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Euro Area Monetary Policy

Measuring Unconventional Monetary Policy in the Euro Area: a Focus on Sovereign Spreads

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Abstract

This master's thesis delves into the intricate interplay between European Central Bank (ECB) policy decisions, market reactions, and economic outcomes within the realm of monetary policy analysis. By harnessing the high frequency Euro Area Monetary Policy Event-Study Database (EA-MPD), it builds upon prior research endeavors to translate ECB policy communication onto the yield curve. It extends its focus beyond 2018, encompassing pivotal events such as the pandemic and energy crises. Moreover, the work challenges the prevalent reliance on risk-free Overnight Index Swap rates for assessing ECB policies. Instead, it underscores the significance of sovereign spreads, particularly in the context of the European debt crisis, by introducing an new 'Save-The-Euro' factor. This factor introduces an additional structural shock that refines the understanding of evolving monetary strategies. Within this framework, the influence of the ECB's policy communication on various asset prices is investigated. By doing so, it aims to provide insights into the broader impact of the ECB's decisions on the financial landscape

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Chapter 1

Introduction

Understanding the interactions between central bank actions, market responses, and economic outcomes remains a crucial endeavor. The European Central Bank's (ECB) policy decisions have elicited a range of academic inquiries aimed at comprehending the underlying mechanisms driving market reactions and policy effects. [Altavilla et al., 2019] publish a paper utilizing the Euro Area Monetary Policy Event-Study Database (EA-MPD), providing valuable insights into the dynamics of ECB policy communication and its subsequent impact on asset prices and yields. However, as with any scholarly discourse, constructive critique and counterarguments often pave the way for deeper understanding and refinement of research findings. Wright [2019]'s examination challenges the prevailing notion that ECB monetary policy primarily operates through the term structure of risk-free Overnight Index Swap (OIS) rates. Instead, Wright emphasizes the pivotal role of sovereign spreads in certain critical policy junctures, notably during the European debt crisis. This commentary underscores the importance of comprehending the nuances of the unique circumstances that central banks face, as well as the evolving nature of monetary policy transmission mechanisms. In this context, this master thesis aims to engage with and build upon the insights presented in both papers. This thesis seeks to address the following key questions:

- How does monetary policy affect asset prices post 2018, including episodes such as the pandemic and energy crisis?
- What is the evidence for monetary policy to be decomposed into a Save-The-Euro factor, enabling the incorporation of an extra structural shock in macroeconomic models, aligning with the argument for the role of sovereign spreads during pivotal policy episodes such as the European debt crisis?

By analyzing the empirical evidence and extending it with a spread factor, we seeks to contribute to the ongoing dialogue surrounding the multifaceted nature of monetary policy surprises.

Chapter 2

Theoretical background

General econometric concepts descriped in this section are sourced from New Introduction to Multiple Time Series Analysis [Lutkepohl, 2005] and the course Applied Macroeconomics [UCL].

2.1 OIS curve and Expectation Hypothesis

An **overnight interest rate swap** (OIS) is a financial contract between two parties in which they exchange interest payments based on a fixed interest rate and an overnight reference rate, typically linked to a central bank's policy rate. In this arrangement, one party agrees to pay a predetermined fixed interest rate, while the other party agrees to pay a floating rate that is determined by the daily observed overnight reference. It's important to note that these overnight rates can apply to various maturities. In practice, each night, the difference between the fixed rate and the realized overnight rate is calculated. The calculated difference is multiplied by the notional principal amount agreed upon in the swap contract. Then, there is an exchange of money between the two parties that reflects this difference. The party that agreed to pay the fixed rate compensates the other party for any positive difference between the fixed rate and the actual overnight rate, while the party paying the floating rate compensates for any negative difference. Since these transactions involve minimal risk due to the absence of principal exchange (only the interest rate difference multiplied by the notional amount is exchanged, and so only a fraction of the notional amount is at risk), they serve as a reliable estimator for risk-free interest rate accepted by market participants.

An **inflation-linked swap** (ILS) is similar to an OIS, a financial contract wherein two parties exchange payments that are modified to account for fluctuations in inflation. In this arrangement, one party pays a fixed rate. On the other side, the second party pays a floating rate that is associated with an inflation index such as the Consumer Price Index (CPI). These instruments serve as more than just financial tools – they operate as estimators of agents' inflation expectations. The fixed rate, signed in a contract with a certain maturity, acts as a valuable indicator of the market's forecast for inflation for that maturity.

In both cases, short and long rates are connected according to a theory called the expectation hypothesis. This hypothesis states the long rates are the compounded expectations of the economic agents of the future evolution of short rates.

The **expectation hypothesis** suggests that long-term interest rates are determined by the market's expectations of future short-term interest rates. According to this hypothesis, an investor should be indifferent between holding a long-term bond and a series of short-term bonds over the same period. Mathematically, it can be represented as (approximating the compounded rate by a sum):

$$r_{LT} = \frac{1}{n} \sum_{i=1}^{n} r_{ST_i}$$

In practice however, this theory does not hold, because market participants require premia for the risk of having their money stuck for a longer period, as well as the risk coming from inflation.

The **risk premium** for holding longer-term OIS contracts reflects the compensation that investors demand for the uncertainty and potential volatility of future overnight rates.

$$RP = r_{LT} - r_{ST}$$

The **inflation** premium reflects the compensation that investors seek to protect themselves against the eroding purchasing power of their money due to inflation.

$$IP = r_{LT} - r_{\text{real}}$$

Figure 2.1 plots the shape of the Overnight Indexed Swap (OIS) rate curve. This curve is vital for understanding monetary policy. A typical OIS curve rises slightly over time due to risk and inflation factors. A steep curve suggests expectations of rising short-term rates. A flat curve indicates expectations of stable or decreasing rates, or even an impending economic crisis, which pushes investors to long-term bonds, lowering their yields and the curve's tail. Interest rate announcements impact the curve's beginning, while Quantitative Easing and Forward Guidance target longer-term rates, influencing the curve's tail.

In summary, the shape of the Overnight Indexed Swap (OIS) curve serves as a valuable repository of information encompassing not only current OIS rates but also the market's outlook on future rates. Beyond these fundamental components, the OIS curve encapsulates additional layers of insight, such as risk and inflation premiums that investors require as compensation for uncertainties and potential loss of purchasing power.

The significance of the OIS curve endures, even in the era of unconventional monetary policy measures. These non-traditional interventions, such as quantitative easing and forward guidance,

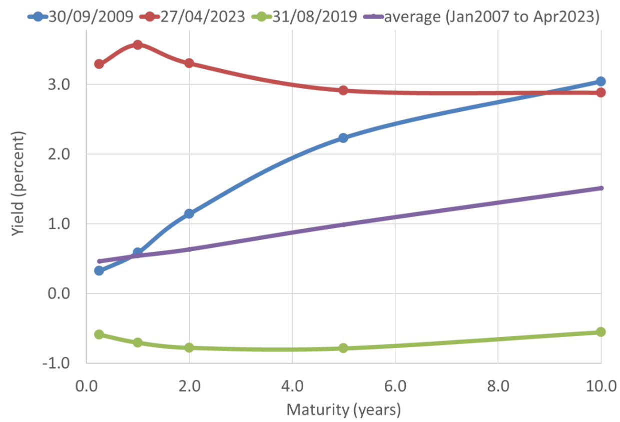


Figure 2.1: source: ECB

can influence the OIS curve's configuration, reinforcing its role as a key barometer for central banks to assess the effectiveness of their policy decisions and communication strategies. However, as noted by Wright [2019], The evolution of economists' perspective on monetary policy has shifted from a focus solely on policy short rates to a broader consideration of the term structure of risk-free rates, especially in the context of unconventional monetary policies. Instances like the European debt crisis revealed that certain events had significant impacts on spreads between sovereign bonds rather than OIS rates. Notably, during the crisis, ECB actions had pronounced effects on sovereign spreads, highlighting the need to go beyond OIS rates to understand monetary policy implications. Although viewing euro area monetary policy through OIS rates suffices for most policy scenarios, the crisis of 2011–2012 stands as a case where it was not sufficient. While the debt crisis episode might constitute a modest portion of overall euro area monetary policy surprises throughout the euro's history, it remains a pivotal consideration for European policymakers. The nature of monetary policy factors isn't static; they evolve in response to the challenges central banks confront.

2.2 Factor Model

A natural tool to analyse the high frequency variations of macroeconomic data, analogously to [Stock and Watson, 2012] is a factor model, which can be obtained using eigenvalue decomposition and rotation techniques. The process involves several steps to extract meaningful and interpretable factors from the observed data. A few preliminary concepts need to be introduced in order to fully understand it.

2.2.1 Principal components analysis (PCA)

Principal Component Analysis (PCA) is a robust statistical method that simplifies intricate data by reducing its dimensions. It achieves this by pinpointing principal components—perpendicular axes within the data's space—that unveil the directions of highest variability. The leading principal component encapsulates the most significant variance, while successive components capture the remaining variance in descending order of importance. PCA's underlying mathematical framework hinges on the eigenvalues and eigenvectors of the data's covariance matrix. Through this process, the original data gets transformed into a novel coordinate system defined by these principal components, providing a concise representation of data variability. Here's how PCA is executed step by step:

1. Calculate the mean vector $\bar{x}$ by summing up all data points and dividing by the total count:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

.

2. Construct the centered data matrix X_{centered} by subtracting the mean vector from each data point:

$$X_{\text{centered}} = X - \bar{x}$$

3. Determine the covariance matrix Cov by multiplying the centered data matrix with its transpose and normalizing by $n-1$:

$$\text{Cov} = \frac{1}{n-1} X_{\text{centered}}^{T} X_{\text{centered}}$$

4. Find the eigenvalues λ_i and corresponding eigenvectors v_i that satisfy the equation

$$\text{Cov} v_i = \lambda_i v_i$$

5. Create the reduced data matrix Y by projecting the centered data onto the top k eigenvectors, denoted asV_k:

$$Y = X_{\text{centered}} V_k$$

It can be show mathematically that the above described procedure establishes the axes based on the maximization of variance criterion. To ensure fairness and prevent bias due to differing scales, it's essential to normalize the features before undergoing the transformation.

