Time Varying IV-SVARs and the Effects of Monetary Policy on Financial Variables*

Robin Braun
Bank of England
robin.braun@bankofengland.co.uk

George Kapetanios
King's College, London
george.kapetanios@kcl.ac.uk

Massimiliano Marcellino
Bocconi University, IGIER and CEPR
massimiliano.marcellino@unibocconi.it

February 18, 2022

preliminary and incomplete - please do not circulate

Abstract

This paper studies shock propagation in various types of time-varying structural VARs identified with external instruments. We derive the asymptotic distributions of the relevant quantities using kernel estimators which allow for non-parametric time-variation. Our estimators are simple, computational trivial and allow to account for potentially weak instruments. We illustrate the methods studying the effects of ECB and BoE monetary policy surprises on financial variables. We document substantial evidence of time variation, suggesting that overall monetary policy has become more effective at steering financial conditions.

JEL classification: C14, C32, C53, C55

Keywords: Time-varying parameters, Non-parametric estimation, Structural VAR, External instruments, Monetary shocks, Impulse response analysis

*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of England. We thank for comments participants at seminars at the European Central Bank, Bocconi University, Bank of England, Kings College, the FriendlyFaces workshop and the CFE 2021.

1 Introduction

Instrumental Variables (IV) identification of structural VARs has become very popular (SVARs-IV). Only with respect to the impact of monetary policy, a non-exhaustive list of influential studies includes Gertler and Karadi (2015), Caldara and Herbst (2019), Lakdawala (2019), Kerssenfischer (2019), Jarocinski (2021), and Miranda-Agrippino and Ricco (2018). At the same time, underlying econometrics is also rapidly evolving. After the pioneering contributions of Mertens and Ravn (2013) and Stock and Watson (2012), methods to conduct Bayesian inference have been developed by Arias et al. (2021) and Giacomini et al. (2021); the connection to local projections and the robustness to non-invertibility has been studied by Plagborg-Møller and Wolf (2021); and inference under weak identification is covered in Olea et al. (2021). Furthermore, Paul (2020) introduced the possibility to allow for time varying parameters in a Bayesian setting.

In this paper we contribute to this literature both theoretically and empirically. From a theoretical point of view, we introduce changing parameters in SVAR-IVs, meant to capture various potential sources of parameter changes such as institutional modifications, technological developments, globalization or an evolving policy toolkit. Unlike Paul (2020), we take a non-parametric approach for the time-variation in the parameters and only impose some persistence and smoothness conditions on the pattern of parameter evolution. Formally, we extend to the SVAR-IVs the classical kernel based estimators introduced by Giraitis et al. (2014) and adapted for IV estimation by Giraitis et al. (2021). To implement our approach, we extend two popular estimators for impulse response functions in SVAR-IV's: the VAR-X estimator of Paul (2020) and the internal IV-VAR estimator suggested in Plagborg-Møller and Wolf (2021). While the first is particularly simple to implement in a time-varying framework, the second may shield against non-invertibility, that is the situation when shocks are not recoverable from contemporaneous and lagged forecast errors.

In order to conduct inference about IRFs, we proceed in two steps. First, we derive the asymptotic theory for the corresponding reduced form quantities which characterize the join dynamics of the endogenous time series and the external instrument. We then follow Olea et al. (2021) to construct confidence sets via an inversion of the Anderson-Rubin test statistic. This has the advantage that it provides robustness of the IRFs confidence set to a situation where the instrument is only weakly correlated with the shock of interest.

We apply our method to study the time varying effects of monetary policy on financial variables. To this end, we run a series of time-varying SVAR-IVs for the Euro Area and the UK, spanning daily data from 2004 to 2019. The models include interest rates at different maturities, the exchange rate, stock prices and (non-financial) corporate bond yields and spreads. The sample we consider covers important structural events which a priori, are likely to have altered the way monetary policy transmits to financial conditions. This includes reaching the Zero Lower Bound (ZLB) in the aftermath of the financial crisis, the introduction of Large Scale Asset Purchases and forward guidance, and the use of negative interest rates. Understanding how these events have impacted the effectiveness of monetary policy is important for central banks: if the change in policy mix, partly due to the ZLB, was less successfully in steering financial conditions a central bank might need to respond more aggressively to avoid it in the first place, or consider a higher inflation target. On the other hand, if policy has remained equally effective, this might be less of a concern.

In order to identify a monetary policy shock within our time-varying VAR models, we use an external instrument that builds on the monetary event study literature pioneered by Kuttner (2001) and Cochrane and Piazzesi (2002). Specifically, we use the high-frequency surprise of the 2-year OIS rate around a narrow window (30 minutes) of policy announcements as an instrument for the policy shock. Our choice of a medium term interest rate is motivated by our goal to identify the (time-varying) effects of average monetary policy. Since we do not further distinguish conventional from unconventional tools (and sub-dimensions thereof), we need to rely on a medium term interest rate that is sensitive to both, news in conventional and unconventional policies.[1]

Our findings suggest that in the Euro Area and the UK, there is considerable time-variation in the dynamic effect of monetary policy on financial variables. While monetary policy acted primarily through short-term interest rates in the past, towards the second half of the sample we document a strong responses of 2- and 10- year rates, broadly consistent with the introduction of non-standard policy tools. Furthermore, we find evidence that monetary policy has become more effective at steering financial conditions. These results are robust to applying an alternative identification scheme following Rigobon (2003) and to controlling for information shocks, that are shocks which push interest rates and stock prices into the same direction at policy announcement dates. Also, we show that results do not materially change when we further condition on simple factors that characterize unconventional policies introduced in the aftermath of the financial crisis (Swanson; 2021; Altavilla et al.; 2019).

