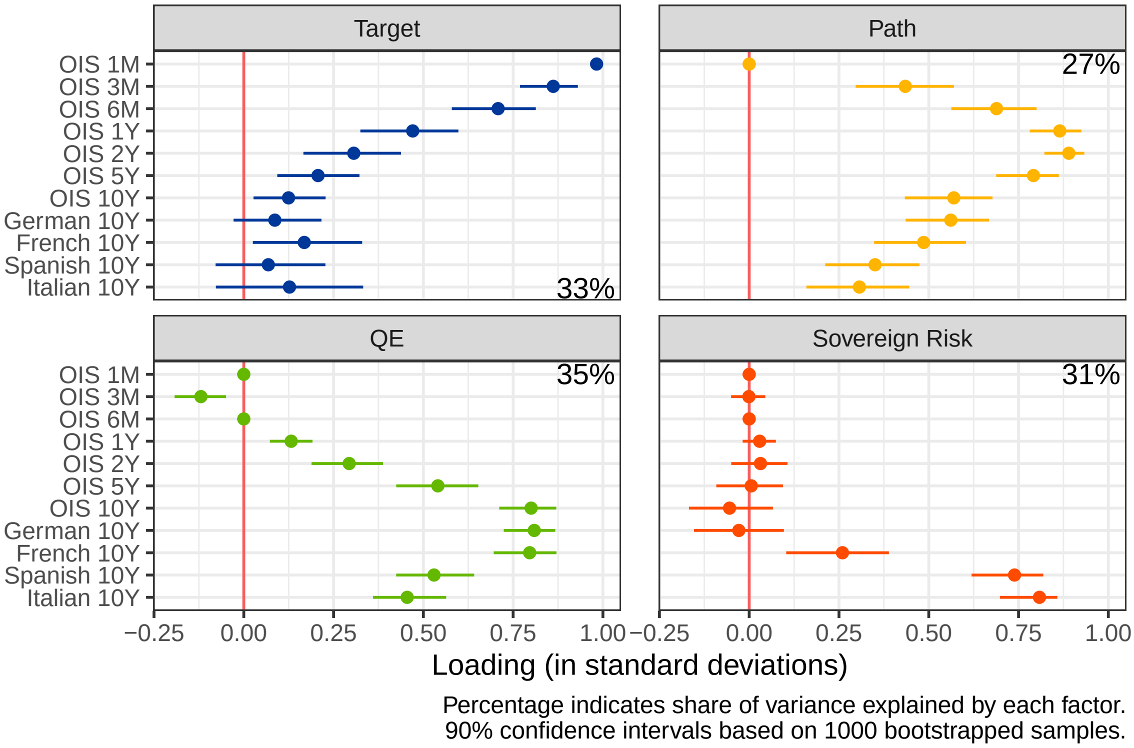
- Unit length restrictions: $\forall j \in \{1,2,3,4\} : u'_{\cdot,j}u_{\cdot,j} = 1$
- Orthogonality restrictions: $\forall m,n \in \{1,2,3,4\}, m < n : u'_{\cdot,m}u_{\cdot,n} = 0$
- Economic restrictions: $\tilde{\Lambda}_{2,OIS\ 1M} = \tilde{\Lambda}_{3,OIS\ 1M} = \tilde{\Lambda}_{4,OIS\ 1M} = \tilde{\Lambda}_{3,OIS\ 6M} = \tilde{\Lambda}_{4,OIS\ 6M} = 0$
- Sign normalisation: $\tilde{\Lambda}_{1,OIS\ 1M} > 0$, $\tilde{\Lambda}_{2,OIS\ 1Y} > 0$, $\tilde{\Lambda}_{3,OIS\ 10Y} > 0$, $\tilde{\Lambda}_{4,IT10Y} > 0$

An additional adjustment to our rotation is that we want the third factor to minimise the variance of movements across sovereigns when converted to basis points. If no further adjustment is made, this does not hold true because the loadings are computed based on standard deviations, given our choice to scale the input data to unit variance. To address this, we adjust the minimisation problem so that the objective function is in fact $\min \operatorname{var}(\Theta \odot \tilde{\Lambda}_{3,j\in\{8,\ldots,11\}})$, where $\underset{1\times 4}{\Theta}$ contains the standard deviation of each of the four sovereign yields, and $\odot$ indicates element-wise multiplication. This implies that the third factor is as equal as possible across countries once we convert the loadings into basis points, rather than in standard deviations.

Figure 2 shows the loadings, measured in standard deviations, resulting from the structural identification approach that solve the optimisation problem defined above. The loadings of each asset on each factor allow us to interpret which monetary policy instrument they may capture. *Target* is a downward sloping factor, capturing movements in the short-term rate. *Path* is a hump-shaped factor, capturing movements peaking between

[5] Section A in the appendix shows a simpler computational method to solve this problem.

Figure 2: Loadings of factors on conventional approach, in standard deviations.

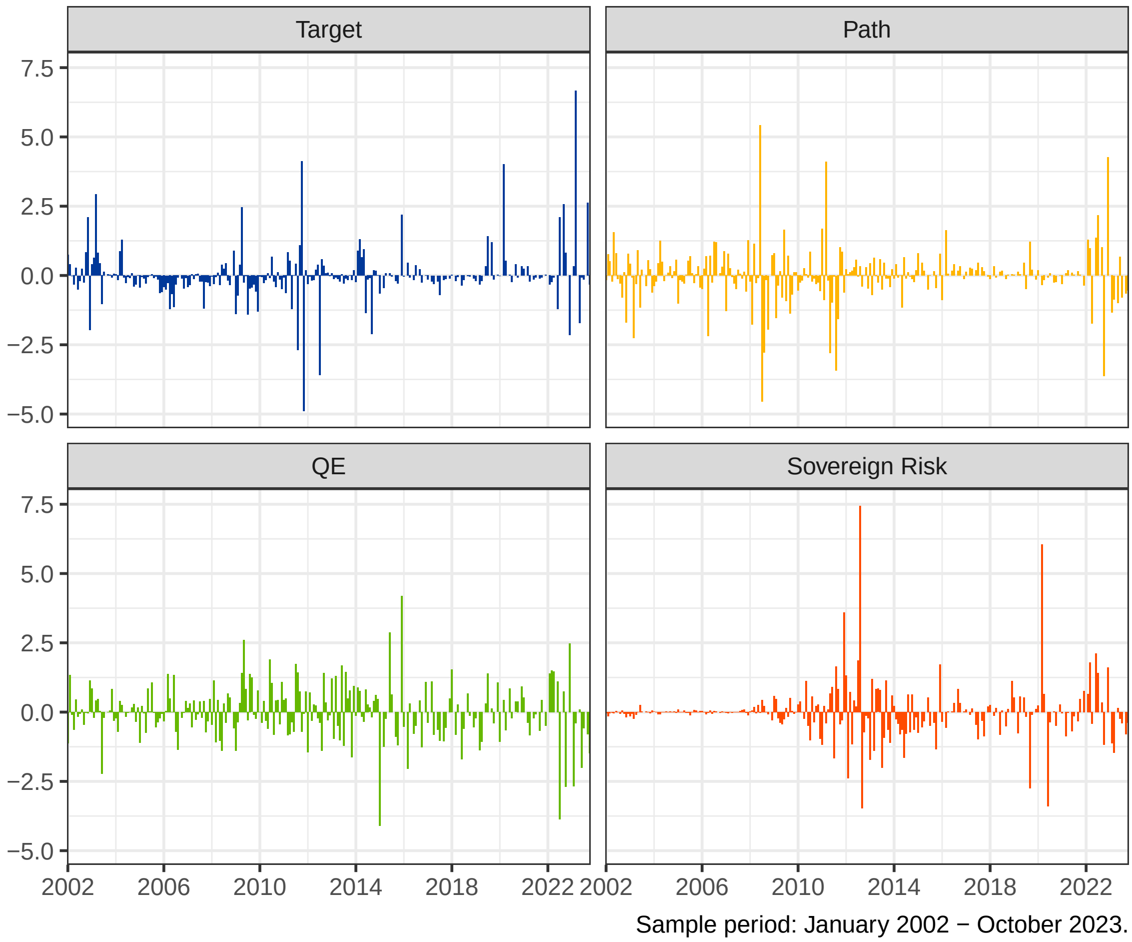


6m and 2 years. *QE* is an upward sloping factor, capturing movements peaking in the 10 year and moving all sovereign yields in the same direction. *Sovereign risk* is a spread-widening factor: it drives Spanish and Italian yields higher, keeping risk-free long rates and German yields stable, and with mild movements on the French yield. The effect of this factor is in line with the 'market-stabilization QE' factor of Motto and Özen (2022).

Since Figure 2 shows the loadings measured in standard deviations for each yield, one unit of impact may translate into different impacts on the yields. Table 2 also shows the standard deviation of each asset, explaining why the QE factor has a somewhat imbalanced impact in standardised terms. To minimise the impact across countries after converting the loading into basis points, it must be that the impact in standard deviations is lower for countries with higher standard deviation, such as Italy and Spain. Figure D7 in Appendix shows the loadings measured in basis points. The impact of the *QE* factor when measured in basis points is more homogeneous across countries. The *sovereign risk* factor, which loads more heavily on more volatile yields, leads to strong movements when measured in basis points.

Figure 3 shows corresponding policy surprises over the full sample period and that *target*, affecting short-term rates, and *path*, affecting medium-to-longer-term interest rates

Figure 3: Value of the factors in the conventional approach across the sample.



have been as prominent before as after the onset of the GFC which spawned a range of novel monetary policy instruments, including the ECB's formal adoption of forward guidance in 2013. Yet *QE* and especially *sovereign risk*, affecting long-term interest rates and sovereign yield spreads, respectively, are clearly more visible only in the wake of the GFC. In addition, policy surprises appear to be clustered around specific episodes and generally are either large, affecting interest rates by over 5 basis points or small and noisy, suggesting heavy tails in the distribution of these surprises.

The structural approach to rotating principal components employed here closely resembles those discussed perviously in the literature. Brand et al. (2010) cover the ECB's Governing Council meetings between November 2000 and July 2007. In their rotated factors approach, they rotate two factors in a similar approach to Gürkaynak et al. (2005) for the US. By imposing that only one of the two factors can have a non-zero loading in the short end of the forward curve, they distinguish between 'jump' factor and a 'path' factor. They also demonstrate that both factors can be equally well and consistently identified from either narrow time windows split between the release of the interest-rate press release and the subsequent press conference or a large window capturing both events.

Altavilla et al. (2019) extend the set of factors and provide a dataset that has been widely used in the literature. They include in their decomposition risk-free assets with the same maturities as we do, but they do not include sovereign assets, despite providing these in their dataset. They extract three factors from the press conference window which, after rotation, they name 'timing', 'forward guidance', and 'quantitative easing'. To identify these, they impose that the QE factor must have minimal variance before August 2008, and that both the QE factor and the timing factor have a zero loading on the OIS 1-month. In an application for the US, Swanson (2021) identifies three similar dimensions of policy surprises.

Wright (2019) notes that this approach does not adequately address the sovereign risk dimension of monetary policy surprises in the euro area. Our paper explores this dimension, although we acknowledge that we are not the first to do so. Mira Godinho (2021) extends the set of assets of Altavilla et al. (2019) in the same way we do by including the 10-year rates for the four largest economies in the euro area. He identifies a fourth factor, named 'spread', similar to our *sovereign risk* factor, which is identified by imposing that it has zero loadings on risk-free interest rates. Motto and Özen (2022) extend Altavilla et al. (2019) in a similar direction, by including 2-, 5-, and 10-year yields for France, Spain, and Italy. They identify a 'market-stabilisation QE' factor, which contrast with the 'Conventional QE' factor, by imposing that the new factor must also have 0 loading on the 1-month OIS, that it must drive the 5-year risk-free rate and the 5-year Italian sovereign yield in opposite directions, and that it must have the lowest possible variance outside of the sovereign debt crisis period and the Covid-19 pandemic. Fanelli and Marsi (2022) use zero and sign restrictions to identify three dimensions: 'monetary', similar to a standard policy shock, 'information', reflecting information effects, which we discuss later, and 'spread', similar to *sovereign risk*. Tuteja (2023) extracts four factors, and finds a 'sovereign risk factor' that he identifies by imposing that the fourth factor has a zero-loading on the 10-year OIS, and that both the QE and this new factor have minimal variance before the pre-crisis period. Leombroni et al. (2021) also find a sovereign risk premium channel in ECB communications.

4 Identifying multi-dimensional indicators of monetary policy with Varimax

Imposing economic identifying assumptions has helped to rationalise how specific monetary policy instruments can be conceived to affect specific asset price segments. Yet, any structural rotation is observationally equivalent. This approach, to some extent, presupposes the final outcomes. For example, when one imposes that only one of multiple factors can affect the shortest maturity risk-free rates, it naturally emerges that one factor is the key driver of the short-end of the yield curve. In addition, the structural approach does not factor in information from tails of the distribution of factors that are associated to specific important monetary policy news.

It would be desirable if one could use a rotation that identifies the underlying structural shocks without imposing a-priori economic identifying restrictions. In this paper, we find that the Varimax rotation of principal components, as introduced by Kaiser (1958), is able to identify typical monetary policy factors that correspond to those found in the literature and relate to specific and interpretable monetary policy instruments. The Varimax rotation is the orthonormal matrix $\underset{k\times k}{U}$ that maximises:[6]

[6] See Jolliffe (2002, p. 153–154).

$$\sum_{j=1}^{k}\left[\sum_{m=1}^{n}(U\Lambda)_{j,m}^{4}-\left(\frac{1}{n}\sum_{m=1}^{n}(U\Lambda)_{j,m}^{2}\right)^{2}\right] \tag{1}$$

The objective is to maximise the variance of the squared loadings of each factor. Intuitively, Varimax rotates the loadings to make each factor as sparse as possible. The objective function tries to attribute each factor to as small a subset of assets as possible, leading to large (absolute) loadings on some assets and small (absolute) loadings on the remaining, instead of affecting many assets similarly. This sparsity has led to the wide use of Varimax for exploratory data analysis, as it eases interpretation of principal components. The practice had however been viewed with suspicion by statisticians, given rotational invariance.[7]

Rohe and Zeng (2023b) have, however, shown that if the true loadings are sparse and the principal components are leptokurtic (i.e. they have large tails), then Varimax actually allows for identification and inference of the underlying structural factors. This is arguably the case in monetary policy surprises, as it is well accepted that (i) policy instruments have concentrated effects on parts of the yield curve, and (ii) asset price responses are particularly pronounced for significant monetary policy announcements but otherwise tend to be contained. We show later that outliers are more common than a Gaussian distribution would predict.

In a Gaussian world, there is rotational invariance, as any rotation of the factors appears equally admissible. That is not the case in a non-Gaussian world. Maxwell (1860), as cited by Rohe and Zeng (2023b) shows that the Gaussian distribution is the only distribution of independent random variables that is rotationally invariant. For non-Gaussian, independently distributed random variables, it is possible, at least in theory, to identify the rotation axes. In our specific application, the information in the fat tails helps to recover the monetary policy structural shocks driving the surprises without imposing any economic identifying restriction. The intuition for this feature is that leptokurtic factors lead to simultaneous outlier movements in the assets driven by the the same factors, but not in assets driven by different factors. Intuitively, if different assets have large outliers on the same dates and the true loadings are sparse, the most likely explanation is that they are driven by the same underlying structural factor.

[7]See Rohe and Zeng (2023a).

This reasoning is similar to the one used by Jarociński (2024), although our approach differs significantly from his, as Varimax does not depend on distributional assumptions.[8] Our approach also aligns more closely with the traditional method of obtaining principal components from a large set of asset prices and rotating them. However, there is an analogy between the two methods: in the absence of fat tails, when data are normally distributed, the likelihood function becomes flat. In such cases, the Varimax approach also lacks statistical power to identify underlying rotation of the principal components that generates the observable data.

Despite its popularity in other fields, the Varimax rotation of principal components has seldom been used in economics, and particularly in papers related to ours. Zhou (2018) uses Varimax to rotate two principal components obtained from the yield curve in a robustness check in an analysis on the signalling effect of asset purchases by the ECB. Chen et al. (2014) and Park and Um (2016) use Varimax to rotate two principal components extracted from high frequency movements in US treasury yields, and find factors similar to our *path* and QE factors. While these authors find the factors easy to interpret, consistent with the popular use of Varimax, they do not assign a structural interpretation to their results.