2.2.2 Factor loadings

Factor loadings are the specific coefficients obtained when regressing identified factors against the original dimensions within the dataset. These coefficients provide insights into the primary dimensions of the original data that exert the most influence on each factor. The factor loadings are related to the principal components, but there are differences. A factor could load onto a dimension that is orthogonal to its corresponding principal components, if the dimensions of the original dataset exhibit correlations.

2.2.3 Quadratic optimization and Factor rotation

Factors can be rotated using a rotation matrix. This concept coming from linear algebra corresponds intuitively to rotating the axis in a hyperdimensional plan, in order for the axis, i.e. the principal components, to be aligned with concepts that we understand more, and not be a mix of them. We therefore need to find the appropriate rotation matrix. A rotation matrix should satisfy **orthogonality** and **normality** constraints. In essence, this is saying that the column vectors of the rotation matrix should be orthonormal, and be the new orthonormal basis of the space. We can also add additional constraints and an objective function (to be minimized) to obtain a rotation matrix that will make the factors interpretable. All of these constraints, as well as the objective function are typically given to a solver. In the case of non-linear constrains, which is the case when imposing orthonormality and independence constraints we use a quadratic solver. An example of this is solnl [Nlc] in the R language. This package allows to solve optimization problems formulated as:

$$
\begin{aligned}
&\min\ f(x) \\
&\text{s.t.:} \\
&\quad ceq(x) = 0 && \text{Equality Constraints} \\
&\quad c(x) \leq 0 && \text{Inequality Constraints} \\
&\quad Ax \leq B && \text{Linear Inequality Constraints} \\
&\quad Aeqx \leq Beq && \text{Linear Equality Constraints} \\
&\quad lb \leq x \leq ub && \text{Bounds on Decision Variables:}
\end{aligned}
$$

2.3 VAR(p) model

A VAR(p) model, which stands for Vector Autoregressive model of order p, is a powerful tool in time series analysis that extends the autoregressive concept to multiple interrelated variables. Unlike univariate autoregressive models, which focus on a single variable's dependence on its past values, a VAR model accounts for the interactions and mutual influences among p specifies the number of previous time steps considered, allowing the model to capture complex temporal dynamics. Mathematically,

$$Y_t = \sum_{i=1}^{p} B_i Y_{t-i} + \eta = B(L)Y_t + \eta, \quad \eta \sim N(0, \Omega) \tag{2.1}$$

which in the case for example of a 3-variable var with two lags becomes:

$$\mathbf{Y}_t = \begin{bmatrix} B_{1,11} & B_{1,12} & B_{1,13} \\ B_{1,21} & B_{1,22} & B_{1,23} \\ B_{1,31} & B_{1,32} & B_{1,33} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{3,t-1} \end{bmatrix} + \begin{bmatrix} B_{2,11} & B_{2,12} & B_{2,13} \\ B_{2,21} & B_{2,22} & B_{2,23} \\ B_{2,31} & B_{2,32} & B_{2,33} \end{bmatrix} \begin{bmatrix} Y_{1,t-2} \\ Y_{2,t-2} \\ Y_{3,t-2} \end{bmatrix} + \begin{bmatrix} \eta_{1,t} \\ \eta_{2,t} \\ \eta_{3,t} \end{bmatrix}$$

(2.2)

The above presented model is typically called the 'reduced form VAR'. If one explicitely models the contemporaneous relationships (through A_0) between the different time series, as in the following model, the we say it is a 'structural VAR' (SVAR), mathematically:

$$A_0 Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t = A(L) Y_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, I_K) \tag{2.3}$$

where the shocks are assumed to be exogenous, uncorrelated, and normally distributed with zero mean and with an identity covariance matrix without loss of generality.

2.3.1 Assumptions

First and foremost, the VAR model assumes stationarity of the time series variables involved. This assumption implies that the statistical properties of these variables, such as mean and variance, remain constant over time. Furthermore, their relationships can be adequately captured by a linear combination of lagged values of themselves and their contemporaneous values. Another crucial assumption is the absence of omitted variables and omitted variable bias. This implies that the included variables in the VAR model account for all the relevant factors that might influence the behavior of the variables under consideration. Additionally, the VAR model assumes that the relationships among the variables are stable over time, implying that the coefficients of the lagged variables remain constant.

2.3.2 Reduced form VAR

Following [Lutkepohl, 2005] we can write a reduced form VAR of n variables, p lags and estimated on T data points:

$$Y \in R^{T\times n} \quad = X \in R^{T\times(np+1)} \quad \Gamma \in R^{(np+1)\times n} \quad + u \in R^{T\times n}$$

$$
Y = \begin{bmatrix} Y_{t_1} \\ \vdots \\ Y_{t_T} \end{bmatrix}^{T\times n} \quad X = \begin{bmatrix} \begin{bmatrix} 1 & \boldsymbol{Y'_{t_1-1}} \dots \boldsymbol{Y'_{t_1-p}} \end{bmatrix} \\ \vdots \\ \begin{bmatrix} 1 & \boldsymbol{Y'_{t_T-1}} \dots \boldsymbol{Y'_{t_T-p}} \end{bmatrix} \end{bmatrix}^{T\times(np+1)} \quad \Gamma = \begin{bmatrix} C \\ A'_1 \\ \vdots \\ A'_p \end{bmatrix}^{(np+1)\times n} \quad u = \begin{bmatrix} \nu_1 \\ \vdots \\ \nu_T \end{bmatrix}^{T\times n}
$$

Then, the OLS estimator is given by $\hat{\Gamma} = (X'X)^{-1}X'Y$. Under standard assumptions of linearity, strict exogeneity of error term, no perfect collinearity between independent variables, homoscedasticity, the OLS estimator can be show to be consistent and asymptotically normally distributed.

Reverse causality and simultaneity bias

Consider the following 2-variable-2-lag VAR example:

$$
\begin{bmatrix} B^0_{11} & B^0_{12} \\ B^0_{21} & B^0_{22} \end{bmatrix} \begin{bmatrix} \text{infl}_t \\ \text{gov}_t \end{bmatrix} = \begin{bmatrix} B^1_{11} & B^1_{12} \\ B^1_{21} & B^1_{22} \end{bmatrix} \begin{bmatrix} \text{infl}_{t-1} \\ \text{gov}_{t-1} \end{bmatrix} + \begin{bmatrix} \eta \\ \eta \end{bmatrix}
$$

$$
B^0 Y_t = B^1 Y_{t-1} + \eta \tag{2.4}
$$

It can be rewritten as follows in order to be estimated by OLS:

$$
Y_t = (B^0)^{-1} B^1 Y_{t-1} + (B^0)^{-1}\eta \tag{2.5}
$$

$$
Y_t = B' Y_{t-1} + \eta' \tag{2.6}
$$

On can see that the OLS estimation will suffer from reverse causality bias, in the case of the contemporaneous relationships modeled by B^0. No correlation between inf_t and gov_t is consistent with both $B^0_{12} = 0 = B^0_{21} = 0$ or B^0_{12} and B^0_{21} being large and of opposite sign. Note that the B^1 coefficients do not suffer from this problem, as reverse causality is not an issue when dealing with 2 variables which are in a different time-period.

The SVAR approach is about explicitely modelling the contemporaneous relationships, and imposing that the shocks be structural, i.e. uncorrelated.

$$
A^0 Y_t = A^1 Y_{t-1} + \varepsilon \tag{2.7}
$$

$$
Y_t = (A^0)^{-1} A^1 Y_{t-1} + (A^0)^{-1}\varepsilon \tag{2.8}
$$

By imposing that A^0 is such that the shocks ε are orthogonal, as well as some aditional constraints drawn form economic theory, necessary to uniquely identify A^0, we obtain a structural VAR.

2.3.3 Structural VAR

Reduced form Vector Autoregressive (VAR) models are effective in capturing contemporaneous effects among variables, but they do not inherently account for the direction of causality, potentially leading to challenges in identifying reverse-causality issues. Moreover, in reduced form VAR models, the underlying shocks are often correlated, which can complicate the interpretation of impulse response functions and the assessment of the isolated effects resulting from a shock to a specific variable.

To address these limitations, Structural VAR (SVAR) [Sims, 1980] models are commonly employed. SVAR models provide a framework for disentangling the relationships between variables by incorporating economic theory or other relevant domain knowledge. This enables researchers to establish causal relationships and differentiate between exogenous shocks and endogenous responses. By imposing identification restrictions on the model, SVARs can help isolate the unique impact of each shock on the variables of interest, making it easier to interpret and analyze the effects of individual shocks. The structural VAR cannot be directly identified through OLS estimation.

Given a specific dataset and model specifications, a reduced form Vector Autoregressive (VAR) model will yield a unique representation. In contrast, when moving to Structural VAR (SVAR) models, the number of possible specifications will correspond to the number of possible imposed restriction schemes. These restrictions are what guide the transformation of reduced form coefficients into the structural VAR coefficients. Therefore, the uniqueness of the structural VAR model arises from the specific set of restrictions applied to the underlying reduced form relationships.

From reduced to structural VAR

We have a structural VAR of the form

$$A_0 Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t = A(L) Y_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, I_K) \tag{2.9}$$

and corresponding reduced form VAR

$$Y_t = \sum_{i=1}^{p} B_i Y_{t-i} + \eta_t = B(L) Y_t + \eta_t, \quad \eta_t \sim N(0, \Omega) \tag{2.10}$$

The mappings between the two model, obtained by premultiplying our SVAR with A_0^{-1} (assuming A_0 is invertible) and identifiying the terms in the two equations, are given by:

- relationship between residuals and structural shocks:

$$\eta_t = A_0^{-1}\varepsilon_t$$

- relationship between reduced form parameters and structural parameters:

$$B_i = A_0^{-1}A_i \quad i = 1, ..., p$$

- link between the covariance matrices since $E(\varepsilon_t\varepsilon_t') = I_k$ by construction:

$$\Omega = E(\eta_t\eta_t') = E(A_0^{-1}\varepsilon_t\varepsilon_t'(A_0^{-1})') = A_0^{-1}E(\varepsilon_t\varepsilon_t')(A_0^{-1})' = A_0^{-1}(A_0^{-1})'$$

The reduced form VAR however is uniquely estimable which means we can estimate η_t and Bi. If we can find A_0 we will be able to recover the structural parameters and shocks to recover the structural VAR model. Unfortunately, A_0 is not uniquely identified, as it's expression is derived from:

$$\Omega = A_0^{-1}(A_0^{-1})' \quad \Omega \in R^{kxk}$$

where Ω is the covariance matrix of the residuals of the reduced form, and can be estimated from the data. However, since Ω is a covariance matrix, it is symmetric and has only $k(k+1)/2$ unique elements and hence we have a set of $k(k+1)/2$ unique constraints, to estimate k^2 unique parameters of A_0. This means we will have to impose some additional restrictions. Otherwise we are stuck with an un-identified matrix, the same problem we initially started with when trying to solve the SVAR. This can also be seen by writing Ω as:

$$\Omega = A_0^{-1}QQ'A_0^{-1\prime}$$

with Q orthonormal matrix such that $QQ' = I$

In conclusion, identifying the SVAR from the reduced form VAR involves applying the right set of restrictions to A_0 drawn from economic theory in addition to the constraints drawn from its expression in function of the covariance matrix of the reduced form residuals.