Related Literature

Methodologically, our paper ties on seminal work of Primiceri (2005) who introduced time-varying parameter into VARs (TVP-VARs). Using a Bayesian framework, Paul (2020) further extended the TVP-VAR methodology to allow for identification of IRFs via external instruments. Our methodological approach is distinct in various aspects. First, we rely on an entirely frequentist, non-parametric approach that leverages kernel estimators. This has several practical advantages. First, it requires no parametric choice for the law of motion underlying the parameters, but instead relies on non-parametric smoothness conditions. Second, it is computationally straightforward, can handle large (e.g. daily) datasets, and is practical also if variables are included in (log) levels. Moreover, the frequentist environment allows us to use robust inference methods for IRFs valid also under weak identification by the external instrument. Finally, we also include the internal-IV estimators of Plagborg-Møller and Wolf (2021), which allows for inference robust to non-invertibility of the VAR.

[1] As we show in the Appendix, factors that characterize news for the entire term structure of risk free interest rates all load significantly on the 2 year surprise, which supports our choice.

The econometric theory underlying the kernel based estimators for TVP IV-SVARs largely builds on earlier work of Giraitis et al. (2014), Giraitis et al. (2018) and Giraitis et al. (2021). However, our paper provides additional results required to accommodate identification of VARs via external instrument. Those include new results for the asymptotic distribution of the covariance matrix estimator, and the joint distribution of neighbouring estimators, required to standardize IRFs across time.

As for our empirical analysis, we relate to the literature that studies the effect of monetary policy on financial variables exploiting an event-study approach. Since Kuttner (2001) and Cochrane and Piazzesi (2002), a large body of papers have exploited high frequency variation in interest rates and asset prices around monetary policy announcement, and studied their impact on financial markets more broadly. Compared to this literature, we focus on the time-varying effects of monetary policy, which we argue is particularly useful in the light of a sample period that spans large structural events such as the Zero Lower Bound and introduction of non-standard policy tools. Also, the use of VAR methodology allows to study the dynamic effect of monetary policy, allowing to answer questions relating to persistence of policy shocks on financial conditions.

Unlike Gürkaynak et al. (2005), Altavilla et al. (2019) and Swanson (2021) our benchmark analysis does not further disentangle conventional from unconventional policy and dimensions thereof. Instead, we let the time-varying parameter framework take care of a changing policy toolkit. Whether monetary policy has become more or less successfully in steering financial conditions can be answered using an average policy shock. Also, we show that conditioning on simple factors designed to disentangle surprises in conventional an unconventional policies is not enough to explain the time variation we document for financial conditions.

Finally, Wright (2012) uses a daily-frequency VAR model to study the dynamic effects of monetary policy on financial variables in the US. His sample exclusively focuses on the zero lower bound, and unlike our analysis, the model doesn't allow for time varying coefficients.

Also, the identification strategy relies on a heteroskedasticity, assuming that monetary policy shocks are more volatile on central bank announcement days than a set of control dates (Rigobon; 2003). We show that our benchmark results are robust to using the same identification strategy. As discussed in Rigobon and Sack (2004), identification by heteroskedasticity can be implemented via an IV regression, which we show can be perfectly accommodated within an IV-SVAR.

Outline

The paper is organized as follows. Section 2 first revisits identification of Impulse Response functions (IRFs) in IV-SVARs and then develops inference for IRFs in IV-SVARs with time varying parameters. Section 3 introduces the basic empirical application on the effects of ECB monetary policy on financial variables. Section 4 concludes.

2 Methodology

In this section, we introduce the methodology. We start revising the identification of SVAR models via external instruments. We then generalize the model towards time-varying coefficients and discuss inference of reduced form quantities via simple kernel based methods. Finally, we make use of the reduced form results to compute confidence sets of impulse response functions which is our object of interest.

2.1 Identification of Impulse Response functions via external instruments

Throughout this paper, we consider the n-variate SVAR(p) model given by:

$$y_t = \nu + \sum_{i=1}^{p} A_i y_{t-i} + B\varepsilon_t, \quad \varepsilon_t \sim (0, I_n), \tag{1}$$

where $y_t = (y_{1t}, \ldots, y_{nt})'$ is a $n \times 1$ vector of endogenous time series, ν is a $n \times 1$ vector of intercepts, and $A_i, i = 1, \ldots, p$ are $n \times n$ matrices of autoregressive coefficients. The dynamics of the system is assumed to be driven by n structural shocks ε_t, where we assume that the elements of ε_t are orthogonal and standardized to unit variance. The $n \times n$ matrix B is the contemporaneous impact matrix and reflects the immediate responses of the variables y_t to the structural shocks ε_t. For the moment, we assume that the model is stable, which implies that the SVAR(p) has a MA(∞) representation given by $y_t = \mu_y + \sum_{j=0}^{\infty} C_j(A)B\varepsilon_{t-j} = \mu_y + \sum_{j=0}^{\infty} \Theta_j \varepsilon_{t-j}$, where $\mu_y = \mathrm{E}(y_t)$ and the $n \times n$ coefficient matrices $\Theta_j = C_j(A)B$, are the structural impulse response functions (IRFs). The reduced form MA(∞) matrices $C_j(A)$ can be computed recursively from $C_j(A) = \sum_{i=1}^{j} C_{j-1}(A)A_i$ with $C_0(A) = I_n$ and $A_i = 0$ for $i > p$.