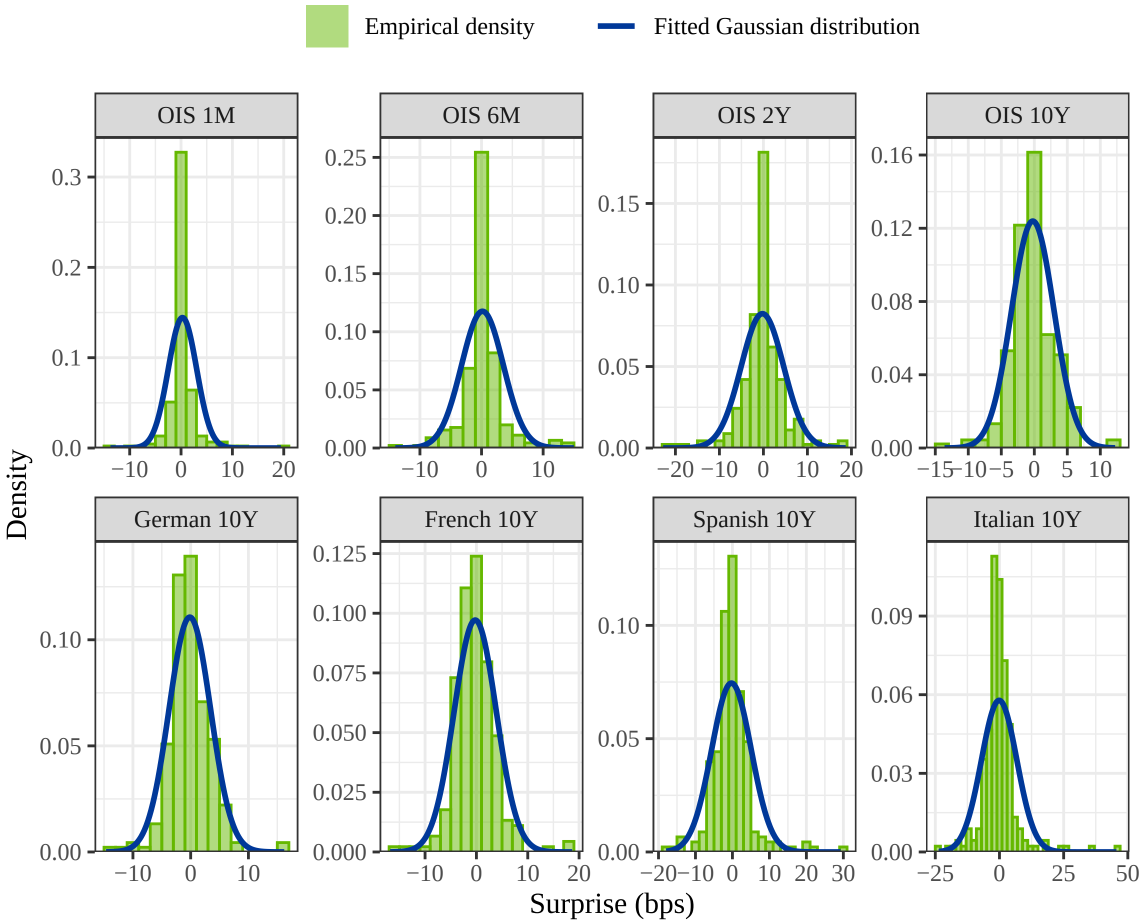
Fat tails in monetary policy surprises

Before we show the results of the Varimax rotation applied to the same set of assets as the conventional approach in Section 3, we analyse the distribution of monetary policy surprises. Monetary policy surprises in the euro area are clearly fat-tailed, significantly beyond what would be predicted by a normal distribution. Jarociński (2024) shows a similar feature of US monetary policy surprises.

Table 2 shows the first four sample moments for surprises in a selected set of assets. For all the assets shown, *excess kurtosis*, kurtosis *in excess* of the normal distribution's kurtosis of 3, is positive and statistically significant. The most extreme example among risk-free rates is the case of the 1-month OIS, the closest maturity to the policy rate. In March 2023, the ECB surprised market participants with a 50 bp interest rate hike, when market participants were mostly expecting a 25 bp change. The high frequency surprise

[8] In the baseline model, Jarociński (2024) works with the US data and uses three risk-free rates and stock market returns. He assumes that the movements in the prices of these four assets around FOMC meetings are driven by four shocks with a Student-t distribution. Similar to our case, he finds factors similar those found in the literature for the US. He also applies his approach to principal components extracted from a broader set of asset price movements.

Figure 4: Empirical distribution of high-frequency responses in interest rates to monetary policy news.



of the OIS 1-month around the event was 19 bps, 7 standard deviations away from the mean. A movement this large would occur less than once in 100 billion meetings according to a normal distribution fitted on all the historical data, including this event itself.

Figure 4 shows the distribution of high-frequency responses in selected interest rates to monetary policy news. The columns are the empirical histogram, while the line is the density of a Gaussian distribution fit to the data. It is clear that the empirical distributions have higher density around the mean and larger tails than a Gaussian distribution.

These fat tails persist in the principal components. Table 1, shown earlier, presents the summary statistics of principal components extracted from the surprises of the 11 assets in the baseline decomposition discussed in Section 3, with confidence intervals obtained by bootstrapping.[9] The principal components are linear combinations of the surprises and,

[9]To compute the confidence intervals, we draw new samples with replacement with the same size from the original set of monetary policy surprises. Then, we compute the principal components for each new

Table 2: Empirical moments of the monetary policy surprises in selected assets.

Variable	N obs.	Mean	St. Dev.	Skewness	Excess kurtosis
OIS 1M	226	0.3	2.8	1.5	15.7
		[0.0, 0.6]	[2.1, 3.4]	[-1.0, 3.2]	[7.2, 22.7]
OIS 3M	226	0.2	3.0	1.0	7.5
		[-0.1, 0.5]	[2.5, 3.5]	[-0.1, 1.9]	[5.0, 10.5]
OIS 6M	226	0.2	3.4	0.8	5.9
		[-0.2, 0.5]	[2.8, 3.9]	[-0.2, 1.6]	[3.9, 7.9]
OIS 1Y	226	0.0	4.3	0.3	5.4
		[-0.4, 0.5]	[3.7, 4.9]	[-0.7, 1.2]	[3.5, 7.3]
OIS 2Y	226	-0.2	4.8	-0.2	5.2
		[-0.8, 0.3]	[4.1, 5.5]	[-1.1, 0.8]	[3.2, 7.0]
OIS 5Y	226	-0.4	4.5	-0.2	3.8
		[-0.9, 0.1]	[3.9, 5.1]	[-1.0, 0.6]	[2.0, 5.1]
OIS 10Y	226	-0.2	3.2	0.0	2.3
		[-0.6, 0.1]	[2.8, 3.6]	[-0.6, 0.7]	[0.7, 3.4]
German 10Y	226	-0.2	3.6	0.3	4.1
		[-0.5, 0.2]	[3.1, 4.1]	[-0.6, 1.2]	[1.4, 5.5]
French 10Y	226	-0.2	4.1	0.5	4.8
		[-0.7, 0.2]	[3.5, 4.7]	[-0.5, 1.3]	[2.4, 6.2]
Spanish 10Y	226	-0.3	5.4	1.2	6.8
		[-0.9, 0.3]	[4.5, 6.2]	[0.1, 2.0]	[3.4, 9.8]
Italian 10Y	226	-0.1	6.9	2.0	12.6
		[-0.9, 0.6]	[5.4, 8.3]	[0.1, 3.0]	[4.5, 17.9]
Eurostoxx 50	226	-0.1	0.7	-1.3	5.6
		[-0.2, 0.0]	[0.6, 0.8]	[-1.9, -0.3]	[1.2, 8.0]
Eurostoxx Banks	226	-0.2	1.2	-2.0	11.0
		[-0.3, -0.1]	[1.0, 1.5]	[-2.7, -0.1]	[1.2, 15.1]
Eurostoxx VSTOXX	226	-0.2	2.0	3.2	28.3
		[-0.4, 0.0]	[1.5, 2.6]	[-0.2, 4.4]	[1.0, 35.4]
SD 3M Euribor 1Y ahead	226	-0.9	3.0	-1.3	11.0
		[-1.3, -0.6]	[2.4, 3.6]	[-2.6, 0.5]	[3.6, 16.2]
Corp. Bond Spread IG NFC	226	-0.1	2.1	1.1	7.7
		[-0.3, 0.1]	[1.7, 2.4]	[-0.3, 2.0]	[3.2, 10.8]
Corp. Bond Spread IG Fin	226	-0.1	2.8	2.1	13.6
		[-0.4, 0.2]	[2.2, 3.4]	[0.2, 3.1]	[5.7, 19.4]
Corp. Bond Spread HY NFC	226	-0.6	11.6	2.3	15.4
		[-1.9, 0.6]	[8.9, 14.1]	[-0.1, 3.3]	[3.5, 21.5]
Corp. Bond Spread HY Fin	226	-0.4	18.8	5.0	61.5
		[-2.3, 1.8]	[10.5, 26.4]	[-2.8, 7.6]	[9.7, 83.1]
EUR / USD	226	0.0	0.5	0.4	2.7
		[-0.1, 0.0]	[0.4, 0.6]	[-0.3, 1.1]	[0.0, 5.1]

Notes: Yields are measured in basis points. Excess kurtosis refers to kurtosis in excess of the normal distribution, i.e., 3. Confidence intervals are shown in brackets below the point estimate. They have 90% coverage and are obtained by bootstrapping. Sample period:January 2002–October 2023.

as expected, also display strong tails. The excess kurtosis, i.e. the kurtosis in excess of the normal distribution's 3, is positive for all the factors, and the bootstrapped confidence intervals are clearly away from zero.[10]

Baseline monetary policy instruments

The evidence documented in Table 2 strongly supports the argument that monetary policy surprises are leptokurtic, and, with leptokurtic and orthogonal principal components at hand, we can proceed to apply the Varimax rotation to identify the tails of the data generating process. We show that when we apply the Varimax rotation to that baseline set of risk-free interest rates and sovereign yields, interpretable factors similar to the ones in the literature emerge naturally without imposing economic identifying restrictions, despite the observational equivalence problem discussed in Section 2.

To provide additional insight, not only on the procedure but also on the hierarchy of the underlying dimensions of monetary policy surprises, we gradually rotate an increasing number of principal components from our dataset. Figure 5 shows the results of this exercise. We also provide bootstrapped confidence intervals for the estimates of the factor loadings.[11]

The first row of Figure 5 shows factor loadings with only one principal component and without rotation. The loadings on the different assets show that this single factor is a generic monetary policy factor which increases risk-free and sovereign yields across maturities.

When we extract a second factor, the Varimax rotation disaggregates the generic policy factor into two factors that affect different maturity segments of the yield curve. The first factor loads on longer maturities from 2- to 10-years, while the second factor affects mostly the short-end of the curve from 1-month to 1-year yields.

As we increase the number of factors to three, the factor that loads more strongly on

sample, the sample moments, and finally the quantiles of those sample moments reported in the intervals in the table.

[10] While Rohe and Zeng (2023b) do not provide tight bounds to assess how much kurtosis is needed for identification, Han and Zhang (2023) comment their paper and show that identification improves as the number of events and kurtosis increases, and decreases with the number of principal components.

[11] To obtain these, we: 1) draw samples from the original dataset with the same number of observations, allowing for repeated drawings of the same observation; 2) extract principal components and apply the Varimax rotation to each of these samples; 3) normalise the sign and the order of the columns to ensure consistency by comparing the correlation of the rotated loadings with those of the point estimate. Having computed the Varimax estimate for each of the samples, we compute confidence intervals by calculating the quantiles of interest. The procedure of resampling events from the original dataset is the method we follow for all bootstrapped calculations shown in this paper.

short-term maturities remains stable. However, the first factor has now been disaggregated into one that affects mostly risk-free rates, and another that generates a widening of sovereign spreads.

When moving to the model with four principal components, a new factor emerges that affects mostly the maturities from 3-months to 5-years, at the "expense" of factors 1 and 2 and, finally, adding a fifth factor yields an idiosyncratic factor without a clear pattern and without significant loadings on any of the assets.

In contrast to the four baseline monetary policy factors that each explain at least 20% of the variance, the fifth rotated factor explains only 1% of the variance of the data. The redundancy of this dimension with little explanatory power is also reflected in the stability of the loadings of the first four factors, leaving their identification intact. This evidence suggests that with the current set of assets, four factors are sufficient to span the underlying monetary policy dimensions for the baseline set of assets.

Despite the fact that adding a fourth principal component adds only 4 p.p. of explained variance in the original data, as shown in Table 1, once we rotate factors all four factors matter, as the explained variance is redistributed to the different factors and all contribute materially to the variation of asset prices around Governing Council meetings, from 19 p.p. to 33 p.p. of the 96% of variance explained. If only three factors were "available", Varimax would subsume the fourth factor into the two other risk-free factors, losing only a small percentage of aggregate explanatory power. Despite Varimax identification relying strongly on outlier events, bootstrapped confidence intervals, which randomly discard and resample events, are narrow and do not change the interpretation of the results.

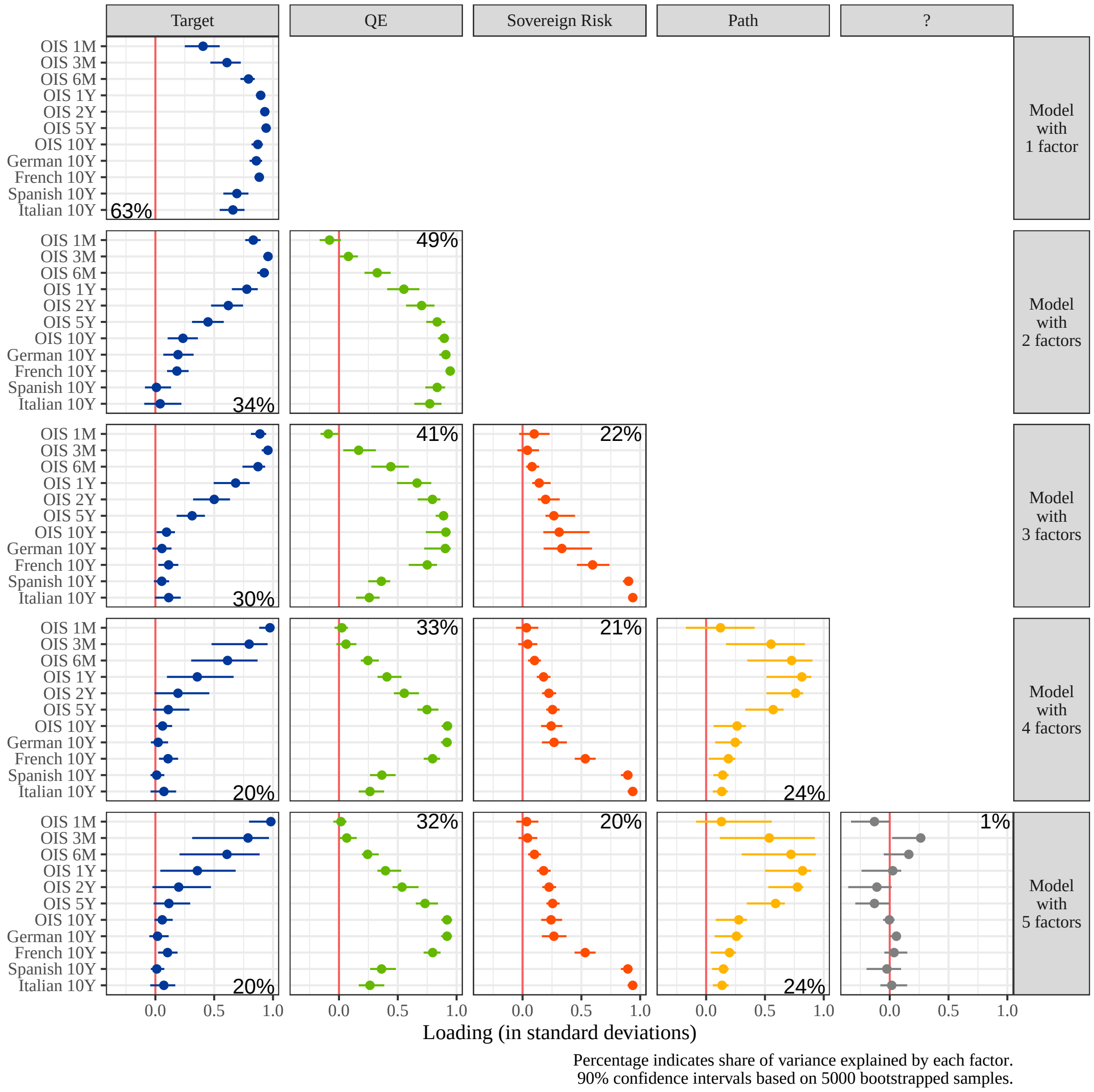
This behaviour of Varimax in that it disaggregates broad factors into more detailed dimensions as we increase the number of principal components rotated is consistent with what Rohe and Zeng (2023b) document. They note that it is a "common empirical phenomenon [when applying Varimax to an increasing number of factors that]; many times the factors have something resembling a hierarchical structure".[12]

With the four factors at hand, it is reasonable to interpret them as representing 1) movements in the policy rate, similar to the *target* factor; 2) the term-premium compression channel of asset purchases, similar to the *QE* factor from the conventional approach;[13]

[12] In their application on academic citation data, they find rotated factors for a small number of principal components represent broad scientific fields, while rotated factors from an increasing number of principal components represent narrower scientific fields.

[13] Note that while the loadings on Spanish and Italian yields appear smaller than those of the German and French yields, these are measured in standard deviations. Given these assets are more volatile than

Figure 5: Varimax rotation applied to an increasing number of principal components for the baseline set of assets.