2.3.4 Identifying SVAR through external instruments

Instrumental Variable (IV) analysis is a statistical method used to address the challenge of establishing causal relationships in situations where confounding factors might distort regression analysis. It involves introducing an instrumental variable, which is correlated with the independent variable of interest but not directly with the dependent variable. This variable serves as a tool to untangle causation by breaking the link between cofounding factors and the independent variable. The instrumental variable must fulfill conditions of relevance and exogeneity – being correlated with the independent variable and having no direct influence on the dependent variable except through its effect on the independent variable. The analysis typically comprises two stages: firstly, regressing the instrumental variable on the independent variable to estimate their relationship, and secondly, employing the predicted values from the first stage to ascertain the causal effect of the independent variable on the dependent variable. It's a powerful approach to mitigate endogeneity bias, although its effectiveness hinges on the credibility of the chosen instrumental variable. This approach has also been extended to Vector Autoregressive (VAR) models, enabling researchers to tackle endogeneity and identification challenges in multivariate time-series data.

Impulse response function

[Stock and Watson, 2012] derive an approach to identify impulse response functions from external instruments in macroeconmic models. Given a factor model:

$$X_t = \Lambda F_t + e_t \tag{2.11}$$

where Λ are the factor loadings and ΛF_t is called the common component of X_t. The factors are modeled as evolving according to a VAR:

$$\Phi(L)F_t = \eta_t \tag{2.12}$$

This var is assumed to be stationary, giving the moving average representation for F_t:

$$F_t = \Phi(L)^{-1}\eta_t \tag{2.13}$$

We assume that r innovations η_t are linear combinations of r structural shocks ε so that:

$$\eta_t = H\varepsilon_t = \begin{bmatrix} H_1 & \cdots & H_r \end{bmatrix} \begin{pmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{r,t} \end{pmatrix} \tag{2.14}$$

Thus we have that $\Sigma_{\eta\eta} = H\Sigma_{\varepsilon\varepsilon}H'$, where $\Sigma_{\eta\eta} = E(\eta_t\eta_t')$ and $\Sigma_{\varepsilon\varepsilon} = E(\varepsilon_t\varepsilon_t')$. We also assume this relationship to be invertible: $\varepsilon_t = H^{-1}\eta_t$. Substituting the expression for F_t and η_t in the equation for X_t yields:

$$X_t = \Lambda\Phi(L)^{-1}H\varepsilon_t + e_t \tag{2.15}$$

$\Phi(L)$ is identified from the reduced form, so only H remains to be found. The instrumental variable Z_t is assumed to satisfy the following three conditions:

1. Relevance: $E(\varepsilon_{1t}Z_t) = \alpha \neq 0$
2. Exogeneity: $E(\varepsilon_{jt}Z_t) = 0$ j=2,...,r
3. Uncorrelated shocks: $\Sigma_{\varepsilon\varepsilon} = diag(\sigma^2_{\varepsilon_1}, ..., \sigma^2_{\varepsilon_r})$

The first and second conditions imply:

$$E(\eta_t Z_t) = E(H\varepsilon_t Z_t) = \begin{bmatrix} H_1 & \cdots & H_r \end{bmatrix} \begin{bmatrix} E(\varepsilon_{1,t} Z_t) \\ \vdots \\ (\varepsilon_{r,t} Z_t) \end{bmatrix} = H_1 \alpha \tag{2.16}$$

Given Π, the matrix of coefficients from regressing Z_t on η_t, then:

$$\begin{aligned} \Pi \eta_t &= E(Z_t \eta_t') \Sigma_{\eta\eta}^{-1} \eta_t \quad \text{[OLS estimator]} \\ &= \alpha H_1' (HDH')^{-1} \eta_t \qquad \text{[definition } \eta\text{, (2.16)]} \\ &= \alpha (H_1' H'^{-1}) D^{-1} (H^{-1} \eta_t) \qquad [(AB)^{-1} = B^{-1} A^{-1}] \\ &= (\alpha / \sigma_{\varepsilon 1}^2) \varepsilon_{1t} \qquad [H_1' H'^{-1} = e_1] \end{aligned} \tag{2.17}$$

Which, essentially, says that a shock identified using the instrument Z_t is the predicted value from the population regression of Z_t on the (non structural) innovation η_t, up to scale/sign. This scaling issue is solved by normalizing the shock to have a unit effect on some desired variable, for example, in the case of an monetary policy shock, it could be normalized to have a unit effect on the 1 month OIS rate.

Model identification

[Olea et al., 2021] provide an in depth analys of inference in structural VARs with external instruments. In particular, the following example helps to shed light how external instruments are used for SVAR model identification: Assuming the following vector autoregression with one lag and two variables, and where we have written the innovations in term of the structural shocks:

$$\begin{aligned} \mathbf{Y}_{1,t} &= \mathbf{e}_1' \mathbf{A}_1 \mathbf{Y}_{t-1} + \boldsymbol{H}_{11} \boldsymbol{\varepsilon}_{1,t} + \boldsymbol{H}_{12} \boldsymbol{\varepsilon}_{2,t}, \\ \mathbf{Y}_{2,t} &= \mathbf{e}_2' \mathbf{A}_1 \mathbf{Y}_{t-1} + \boldsymbol{H}_{21} \boldsymbol{\varepsilon}_{1,t} + \boldsymbol{H}_{22} \boldsymbol{\varepsilon}_{2,t}, \end{aligned}$$

where $\boldsymbol{e_j}$ denotes the jth column of the identity matrix I_n, $\boldsymbol{H}_{11} = 1$ because we are identifying up to scale and $\boldsymbol{H}_{21}$ is the parameter of interest. Using the first equation to solve for $\boldsymbol{\varepsilon}_{1,t}$ and substituting it in the second equation yields

$$\mathbf{Y}_{2,t} = \boldsymbol{H}_{21} \mathbf{Y}_{1,t} + \boldsymbol{\gamma}' \mathbf{Y}_{t-1} + \delta \boldsymbol{\varepsilon}_{2,t}.$$

The parameter of interest $\boldsymbol{H}_{21}$ can be obtained from the instrumental variable (IV) regression of the outcome variable $\mathbf{Y}_{2,t}$ on the normalized variable $\mathbf{Y}_{1,t}$ after controlling for lags of $\mathbf{Y}_t$. The assumptions taken implie that $\mathbf{z}_t$ is a valid instrumental variable in the conventional sense: (i) $\mathbf{z}_t$ is correlated with the endogenous regressor $\mathbf{Y}_{1,t}$ and uncorrelated with the error $\boldsymbol{\varepsilon}_{2,t}$.

Chapter 3

Methodology and motivation

3.1 Unique features of the ECB

The European Central Bank stands out due to its role within a monetary union that lacks a corresponding fiscal union, setting it apart from central banks in nations with more integrated fiscal and monetary policies. This distinction has significant implications, particularly evident during periods such as the European debt crisis. Unlike central banks in countries like the US, UK, or Japan, the ECB's policy actions have a profound impact on the sovereign spreads between countries' bonds, which reflects the varying borrowing costs and financial vulnerabilities of different Eurozone members. This is due to the absence of a unified fiscal policy framework, resulting in the potential for multiple equilibria, where countries can either face high borrowing costs and default risks or enjoy lower borrowing costs and financial stability. The ECB's actions can influence which equilibrium prevails, enabling it to shift from a paradigm of monetary dominance to one of fiscal dominance by credibly committing to purchase the debt of countries facing high borrowing costs. This was particularly evident during the European debt crisis of 2011-2012, where the ECB's interventions significantly impacted sovereign spreads, contributing to the resolution of the crisis. As such, the ECB's unique features arise from its role in managing the intricate interplay between fiscal and monetary policies in a diverse group of Eurozone countries, thereby shaping its policy considerations and challenges in distinctive ways compared to other central banks.

3.2 Motivation for adding a spread factor

The decision to incorporate a spread factor into [Altavilla et al., 2019] analysis arises from this distinct nature of the European Central Bank (ECB) and its policy environment. The effects of the ECB's policy actions extend beyond traditional risk-free interest rates (OIS rates) to impact sovereign spreads between different countries' bonds. This addition ensures a comprehensive examination of the ECB's policy impact, capturing its distinct role in managing the complexities of a diverse group of Eurozone nations, as suggested by Wright [2019]. In addition, similar research like Fanelli and Marsi [2022] find, using high frequency data, an unconventional monetary shock, an information shock, an a third shock, which they label 'spread shock', resulting from the ECB management of fragmentation risk in the sovereign bond market.

3.2.1 Save or don't save the euro

Note that the 'save the euro' factor should be constructed to align with a monetary shock, where a positive variation corresponds to a contractionary monetary policy. As such, a better label for this factor would be 'Not Save The Euro', as an increase in the factor would indicate an increased fragmentation of sovereign yields. For example, during the EU debt crisis this would be an episode where the ECB delays targeted OMT transactions, increasing sovereign spreads in the EU and general increase of interest rates.