Throughout this paper, we will focus on the impulse responses to a single shock. Without loss of generality, let this shock be the first in the system ($\varepsilon_{1,t}$) and call it the *target shock*. Corresponding IRFs are given by:

$$\frac{\partial Y_{i,t+k}}{\partial \varepsilon_{1,t}} = e_i' C_k(A) B e_1. \tag{2}$$

Note that this IRF is not identified without further assumptions. The reason is that the same reduced form dynamics of the VAR forecast errors $u_t = B\varepsilon_t$ are obtained for any other structural model $\tilde{B} = BQ$ where Q is an orthogonal rotation matrix ($\{Q : Q'Q = I_n, Q' = Q\}$). To see this, note that the covariance matrix of the reduced form errors $\mathrm{E}(u_t) = \Sigma_u$ is related to the structural parameters by $\Sigma_u = BB' = BQQ'B = \tilde{B}\tilde{B}'$. Throughout this paper, we rely on an identification strategy that involves an external instrument z_t that acts as external instrument for the target shock (Stock and Watson; 2012; Mertens and Ravn; 2013).

Assumption 1 (External Instrument)**.** *Let z_t be an instrument for the first shock. The stochastic process $\{(\varepsilon_t, z_t)\}_{t=1}^{\infty}$ satisfies:*

1. *$E(z_t \varepsilon_{1t}) = \alpha \neq 0$,*
2. *$E(z_t \varepsilon_{jt}) = 0$ for $j \neq 1$.*

Let $B_{\bullet 1}$ be the first column of B. Then, under assumption 1, it holds that

$$\mathrm{E}(z_t u_t) = \Gamma = \mathrm{E}(z_t B \varepsilon_t) = \alpha B_{\bullet 1},$$

meaning that the first column of $B_{\bullet 1}$ is identified up to scale. Furthermore, if the IRF is normalized to increase the first variable by unity on impact (B_{11}), it holds that $\Gamma_{11} = \mathrm{E}(z_t u_{1,t}) =$

α, implying $B_{\bullet 1} = \Gamma/e_1'\Gamma$.[2] Therefore, under IV identification the (standardized) IRF is given by:

$$\lambda_{k,i} = e_i' C_k(A)\Gamma/e_1'\Gamma.$$

Inference for $\lambda_{k,i}$ is discussed extensively in the literature, and has been robustified in many directions (see e.g. Olea et al. (2021) for robust inference under weak identification and Jentsch and Lunsford (2021) for robust inference under heteroskedastic of unknown form).

2.2 Inference on impulse response functions under stochastic coefficients

In this paper, we conduct inference for impulse response functions when parameters of the data generating process are slowly evolving over time. Analytically, our framework is based on a SVAR model with time-varying coefficients that reads:

$$y_t = A_{1t}y_{t-1} + A_{2t}y_{t-2} + \ldots + A_{pt}y_{t-p} + B_t\varepsilon_t, \tag{3}$$

where $\mathrm{E}_t(\varepsilon_t) = 0$, $\mathrm{E}_t(\varepsilon_t\varepsilon_t') = I_n$ and $\mathrm{E}_t(u_t u_t') = \Sigma_t = B_t B_t'$. Also, let $\Gamma_t = \mathrm{E}_t(z_t u_t)$. At this point, one approach would be to impose a specific assumption about how time variation is generated, e.g. via a random walk, allowing for likelihood based inference (Paul; 2020). Instead, in this paper we follow the non-parametric approach along the lines of Giraitis et al. (2014, 2018), which assumes a bound on the degree of time variation that can be allowed for in order to conduct asymptotic inference via kernel-based estimators:

Assumption 2. *Let $\beta_t = \mathrm{vec}\left([A_{1t}, \ldots, A_{pt}]\right)$, $\sigma_t = \mathrm{vech}(\Sigma_t)$, and $\theta_t = [\beta_t', \Gamma_t', \sigma_t']'$. Then:*

$$\sup_{j \le h} ||\theta_t - \theta_{t+j}||^2 = O\left(\frac{h}{t}\right), ||\theta_t|| < \infty, \textit{ for all } t$$

Specifically, assumption 2 states that the model parameters are bounded and that changes to those parameters are restricted to be small. The rate is assumed, for simplicity, to be of the order T^{-1} but in previous work (see, eg, Giraitis et al. (2018)), a relaxation to an order given by

[2] Alternatively, one can use the additional moment condition $B_{\bullet 1}' B_{\bullet 1} = e_1 \Sigma_u e_1'$ to back out an IRF corresponding to a shock of size one standard deviation.