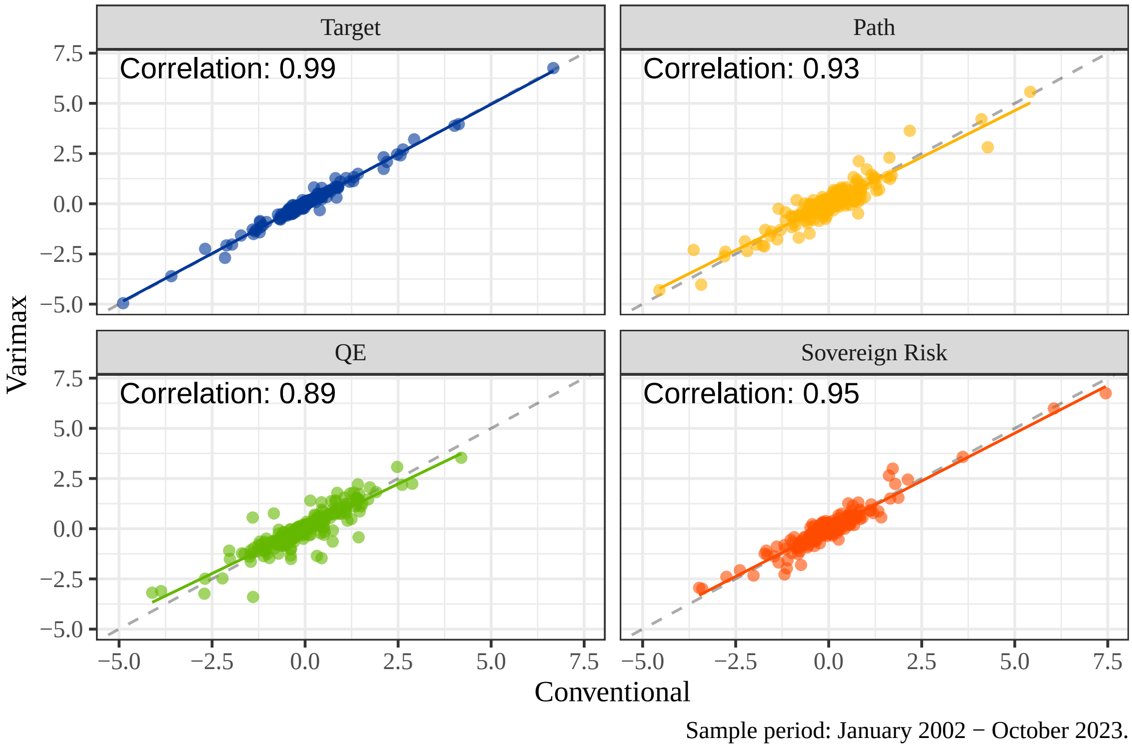


3) the transmission channel of programmes like PEPP, similar to the *sovereign-risk* factor; and 4) a factor representing communication about the near- and medium-term path of policy, similar to the *path factor*. It is striking that such a pattern emerged without any economic assumption, based only on the statistical properties of the data.

Comparing Figures 2 and 5 suggests that the factors identified by the two approaches are quite similar. Analysis of factor loadings reveals correlation coefficients of 1.00 for *target*, 0.82 for *path*, 0.88 for *QE*, and 0.95 for *sovereign risk*. Figure 6 further confirms that despite fundamental methodological differences, the two approaches deliver very similar

risk-free rates in these windows, the relative difference in loadings measured in basis points is smaller. This aspect was also discussed in Section 3 for the conventional approach.

Figure 6: Comparison of the values of the monetary policy factors in each ECB Governing Council meeting estimated with Varimax and with the conventional approach.



results, with factors showing correlations approximately 0.9 or higher between the two sources.

As we have shown, using Varimax to rotate principal components extracted from monetary policy surprises leads to meaningful monetary policy factors that are consistent with economic theory. This is achieved even though for identification the method utilises only statistical information, rather than economic assumptions. To validate this finding, we also apply the Varimax rotation to other settings from papers in the literature that are closest to ours, namely Altavilla et al. (2019) and Motto and Özen (2022) for the euro area, and Swanson (2021) for the US. We show the results of this analysis in Section B in the Appendix. The results indicate that the similarities between the findings from the Varimax approach and the conventional approach used in this paper are not specific to our dataset and economic identification restrictions, as other papers in this literature have also generally imposed economic restrictions that the statistical Varimax identification agrees with. The fact that similar results are obtained from distinct approaches that separately use economic and statistical information for identification bolsters confidence both that Varimax can identify factors in line with economic theory, and that the literature has imposed reasonable economic identifying restrictions, even if those were not required for identification.

5 Varimax identification of additional dimensions of monetary policy surprises

We use Varimax to identify additional dimensions of monetary policy surprises based on an extended set of assets. Relative to the conventional approach, using Varimax to identify additional dimensions of monetary policy has practical advantages, as it does not require imposing strong economic identifying assumptions, which become less credible and more uncertain as one goes beyond well-established instruments. In addition, rather than the economist trying to find specific dimensions, which are always unclear as to whether they are relevant in practice, Varimax provides an exploratory approach to structural analysis, selecting factors that are statistically relevant, as well as ranking their importance hierarchically as we saw in the discussion on Figure 5.

Information effects

In the first extension to the baseline set of indicators, we study the dimensions associated with equity prices, an important component of risk assets. The inclusion of the movement of stock prices around monetary policy meetings has usually been done with two distinct but not necessarily conflicting channels in mind.

The first channel relates to information effects, meaning that when monetary policymakers communicate, they not only reveal information about policy shocks but also provide their assessment of the economy. This assessment may provide new information to market participants, possibly due to earlier or better access to information by central banks, thereby confounding the true policy shocks (see Nakamura and Steinsson (2018); Jarociński and Karadi (2022); Miranda-Agrippino and Ricco (2021); Acosta (2023) for the US and Jarociński and Karadi (2022); Andrade and Ferroni (2021); Kerssenfischer (2022); Fanelli and Marsi (2022) for the euro area). A common approach to identify this channel, sometimes named Delphic forward guidance, is to search for monetary policy events where risk-free rates and stock prices moved in the same direction. In a typical monetary policy tightening shock, risk-free rates should increase while the stock market declines. If the two assets move in the same direction, it may reflect that communication by the central bank provided information about the macroeconomic environment that would lead them to co-move positively as market participants reassess the state of the economy.

The second channel emerging from the inclusion of stock prices relates to a risk dimension, as e.g. identified by Kroencke et al. (2021), Cieslak and Schrimpf (2019) or Cieslak and Pang (2021). While the primary monetary policy dimensions pertain to risk-free yields or to sovereign risk in particular, this channel focuses on the implications of monetary policy on risky assets. Such a dimension captures the impact of monetary policy on risk that go beyond the direct impact of monetary policy instruments. It reflects how monetary policy decisions and communication can influence investor behaviour and market risk perceptions, affecting stock prices and other risk-laden financial instruments. Along these lines, Kroencke et al. (2021) propose a distinct 'risk-shift' dimension alongside a 'short-rate' and 'long-rate' monetary policy factor. They find that stock-prices respond particularly because of 'risk shifts' in response to policy announcements.

Table 3 shows the summary statistics of principal components extracted from adding the Eurostoxx 50 to the baseline set of assets. The results show that the principal components remain fat-tailed. Figure 7 shows the Varimax rotation applied to four and five principal components. In the model with 4 factors, we recover the same factors we found in the baseline approach from Section 4. In this set of policy factors, the loading of stock market returns is strongest in the *sovereign risk* factor. It declines by almost as much as the Italian yield increases (in standardised changes), and it does not react significantly to other policy shocks.

When allowing for a fifth factor to explain this extended data set, we find no evidence of a central-bank information channel, but instead a risk channel and a general *risk-shift* factor. The *sovereign risk* factor is now disaggregated into two factors with similar loadings, correlated at 0.78. Both *sovereign risk* and the new *risk-shift* factor generate a widening of sovereign spreads and a decline in the stock market index, with the key difference being whether the impact was more dominant on the sovereign yields or in the stock market, consistent with the 'risk-shift' factor in Kroencke et al. (2021).

Table 4 helps to illustrate how Varimax identifies these factors, showing the meetings with the largest reactions in the *sovereign risk* and *risk-shift* dimension, and it includes the changes in the Italian-German 10-year sovereign spread, as well as the Eurostoxx 50. While there are events like March 2020 (market disappointment in context of the Covid-19

Table 3: Summary statistics of principal components extracted from the baseline set of assets and the Eurostoxx 50.

Variable	N obs.	Mean	St. Dev.	Skewness	Excess kurtosis	Contrib. Variance
PC1	226	0.0	2.7	-0.4	3.5	59%
		[0.0, 0.0]	[2.6, 2.7]	[-0.9, 1.0]	[2.0, 5.0]	[55%, 63%]
PC2		0.0	1.5	-0.5	6.7	20%
		[0.0, 0.0]	[1.4, 1.7]	[-1.5, 1.4]	[3.0, 10.5]	[17%, 24%]
PC3		0.0	1.2	2.0	12.0	12%
		[0.0, 0.0]	[1.0, 1.3]	[-2.4, 2.4]	[1.0, 15.8]	[8%, 15%]
PC4		0.0	0.7	0.0	2.7	4%
		[0.0, 0.0]	[0.6, 0.8]	[-0.7, 0.7]	[0.8, 4.6]	[3%, 5%]
PC5		0.0	0.6	0.2	3.2	3%
		[0.0, 0.0]	[0.5, 0.7]	[-0.7, 0.7]	[0.7, 5.4]	[2%, 4%]

Notes: The principal components are extracted from the baseline set of 11 assets, comprising the OIS 1-month, 3-month, 6-month, 1-year, 2-year, 5-year, 10-year, the 10-year German, French, Italian, and Spanish sovereign yields, and the Eurostoxx 50. Squared brackets indicate 90% intervals obtained with bootstrapping by resampling with replacement the dates of monetary policy surprises, obtaining new principal components from each new sample, and then computing the moments for each sample. Excess kurtosis refers to kurtosis in excess of the normal distribution, i.e., 3. 'Contrib. Variance' refers to the percentage that each principal component explains of the variance in the input data. Sample period is from January 2002 until October 2023.

Figure 7: Varimax rotation applied to principal components for a first risk-extended set of assets.

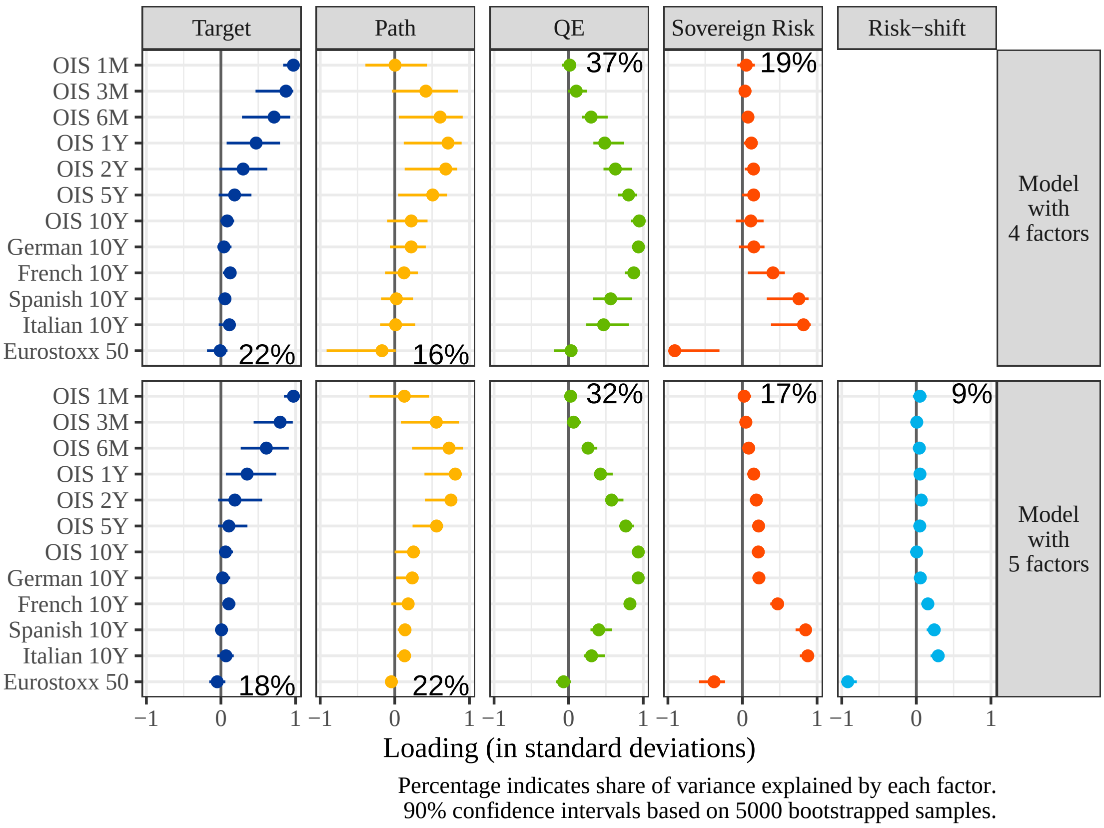


Table 4: Comparison of largest movements in the Sovereign risk and Risk-shift factors.

Date	Italian 10Y - German 10Y	Eurostoxx 50	Sovereign Risk	Risk-shift
November 2002	0	-1.6%	-1.2	2.7
July 2009	2	-1.7%	-1.0	2.9
December 2011	16	-1.1%	3.8	0.0
August 2012	40	-2.8%	6.9	1.2
September 2012	-14	1.2%	-3.0	-0.7
October 2015	-6	2.0%	-0.9	-2.7
December 2015	10	-3.6%	1.7	4.1
March 2020	46	-4.0%	5.1	3.6
June 2020	-23	0.0%	-3.6	1.1

Notes: The movements in the Eurostoxx 50 are in percentage and in the Italian and German 10-year sovereign yields are in basis points. Sample period is from January 2002 until October 2023.

crisis), December 2015 (market disappointment in context of 10-bp cut and an extension of APP), and August 2012 (follow-up to the 'whatever it takes' speech by President Draghi) where the Italian-German spread and the Eurostoxx 50 move significantly in opposite directions, there are other days where a large movement by one of them is accompanied by a muted or equal-sign reaction of the other. For example, a strong *sovereign risk* easing in June 2020 following the announcement of the expansion of the PEPP envelope left the Eurostoxx 50 unchanged.

Conversely, a strong decline in July 2009 of the Eurostoxx 50 of 1.7%, around 2.5 times its historical standard deviation, was accompanied by a very minor widening of sovereign spreads, leading the model to interpret it more strongly as a tightening in the risk-shift dimension. Events like these are key for Varimax to identify these two dimensions separately, as they show that the outliers in these assets do not always coincide. With four factors, Varimax would group these two together, as it is true in some cases, but when allowed to disaggregate into a larger set of indicators, it separates them into different dimensions.

More generally, there is no factor in which the loadings of the Eurostoxx 50 and risk-free rates move in the same direction. This evidence would suggest that either the information effects dimension is not fat-tailed enough to be identified by the Varimax rotation or it is not a sufficiently relevant mechanism of monetary policy surprises in the euro area.

Jarociński and Karadi (2022) document that the reaction to monetary policy meetings in both the US and the euro area may lead stock prices and risk-free interest rates in the same direction. Using their benchmark assets, the 3-month OIS and the Eurostoxx 50, we find around 40% of meetings in the euro area dataset have this type of reaction. However, this does not necessarily reflect the existence of a strong information effect channel. In the limit, if one factor with sparse loadings drives the short-term risk-free rates, and another orthogonal factor drives the stock market, one would even expect them to move in the same direction 50% of the time.

Therefore, the main question is whether these short-term interest rates and stock prices are driven by orthogonal shocks or not. Looking at the loadings shown in Figure 7, we find this is broadly the case. The Eurostoxx 50 tends to react more strongly to the *sovereign risk* and *risk-shift* dimensions, and almost barely to the other types of policy shocks. This suggests that days with significant outliers in one asset dimension are not the same as days with significant outliers in the other asset dimension. Therefore, the most likely explanation is that they are driven by different channels, namely a sovereign risk and a general risk channel.

Such an interpretation is also consistent with the analysis of Motto and Özen (2022), who find that 'information effect'-type events in the euro area may be confounded by the sovereign risk channel. In their case, this channel moves the stock market and risk-free rates in the same direction due to a flight-to-safety effect imposed by their identification restrictions. While we do not find this flight-to-safety behaviour directly, as no risk-free yield declines in response to a tightening *sovereign risk* shock, such qualitative interpretation of these movements is consistent with our findings.

For the US, evidence of information shocks is also not fully clear cut. Cieslak and Pang (2021) and Cieslak and Schrimpf (2019) show that for the Federal Reserve, the ECB, the Bank of Japan and Bank of England monetary policy announcements feature non-monetary policy news on top of monetary policy and risk premia shocks and that what Gürkaynak et al. (2005) identify as path component of monetary policy importantly reflects risk premia, too. Bauer and Swanson (2022) find that the central bank information channel is rather characterised by a "Fed-response-to-news" channel: the Federal Reserve responds to the same macro-news as the public and macroeconomic expectations from surveys cannot be explained by Fed announcements. Instead of a genuine information effect, the Fed looks like responding to information that was available only up to the time of the earlier survey cut-off date of a survey, when in fact it reacts to a more complete macro-information set available by the new cut-off date.

While in other approaches, the econometrician assumes the existence of information effects by the identification restrictions imposed (Jarociński and Karadi, 2022; Kerssenfischer, 2022; Fanelli and Marsi, 2022), our more agnostic approach does not find evidence for this channel being empirically relevant in the high frequency reaction to monetary policy events, at least in the euro area.[14] The factors we identify without imposing economic restrictions are consistent with the existing literature and explain 98% of the variance in the assets we include.

Risk channel

Based on this evidence of a risk channel, we further investigate the risk dimensions operating around monetary policy decisions in the euro area. We extend the dataset to include the high-frequency movements of the Eurostoxx Bank index and the EUR/USD exchange rate from the EA-MPD (Altavilla et al., 2019). We also add the changes in the Eurostoxx VSTOXX (an indicator of stock market implied volatility), the option-implied standard deviation of the 3-month Euribor 1-year ahead (a risk-neutral indicator of interest rate uncertainty), as well as corporate bond spreads for investment grade and high-yield issuers, separated for the financial and non-financial sectors. The latter group of variables enter in daily changes, as we do not have access to high frequency versions of these. In addition, some of these assets may not be liquid enough for high frequency analysis. Table 5 compares the variance of daily changes in all the variables on Governing Council meeting days versus other Thursdays. All the variables are more volatile on ECB Governing Council meeting days, suggesting they may be part of monetary policy transmission channels.[15]

The results of applying Varimax to this extended data set are shown in Figure 8. Figure 9 shows the values of the factors in the historical data. The first row of Figure 8 shows the result of extracting a single principal component from the variation in this set of assets. The variables react as expected to a monetary policy tightening: risk-free and sovereign yields increase; the exchange rate appreciates, stock market indices decline, and

[14] Jarociński (2024) finds evidence of an information effect channel in the US using an agnostic approach that has a similar intuition to ours but different methodology.