3.3 EA-MPD

The Euro Area Monetary Policy Event-Study Database (EA-MPD) is a publicly available dataset, released by researchers at the European Central Bank. This database was created to investigate the impact of European Central Bank policy communications on financial markets. EA-MPD contains intra-day asset price changes connected to the ECB's policy communication, focusing on how policy-related events influence yield curve movements, but also other variables such as stock indices, sovereign yields and exchange rates. Because it contains the *variation* in basis points of macroeconomic variables during key time-windows following ECB announcements, EA-MPD serves as a key resource for researchers and policymakers to identify monetary policy shocks and its impact on asset prices and financial markets. The dataset was released with a analysis identifying 4 monetary policy surprises, named Target, Timing, Forward Guidance and Quantitative Easing. This analysis can be adapted for examining the effects of policy-related events in other economic contexts as well.

The EA-MPD database, available to download for free, encompasses 45 economic variables expressed in basis points within a specific time window, distributed across three sheets representing the press-release, press-conference, and combined monetary event windows. The variables comprise Overnight Index Swap (OIS) rates across 16 maturities (ranging from 1 month to 20 years), German Bund yields (DE) across 12 maturities (from 3 months to 30 years), as well as Italian (IT), Spanish (ES), and French (FR) government bond yields at 2-year, 5-year, and 10-year maturities.

Figure 3.1 shows how a policy announcement following the general council meeting can be divided into two main windows. The first window pertains to changes influenced by policy decisions, called the pres-release period. The second window, affected by the press conference, involves more comprehensive announcements by the president of the ECB. These announcements contain details

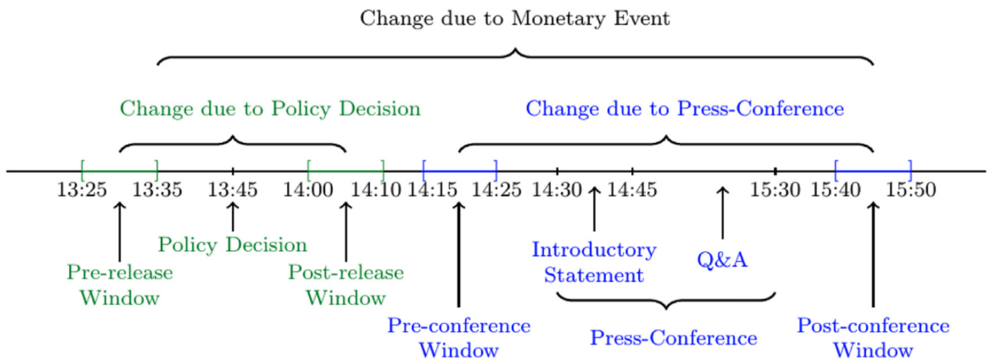


Figure 3.1: from Altavilla et al. [2019]

about long-term intentions, quantitative easing programs, and related matters. Within this timeline, two crucial timestamps stand out: the monetary policy decision **press release at 13:45** and the initial statement during the **press conference at 14:30**. Figure 3.2 shows that some of the OIS rates are not available for the full period. This is solved by proxying them by German treasury bonds with the same maturity.

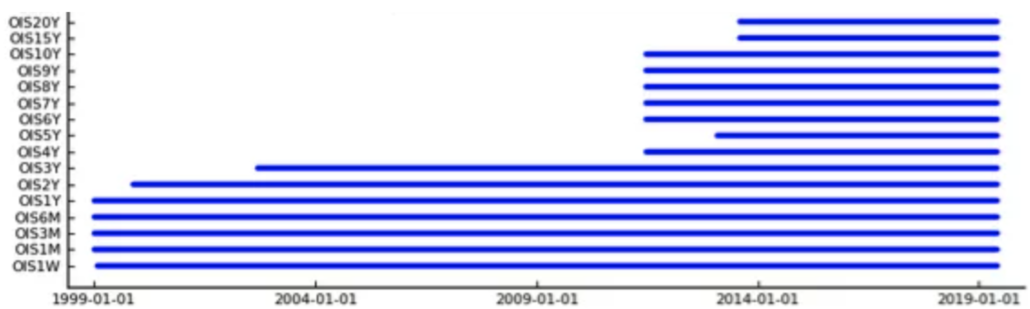


Figure 3.2: This figure represents the data coverage for OIS rates in the EA-MPD database.

3.4 Methodology

We leverage the EA-MPD database as our primary data source, housing an extensive array of economic indicators responsive to ECB announcements, including Overnight Index Swap (OIS) rates, sovereign yield, exchange rates, and other indices. To derive latent monetary policy shocks, we employ principal component analysis on the EA-MPD database, resulting in factors that encapsulate the influences of shocks, named the Target factor for press release shocks and Timing, Forward Guidance, Quantitative Easing (QE), and an additional Spread (Save-The-Euro) factor introduced

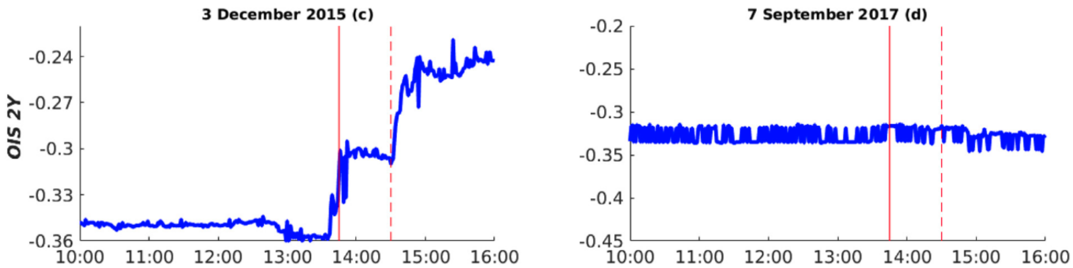


Figure 3.3: Note here again the two import times. first at **13:45** we have the monetary policy event announcement, and then around **14:30** there is the press conference statement. On some days this information cause strong reactions from the market, mostly when the event is unexpected by the agents. From Altavilla et al. [2019]

to capture distinct aspects of monetary policy surprises. These factors shape our subsequent analysis.

We perform an initial regression analysis. This analysis involves regressing the changes in OIS rates, sovereign rates, stock and banking indices, and exchange rates over a defined time window onto the monetary policy factors identified within that same window. This preliminary step provides us with a nuanced understanding of how these macroeconomic indicators respond to the identified monetary policy factors. The impact on stock market dynamics show mixed results, but as found by Altavilla et al. [2019], this can be explained by the Delphic-Odyssean framework. This approach allows us to gain insights into the interactions between monetary policy factors and the diverse macroeconomic indicators under consideration.

To delve deeper into the interdependencies between macroeconomic variables, a reduced-form Vector Autoregressive (VAR) model is estimated, encompassing 2-year OIS rate, log of the EUR-USD exchange rate, log of the Euro Stoxx 50 stock index, and 2-year inflation-linked swap (ILS2Y). Employing these variables, an instrumental VAR framework is established that relies on the previously identified monetary policy factors as external instruments, aligning with relevance and exogeneity criteria. Instrumentalizing the VAR residuals, each instrument captures a specific component correlated with its respective policy surprise. These steps facilitate the disentanglement of the effects of Target, Timing, Forward Guidance, QE, and Spread factors. The estimated coefficients from this framework provide detailed insights into how each shock influences the macroeconomic indicators.

Chapter 4

Empirical Model Development and Results

Replication code from the [Altavilla et al., 2019] analysis can be found online, implemented in Julia. The empirical model presented in this and the following section is based on a translation of the Julia code into R, modified with more recent data as well as a new Save-The-Euro factor denoted as SEUR.

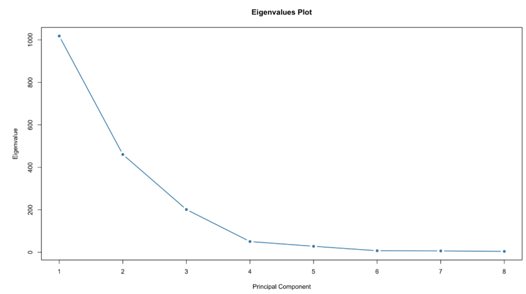
4.1 Factor model

This section details the implementation details and results of a factor model inspired by previous research and extended with a Save-The-Euro factor, estimated on the EA-MPD database including OIS rates at different maturities as well as the spread between the Italian 2 year rate and the German 2 year rate.

4.1.1 Principal Components Analysis

PCA identifies the principal components (also known as eigenvectors) of the data, which are linear combinations of the original variables, along axis of highest variance/information. Figure 4.1a shows the eigenvalues, ranked from highest to lowest, of the covariance matrix of the dataset constituted of OIS rate variations from 1 month to 10 years with the Italian-German 2 year spread from the EA-MPD database from the press release conference window. It is typically strongly decreasing, especially in the case of the OIS term structure, and explains why one often takes 1 to 3 principal components for further analysis, as they capture most of the variation of the dataset.

In the context of the factor model, the principal components obtained from the eigenvalue decomposition are used as the initial factor estimates. However, these principal components may



(a) PCA eigenvalue of the press conference window

Table 1
Test of number of factors characterizing monetary policy announcements.

	Press release window		Conference window	
	Pre-QE	Full sample	Pre-QE	Full sample
$H_0 : k = 0$	46.20 (0.001)	49.12 (0.000)	105.50 (0.000)	108.49 (0.000)
$H_0 : k = 1$	18.77 (0.174)	22.55 (0.068)	33.73 (0.002)	39.42 (0.000)
$H_0 : k = 2$			14.87 (0.062)	17.44 (0.026)
$H_0 : k = 3$				4.07 (0.254)

(b) Source: Altavilla et al. [2019]

Figure 4.1

not be directly interpretable as specific factors of interest, and their loadings on the original variables might not have a clear economic interpretation. Figure 4.1b show the result of a Wald test on the EAMPD database, which finds that 1 factor should be enough (or at least one cannot reject that it is not enough) to characterise the press release window, and 3 factors for the press conference window. This argument explains why the Target factor is identified in the press release window, while the Timing, Forward Guidance and Quantitative easing factors for the press conference window. In the following section, we decide to keep 4 factors for the press conference window, but by choosing a specific rotation, we effectively redistribute the variance from the 3 main factors into 4 factors, which includes an additional spread factor.

Figure 4.2 shows the resulting 4 most significant vectors.