$T^{-\gamma}$, $0 < \gamma \leq 1$, has been shown to be feasible. Such an order is equivalent to a mild Lipschitz condition on the smoothness of the parameters and is much milder that existing conditions in the time-varying literature. Note that unlike most other existing work, it is not assumed that parameters are smooth deterministic functions of time but, instead, we place a restriction on their differences. Further, parameters can be allowed to be stochastic (see, again Giraitis et al. (2014, 2018)), at the expense of further complexity in the statement of theoretical results. For simplity we assume that parameters are a sequence of deterministic constants and that $\gamma = 1$. Under Assumption 2, Giraitis et al. (2018) show that the MA(∞) representation can be expressed as:

$$y_t = \sum_{k=0}^{\infty} C_k(A_t) B_t \varepsilon_{t-k} + o_p(1). \tag{4}$$

Equation (4) states that under assumption 2, the MA(∞) representation of the TVP-SVAR is asymptotically given by that of a fixed-coefficient model, but replacing A and B with their time-varying counterparts. Under unit standardization, the corresponding time-varying IRFs are then given by[3]:

$$\lambda_{k,i,t}^{(0)} = e_i' C_k(A_t) B_t e_1 = e_i' C_k(A_t) \Gamma_t / e_1' \Gamma_t. \tag{5}$$

In a time-varying setting, however, it can be difficult to interpret differences in (5) across time. The reason is that as soon as $B_{11,t}$ is subject to considerable time-variation, standardizing the impulse responses to increase the first variable by one unit requires the shock size to adjust over time. Therefore, we follow Paul (2020) and make use of the assumption that the relationship between the instrument and the target shock, given by $E(z_t \varepsilon_{1t}) = \alpha$, is fixed over time. In that case, all the time-variation observed in $\Gamma_t = \alpha B_t$ can be attributed to difference in the transmission mechanism (B_t). A meaningful standardization corresponding to a fixed shock size is obtained by increasing the first variable by unity at a fixed time point t_b, rather than at

[3] Alternatively, one might pursue a simulation based approach to obtain a more accurate picture as advocated in Koop et al. (1996), which is based on the exact MA(∞) representation.

each point in time. This yields the following definition of an time-varying IRF:

$$\lambda^{(1)}_{k,i,t} = e_i' C_k(A_t)\Gamma_t / e_1'\Gamma_{t_b} \tag{6}$$

2.3 Joint inference for the reduced form parameters

In order to conduct inference for $\lambda^{(0)}_{k,i,t}$ and $\lambda^{(1)}_{k,i,t}$, we proceed in two steps. We start deriving the joint asymptotic distribution of simple kernel-based estimators of the reduced form parameters A_t, Γ_t and Γ_{t_b}. In a second step, we construct confidence sets for the impulse responses that are valid regardless of proxy strength, inverting the Anderson and Rubin statistic as suggested in Olea et al. (2021).

In order to estimate A_t, Γ_t and Γ_{t_b}, we extend two popular estimation approaches using the kernel based estimators. The first relies on augmenting the VAR model with the external instrument as exogenous regressors ("VAR-X"), as pioneered by Paul (2020). This approach is fairly simple and allows to estimate all reduced form quantities in a single step. Our second approach involves augmenting the VAR model with the external instrument ("internal IV-SVAR"), as suggested in Plagborg-Møller and Wolf (2021). The resulting standardized IRF estimates are robust to non-invertibility, that is the situation when the structural shock aren't recoverable from the reduced form errors of the VAR model.[4]

The VAR-X approach relies on estimating the parameters of the following auxiliary regression model:

$$y_t = A^{\dagger}_{1t} y_{t-1} + A^{\dagger}_{2t} y_{t-2} + \ldots + A^{\dagger}_{pt} y_{t-p} + \Gamma^{\dagger}_t z_t + u^{\dagger}_t, \qquad u^{\dagger}_t \sim (0, \Sigma^{\dagger}_t).$$

As shown in Paul (2020), under the additional assumption that z_t is unpredictable by lagged values of y_t, the IRF functions of the IV-SVAR can be consistently estimated by using $\lambda^{(1)}_{k,i,t} = e_i' C_{kt}\left(\beta^{\dagger}\right)\Gamma^{\dagger}_t/(e_1'\Gamma^{\dagger}_t)$ and $\lambda^{(2)}_{k,i,t} = e_i' C_{kt}\left(\beta^{\dagger}\right)\Gamma^{\dagger}_t/(e_1'\Gamma^{\dagger}_{t_b})$. Denote by $x^{\dagger}_t = [y'_{t-1}, y'_{t-2}, \ldots, y'_{t-p}, z_t]$

[4] Specifically, once the instrument is added to the system, the augmented VAR is only non-invertibility up to the measurement error underlying the instrument. For IRFs, however, the measurement error produces the same attenuation bias which cancels out when appropriately standardized. See also Noh (2017) and Miranda-Agrippino and Ricco (2019) for more results.

and $\beta_t^\dagger = \mathrm{vec}\left(\left[\Gamma_t^\dagger, A_{1t}^\dagger, \ldots, A_{pt}^\dagger\right]\right)$. Then, we consider the kernel based estimator given by:

$$\hat{\beta}_t^\dagger = \left[I_n \otimes \sum_{j=1}^{T} w_{t,j}\left(H\right) x_j^\dagger (x_j^\dagger)'\right]^{-1} \left[\sum_{j=1}^{T} w_{t,j}\left(H\right) \mathrm{vec}(x_j^\dagger y_j')\right] \tag{7}$$

where $w_{t,j}\left(H\right) = K(|t-j|/H)$ is a Kernel function as to ensure more distant observations get discounted when forming the estimate at time t. Note that to evaluate $\lambda_{k,i,t}^{(2)}$, the estimator is also constructed at $\hat{\beta}_{t_b}^\dagger$. To study the properties of the estimator, we make the following two assumptions:

Assumption 3. $\varepsilon_t = (\varepsilon_{1t}, \cdots, \varepsilon_{mt})'$ *is an iid process such that* $E[\varepsilon_{i1}^4] < \infty$. z_t *is a stationary,* α*-mixing process with exponentially declining mixing coefficients, such that* $E[z_1^4] < \infty$. *Further,* $E[y_{i0}^4] < \infty$ *for* $i = 1, \cdots, n$.