[15] The high yield financial corporate bond spread series starts only in 2007. To avoid dropping a significant part of our sample, we impute values for earlier dates based on fitted values from a regression of the daily changes on the changes in the other three corporate bond spread indicators. Similarly, some of the OIS series have fewer observations than included in our high-frequency database. In their case, we follow Altavilla et al. (2019) and impute missing data from the changes in the German sovereign yield with the same maturity.

Table 5: F-test for ratio of variances. Testing hypothesis that variance of daily changes since 2002 on ECB Governing Council meeting days is the same as on other Thursdays vs being greater on Governing Council days.

Asset	Estimate	P-value	95% Conf. interval	N GovC days	N other days
OIS 1M	4.89	0.00	(4.11, Inf)	212	837
OIS 3M	6.20	0.00	(5.21, Inf)	212	838
OIS 6M	7.07	0.00	(5.94, Inf)	212	837
OIS 1Y	5.18	0.00	(4.36, Inf)	212	836
OIS 2Y	3.30	0.00	(2.78, Inf)	212	838
OIS 5Y	2.72	0.00	(2.25, Inf)	170	693
OIS 10Y	1.92	0.00	(1.58, Inf)	168	689
German 10Y	1.72	0.00	(1.45, Inf)	224	907
French 10Y	1.72	0.00	(1.45, Inf)	224	907
Spanish 10Y	2.39	0.00	(2.02, Inf)	224	907
Italian 10Y	2.50	0.00	(2.11, Inf)	224	907
Eurostoxx 50	2.01	0.00	(1.69, Inf)	223	890
Eurostoxx Banks	1.80	0.00	(1.52, Inf)	223	891
Eurostoxx VSTOXX	1.53	0.00	(1.29, Inf)	227	915
SD 3M Euribor 1Y ahead	2.53	0.00	(2.14, Inf)	227	911
Corp. Bond Spread IG NFC	1.47	0.00	(1.25, Inf)	227	942
Corp. Bond Spread IG Fin	1.44	0.00	(1.22, Inf)	227	942
Corp. Bond Spread HY NFC	1.16	0.07	(0.98, Inf)	227	942
Corp. Bond Spread HY Fin	2.02	0.00	(1.66, Inf)	167	742

interest rate uncertainty increases. More unexpectedly, corporate bond spreads decline slightly, although not far from zero. Stock market volatility is unchanged.

When we extract three principal components from the variation in the data, Varimax identifies three dimensions of policy. The first two we obtain are the *target* and *QE* factors discussed in earlier sections. A separate forward-guidance factor no longer emerges naturally. The third factor is broader than the *sovereign risk* dimension discussed earlier and similar to the general *risk-shift* factor identified when adding the Eurostoxx 50 to the sample. This shock leads to a widening of sovereign spreads, a decline in stock prices of banks and non-financial firms, an increase in stock market implied volatility, and an increase in corporate bond spreads across sectors and rating classes.

With five factors, the dimensions more strongly associated with risk-free rates, *target* and *QE*, are stable. The broad risk-shift factor we identify is now disaggregated into three distinct subcomponents representing different dimensions of risk around monetary policy decisions. In the first dimension, it recovers the *sovereign-risk* factor discussed earlier. As second and third dimension, a *policy uncertainty* factor and a *corporate risk* factor emerge that are discussed in the following subsections.

Figure 8: Varimax rotation applied to an increasing number of principal components for a risk-extended set of assets.

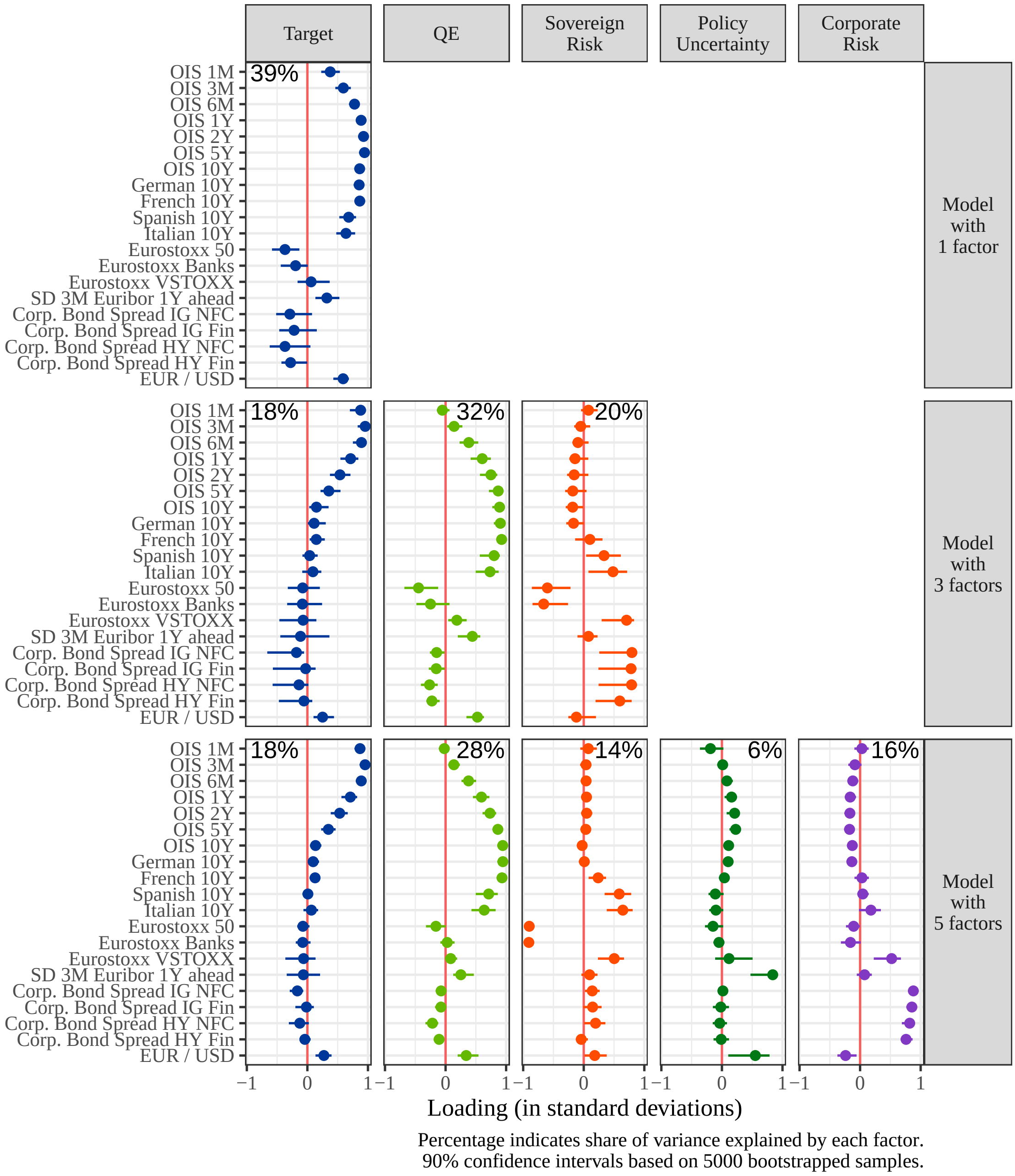
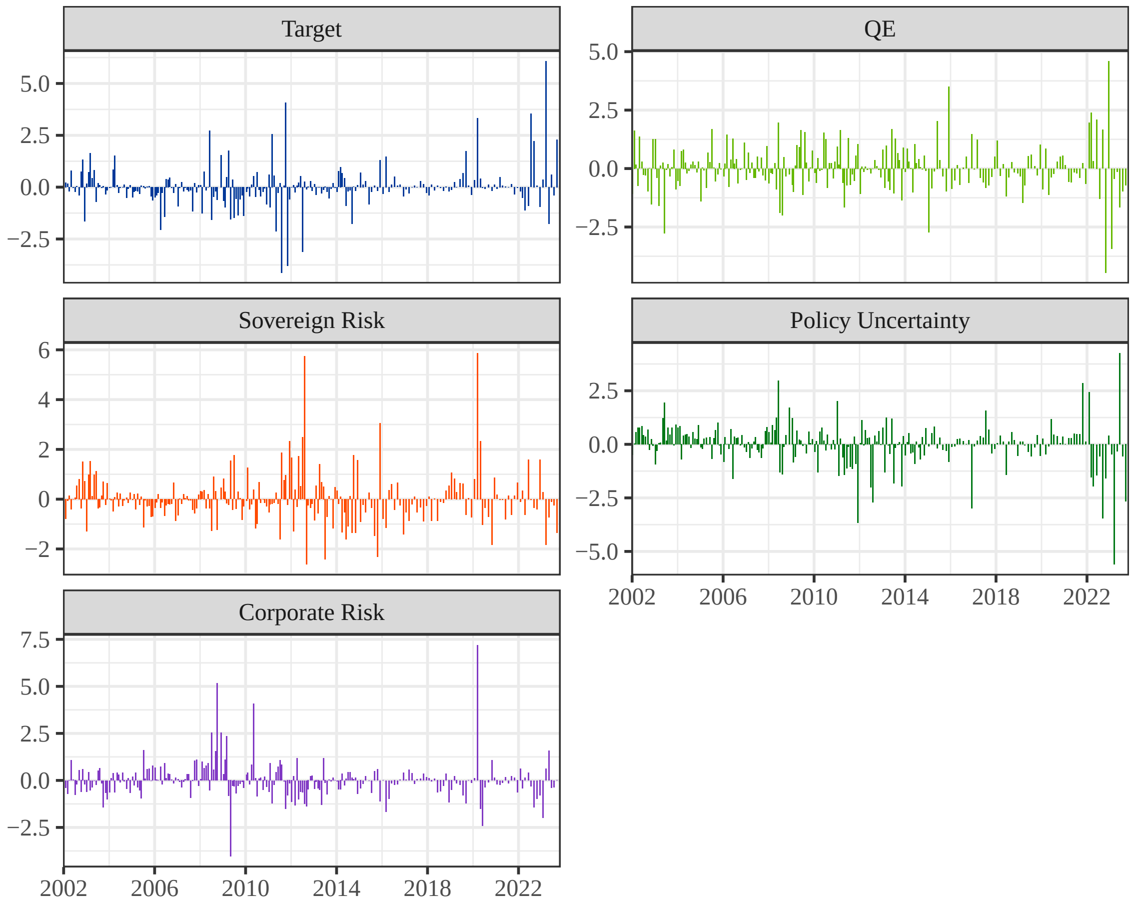


Figure 9: Value of the factors in the Varimax approach with the risk-extended factors.



Sample period: January 2002 − October 2023.

Monetary policy uncertainty

The first of the new risk factors is *policy uncertainty.* This dimension of policy generates a strong increase in the risk-neutral option-implied standard deviation of the 3-month Euribor 1-year ahead. This indicator broadly represents uncertainty about the short-term risk-free rate in a year, although it may also include a risk premium component.

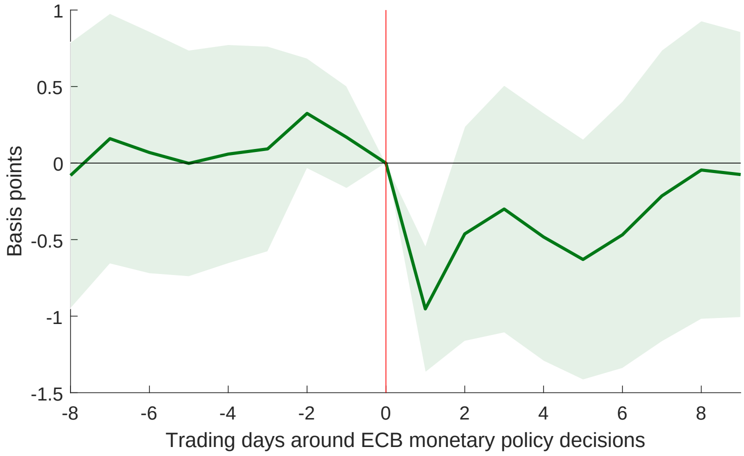
The indicator is similar to the 'monetary policy uncertainty' factor of Bauer et al. (2022), which used as a proxy the risk-neutral standard deviation of three-month LIBOR rate at a one-year horizon estimated from Eurodollar futures and options. Bauer et al. (2022) find an uncertainty cycle around FOMC meetings in the US, where announcements resolve uncertainty, which then tends to grow again between meetings. They also find that changes in monetary policy uncertainty around FOMC announcements are often due to forward guidance.

Similar as Bauer et al. (2022) for the US, we find that ECB policy announcements tend to reduce interest rate uncertainty in the euro area. Figure 10 illustrates the existence of an analogous 'ECB monetary-policy uncertainty cycle', albeit of smaller magnitude. Average uncertainty over the short-term interest rate one-year-ahead is stable before the meeting, drops on the day of the meeting by around one basis point on average (see also Table 2) and then gradually recovers. With an excess kurtosis of 11, the interest rate uncertainty is one of the indicators with the strongest outliers.

Table 6 shows the largest absolute values of the *policy uncertainty* factor. The largest drop in *policy uncertainty* is associated with policy decisions and announcements in March 2023, in the context of the financial turmoil associated with the collapse of Silicon Valley Bank. The policy announcements in December 2011 of a cut in key interest rates and of a range of nonstandard policy measures, including the launch of three-year longer-term refinancing operations and a reduction in reserve requirements, lowered uncertainty. Likewise, the policy decisions in September 2022, including communication of intentions to raise interest rates further, also lowered uncertainty. Most recently, the announcement in September 2023 that policy interest rates have reached levels that if maintained will contribute to achieving the ECB's inflation target, understood as interest rates having approached their peak, has significantly reduced monetary policy uncertainty too.

As we demean all indicators before extracting principal components, the statistically significant average decline of the 3-month Euribor 1-year ahead uncertainty by one basis point in our sample is not directly visible in the results, and the coefficients show differ-

Figure 10: ECB monetary-policy uncertainty cycle.



Notes: Average change in the standard deviation of the implied distribution of 3-month Euribor 1-year ahead on trading days the week before and after ECB Governing Council meetings, relative to the day before the meeting. Shaded areas show 95% confidence intervals based on White standard errors.

Table 6: Monetary policy risk-extended factors and change in the standard deviation of the option-implied 3-month Euribor 1-year ahead on the days with the largest movements in *policy uncertainty*.

Date	Target	QE	Sovereign Risk	Policy Uncertainty	Corporate Risk	SD 3M Euribor 1Y ahead
March 2023	6.1	-0.4	-1.8	-5.6	0.6	-21
June 2023	0.6	-1.6	-0.1	4.3	-0.4	11
December 2011	-0.6	1.1	2.3	-3.7	-0.2	-9
September 2022	2.2	1.7	-0.4	-3.5	-1.4	-8
December 2016	-0.4	1.5	-1.4	-3.0	0.4	-6
June 2008	2.7	2.0	-0.4	3.0	-0.5	8
October 2021	-0.4	0.2	0.1	2.9	0.1	10
August 2012	0.3	0.0	5.8	-2.7	-1.2	-2
September 2023	2.3	-0.7	-1.4	-2.7	0.0	-9
February 2022	-0.2	2.0	-0.1	2.4	0.6	8

ences in the reaction of the indicator relative to this average. Note also that, if policy decisions generate a decrease in uncertainty regardless of their direction, our indicators would not be able to capture this as they are linear.

Figure 8 shows that, as discussed in Bauer et al. (2022) for the US, market-based interest rate uncertainty is more strongly associated with medium-term maturities. In the policy uncertainty factor, medium-term interest rates also increase slightly, but in a statistically significant way, possibly associated with an increase in term premia, and the exchange rate appreciates significantly. Conversely, looking at the high-frequency impact of policy factors on the standard deviation of the 3-month Euribor 1-year ahead, a *QE* and *sovereign risk* tightening increase interest rate uncertainty.

Corporate risk

The final new risk factor is one that spans the dimensions of risky assets beyond sovereign risk which we label *corporate risk* factor. It leads to an increase in corporate bond spreads across rating classes and across sectors, as well as an increase in stock-market implied volatility, although without a significant decline in stock market indices. It also leads to a slight decline in risk-free rates and a weakening of the euro exchange rate.

The *target* and *QE* factors reflect the monetary policy dimensions on risk-free assets, the *policy uncertainty* factor reflects the uncertainty around risk-free assets, and the *sovereign risk* factor captures the specific dimension of fragmentation risks within a currency union. The *corporate risk* factor captures the dimension of any policy or economic information relevant to risky (corporate) asset prices that is not captured by risk-free rates or the sovereign dimension.

The profile of the *corporate risk* factor aligns with the taxonomy and 'risk-shift' factor identified in Kroencke et al. (2021). Similar to the *corporate risk* factor, their 'risk-shift' factor has relatively little loading on risk-free yields, with most loadings on changes in the VIX volatility index. The 'risk-shift' factor also strongly loads on CDS spreads and moderately on foreign exchange futures.

With their risk-shift' factor, Kroencke et al. (2021) can explain a large share of stock price movements around FOMC announcements without including the stock market index itself in the principal component analysis. In contrast, we include changes in the Eurostoxx 50 in the underlying set of assets to identify the monetary policy dimensions. In fact, the Eurostoxx 50 does not significantly load on the *corporate risk* factor but is mostly associated with the *sovereign risk* dimension. While this may seem surprising at first, it is important to remember that, unlike in the US, *sovereign risk* is a key dimension of monetary policy transmission in the euro area than in the US, given the economic structure of the former, and can be more directly linked to monetary policy instruments (e.g., PEPP) than the more implicit 'risk-shift' dimension.