4.1.2 Factor Rotation

The next step is to perform factor rotation to make the factors more understandable. Rotation involves applying an isometric transformation to the initial factor estimates to obtain new factors that have simpler and clearer structures in terms of their loadings on the original variables. The goal of rotation is to find a new set of factors that better align with specific factors of interest, such as the 'Target', 'FG', and 'QE' factors in the context of the monetary policy surprises discussed in previous research. Rotation does not change the total explained variance of the factors but only alters their loadings.

We adapt the rotation optimization problem by adding a fourth factor SEUR (Save the Euro). In addition to orthonormality constraints, as well on preventing the second (FG) and third (QE) factor from loading on the 1 month OIS rate, we add the constraint that the fourth factor (SEUR) cannot load on the 1 month OIS rate, and that the second and third factors cannot load on the IT2Y-DE2Y spread. These constraints are sufficient to ensure that the Target/Timing factor will be associated to the 1 month OIS rate, and the SEUR factor will be associated to the spread, while maintaining QE and FG mostly unchanged. Note that the same rotation is applied for both the

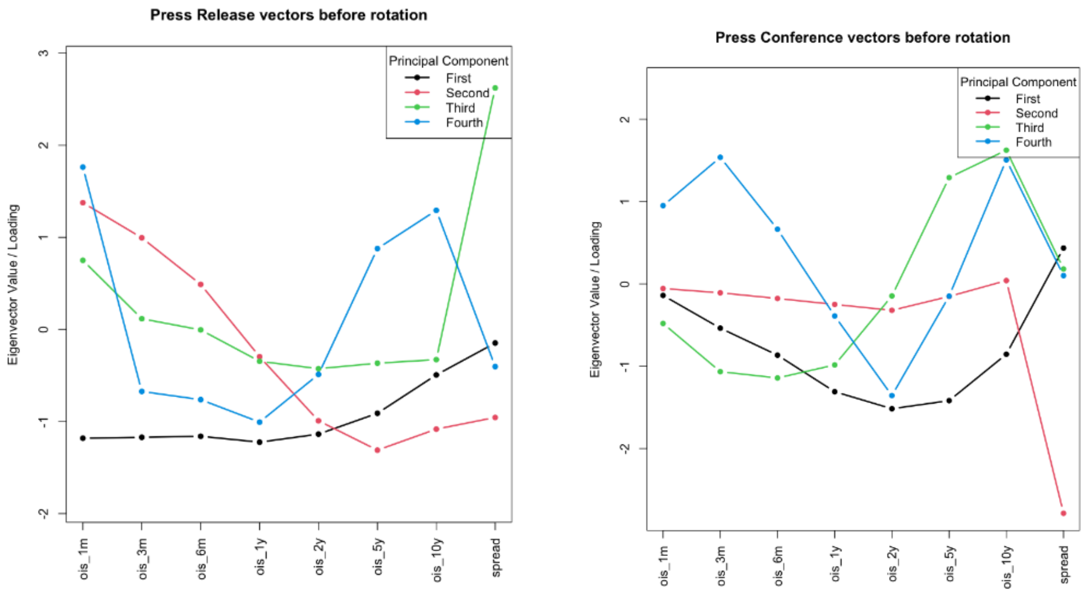


Figure 4.2: Eigenvectors corresponding to the 4 biggest eigevalues after PCA decomposition of the OIS rates and italiy-germany 2 year spread form the high frequencey database EA-MPD database `2002-01-03` to `2023-06-15`.

press release and press conference window, but only the first factor is kept in the case of the press release window. 1 Factor is uncovered for the press release window, and 4 in the press conference window:

- **Target** (Press Release Window): In the press release window, a factor labeled 'Target' is uncovered. This factor is strongly correlated with changes in short-term interest rates, specifically those at short maturities. It is associated with the surprise related to the target interest rate set by the central bank. When this factor is dominant, it indicates that changes in interest rates during this window are primarily driven by the central bank's target rate surprise.

- **Timing** (Press Conference Window): During the press conference window, four distinct factors are identified. One of these factors is labeled "Timing." This factor captures changes in the timing of future monetary policy actions. It reflects the market's perceptions of when policy changes are likely to occur. The Timing factor tends to be more correlated with very near-term interest rate changes, within the next six months, indicating that it captures shifts in expectations about imminent policy actions.

- **Forward Guidance FG** (Press Conference Window): Another factor identified in the press conference window is 'Forward Guidance'. This factor represents the central bank's communication about its future policy intentions and direction. It influences interest rates across various maturities, with a characteristic hump-shaped pattern. It suggests that changes in this factor impact expectations about policy changes over a period of about two years.

- **Quantitative Easing QE** (Press Conference Window): The analysis reveals a 'Quantitative Easing' factor in the press conference window. This factor is differentiated from Forward Guidance by having a stronger impact on interest rates as the maturity of the financial instrument increases. Quantitative Easing refers to the central bank's strategy of purchasing financial assets of longer maturity to stimulate the economy, therefore its effect on interest rates is more pronounced for longer-term maturities.

- **Save the Euro SEUR** Factor (Press Conference Window): The fourth factor identified in the press conference window is labeled as 'Save the Euro' (SEUR). Its interpretation involves the central bank's efforts to maintain the stability of the EURO currency, which can impact market perceptions and interest rates. As noted by [Wright, 2019], in normal conditions, German and Italian yields move in the same direction. However, during the debt crisis, the opposite was happening. The crisis caused investors to flee towards German bonds, lowering their yield and increasing the spread with Italian bonds, whose yields were increasing. This can be seen as a contractionary monetary policy shock. When the EU decided to bail out states in difficulty, the spread reduced. These shocks had varying effects of the EURO, as suggested by Ehrmann et al. [2014].

The structure of the factor models of the press conference and press release windows are:

$$X = F\Lambda + \epsilon \tag{4.1}$$

where F denotes the factors, Λ the base vectors and ϵ the residuals. However, the latent factors cannot be interpreted as monetary policy surprises: factors are unique up to a orthonormal transformation. This means that for every (4x4) matrix U satisfying

$$UU' = I$$

we can equivalently express X as:

$$X = \tilde{F}\tilde{\Lambda} + \tilde{\epsilon} \text{ where } \tilde{F} = FU \text{ and } \tilde{\Lambda} = U'\Lambda \tag{4.2}$$

Let F^{pre} denote the factor matrix for all the pre-crises monetary policy events. The third factor, whose expression is $F^{\text{pre}}U_3$ in the pre-crisis period, is constructed to align with Quantitative Easing, by minimizing its pre-crisis variance given by $\frac{1}{T}\sum_{t=1}^{T}(F_t^{\text{pre}}U_3)^2$, where T is the number of pre-crises (before 2008) policy events. The rotation matrix $\{u_{ij}\}$ can thus be obtained by minimizing this objective function, under the previously discussed constraints designed to align the factors with known monetary policy concepts:

$$
\begin{aligned}
U^* = \underset{\{u_{ij}\}}{\text{argmin}} \quad & \frac{1}{T}\sum_{t=1}^{T}(F_t^{\text{pre}}U_3)^2 \\
\text{subject to} \quad & (UU')_{1,1} = 1, \quad (UU')_{2,2} = 1, \quad (UU')_{3,3} = 1 \quad (UU')_{4,4} = 1 && (I) \\
& (UU')_{1,2} = 0, \quad (UU')_{1,3} = 0, \quad (UU')_{1,4} = 0 \quad (UU')_{2,3} = 0 \\
& \quad (UU')_{2,4} = 0 \quad (UU')_{3,4} = 0 && (II) \\
& U_2'\Lambda_1 = 0, \quad U_3'\Lambda_1 = 0 \quad U_4'\Lambda_1 = 0 && (III) \\
& U_2'\Lambda_8 = 0, \quad U_3'\Lambda_8 = 0 && (IV)
\end{aligned}
$$

where (I) impose normality constraints, (II) imposes orthogonality constraints, (III) imposes Factor 2,3,4 (FG, QE, SEUR) don't load on the 1 month OIS and (IV) imposes that Factor 2,3 (FG, QE) don't load on the IT2Y-DE2Y spread. We use the `solnl` function from the [Nlc] package in R to solve this problem.

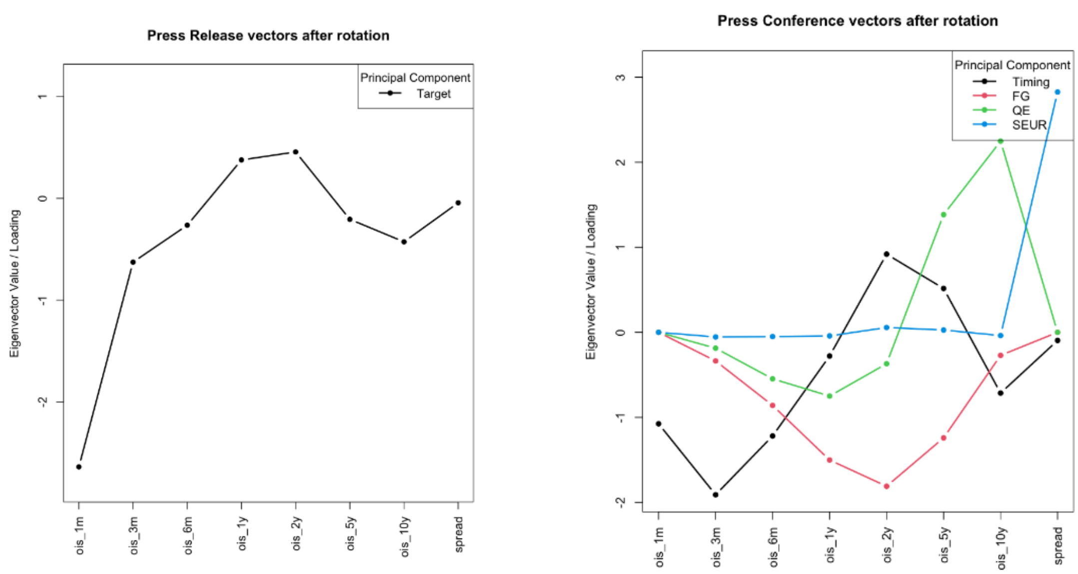


Figure 4.3: Eigenvectors after rotation

On figure 4.3, plotting the base vectors after rotations allows to develop some intuition as to what the optimization problem did to the eigenvectors of the PCA. Vector dimension coefficients should be interpreted in terms of absolute value, in terms of magnitude (postive or negative) in the different directions of the original space. First we can see that the Target vector has a large value for the 1 month OIS and smaller values for the other rates. This is very much expected behaviour as the announced short rate should influence 1 month OIS the most. In the press conference window, we can see that the base vectors for FG, QE and SEUR are 0 for the 1 month OIS, and that the

Timing, FG, QE vectors have a 0 coefficient on the IT2Y-DE2Y spread dimension. Furthermore, we can notice a large value for the 10y OIS for the FG factor, and a large value of the Italian-German 2 year spread for the SEUR factor. All in all, the vectors have a shape that aligns with what would have been expected.