Assumption 4. K *is a non-negative bounded function with a piecewise bounded derivative* $\dot{K}(x)$ *such that* $\int K(x)dx = 1$. *If* K *has unbounded support, we assume in addition that*

$$K(x) \leq C\exp(-cx^2), \quad |\dot{K}(x)| \leq C(1+x^2)^{-1}, \quad x \geq 0, \qquad \textit{for some } C > 0,\ c > 0. \tag{8}$$

For our empirical application, we use a Gaussian kernel $K_{j,t}(H) \propto \exp\left[-\frac{1}{2}\left(\frac{j-t}{H}\right)^2\right]$, further normalized such that $\sum_j w_{t,j} = H$. Under assumptions 2-4, we show in the Appendix that:

Theorem 1 (joint asymptotic normality of reduced form parameters (VAR-X)). *Let Assumptions 2-4 hold and* $H = o_p(T^{\frac{1}{2}})$. *Let* $\Pi_{x,t}^\dagger = plim_{T\to\infty}\frac{1}{H}\sum_{j=1}^T w_{j,t} x_j^\dagger (x_j^\dagger)'$, $\Pi_{ww,t}^\dagger = plim_{T\to\infty}\frac{1}{H}\sum_{j=1}^T w_{j,t}^2 x_j^\dagger (x_j^\dagger)'$ *and* $\Sigma_t^\dagger = E_t(u_t^\dagger u_t^{\dagger\prime})$. *Then, it holds that:*

$$\sqrt{H}\left(\hat{\beta}_t^\dagger - \beta_t^\dagger\right) \xrightarrow{d} \mathcal{N}\left(0, \Sigma_t^\dagger \otimes \left(\Pi_{x,t}^\dagger\right)^{-1} \Pi_{ww,t}^\dagger \left(\Pi_{x,t}^\dagger\right)^{-1}\right).$$

To construct standardized impulse response function $\lambda_{k,i,t}^{(2)} = e_i' C_{kt}\left(\beta^\dagger\right)\Gamma_t^\dagger/(e_1'\Gamma_{t_b}^\dagger)$, it can be useful to consider the joint asymptotic distribution of $\hat{\beta}_t^\dagger$ and $\hat{\beta}_{t_b}^\dagger$, particularly when t is close to t_b. Let $\Theta_t^\dagger = \left[\Gamma_t^\dagger, A_{1t}^\dagger, \ldots, A_{pt}^\dagger\right]$ and define as $\beta_{t,t_b}^\dagger = \mathrm{vec}([\Theta_t^{\dagger\prime}, \Theta_{t_b}^{\dagger\prime}]')$. Also, let $X^\dagger = [x_1^{\dagger\prime}, \ldots, x_T^{\dagger\prime}]'$ and $w_t(H) = [w_{t,1}(H), \ldots, w_{t,T}(H)]'$. Further, define $X_{wt} = w_t(H) \odot X^\dagger$ where $\odot$ for the pointwise multiplication, $X_{w,t,t_b}^\dagger = \mathrm{diag}(X_{wt}^\dagger, X_{wt_b}^\dagger)$ and $X_2^\dagger = \mathrm{diag}(X^\dagger, X^\dagger)$. Finally, let $I_2 = [1,1]' \otimes I_T$.

Corollary 2. *Let Assumptions 2-4 hold and* $H = o_p(T^{\frac{1}{2}})$. *Define: Let* $\Pi_{x,t,t_b} = plim_{T\to\infty}\frac{1}{H}X_{w,t,t_b}^{\dagger\prime}X_2^\dagger$ *and* $\Pi_{ww,t,t_b} = plim_{T\to\infty}\frac{1}{H}X_{w,t,t_b}^{\dagger\prime}X_{w,t,t_b}^\dagger$. *Then,*

$$\sqrt{H}\left(\hat{\beta}_{t,t_b}^\dagger - \beta_{t,t_b}^\dagger)\right) \xrightarrow{d} \mathcal{N}(0, \Sigma_t \otimes \left(\Pi_{x,t,t_b}\right)^{-1} \Pi_{ww,t,t_b} \left(\Pi_{x,t,t_b}\right)^{-1})$$

Our second estimator is based on augmenting the VAR model with the instrument (internal IV-SVAR). Define $\tilde{y}_t = [z_t, y_t']'$. Then, the auxiliary model underlying this approach reads:

$$\tilde{y}_t = \tilde{A}_{1t}\tilde{y}_{t-1} + \tilde{A}_{2t}\tilde{y}_{t-2} + \ldots + \tilde{A}_{pt}\tilde{y}_{t-p} + \tilde{u}_t, \qquad \tilde{u}_t \sim (0, \tilde{\Sigma}_t) \tag{9}$$