Although the *corporate risk* channel is in spirit also similar to the risk-premium dimension(s) identified in Cieslak and Schrimpf (2019) and Cieslak and Pang (2021), there is an important difference: while both types of factors span the risk dimension of monetary policy, the co-movement of stocks and bonds is a central element of the risk premium factor(s) in Cieslak and Schrimpf (2019) and Cieslak and Pang (2021). This is contrary to the *corporate risk* factor or 'risk-shift' factors that load only to a very limited extent

Table 7: Monetary policy risk-extended factors and change in corporate bond spreads on the days with the largest movements in *corporate risk*.

Date	Target	QE	Sovereign Risk	Policy Uncertainty	Corporate Risk	Corp. Bond Spread IG NFC	Corp. Bond Spread IG Fin	Corp. Bond Spread HY NFC	Corp. Bond Spread HY Fin
March 2020	3.3	0.8	5.9	-0.5	7.2	12	19	82	59
October 2008	-0.6	-0.3	-1.2	0.4	5.2	8	2	37	200
May 2010	0.5	-0.1	0.4	0.8	4.1	9	14	31	31
May 2009	-1.6	0.9	1.5	0.2	-4.0	-4	-10	-34	-106
December 2008	1.5	-0.2	0.5	1.7	2.5	7	10	12	17
July 2008	-1.6	-1.9	-1.3	-1.3	2.5	3	3	62	29
June 2020	0.0	-0.4	-1.0	1.2	-2.4	-8	-8	-11	-15
March 2009	0.5	0.1	-0.2	-0.6	2.4	0	13	36	-3
February 2023	0.4	-3.4	0.3	-0.5	-2.0	-4	-7	-6	-7
January 2002	0.7	-1.1	0.3	-0.5	-1.8	-3	-1	-41	-21

on movements in bond yields.

The largest movements of the corporate risk factor displayed in Table 7 can be predominantly associated with crises periods and liquidity provision announcements. The largest realisation of the *corporate risk* factor is in March 2020, triggered by market disappointments in the context of the Covid-19 crisis. In contrast, a large *corporate risk* easing during the Covid-19 crisis follows the announcement of an expansion of the PEPP envelope in June 2020. Similar narratives shape the large *corporate risk* movements around the GFC. Events such as July 2008 (hike on the eve of the financial crisis), October and December 2008 (stronger-than-expected easing measures), as well as March 2009 (no soothing of market concerns despite extensive liquidity measures) can be associated with market disappointments, whereas the event in May 2009 (LTROs, collateral measures, and CBPP) can be associated with announcements of liquidity-providing measures during the GFC.

6 Financial propagation of different indicator sets

In this section, we analyse how the different dimensions of monetary policy, identified in Sections 4 and 5, affect asset prices and risk appetite over time and across a broader range of financial indicators.

Transmission of monetary policy factors to other asset classes

We employ daily proxy Bayesian VARs (Proxy-BVAR) to analyse the transmission of the different monetary policy factors to the stock market, inflation indicators and the exchange rate over time, extending our assessment beyond their yield curve effects.

Following Altavilla et al. (2019), we focus on the transmission to the daily financial variables, such as Eurostoxx 50, the EUR/USD exchange rate and 2-year inflation-linked swaps (ILS) as financial indicator for inflation at a horizon that aligns with transmission lags. In contrast to Altavilla et al. (2019), each monetary policy factor loads on the asset that most accurately represents the respective monetary policy factor. We run a series of Proxy-BVARs, each time connecting the monetary policy indicators with different financial assets. The *target* factor is transmitted via the OIS 3-month, *path* via the OIS 2-year, *QE* via the OIS 10-year and *sovereign risk* is transmitted via the Italian-German 10-year spread. For the risk-extended factors, *policy uncertainty* is transmitted via the standard deviation of the option-implied distribution of the 3-month Euribor 1-year ahead and *corporate risk* via investment-grade (IG) non-financial corporate (NFC) bond spreads. We run the Proxy-BVAR from the beginning of 2014 until November 2023, the time period in which all four main monetary policy dimensions were active.

The identification strategy follows Stock and Watson (2012) and Mertens and Ravn (2013) and uses the identified high-frequency monetary policy shocks as external instrument Z_t. The reduced-form VAR can be represented by

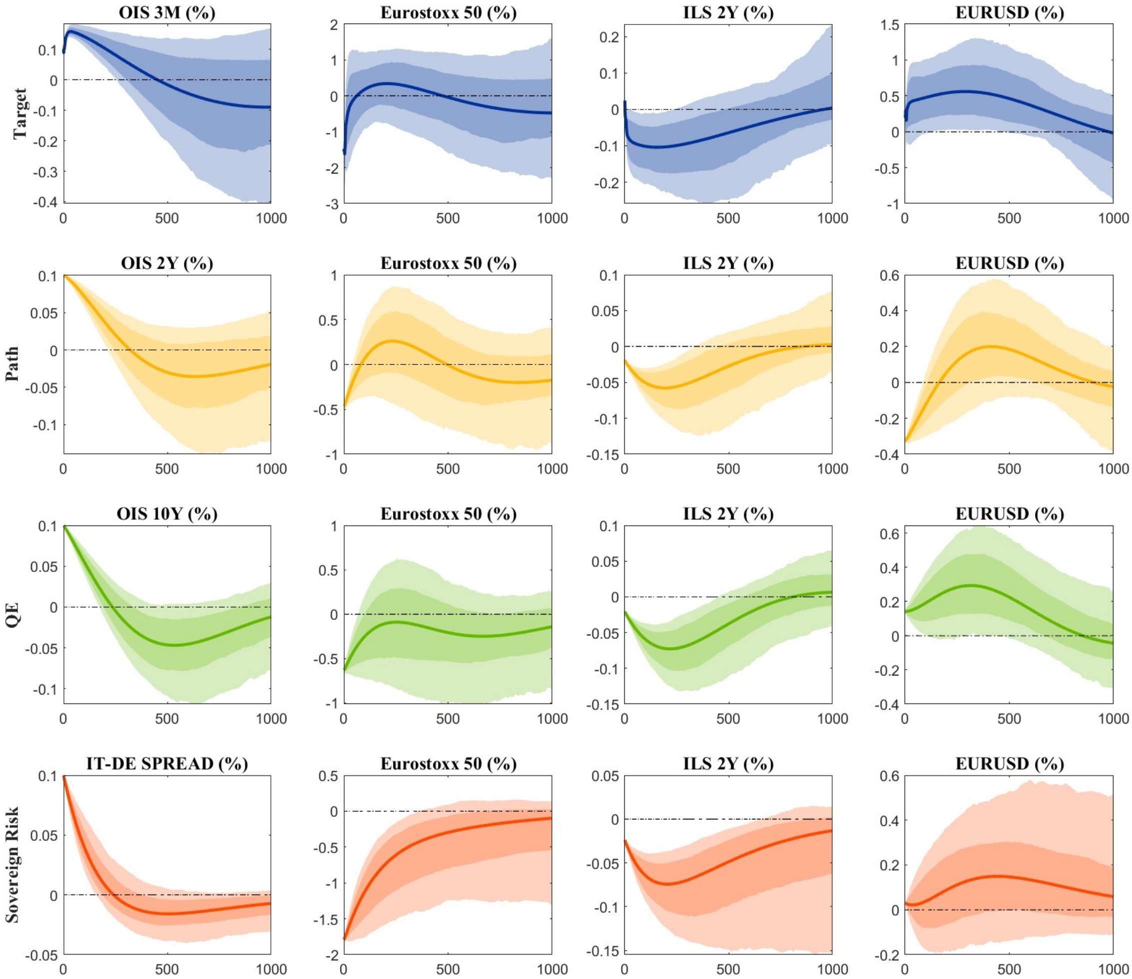
$$Y_t = c + \sum_{j=1}^{p} B_j Y_{t-j} + A_0 u_t \tag{2}$$

where Y_t is a vector consisting of the variables outlined above. The aim is to identify the column of matrix A_0 corresponding to the contemporaneous effect of the monetary policy shock. The instrument must satisfy two crucial assumptions: the relevance assumption which requires the instrument to be correlated with the monetary policy shock of interest, u_t^m, and the exogeneity assumption which requires it to be be orthogonal to the other shocks u_t^{nonm}.

$$E(Z_t u_t^m) = \alpha \neq 0 \qquad E(Z_t u_t^{nonm}) = 0 \tag{3}$$

Figure 11 displays the transmission of the four monetary policy factors of the baseline decomposition identified with Varimax. The picture is complemented by Figure 12, displaying the transmission of the risk-extended monetary policy factors. The response to *target*, *QE* and *sovereign risk* shocks in the baseline decomposition (Figure 11) and in

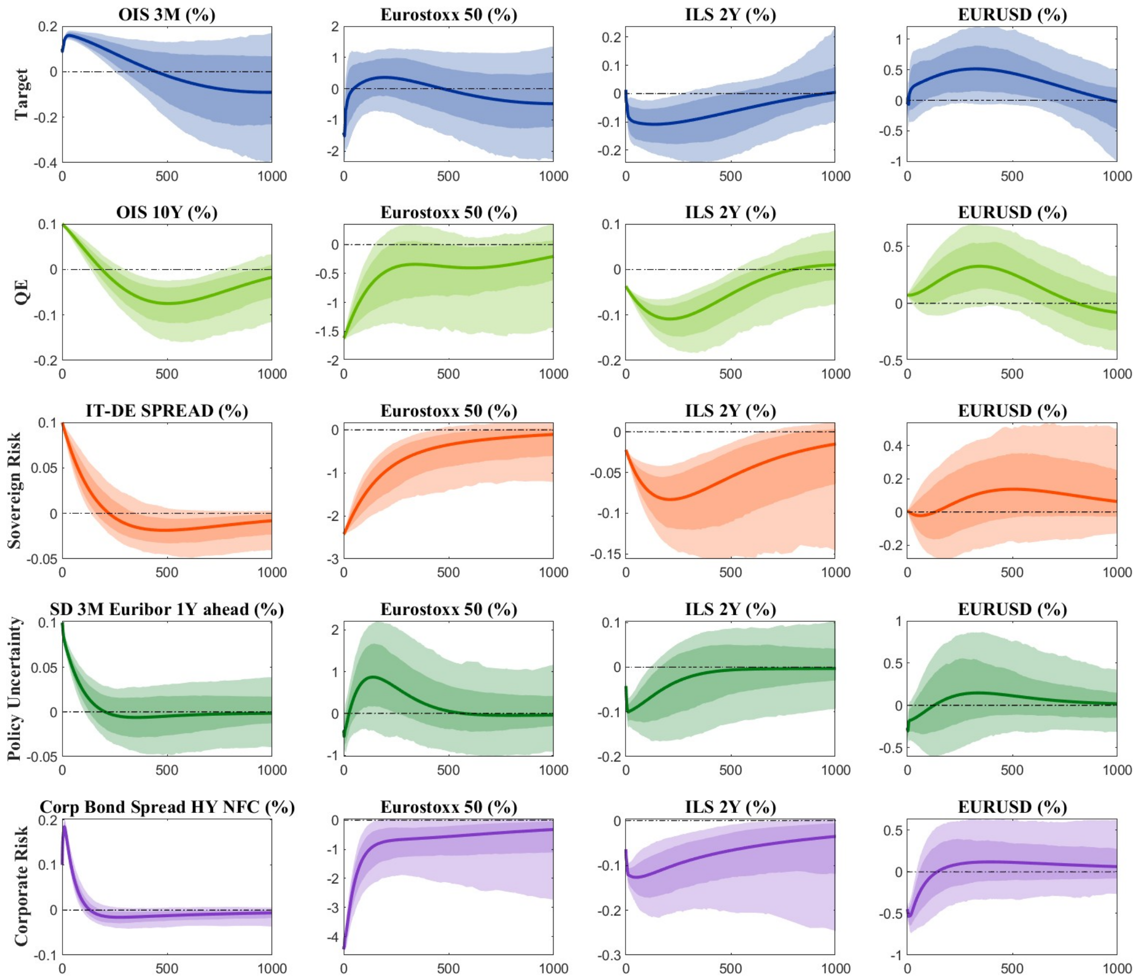
Figure 11: Daily financial Proxy VAR with the Varimax baseline monetary policy factors as instruments.



the risk-extended decomposition (Figure 12) align closely both qualitatively and quantitatively. Similarly, the response of the shocks from the Varimax identification matches the response of the shock from the structural factors in Section 3 as can be seen in Figure D8.

We focus first on the transmission of the four core monetary policy factors in the baseline model. Each of the monetary policy factors in the baseline model in Figure 11 leads to an initial decrease in the Eurostoxx 50, the 2-year ILS and an appreciation of the euro, with the exception of an initial depreciation in response to a *path* shock. Despite generally wide confidence bands for *target* shocks, it has the strongest transmission on the 2-year ILS and on the EUR/USD exchange rate on impact. In response to a *path* shock, the euro initially depreciates although the effect quickly reverses and becomes insignificant. While this initial reaction would not be consistent with interest rate parity adjustments, it may be connected to monetary policy uncertainty as the response to a policy uncertainty shock in Figure 12 is similar. The transmission of *QE* and *sovereign risk* shocks tend to be more persistent. Among the four baseline factors, the impact of *sovereign risk* shock on the Eurostoxx 50 is the most pronounced, and even more strongly so for the risk-extended specification.

Figure 12: Daily financial Proxy VAR with Varimax risk-extended monetary policy factors as instruments.



Turning the focus to the additional risk-extended monetary policy dimensions, an increase in *policy uncertainty*, as shown in Figure 12, leads to a decline in the Eurostoxx 50, an initial depreciation of the euro, and a pronounced response in the 2-year ILS. The peak impact of policy uncertainty on the 2-year ILS is comparable to the effects of core monetary policy *target*, *QE*, and *sovereign risk* shocks. This response aligns with the general transmission channel documented in the literature that an increase in monetary policy uncertainty negatively impacts economic activity and leads to a decline in inflation (e.g. see Mumtaz and Zanetti, 2013; Arce-Alfaro and Blagov, 2023). The decline in the stock market and the depreciation of the euro are consistent with this channel. Concurrently, some studies in the finance literature studying the interaction of monetary policy and uncertainty suggest that monetary policy is more effective in a low-uncertainty regime (e.g. see Tillmann, 2020; De Pooter et al., 2021).

Similarly, a contractionary *corporate-risk* shock leads to a pronounced decline in the Eurostoxx 50, the 2-year ILS, and a depreciation of the euro. The strong stock market decline in response to *sovereign risk* and *corporate risk* shocks is consistent with findings by Kroencke et al. (2021), who highlight the significant influence of the "risk-shift factor" on stock price movements. Kroencke et al. (2021) also rationalise the less pronounced impact of policy uncertainty on the stock market, as policy uncertainty primarily captures the uncertainty of risk-free yields.

The Proxy-BVAR methodology used above restricts the investigation of factor transmission to a limited set of asset prices, since adding a more granular set of yields across maturities would exacerbate dimensionality issues in a VAR. This limitation can be overcome using a dynamic factor model which allows for the examination of a broader range of asset prices in a more parsimonious manner, particularly for the yield curve, and helps trace the dynamic profile and persistence of monetary policy indicators across the yield curve. Specifically, it helps us to better understand in which factor dimensions and along which maturities transmission effects are more or less persistent.

Therefore, we complement the results of the Proxy-BVAR analysis with the insights from such a dynamic factor model for the four factors of the baseline model. The dynamic factor model and results derived are documented in more detail in Appendix C. Figure C6 in Appendix C illustrates how different monetary policy shocks impact the yield curve over time. It shows that the cross-sectional yield profile of these factors maps into a similarly shaped time profiles. Consistent with the factor loadings, *target* predominantly affects short-term maturities with a downward-sloping time profile over maturities, *path* influences medium-term maturities with a hump-shaped maturity profile that persists over time, and *QE* shocks start with a strong effect on 10-year risk-free and sovereign yields, later spreading to medium-term maturities before dissipating. Finally, *sovereign risk* is particularly concentrated on Italian and Spanish 10-year yields, with only a relatively short-lived impact. The dynamic factor model demonstrates stronger and more persistent effects of these monetary policy shocks on asset prices than the VAR, in line with the findings of Alessi and Kerssenfischer (2019).

Transmission of monetary policy factors to risk appetite

To further illustrate the importance of the risk-taking channel for monetary policy in the euro area, we extend our study to analyse the transmission of the monetary policy factors beyond the assets shown in Figure 11 to a general proxy for the risk appetite. We examine the transmission separately since the construction of the risk appetite proxy includes a subset of the previously considered assets as well as other risk-sensitive variables. To construct a risk appetite index for the euro area, we follow the methodology of Bauer et al. (2023), who constructed a similar index for the US.

Our risk appetite index is based on five risk-sensitive financial indicators, as listed in Table 8. These variables are widely regarded as sensitive to changes in risk appetite. Following Bauer et al. (2023), we assume that the co-movement in these series are primarily driven by changes in risk appetite. The risk appetite index is derived from the first principal component of these five series, representing the linear combination of the variables that account for the highest proportion of variance in the data set. This index captures approximately 45% of the common variation among the components.

Table 8: Components of the daily risk appetite index.