4.1.3 Scaling of the factors

After rotation, the new factors can be interpreted based on their factor loadings on the original variables. The factors with high loadings on certain groups of variables might be associated with specific economic concepts or policy surprises. The factors are then named accordingly to reflect their economic meaning and interpretation. The Target, Timing, FG, QE, and SEUR factors are scaled respectively on 1 month OIS, 6 month OIS, 2Y OIS, 10Y OIS and IT2Y-DE2Y spread. Note that SEUR is scaled on (IT2Y - DE2Y) to make sure a positive variation coincides with a a positive/contractionary monetary policy shock. The identified shocks have a sign such that a positive shock corresponds to a contractionary policy or a raise of interest rates, and a negative shock to an expansive policy shock.

4.1.4 Loadings and variance shares

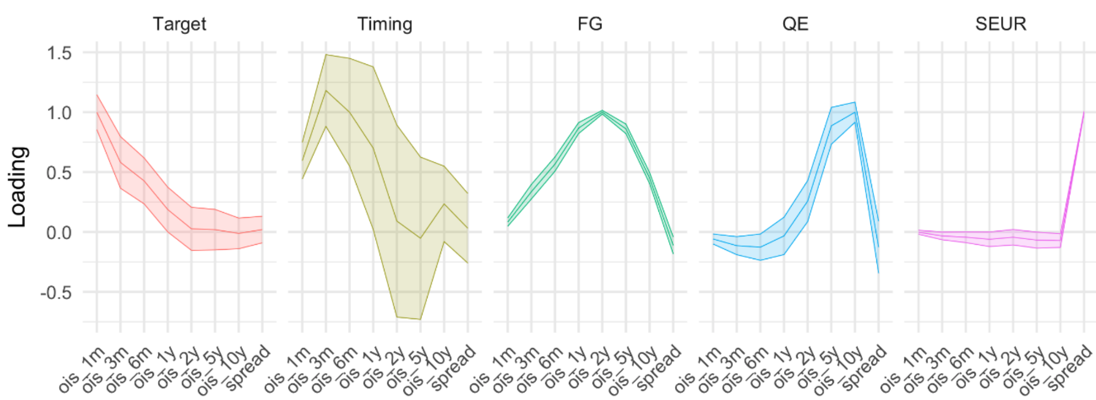


Figure 4.4: Factor loadings on the EA-MPD variables

Figure 4.4 depicts the loadings of the EA-MPD variables on the monetary policy shocks, which are obtained by individual regression of the variables on the factors. Despite the addition of the SEUR factor, the fundamental nature of the other factors/surprises remained largely unchanged, with the alterations brought about by the SEUR factor being limited.

Table 4.1 shows how the different OIS rates and the IT2Y-DE2Y account for the variance in the different monetary policy factors found. Target is mostly explained by short rates, as wel as

	Target	Timing	FG	QE	SEUR
ois_1m	0.93	0.98	0.19	0.14	0.00
ois_3m	0.86	0.45	0.68	0.18	0.02
ois_6m	0.72	0.28	0.88	0.07	0.03
ois_1y	0.32	0.19	0.95	0.01	0.03
ois_2y	0.08	0.12	0.94	0.01	0.02
ois_5y	0.01	0.07	0.84	0.14	0.04
ois_10y	0.00	0.03	0.61	0.37	0.05
spread	0.00	0.00	0.04	0.01	1.00

Table 4.1: Percentage variance explained (R^2) by the OIS rates and the DE2Y-IT2Y spread of the different monetary policy factors.

Timing. Forward Guidance is explained by the medium term OIS rates, Quantitative Easing by the long rates and the SEUR factor by the IT2Y-DE2Y spread.

4.1.5 Monetary policy shocks through time

After rotation of the principal components, one can decompose the EA-MPD dataset in terms of these factors. This estimate of each of the factors through time is depicted in Figure 4.5. The SEUR factor is mainly active between 2010 and 2015, during/after the European debt crisis. Note also how one can observe the effect of the famous "Whatever it takes" discourse on 26 July 2012 from the ECB President Mario Draghi. This caused the Save-The-Euro factor to switch from a mostly contractionary tendency (positive) to an expansive one (negative).

4.2 Estimate causality by regressing the policy surprises

Once the policy surprises are measured, we can establish causality on other macroeconomic variables through OLS. It is reasonable to identify causality in this way as monetary policy does not respond to asset price changes within the day, hence causality goes from monetary policy to asset prices. Table 4.2 and 4.3 show the result of the regression of the yields at different maturies, the stock index STOXX50, the banking index SX7E and different exchange rates in both the press release and press conference windows on the monetary policy surprises of those respective windows. The first table is for the full period, while the second table is estimated after September 2018. These values can be interpreted as the effect of monetary policy surprises - Target in the press release window, Timing, Forward Guidance, Quantitative Easing and Save-The-Euro in the press conference window - on I) yield curve and sovereign spreads II) stock and banking indices III) exchange rates.

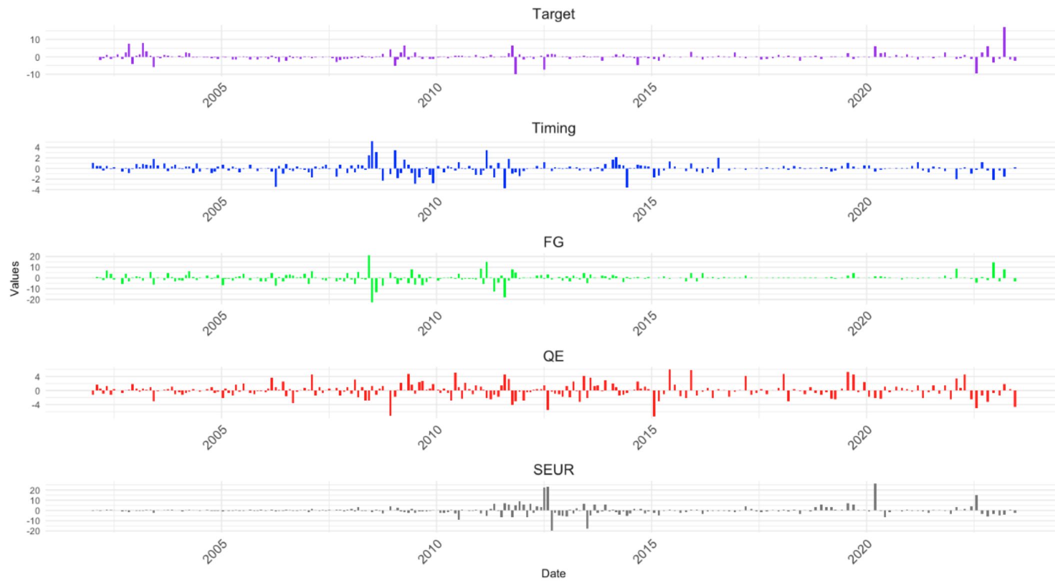


Figure 4.5: Barplot of the factors through time. Factors have been scaled to have unit effect on their respective target macroeconomic variables, which themselves are expressed in basis points.

4.2.1 Yield changes

Shocks related to the Target and Timing exert an influence on short-term OIS rates, while Forward Guidance and Quantitative Easing primarily affect longer-term rates. The high R-squared values observed in regression analyses underscore the substantial explanatory power of the different factors.

The newly found SEUR factor negatively impacts risk-free rates of all maturities. This is consistent with the theory that the EU debt crisis caused investors to flee Italian, Spanish, ... bonds for German bonds, driving up the latter's price and thus driving down the yield of risk-free rates.

4.2.2 Exchange rate changes

Target, Timing, FG and QE all have positive impact on the exchange rate, causing an appreciation. This is consistent with the theory that higher rates attract foreign investors, driving the appreciation.

The impact of the newly found SEUR factor is not as clear. The expected phenomenon of 'preserving the euro', where unexpected easing leads to the appreciation of the euro, does not demonstrate consistent observance throughout the entirety of the study period, as the coefficient found in table 4.3 are small, and in table 4.3 they are mixed. Like Ehrmann et al. [2014] we find mixed results of the SEUR factor on appreciation or depreciation of the EURO.

	Target	R^2	Timing	FG	QE	SEUR	R^2
ois_1m	1***(0.04)	0.72	0.59***(0.04)	0.08***(0.01)	-0.06**(0.02)	0**(0.01)	0.53
ois_3m	0.58***(0.06)	0.32	1.18***(0.03)	0.34***(0.01)	-0.11***(0.01)	-0.03***(0.01)	0.95
ois_6m	0.43***(0.05)	0.22	1***(0.02)	0.57***(0.01)	-0.13***(0.01)	-0.04***(0.01)	0.98
ois_1y	0.19**(0.06)	0.04	0.7***(0.03)	0.87***(0.01)	-0.03**(0.01)	-0.06***(0.01)	0.99
ois_2y	0.03(0.07)	0	0.09**(0.03)	1***(0.01)	0.26***(0.01)	-0.04***(0.01)	0.99
ois_5y	0.02(0.06)	0	-0.05(0.04)	0.86***(0.01)	0.89***(0.02)	-0.07***(0.01)	0.98
ois_10y	-0.01(0.05)	0	0.23***(0.03)	0.45***(0.01)	1***(0.02)	-0.07***(0.01)	0.97
spread	0.02(0.07)	0	0.03**(0.01)	-0.11***(0)	-0.13***(0.01)	1***(0)	1
stoxx50	-0.04***(0.01)	0.07	0.02(0.04)	-0.02(0.01)	-0.01(0.02)	-0.06***(0.01)	0.22
sx7e	-0.03*(0.02)	0.02	0.04(0.06)	-0.02(0.01)	0.09(0.03)	-0.15***(0.01)	0.37
eurusd	0.01(0.01)	0.01	0.06**(0.02)	0.05***(0.01)	0.06***(0.01)	-0.01**(0.01)	0.33
eurgbp	0.01**(0.01)	0.03	0.06***(0.02)	0.04***(0)	0.04***(0.01)	0**(0)	0.35
eurjpy	0.01(0.01)	0.01	0.08***(0.02)	0.05***(0.01)	0.08***(0.01)	-0.01**(0)	0.45

Table 4.2: Estimating causality from `2002-01-03` to `2023-06-15`. Monetary policy shocks are scaled on their respective target macroeconomic variable, while macroeconomic variables are expressed in basis points.