Let $\tilde{\beta}_t = \operatorname{vec}\left(\left[\tilde{A}_{1t}, \ldots, \tilde{A}_{pt}\right]\right)$ and $\tilde{P}_t = \operatorname{chol}(\tilde{\Sigma}_t)$ be the Cholesky decomposition such that $\tilde{P}_t\tilde{P}_t' = \tilde{\Sigma}_t$. For this model, the two standardized time varying impulse response functions are given by $\lambda^{(1)}_{k,i,t} = e_{1+i}'C_{kt}\left(\tilde{\beta}_t\right)\tilde{P}_{\bullet 1,t}/(e_2'\tilde{P}_{\bullet 1,t})$ and $\lambda^{(2)}_{k,i,t} = e_{1+i}'C_{kt}\left(\tilde{\beta}_t\right)\tilde{P}_{\bullet 1,t}/(e_2'\tilde{P}_{\bullet 1,t_b})$. Corresponding kernel-based estimators are given as follows:

$$\hat{\tilde{\beta}}_t = \left[I_{n+1} \otimes \sum_{j=1}^{T} w_{t,j}\left(H\right)\tilde{x}_j\tilde{x}_j'\right]^{-1}\left[\sum_{j=1}^{T} w_{t,j}\left(H\right)\operatorname{vec}(\tilde{x}_j y_j')\right] \tag{10}$$

$$\hat{\tilde{\Sigma}}_t = H^{-1}\sum_{j=1}^{T} w_{t,j}(H)\hat{u}_j\hat{u}_j', \tag{11}$$

where $\hat{u}_j = y_j - (I_{n+1} \otimes x_j')\hat{\tilde{\beta}}_t$. Joint asymptotic normality between the reduced form parameters are given by:

Theorem 3. *[joint asymptotic normality of reduced form parameters (internal IV-SVAR)]Let Assumption 2 hold and* $H = o_p(T^{\frac{1}{2}})$. *Let* $\tilde{\Pi}_{x,t} = plim_{T\to\infty}\frac{1}{H}\sum_{j=1}^{T} w_{j,t}\tilde{x}_j\tilde{x}_j'$, $\tilde{\Pi}_{ww,t} = plim_{T\to\infty}\frac{1}{H}\sum_{j=1}^{T} w_{j,t}^2\tilde{x}_j\tilde{x}$ $plim_{T\to\infty}\frac{1}{H}\sum_{j=1}^{T} w_{j,t}\operatorname{vec}(\tilde{u}_j\tilde{u}_j')\operatorname{vec}(\tilde{u}_j\tilde{u}_j')'$, $\tilde{\sigma}_t = \operatorname{vech}(\tilde{\Sigma}_t)$ *and* L_n *be the* $n(n+1)/2 \times n^2$ *elimination matrix such that* $\operatorname{vech}(A) = L_n\operatorname{vec}(A)$. *Then, the estimators* $\hat{\tilde{\beta}}_t$ *and* $\hat{\tilde{\sigma}}_t$ *are asymptotically independent and:*

$$\sqrt{H}\left(\hat{\tilde{\beta}}_t - \tilde{\beta}_t\right) \xrightarrow{d} \mathcal{N}\left(0, \tilde{\Sigma}_t \otimes \left(\tilde{\Pi}_{x,t}\right)^{-1}\tilde{\Pi}_{ww,t}\left(\tilde{\Pi}_{x,t}\right)^{-1}\right)$$
$$\sqrt{H}\left(\hat{\tilde{\sigma}}_t - \tilde{\sigma}_t\right) \xrightarrow{d} \mathcal{N}\left(0, L_{n+1}\tilde{\Pi}_{uu,uu,t}L_{n+1}' - \tilde{\sigma}_t\tilde{\sigma}_t'\right)$$

Note that under an additional normality assumption of the errors, the asymptotic variance of $\hat{\tilde{\sigma}}_t$ further reduces to $2D_{n+1}^{+}\left(\Sigma_t \otimes \tilde{\Pi}_{uu,t}\right)D_{n+1}^{+'}$, where $\tilde{\Pi}_{uu,t} = \operatorname{plim}_{T\to\infty}\frac{1}{H}\sum_{j=1}^{T} w_{j,t}^2\tilde{u}_j\tilde{u}_j'$ and $D_{n+1}^{+} = (D_{n+1}'D_{n+1})^{-1}D_{n+1}'$ for D_{n+1} the duplication matrix such that $\operatorname{vec}(\tilde{\Sigma}_t) = D_{n+1}\operatorname{vech}(\Sigma_t)$.

Corollary 4. *To be added*

2.4 Inference for impulse response functions

Based on asymptotic results of the reduced form statistics, the Delta Method can be used to construct confidence sets for the estimates of structural impulse response functions: $\hat{\lambda}^{(1)}_{k,i,t} =$