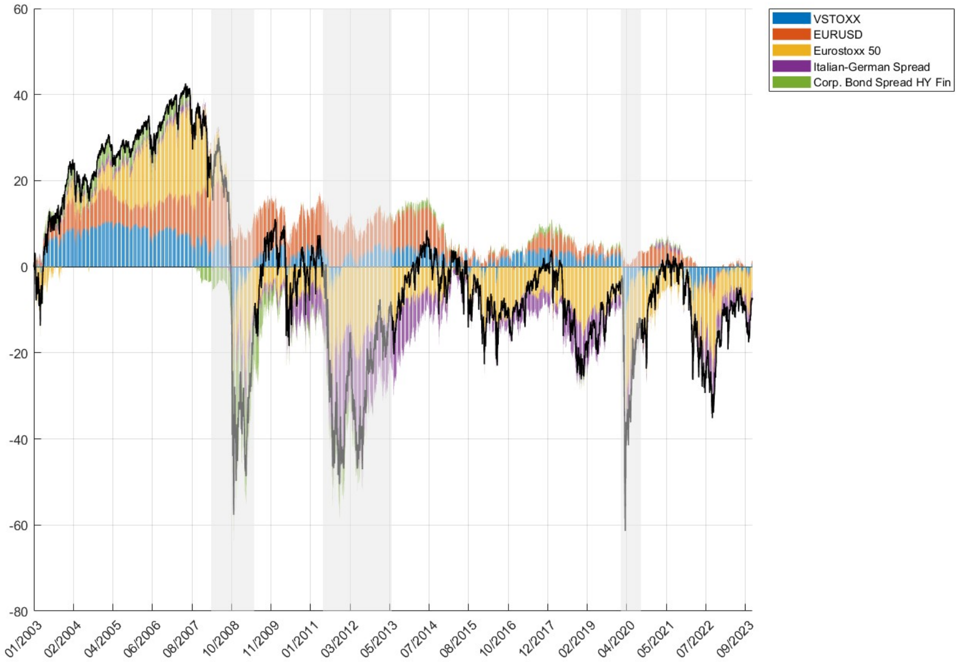
Variable	Transformation	Index Loading
Eurostoxx 50	Daily log changes	0.61
VSTOXX	Daily change	-0.60
Corporate Bond Spread High Yield Financial	Daily change in percentage points	-0.22
EUR/USD	Daily log changes	0.20
Italian-German 10-year Spread	Daily change in percentage points	-0.42

Notes: The loading column shows the weight of each variable in the index.

The right column of Table 8 displays the loading of each variable on the index of risk appetite. Because these components are standardised, the loadings indicate each variable's relative contribution to the index. The direction of each loading indicates whether a variable moves in tandem with or in opposition to the index during shifts in risk appetite. Consistently, a greater risk appetite is associated with higher equity returns, decreased volatility in stocks, narrower sovereign spreads, tighter credit spreads, and stronger currency values. Variables associated with the stock market exert the greatest influence on the index, although all variables contribute significantly.

The accumulated daily changes in the risk appetite index allow us to track overall risk

Figure 13: Decomposition of the risk appetite index.



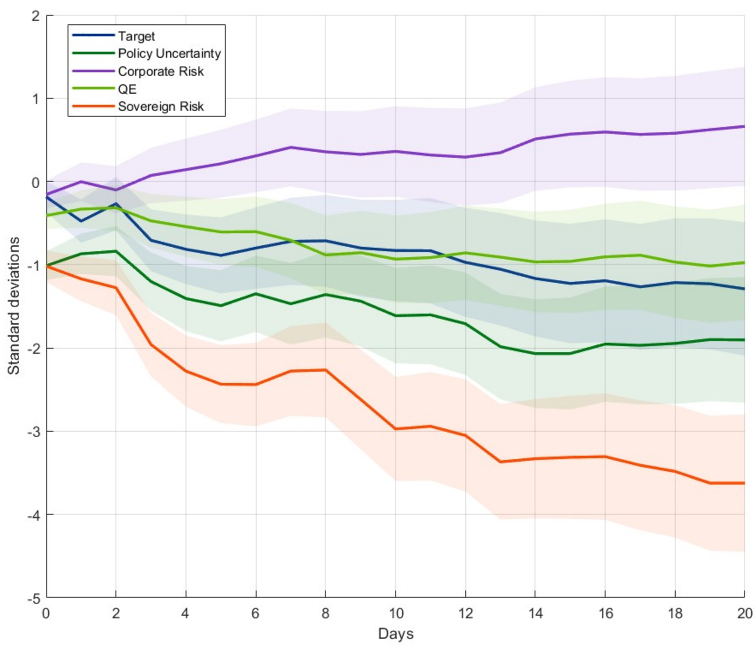
Notes: Black line is the cumulative risk appetite index. Shading denotes recessions as dated by the Centre for Economic Policy Research. Sample period is from January 2003 to November 2023.

appetite at any given time, as depicted by the thick black line in Figure 13. When accumulated over time, developments in the risk appetite indicator align with key historical events. Figure 13 shows that significant slumps in risk appetite can be associated with specific adverse events, such as the GFC in 2008, the sovereign debt crises in 2011, and the Covid-19 pandemic in 2020. There is a consistent pattern of sharp declines in risk appetite followed by gradual recoveries. Figure 13 also illustrates the decomposition of the cumulative risk appetite index into its underlying drivers. It shows that during the sovereign debt crisis, the main driver of reduced risk appetite was the Italian-German sovereign spread, whereas during the pandemic, it was driven by equity markets.

We examine the influence of the different dimensions of monetary policy on risk-appetite. Following Bauer et al. (2023), we employ an event study methodology that allows for both contemporaneous and lagged effects of policy surprises on asset prices. We run separate regressions for different window lengths: the contemporaneous response of the risk appetite index reaction on the announcement days and the cumulative response over the subsequent 20 trading days. The estimated responses and 90% confidence intervals using robust standard errors are shown in Figure 14.

Tightening shocks to all risk-extended monetary policy dimensions, except for the *corporate-risk* factor, significantly dampen risk appetite. In the days following the announcement, the estimated negative effects not only grow in magnitude but also maintain their statistical significance. *Sovereign risk* and *policy uncertainty* shocks have a more substantial influence on risk appetite than the unexpected changes in interest rates through *target* shocks, supporting the observation that the most significant adjustments to risk appetite occur over a medium to long-term horizon, where these identified factors are most pertinent. Contrary to the other factors, the impact of *corporate risk* shocks does not significantly affect the risk appetite, suggesting that the information content in policy news on risk are more prominent for the other risk and uncertainty factors.

Figure 14: Dynamic response of risk appetite to a monetary policy tightening.



Notes: The sample contains Governing Council announcements from January 2014 to October 2023. Shaded areas correspond to 90 percent confidence intervals based on Huber-White heteroskedasticity-robust standard errors

7 Conclusions

A large body of literature identifying monetary policy using high-frequency responses in asset prices to monetary policy news has increasingly documented evidence that monetary policy works in multiple and distinct dimensions which can be associated with specific monetary policy instruments. These approaches have largely relied on rotating principal components based on economic assumptions that disregard statistical features such as information in excess kurtosis. The concentration of asset price responses within specific segments, coupled with their leptokurtic distribution along distinct monetary policy dimensions, presents a unique opportunity for identifying these dimensions.

We employ Varimax rotation instead of economic assumptions, leveraging excess kurtosis without using economic restrictions, thereby suggesting a novel approach to constructing multi-dimensional monetary policy indicators from high-frequency asset price changes.

The Varimax rotation distinguishes itself by rotating factors to achieve sparsity and interpretability. It aims to maximise the variance of the squared loadings of factors across assets while maintaining orthogonality. The goal is to attribute each factor to as small a subset of assets as possible. In our specific setting, the interpretation of this objective is that each policy instrument influences a specific part of the asset price spectrum. The higher kurtosis in the data, the better it enhances the identification of the most crucial and interpretable factors.

Using a baseline approach with risk-free interest rates (1-month to 10-years) three previously identified factors naturally emerge, supporting evidence of ECB policy factors like interest rate 'target', 'path' forward guidance and quantitative easing (QE) (similar to Brand et al., 2010; Altavilla et al., 2019; Motto and Özen, 2022, for the euro area). Likewise, adapting Varimax to the same data and time window choices as in these studies reproduces similar policy factors. This result testifies to the statistical validity of results from these previous approaches of imposing economic identification assumptions. However, we do not find statistical support for central bank macro-information shocks in the euro area (identified by Jarociński and Karadi, 2022, for the US).

Furthermore, once we take sovereign risk, monetary policy uncertainty and risk appetite into account we find evidence of the importance of monetary policy transmission through risk taking. Varimax no longer produces evidence of separate forward-guidance and QE dimensions, but only one factor loading into medium- to longer-term risk-free yields and instead identifies an additional *risk-shift* factor dimension that can be segmented into *sovereign risk*, *policy uncertainty* and *corporate risk*.

Overall, with respect to the potency of ECB communication to affect monetary policy expectations, we show that ECB policy news have affected medium-to-longer term maturities in the period before the GFC as much as it did since the formal adoption of forward guidance as of 2013, and also measurably before the deployment of asset purchase programmes. At the same time, the impact of monetary policy instruments on risky assets, in particular sovereign bond yields, has gained prominence only in the context of the GFC and until very recently.

Finally, we confirm the importance of these distinct channels identified from cross-sectional analysis of asset price movements when analysing their dynamic propagation over time. *QE* and *path* factors display a particularly sustained impact on yields and inflation-linked swaps. When factoring in monetary policy uncertainty and risk appetite there is significant evidence of monetary policy transmitting through risk-taking.

Bibliography

Acosta, M. (2023). The perceived causes of monetary policy surprises.

Adrian, T., Crump, R. K., and Moench, E. (2013). Pricing the term structure with linear regressions. *Journal of Financial Econometrics*, 110:110–138.

Alessi, L. and Kerssenfischer, M. (2019). The response of asset prices to monetary policy shocks: Stronger than thought. *Journal of Applied Econometrics*, 34(5):661–672.

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.

Andrade, P. and Ferroni, F. (2021). Delphic and odyssean monetary policy shocks: Evidence from the euro area. *Journal of Monetary Economics*, 117:816–832.

Arce-Alfaro, G. and Blagov, B. (2023). Monetary policy uncertainty and inflation expectations. *Oxford Bulletin of Economics and Statistics*, 85(1):70–94.

Bauer, M. D., Bernanke, B. S., and Milstein, E. (2023). Risk appetite and the risk-taking channel of monetary policy. *Journal of Economic Perspectives*, 37(1):77–100.

Bauer, M. D., Lakdawala, A. K., and Mueller, P. (2022). Market-based monetary policy uncertainty. *Economic Journal*, 132(644):1290–1308.

Bauer, M. D. and Swanson, E. T. (2022). An alternative explanation for the "Fed information effect". *American Economic Review*, forthcoming.

Brand, C., Buncic, D., and Turunen, J. (2010). The impact of ECB monetary policy decisions and communication on the yield curve. *Journal of the European Economic Association*, 8(6):1266–1298.

Chen, J., Mancini-Griffoli, T., and Sahay, R. (2014). Spillovers from United States Monetary Policy on Emerging Markets: Different This Time? IMF Working Papers 2014/240, International Monetary Fund.

Chen, R.-R. and Scott, L. (1993). Maximum likelihood estimation for a multifactor equilibrium model of the term structure of interest rates. *The Journal of Fixed Income*, 3:14–31.

Cieslak, A. and Pang, H. (2021). Common shocks in stocks and bonds. *Journal of Financial Economics*, 142:880–904.

Cieslak, A. and Schrimpf, A. (2019). Non-monetary news in central bank communication. *Journal of International Economics*, 118:293–315.

Dai, Q. and Singleton, K. J. (2002). Specification analysis of affine term structure models. *The Journal of Finance*, 55:1943–1987.

De Pooter, M., Favara, G., Modugno, M., and Wu, J. (2021). Reprint: Monetary policy uncertainty and monetary policy surprises. *Journal of International Money and Finance*, 114:102401.

Diebold, F. F. and Li, C. (2006). Forecasting the term structure of government bond yields. *Journal of Econometrics*, 131:309–338.

Duffee, G. R. (2000). Term premia and interest rate forecasts in affine models. *The Journal of Finance*, 57:405–443.

Fanelli, L. and Marsi, A. (2022). Sovereign spreads and unconventional monetary policy in the euro area: A tale of three shocks. *European Economic Review*, 150:1–22.

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005). Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, 1(1).

Han, R. and Zhang, A. R. (2023). Rungang Han and Anru R. Zhangs contribution to the Discussion of 'Vintage factor analysis with varimax performs statistical inference' by Rohe & Zeng. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 85(4):1069–1070.

Jarociński, M. and Karadi, P. (2022). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43.

Jarociński, M. (2024). Estimating the Fed's unconventional policy shocks. *Journal of Monetary Economics*.

Jolliffe, I. T. (1995). Rotation of principal components: choice of normalization constraints. *Journal of Applied Statistics*, 22(1):29–35.

Jolliffe, I. T. (2002). *Principal Component Analysis*. Springer Series in Statistics. Springer, New York, NY, 2 edition.

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, 23(3):187–200.

Kerssenfischer, M. (2022). Information effects of euro area monetary policy. *Economics Letters*, 216:110570.

Kroencke, T. A., Schmeling, M., and Schrimpf, A. (2021). The FOMC risk shift. *Journal of Monetary Economics*, 120:21–39.

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.

Leombroni, M., Vedolin, A., Venter, G., and Whelan, P. (2021). Central bank communication and the yield curve. *Journal of Financial Economics*, 141(3):860–880.

Maxwell, J. C. (1860). V. illustrations of the dynamical theory of gases.—part i. on the motions and collisions of perfectly elastic spheres. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 19(124):19–32.

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.

Mira Godinho, F. (2021). How much did the ECB really contribute to ending the sovereign debt crisis? *SSRN Electronic Journal*.

Miranda-Agrippino, S. and Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, 13(3):74–107.

Motto, R. and Özen, K. (2022). Market-stabilization QE. Technical Report 2640, ECB Working Paper Series.

Mumtaz, H. and Zanetti, F. (2013). The impact of the volatility of monetary policy shocks. *Journal of Money, Credit and Banking*, 45(4):535–558.

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

Park, K. Y. and Um, J. Y. (2016). Spillover effects of united states' unconventional monetary policy on korean bond markets: Evidence from high-frequency data. *The Developing Economies*, 54(1):27–58.

Rohe, K. and Zeng, M. (2023a). Karl Rohe and Muzhe Zeng's reply to the Discussion of 'Vintage factor analysis with varimax performs statistical inference'. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 85(4):1094–1098.

Rohe, K. and Zeng, M. (2023b). Vintage factor analysis with Varimax performs statistical inference. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 85(4):1037–1060.

Stock, J. and Watson, M. (2012). Disentangling the channels of the 2007-2009 recession. *Brookings Papers on Economic Activity*, Spring 2012:81–135.

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118(C):32–53.

Tillmann, P. (2020). Monetary policy uncertainty and the response of the yield curve to policy shocks. *Journal of Money, Credit and Banking*, 52(4):803–833.

Tuteja, A. (2023). Monetary transmission to financial markets in the euro area.

Wright, J. H. (2019). Comment on "Measuring euro area monetary policy" by Carlo Altavilla, Luca Brugnolini, Refet Gürkaynak, Giuseppe Ragusa and Roberto Motto. *Journal of Monetary Economics*, 108:180–184.

Zhou, S. (2018). Measuring the Signaling Effect of the ECB's Asset Purchase Programme at the Effective Lower Bound. MPRA Paper 87084, University Library of Munich, Germany.

Appendices

A Alternative computational method to solve the problem in the conventional approach

In Section 3 in the main text, we describe the optimisation problem for the conventional approach to rotate the principal components. This statement of the problem solves for the 16 entries of the U matrix simultaneously. However, there is a simpler approach that solves for each column of the U matrix in iterative fashion, following an algorithm similar to the one described in the appendix of Swanson (2021). This simpler approach converges to a numerical solution more frequently. We can obtain the U matrix using the following procedure:

1. Estimate the third column of the U matrix by numerically solving the minimisation problem, but with only 3 restrictions: zero loading on OIS 1-month and 3-month, and unit length.

2. To obtain the fourth column of the U matrix, find a vector that is orthogonal to the third column (estimated in the previous step), and that generates a zero loading on the OIS 1-month and 3-month. You can do this and the next steps with a solver for a linear system of equations (e.g. `solve` in R), by fixing the first entry of the vector to one, and finding the remaining three entries so that the restrictions are satisfied. Then normalise that vector to unit length.

3. To obtain the second column of the U matrix, find a vector that is orthogonal to the third and fourth columns (estimated in the previous steps), and that generates a zero loading on the OIS 1-month. Then normalise that vector to unit length.

4. To obtain the first column of the U matrix, find a vector that is orthogonal to the second, third, and fourth columns (estimated in the previous steps). Then normalise that vector to unit length.

The resulting matrix is orthonormal, and equal to the one solved with the optimisation problem described in the main text.

B Applying the Varimax rotation to related papers

As we show in the main text, applying Varimax rotation of principal components leads to interpretable monetary policy factors that are consistent with economic theory despite the method using only statistical, rather that economic, information for identification. In this section, we apply the Varimax rotation to other settings from papers in the literature close to ours, namely Altavilla et al. (2019) and Motto and Özen (2022) for the euro area, and Swanson (2021) for the US.

This section statistically validates the results from the above-mentioned studies, when reproducing Varimax factors using the same information set. The results indicate that the similarities between the findings from the Varimax approach and the conventional approach used in this paper are not specific to our dataset and economic identification restrictions, as other papers in this literature have also generally imposed economic restrictions that the statistical Varimax identification agrees with. The fact that similar results are obtained from distinct approaches that separately use economic and statistical information for identification bolsters confidence both that Varimax can identify factors in line with economic theory, and that the literature has imposed reasonable economic identifying restrictions, even if those were not essential for identification. Note that we compare the results from the papers to an equivalent Varimax approach on the same (or as similar as possible) dataset used in the original paper, to isolate the effect of using Varimax identification instead of the respective economic identification method.

B.1 Comparison with Altavilla et al. (2019)

Before applying the Varimax rotation to Altavilla et al. (2019), it is worth highlighting the differences with the approach used in this paper. One important difference between the datasets used to extract factors is that the Altavilla et al. (2019) split their factors into press release ('Target') and press conference windows ('Timing', 'Forward Guidance', 'QE'). They apply the rotation of principal components only to the press conference factors, imposing that only the Timing factor loads on the OIS 1-month, and that the QE factor must have minimal variance before August 2008. To isolate the difference between their economic identification choices and the statistical identification of our method, we apply the Varimax rotation to the same data used in Altavilla et al. (2019). This includes use of the same data vintage, which stops at the September 2018 meeting, rather than the updated data made available by the authors, which includes corrections, e.g., for stale quotes.