4.2.3 Stock changes

The newly found SEUR factor has a very clear negative impact on stocks, both on the STOXX50 and on the banking sector SX7E. This is to be explained by the instability indicated by increasing spreads, which can only have a negative impact on companies and banks working in this climate, as well as the more immediate consequence of causing investors to retreat.

The other identified monetary policy surprises (Target, Timing, FG, QE) have mixed influences on stocks, as can be seen in the full sample 4.2 and in the post-2018 sample 4.3. Results which are shared with Altavilla et al. [2019].

Delphic and Odyssean shocks

[Andrade and Ferroni, 2021] highlight the role of two factors from high frequency monetary surprises: news on future macroeconomic conditions called `Delphic shocks` or `information shocks` and news on future `monetary policy shocks` or `Odyssean shocks`. These two shocks move the yield curve in the same direction but have opposite effects on financial conditions and macroeconomic expectations. They also have a different impact on macroeconomic outcomes so that central bankers cannot infer the degree of stimulus they provide by looking at the mere reaction of the yield curve. Delphic shocks convey positive news about the market, and hence will cause yields, inflation expectation and stock prices to move in the same direction. Odyssean information shock on the other hand, will cause yields to increase, but stocks and inflation expectations to decrease, as a more

	Target	R^2	Timing	FG	QE	SEUR	R^2
ois_1m	0.91***(0.12)	0.6	0.25*(0.15)	-0.03*(0.03)	0.05*(0.04)	0*(0.01)	0.29
ois_3m	0.4**(0.18)	0.12	0.94***(0.11)	0.21***(0.02)	-0.07**(0.03)	-0.02**(0.01)	0.76
ois_6m	0.2(0.17)	0.03	1.2***(0.14)	0.64***(0.03)	-0.18***(0.04)	-0.05***(0.01)	0.94
ois_1y	-0.19(0.19)	0.03	0.99***(0.12)	0.99***(0.03)	-0.09**(0.03)	-0.09***(0.01)	0.98
ois_2y	-0.45**(0.19)	0.13	-0.22**(0.1)	0.9***(0.02)	0.37***(0.03)	-0.03***(0.01)	0.99
ois_5y	-0.45**(0.17)	0.16	-0.17(0.12)	0.75***(0.03)	0.87***(0.03)	-0.07***(0.01)	0.99
ois_10y	-0.34**(0.12)	0.18	0.37**(0.1)	0.55***(0.02)	1.01***(0.03)	-0.08***(0.01)	0.99
spread	-0.13(0.2)	0.01	0.09(0.07)	-0.08***(0.02)	-0.15***(0.02)	1.01***(0.01)	1
stoxx50	-0.02(0.02)	0.02	-0.23(0.16)	-0.13***(0.04)	0.08(0.04)	-0.06***(0.01)	0.51
sx7e	-0.02(0.04)	0	-0.58(0.38)	-0.15(0.08)	0.34(0.1)	-0.14***(0.03)	0.49
eurusd	-0.02*(0.01)	0.07	-0.03(0.11)	0.04(0.03)	0.05(0.03)	-0.02(0.01)	0.32
eurgbp	-0.01(0.01)	0.02	0.09(0.07)	0.05(0.02)	0.03(0.02)	0(0.01)	0.45
eurjpy	-0.03**(0.01)	0.13	-0.02(0.09)	0.05(0.02)	0.09***(0.02)	0(0.01)	0.6

Table 4.3: Estimating causality from `2018-01-01` to `2023-06-15`. Monetary policy shocks are scaled on their respective target macroeconomic variable, while macroeconomic variables are expressed in basis points.

traditional monetary policy shock. Evidence of both type of shocks might be an explanation for the mixed results of the effects of monetary policy shocks on stock prices. Therefore, the presence of these two types of policy can make the response of the stock market, on average, insignificant and can produce the results

Lower rates are good news (lower discount rates and higher demand) but learning that the cyclical state is worse than previously thought is bad news (lower dividends). One can see similar effects on inflation expectations; a positive policy surprise should decrease inflation compensation implied by indexed securities unless the surprise is perceived to be signalling information about high inflationary pressures, in which case inflation compensation will increase

In figure 4.6, the policy shocks are obtained by regressing the OIS2Y rate on the conference factors, in order to obtain the component shocks related to press-conference announcements. Doing this classification for the full monetary shocks yields different results. But it is clear from the figure that the ECB is maintaining a more 'Odyssean' style of conducting monetary policy since 2014, and maintained after 2018, through the pandemic and energy crisis. This transition coincides with forward guidance on future rates starting to be given by the Governing Council of the ECB during press conferences.

The Delphic-Odyssean framework provides an interesting explanation to the mixed impact of monetary shocks on stocks. However, the post-2018 coefficients referenced in table 4.3 still show mixed results of the policy shocks on stocks, with forward guidance having a negative impact, while

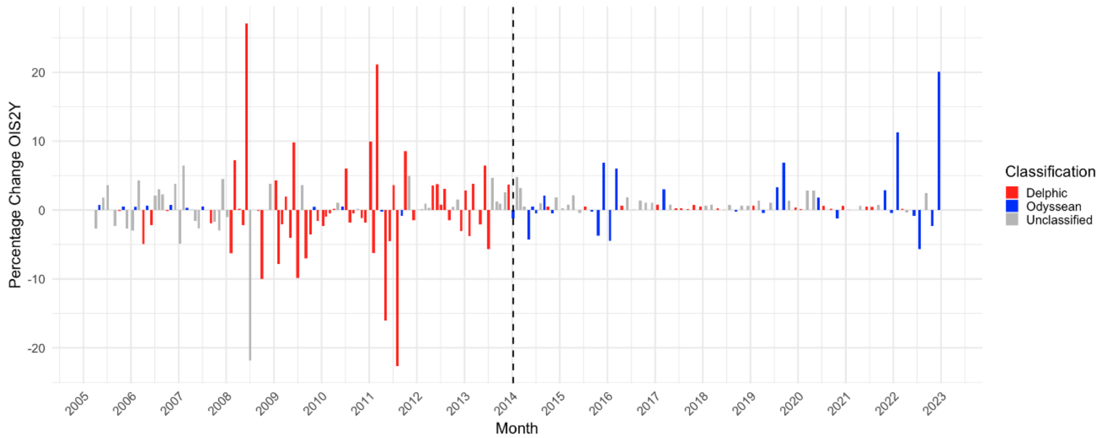


Figure 4.6: Results of the Odyssean-Delphic classification of the monetary policy shocks obtained by regressing the OIS2Y rate on the conference factors.

quantitative easing a positive one, even after the transition from mostly Delphic shocks to Odyssean shocks indicated in figure 4.6.

4.3 SVAR with external instruments

To engage in a more detailed exploration of this issue, a daily VAR framework designed by Altavilla et al. [2019] is used. This strategy draws inspiration from the notion of leveraging high-frequency monetary policy surprises to extract the variance embedded within the VAR's reduced-form residuals, variance inherently associated with monetary policy shocks. This approach, rooted in the works of Stock and Watson [2012] and Mertens and Ravn [2013], entails the use of external instruments for identification purposes. The VAR is made of the 2-year Overnight Index Swap (OIS) rate, the logarithm of the Euro Stoxx 50 stock market index, and the 2-year inflation-linked swap (ILS2Y) and the logarithm of the EUR-USD exchange rate. The instruments are assumed to be relevant and exogenous, formally expressed as $E(Z_t \varepsilon_t^m) = \alpha \neq 0$ and $E(Z_t \varepsilon_t^0) = 0$, for ε_t^m monetary policy shocks and ε_t^0 non monetary policy shocks, these criteria ensure that our chosen instruments are pertinent to monetary shocks while remaining exogenous to non-monetary shocks. In this regard, the instruments are selected as the policy surprises identified previously. These external instruments are Target (press release), Timing, Forward Guidance, Quantitative Easing factor (press conference), and notably, an additional Spread or Save the Euro factor. The methodology involves instrumentalizing the residuals of the VAR, each time focusing on a single instrument. This approach facilitates the disentanglement of the component correlated with specific policy surprises. Although the prospect of simultaneously incorporating all instruments exists, such an approach would result in the identification of a composite monetary policy shock, amalgamating the effects of the various surprises.

ILS2Y and OIS2Y are rates expressed as a percentage. EURUSD and STOXX are transformed by $100 * ln(.)$ so that their irf can be interpreted as a percentage change following:

$$100 * (ln(v_2) - ln(v_1)) \approx 100 * (v_2/v_1 - 1)$$

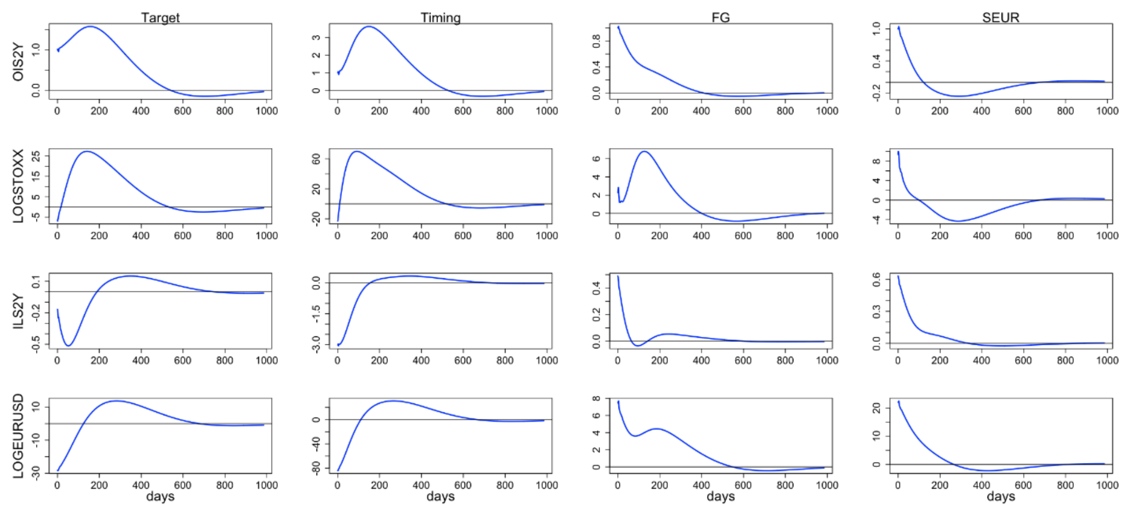


Figure 4.7: Instrumental VAR estimated from 2005-03-31 to 2008-01-03. The shock is scaled to have unit effect on OIS2Y.