$e_i' C_{kt}\left(\hat{\beta}^{\dagger}\right)\hat{\Gamma}_t^{\dagger}/(e_1'\hat{\Gamma}_t^{\dagger})$, $\hat{\lambda}_{k,i,t}^{(1)} = e_{1+i}' C_{kt}\left(\hat{\tilde{\beta}}_t\right)\hat{\tilde{P}}_{\bullet 1,t}/(e_2'\hat{\tilde{P}}_{\bullet 1,t})$, or if desired, the corresponding IRFs standardized by $e_1'\hat{\Gamma}_{t_b}^{\dagger}$ and $e_2'\hat{\tilde{P}}_{\bullet 1,t_b}$ (Lütkepohl; 1990). However, as noted in Olea, Stock and Watson (2021) (OSW henceforth), the Delta method performs poorly if the instrument is just weakly correlated with the first VAR reduced form error, that is if the variance of the estimate in the denominator is large. Therefore, we follow OSW and instead construct the IRFs based on inverting the Anderson Rubin (AR) test statistic which remains valid even if $\alpha \to 0$. To construct the AR confidence set, note for (TVP) IV-SVARs, IRFs can generally be constructed by ratios of:

$$H = \begin{pmatrix} e_i' C_k(\beta_t)\Gamma_t \\ e_1'\Gamma_t \end{pmatrix}, \text{ or } \qquad H = \begin{pmatrix} e_i' C_k(\beta_t)\Gamma_t \\ e_1'\Gamma_{t_b} \end{pmatrix},$$

that is $\lambda_{k,i,t} = H_1/H_2$. To derive the AR confidence set, first note that an application of the Delta Method implies that $\sqrt{H}\left(\hat{H} - H\right) \xrightarrow{d} \mathcal{N}(0,\Omega)$ where Ω depends on the covariance matrix of $\hat{\beta}_t$ or $\hat{\beta}_{t,r_b}$ and the gradient of the IRFs with respect to those parameters. Then, note that the null hypothesis $\hat{\lambda}_{k,i,t} = \lambda_0$ implies $H_1 - \lambda_0 H_2 = 0$, a linear restriction on H. Following OSW, a Wald Test statistic can be set up as $q(\lambda_0) = \frac{H(\hat{H}_1 - \lambda_0\hat{H}_2)^2}{\hat{\omega}_{11} - 2\lambda_0\hat{\omega}_{12} + \lambda_0^2\hat{\omega}_{22}}$. Further inversion yields the AR confidence set of coverage $1-a$ given by $\text{CS}^{AR}\{\lambda_{k,i,t} | q(\lambda_{k,i,t}) \leq \chi^2_{1,1-a}\}$. The inequality $q(\lambda_{k,i,t}) \leq \chi^2_{1,1-a}$ is quadratic in $\lambda_{k,i,t}$ and can be solved in closed form. A few properties are worth mentioning at this point. First, even in an weak instrument case where $\alpha_H = a/\sqrt{H}$ for some fixed a, the AR CS remains valid. Second, the CS may be infinite, but is guaranteed to be finite whenever a Wald test for $e_1'\Gamma_t = 0$ can be rejected at the $1-a$ confidence level. Third, in the strong instrument case, OSW proof that the AR confidence set converges to Delta Method implied confidence intervals. This implies that there is little risk of buying robustness towards weak identification with reduced accuracy or increased expected length.

Note that whenever we standardize by $e_1'\Gamma_{t_b}$, it becomes natural to choose a region of the sample where the instrument is a strong predictor of the first reduced form error. This shields against the issue of weak identification when doing inference.

3 The effects of monetary policy on financial variables in the Euro Area and UK

In the following, we will apply the methodology to study the time varying effect of monetary policy on financial variables in the Euro Area (EA) and United Kingdom (UK).

3.1 Data and identification strategy

Our analysis will be based on VAR models that include a series of key interest rate and financial variables. Specifically, for the Euro Area, we include the 3 month OIS rate, the 2 year OIS rate, the 10 year German government bond yield, the bilateral exchange rate to the dollar ($/eur), the STOXX50 stock price index and corporate bond yields and spreads sourced from Bofa Merrill Lynch.[5] For the UK, we use the 3m OIS rate, the 2- and 10 year Gilt rate, the BoE effective exchange rate index, the FTSE100 stock price index and similar corporate bond yield and spreads for sterling denominated debt.[6] We include interest rates and spreads in levels, while stock prices and the exchange rate are included in 100 times log levels. For both VAR models, we use data from January 2004 until December 2019, which sums up to more than 4000 observations. To model sufficient dynamics across the daily time series, we include a total of $p = 20$ lags, which corresponds to 4 weeks of information in a 5-day business week. Also, in our baseline we set the bandwidth to $H = T^{0.7}$, in line with Kapetanios et al. (2019).

To identify monetary policy shocks in our VARs, we will follow a high frequency identification approach (Gertler and Karadi; 2015; Altavilla et al.; 2019; Swanson; 2021). Specifically, we use the surprise in the 2 year intra day yield around a narrow window (30 minutes) of central bank monetary policy announcements. The idea behind using theses as external instruments is that variation in a narrow window of those announcements are likely to be exogenous. Systematic reactions of the central should be priced-in just before the announcement, and the

[5]The yield is based on tracking the performance of non-investment grade corporate debt (rated lower than BBB3) denominated in euros and publicly issued in the major domestic and international markets. Spreads are option-adjusted over government rates.

[6]Similar to the Euro Area, we use yield and spreads from Merrill Lynch tracking the performance of sterling denominated, non-investment grade corporate debt.

tight intra-day window ensures that most of the variation is not substantially driven by other macroeconomic news. For the ECB, we obtain the series from the Euro Area Monetary Policy Event-Study Database (Altavilla et al.; 2019), and choose to include press release and press conferences. For the UK, we compute those surprises based on MPC decision announcements and the publication of Monetary Policy Reports (previously Inflation Reports).