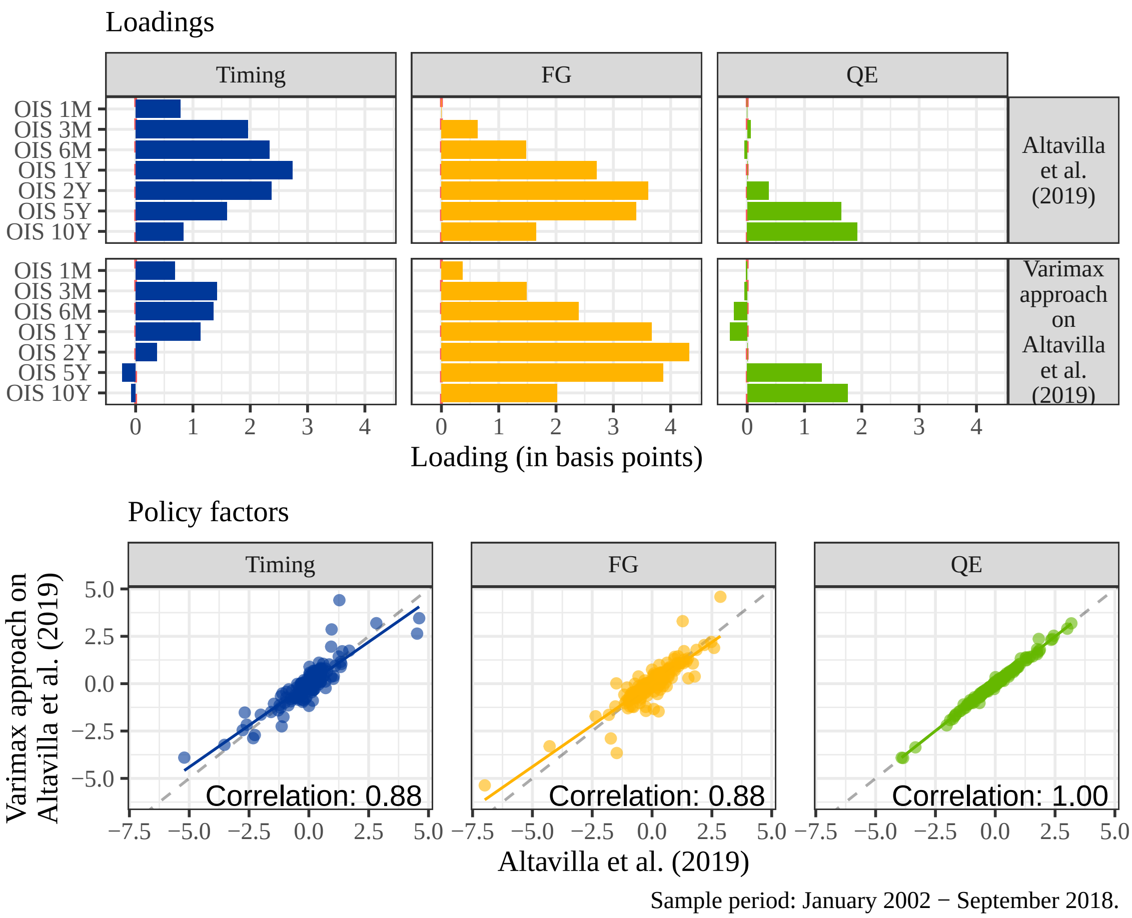
Another important difference between our approaches in the main text and the one followed in Altavilla et al. (2019) is that they do not scale the different assets to have the same standard deviation of movements in the Governing Council windows. Given the smaller magnitude of movements of the OIS 1-month in these windows, it leads to principal components that emphasise explaining more volatile rates relative to others. This aspect, in combination with the separation of the press release and press conference windows, leads to no factor concentrating specifically on the shortest maturities. The choice of standardisation is important when one includes assets with larger movements, such as riskier sovereign yields, and also assets in different measurement units, such as stock prices, which are not directly comparable to interest rates, as we do in Section 5.

Regardless of these differences, in the results that follow we use the same data choices as Altavilla et al. (2019). Figure B1 compares the results in the original Altavilla et al. (2019) with those from applying a Varimax rotation to the same dataset. The top panel of the figure compares the loadings of the two approaches. The Varimax approach (bottom row) shows that factors similar to those in Altavilla et al. (2019) (top row) emerge naturally from the sparsity and the kurtosis of the underlying monetary policy dimensions. Varimax uncovers a 'Timing' factor that is only slightly more concentrated in shorter maturities than the 'Timing' factor in Altavilla et al. (2019); a 'forward guidance' factor with a hump shape loading mostly on the 2-year maturity; and a 'QE' factor loading strongly on longer maturities. The bottom panel shows that the Varimax factors, in the y-axis, are very similar to those in the original paper, in the x-axis, with correlations of 0.88, 0.88, and 1.00.

B.2 Comparison with Motto and Özen (2022)

We also apply the Varimax approach to Motto and Özen (2022), who extract policy factors from the same risk-free assets as Altavilla et al. (2019) and our paper, but additionally include the 2-, 5-, and 10-year sovereign yields for Italy, Spain, and France. As in Altavilla et al. (2019), they extract four factors from the press conference based on non-standardised input data. Their identification restrictions expand on Altavilla et al. (2019) by imposing that a fourth factor must have minimal variance outside the sovereign-debt crisis and pandemic periods, and that it affects the OIS 5-year and the Italian 5-year sovereign

Figure B1: Comparison of the Altavilla et al. (2019) press conference factors and the Varimax approach applied to the same dataset.



yield in opposite directions. Given these identification restrictions, a new factor driving sovereign spreads naturally emerges, representing what we earlier named the *sovereign risk* dimension of euro area monetary policy. This factor disaggregates the original 'QE' factor into a 'conventional QE' and a 'market-stabilization QE' factor.

We apply the Varimax rotation to the principal components based on the data choices of Motto and Özen (2022). Figure B2 shows the results. When we extract four factors and apply the Varimax rotation, we find factors that are somewhat similar to the original factors in the paper, although not as strongly correlated as for Altavilla et al. (2019). In particular, the Varimax approach seems to be struggling with disentangling the risk-free factors, leading to factors that are harder to interpret. As we found in sections 4 and 5, the Varimax approach focuses initially on disentangling two factors from the risk-free rate movements around the full monetary event window, including the press release, and only uncovers a *path*/'forward guidance' dimension that is concentrated around medium-term maturities if given enough factors.[16] Since Motto and Özen (2022) only extract factors from the press conference, a significant part of the variation in short-term risk-free rates is not used, as these policy decisions are communicated in the press release.

We therefore adapt the identification assumptions of Motto and Özen (2022) and reduce the number of factors to three, dropping their 'forward guidance' factor and otherwise keeping everything else the same. The results of this analysis can be seen in Figure B3.[17] The varimax factors are now clearly interpretable. The adapted version of Motto and Özen (2022) and Varimax are strongly aligned on three factors of 'timing', 'conventional QE', and 'Market-Stabilization QE' , with correlation between the policy factors that are all above 0.85. These results also show that the Varimax rotation can provide a useful indication of the number of underlying policy dimensions.

B.3 Comparison with Swanson (2021)

Finally, we apply the Varimax approach to the US using the paper of Swanson (2021). In the paper, the author extracts three factors from US high-frequency data on Federal Funds Rate (FFR) contracts, Eurodollar contracts, and US treasury yields. For identification, Swanson (2021) imposes that the second and third factors do not load on the shortest-maturity FFR contract, and that the third factor must have minimal variance before 2009.

[16] The *path*/'forward guidance' dimensions emerged as one of the four factors in the baseline set of assets but this dimension did not show in the five risk-extended factors.

[17] See Figure B2 for the four factor comparison.

Figure B2: Comparison of the Motto and Özen (2022) press conference factors and the Varimax approach applied to the same dataset.

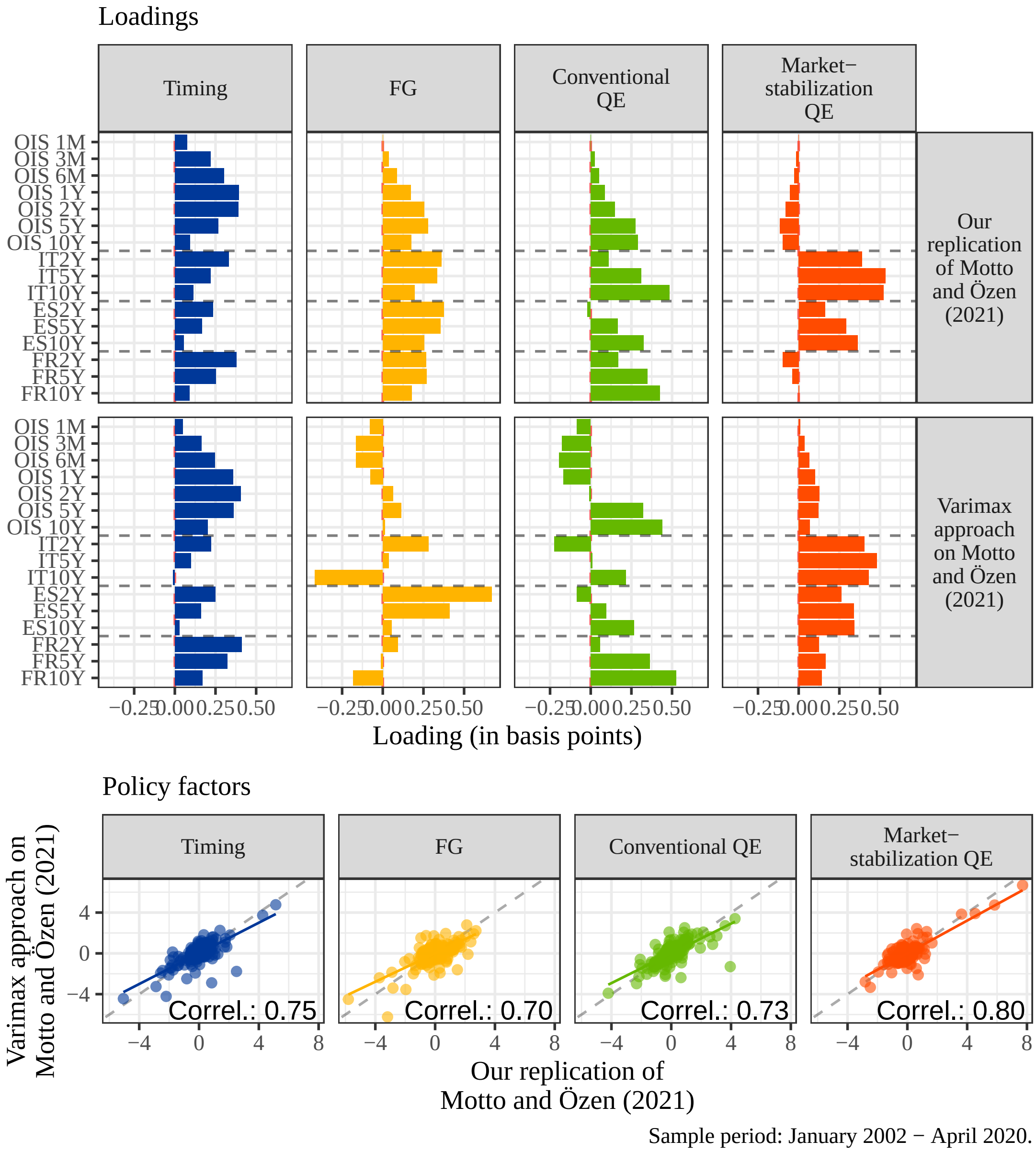
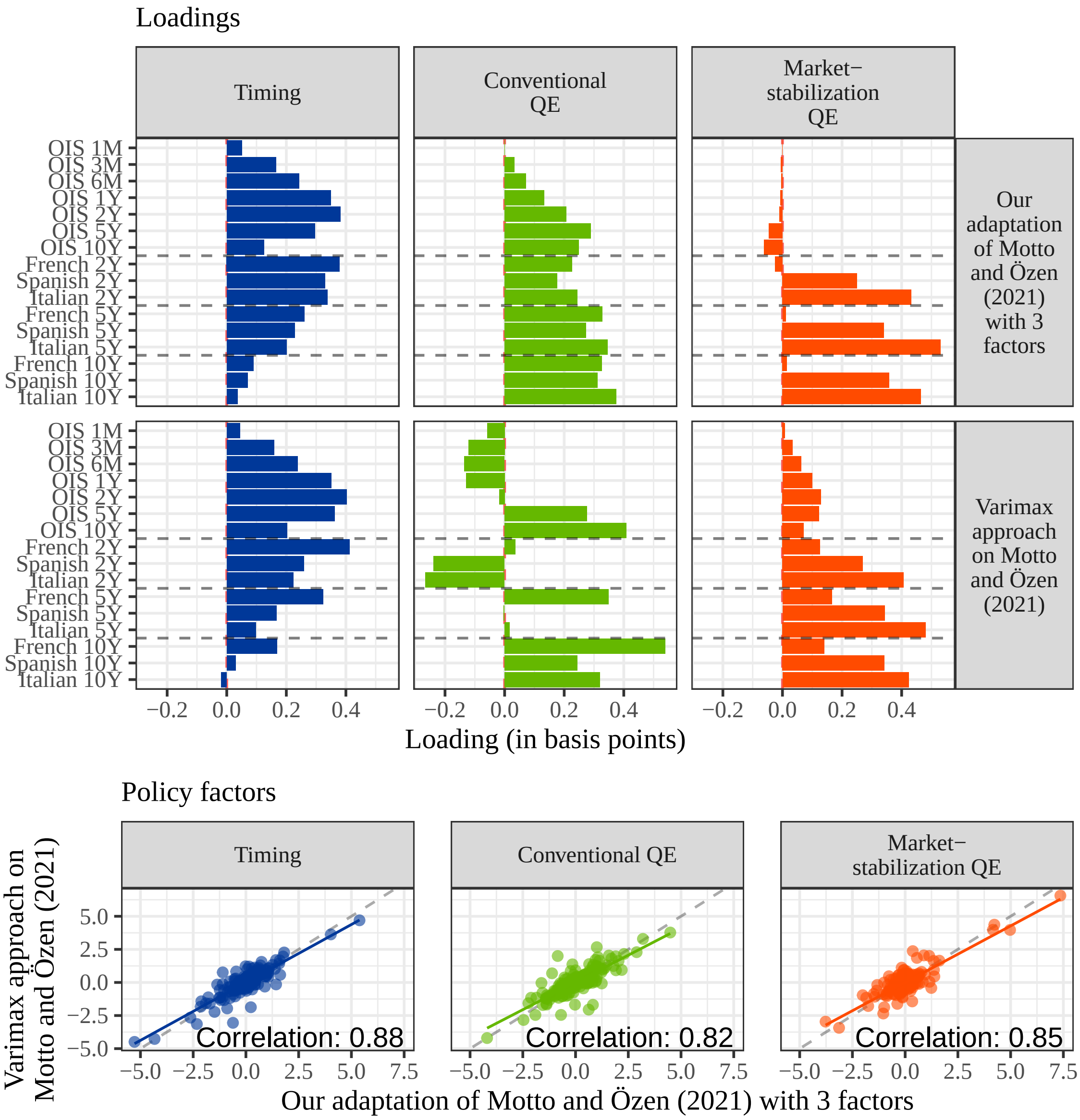
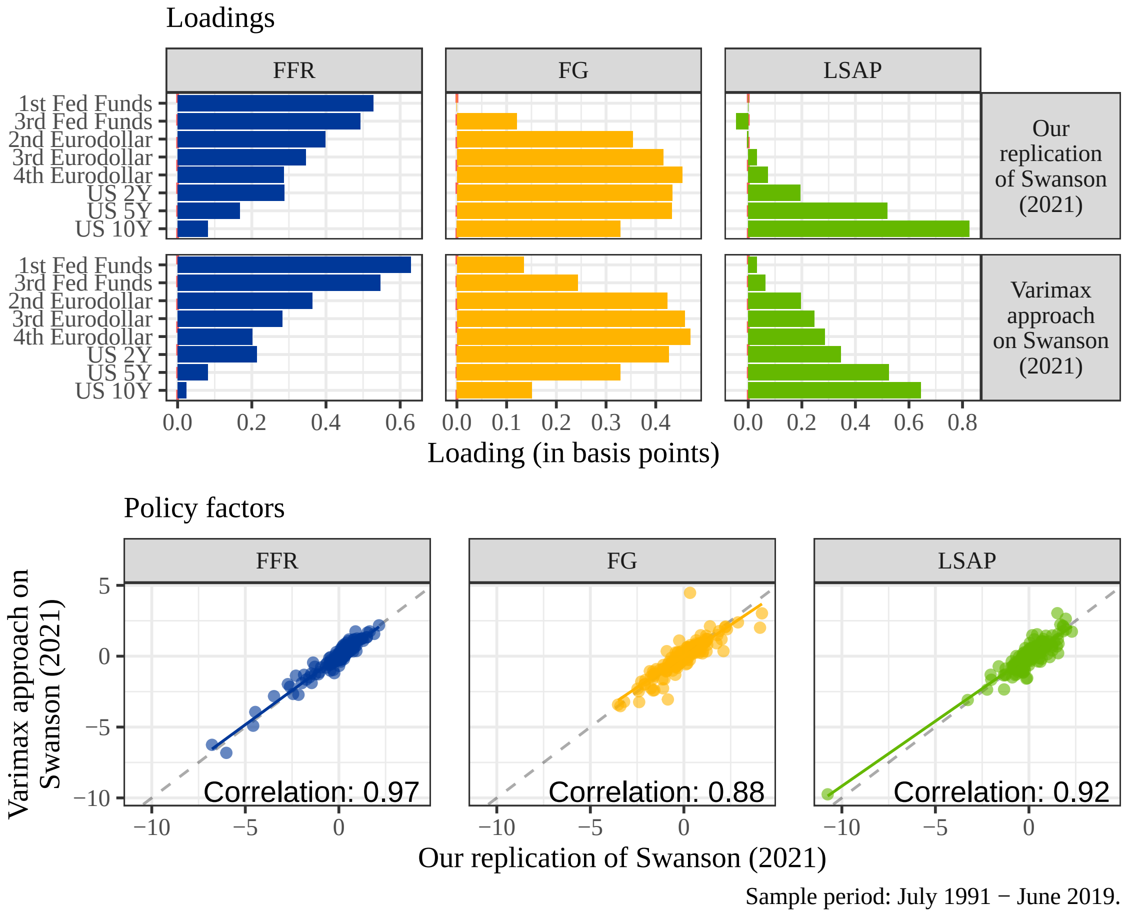


Figure B3: Comparison of an adapted version for three factors of the Motto and Özen (2022) press conference factors and the Varimax approach applied to the same dataset.