Figure 4.7's results are very different from the original study. Diving deeper into their replication files, we actually see that they do this experiment from 2002 until 2008 and without the ILS2Y variable, resulting in a 3-variable VAR for a different estimation period. This, in addition to the addition of the SEUR factor explains the differing results. Forward Guidance policy shocks cause an increase in OIS, stocks, inflation expectations and appreciation of the euro. The SEUR factor appears reinforce this effect. The results are consistent with 'Delphic' shocks and findings of figure 4.6. However, Timing and Target shocks negatively impact inflation swaps, aligning more closely with what is known as 'Odyssean shocks'.

Figure 4.8 shows the impulse responses estimated from 2008 to 2014. As before, the different monetary policy shocks cause an increase in OIS, stocks, inflation expectations and the appreciation of the euro. The SEUR appears to have the same effect as the other shocks, and the results are consistent with 'Delphic' shocks and findings of figure 4.6.

Figure 4.9 shows the impulse response functions estimated from 2014 to 2018. Here, we find that this time a increase in interest rates triggers a decline in stock prices and inflation linked-swaps, consistent with a perceived revelation of negative news, and pointing to 'Odyssean' shocks. Again,

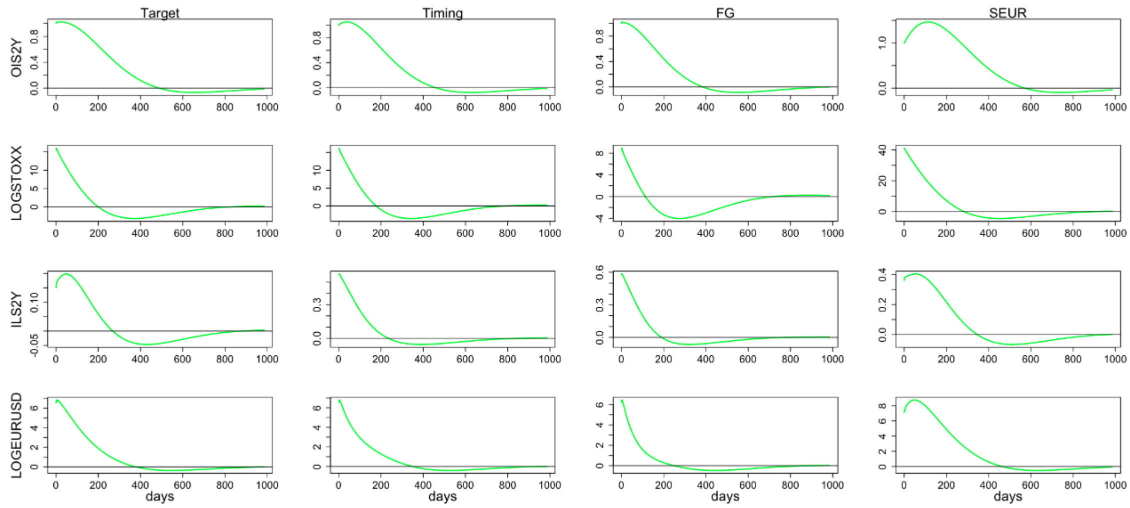


Figure 4.8: Instrumental VAR estimated from 2008-01-03 to 2014-01-01. The shock is scaled to have unit effect on OIS2Y.

consistent with figure 4.6.

Figure 4.10 shows the impulse response functions estimated from 2018 to end of 2022. The results are mixed and unclear, with many shocks having effects lasting beyond 1000 days. A hypothesis for the behaviour of this VAR model would be the relatively strong instabilities related to the pandemic and the energy crisis.

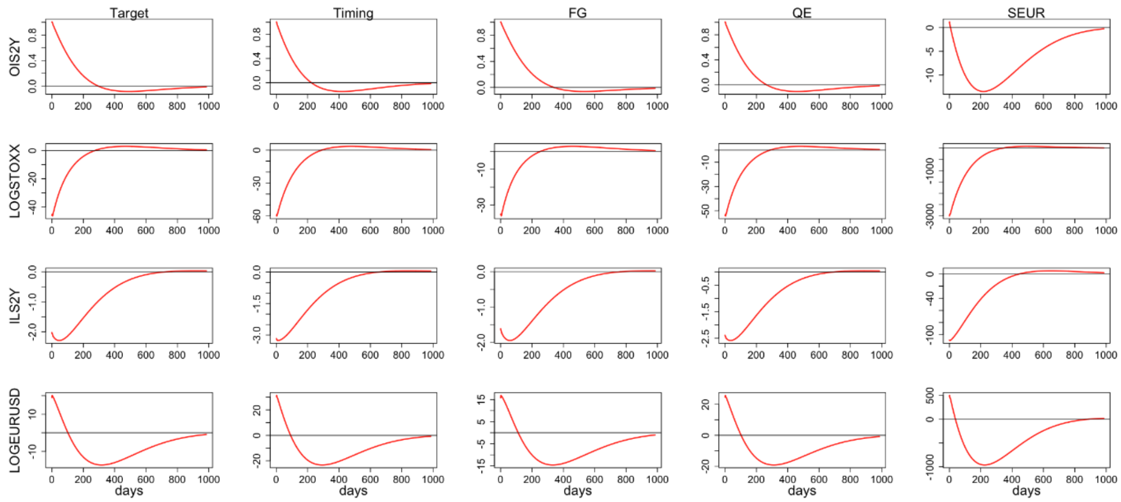


Figure 4.9: Instrumental VAR estimated from 2014-01-03 to 2018-09-13. The shock is scaled to have unit effect on OIS2Y.

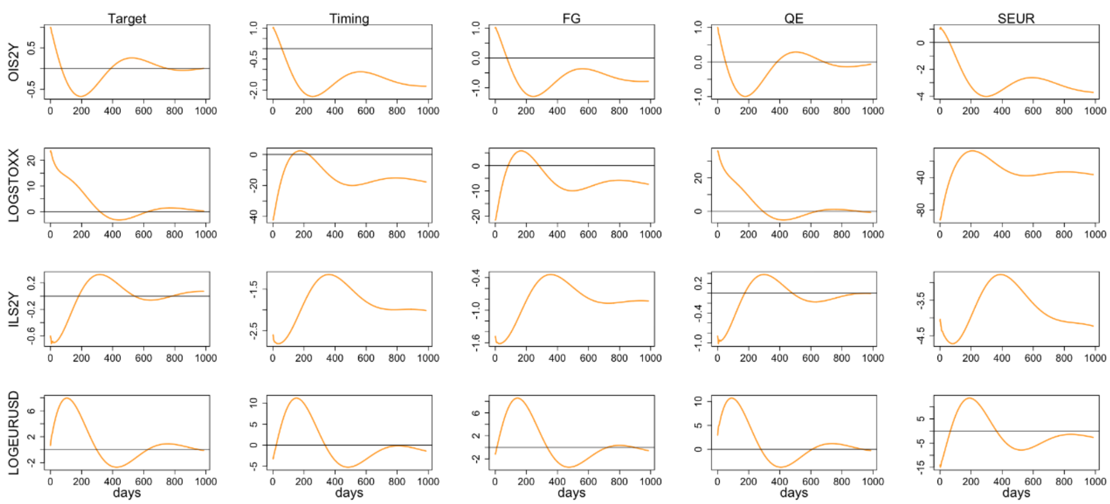


Figure 4.10: Instrumental VAR estimated from 2018-09-13 to 2022-12-30. The shock is scaled to have unit effect on OIS2Y.

Chapter 5

Further work

Several directions for future research could deepen the understanding of the intricate relationships between ECB policy decisions, market reactions, and economic outcomes. Firstly, the implementation of Natural Language Processing models could be explored to map the ECB press releases onto the Overnight Index Swap term structure. For example Parle [2022] creates different measures of monetary policy tilt, closely tracking interest rate expectations, from language processing of the press release statements. This could provide an analysis of how the communication nuances within press releases correlate with shifts in the yield curve, enhancing the comprehension of market expectations and policy transmission, but also providing a valuable tool for central banks to asses their discourse against a predictive model and anticipate the desired outcome. Furthermore, extending the analysis to a comparative examination of other major central banks' policies, such as the Federal Reserve or the Bank of Japan, could offer insights into the distinct characteristics of the ECB's approach. By identifying commonalities and disparities in the relationships between policy decisions and economic variables, this approach would enrich the understanding of the broader global monetary policy landscape.

Chapter 6

Conclusion

In conclusion, this master's thesis delved extensively into the factor analysis presented within the high frequency EA-MPD database by Altavilla and his colleagues.

The previously identified monetary policy shocks remain relevant, as demonstrated by the regression coefficients post 2018, and the Delphic-Odyssean framework confirms the further alignment of the ECB with transparent communication, pointing to 'Odyssean' monetary policy shocks. The VAR estimated for this period shows mixed results and requires further investigation. Having been estimated in unstable times could be an explanation for its behavior.

Furthermore, this study extended its investigation to assess the potential augmentation of the macroeconomic model by incorporating sovereign spreads as an additional monetary policy shock. Through examination of the factor and its relationship with economic variables, the impact is quantified and discussed. A shock to this factor negatively impacts both stocks and risk-free rates at all maturities. However, we find mixed results on exchange rates, similarly to previous research.

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