Sample period: January 2002 − April 2020.

Figure B4: Comparison of the replicated Swanson (2021) factors for the US and the Varimax approach applied to the same dataset.

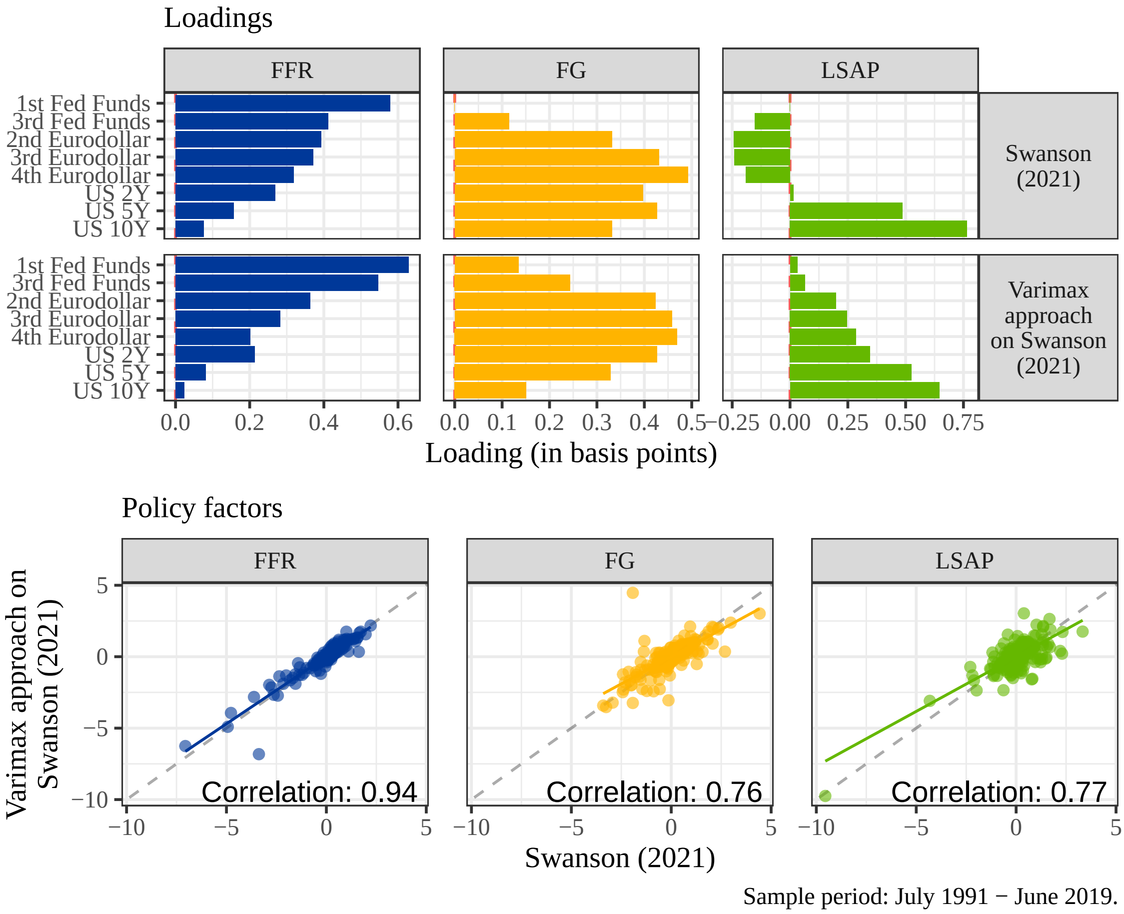


From these restrictions, he identifies three factors: a 'FFR' factor, a 'forward guidance' factor, and a QE factor (named 'LSAP', referencing to large scale asset purchases).

To ensure that any difference between the two approaches are driven by the rotation, we replicate the results of Swanson (2021) using the high-frequency data published by Refet Gürkaynak on his personal website. Figure B4 shows the results. Applying the Varimax approach to US data, we find that three similar factors emerge: a 'FFR' factor, driving the near-term federal funds rate contracts, a 'forward guidance' factor with a hump-shaped profile, and an upward-sloping QE/'LSAP' factor, driving more strongly longer-term yields. Compared to our replication of the results in Swanson (2021), the main difference in a flatter slope in loadings of the *QE*/'LSAP' factors from Varimax.

As before, despite imposing no economic identifying assumptions, Varimax finds similar factors to Swanson (2021). Both approaches yield factors with a correlation of 0.88

Figure B5: Comparison of the published Swanson (2021) factors for the US and the Varimax approach applied to the available dataset.



or higher, as shown in the bottom panel of Figure B4.[18]

C Yield-curve transmission of monetary policy factors over time

When examining the transmission of the monetary policy indicators to financial markets, the VAR methodology employed in the Section 6 allows us to investigate only a small set of asset prices simultaneously due to dimensionality issues. This limitation can be

[18]In appendix Figure B5, we compare the Varimax results with the results of Swanson (2021) released by the author. For this, we take the loadings from Table 3 in the original paper and the factors from the data published in Eric Swanson's personal website. The results are qualitatively similar, although the factors are less strongly correlated. The difference between the published results and our replication may be driven by the use of different data, or by an imperfect replication of the original Swanson (2021) paper, as our replication of his methodology does not produce a perfect match, and we obtain correlations between 0.93 and 0.98 with the factors published. In any case, we highlight Figure B4 to ensure that any differences in our comparison between the conventional and the Varimax results is driven by the rotation.

overcome by a dynamic factor model, which enables the examination of a broader range of asset prices, in particular yields across different maturities. Our objective is to trace the dynamic profile and persistence of monetary policy indicators in a granular manner across the entire yield curve. By employing a dynamic factor model, we can reduce the yield curve to a small number of factors, which is a common approach in the literature (Diebold and Li, 2006; Adrian et al., 2013; Chen and Scott, 1993; Dai and Singleton, 2002; Duffee, 2000).

For this exercise, consider a state-space system of the same set of observables Y_t as employed in Sections 3 and 4 to construct the baseline indicators, paired with the intraday indicators f_t, all at a daily frequency:

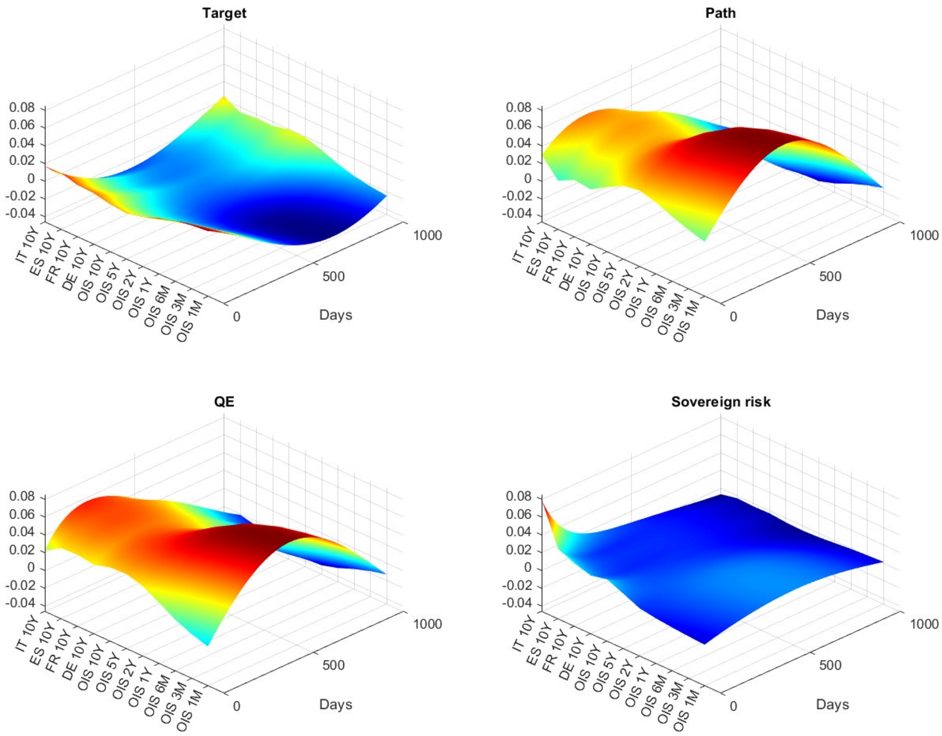
$$Y_t = Cx_t + v_t. \qquad \text{(observation equation)} \tag{4}$$

$$x_t = Ax_{t-1} + Bf_t + u_t \qquad \text{(state equation)} \tag{5}$$

The state variables x_t are affected contemporaneously by the high-frequency indicators that are identified through the varimax rotation with baseline specification explained in Section 4, f_t and are obtained as principal components of Y_t. The impulse-response-functions – defined as $CA^{i-1}B \quad \forall \quad i = 1, \ldots, T$ – can then be calculated to trace out the dynamic impact of f_t on asset prices, through their impact on dynamic factors, over time. The estimation approach is as in Diebold and Li (2006), with factors x_t obtained from principal components and coefficients estimated from direct regressions of yields Y_t on three principal component factors x_t in equation (4) and estimating the autoregressive model (5).

Figure C6 illustrates the dynamic profile of the four baseline monetary policy factors f_t over time. It shows that the cross-sectional yield profile of these factors map into a similarly shaped time profiles. Consistent with the factor loadings, the impact of a *target* shock remains mostly confined to short-term risk-free maturities up to one year and has a downward-sloping impact over time. The transmission of *path* shocks is initially concentrated on medium-term maturities with a hump-shaped yield profile. Over time, the impact becomes increasingly concentrated on short-term yields. In contrast, a *QE* shock initially has the greatest impact on 10-year risk-free and sovereign yields. This effect then transmits to medium and short-term yields with an upward-sloping profile over time before dissipating. The profile of *sovereign risk* shocks is particularly concentrated on Italian and Spanish 10-year yields, with only a relatively short-lived impact.

Figure C6: Dynamic Factor Model with the Varimax baseline monetary policy factors as instruments



Sample period is from January 2014 to November 2023

Consistent with the findings of Alessi and Kerssenfischer (2019), our dynamic factor model indicates stronger and more persistent effects of monetary policy shocks on asset prices across the yield curve than typically obtained using BVARs. Overall, the yield-curve profile of factors maps into comparable dynamic profiles, with *target*, *path* and *QE* shocks exhibiting the most persistent impact.

D Additional Figures

Figure D7: Loadings of factors on conventional approach, in basis points.

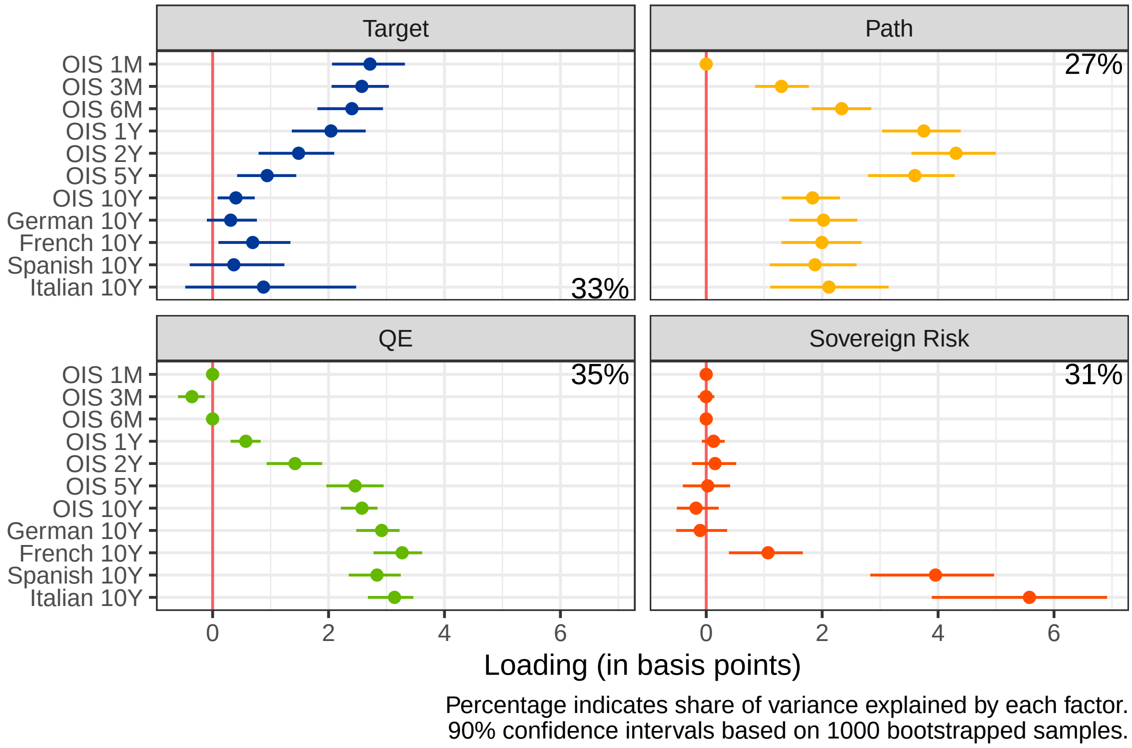
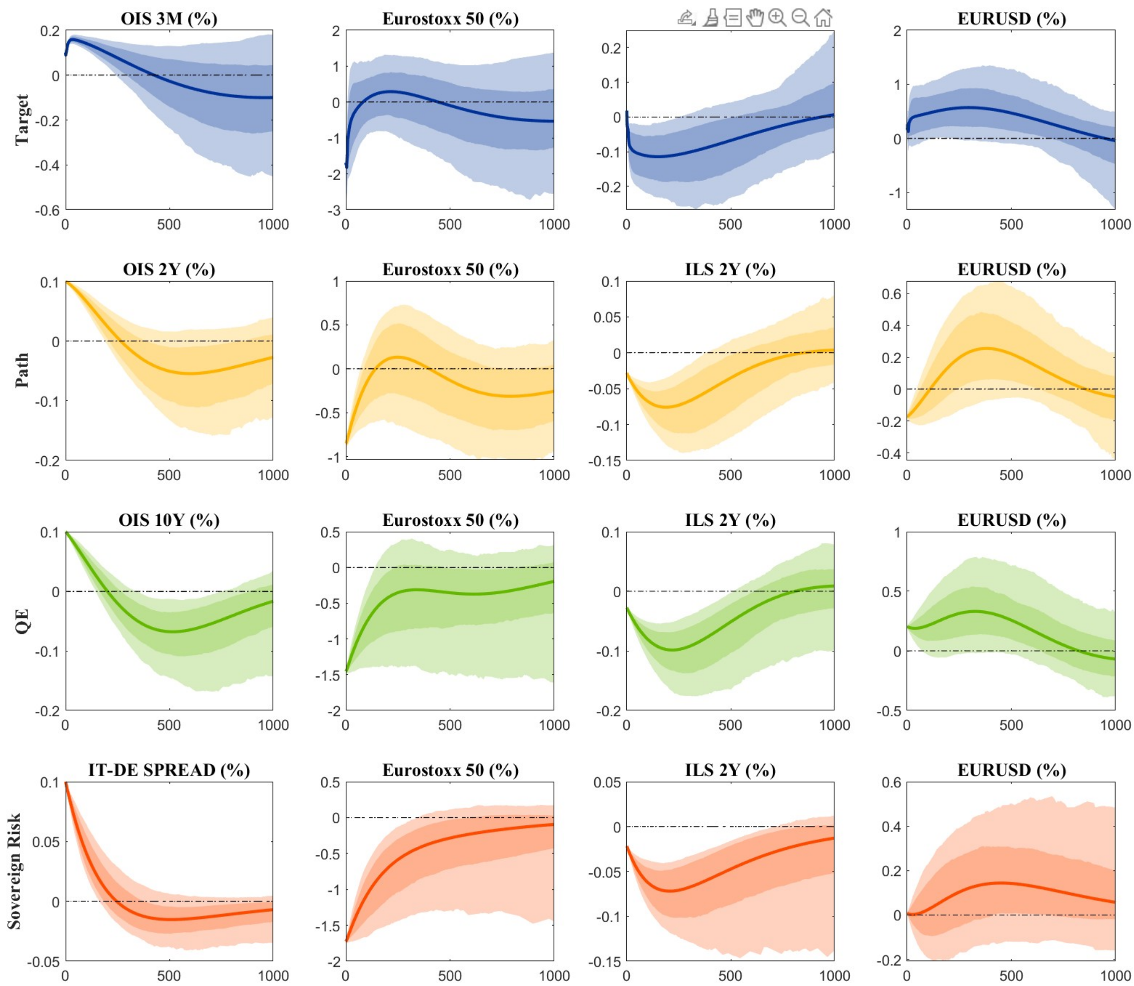


Figure D8: Daily financial Proxy VAR with structural core monetary policy factors as instruments.



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