Our choice for the two year rate is motivated by the fact that we aim to identify an *average* monetary policy shock. In the light of a changing policy mix during our sample, the two year rate is likely to be affected by both conventional an unconventional policies.[7] As we document, it becomes evident that part of the time variation we find in the data is likely to come from a evolving policy mix over time. The extent to which this is the case will be further investigated in section 3.5.

Figure 1 provides a plot of the two external instrument series. For the ECB surprises, there are a total of 173 events inducing an average of 5 basis points variation per announcement. Large surprises occur even during period of the Zero Lower Bound, e.g. on the 3rd of December 2015 when Markets expected a stimulus package that did not materialize. In case of the UK, there are a total of 224 surprises over the sample period, with an average of 4bp variation. Volatility of the surprises seems fairly stable over time, confirming that the IV should be capturing variation from both conventional and unconventional monetary policy.

In order to facilitate comparison of impulse response functions over time, we follow Paul (2020) and assume that the correlation between instrument and structural shock is constant. As discussed in section 2.4, this allows to study IRFs of a constant shock size over time. To operationalize the approach, it requires setting a certain variation in the instrument that is constant over time. Following the definition of the corresponding IRF, $\lambda^{(1)}_{k,i,t} = e_i' C_k(A_t)\Gamma_t / e_1'\Gamma_{t_b}$, this boils down to setting the date t_b, for which the variation is fixed such that the first variable (2 year rate) is increased by one unit. To guide our choice, we note that good candidates for t_b

[7]Formal analysis conducted for the Euro Area (Altavilla et al.; 2019) and the US (Swanson; 2021) confirms this intuition. Specifically, economically meaningful factors underlying the panel of interest rates surprise all load significantly on the 2 year rate.

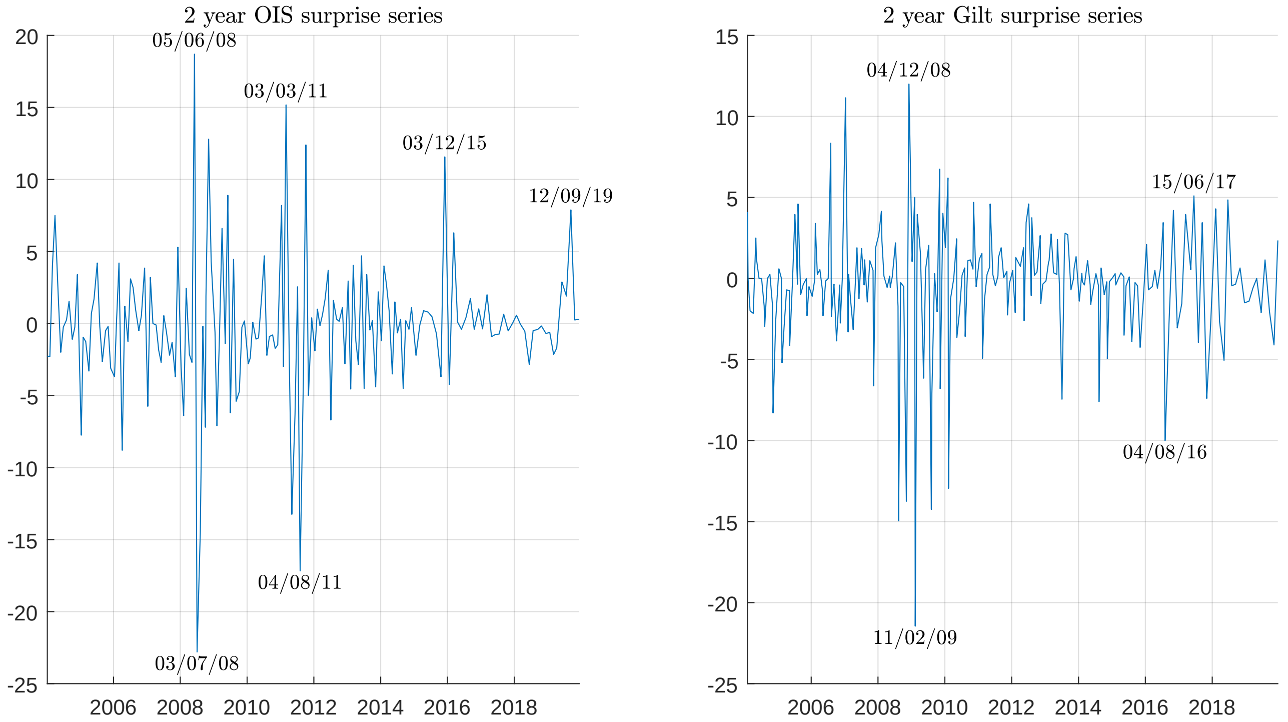

Figure 1: 2 year interest rate surprise series used as external instrument for average monetary policy conducted by the European Central Bank (left) and Bank of England (right).

are locations where the IV is a strong predictor of the first variable, given that otherwise the variance of the IRF might blow up. Table 1 provides Wald test statistics for the null hypothesis that the surprise series do not predict the 2 year rate near date t, that is $H_0 : e_1'\Gamma_t = 0$. For comparability, note that the 5% Critical Value required to reject the null hypothesis is 3.84. For the table, we recomputed the statistic for an equally spaced grid of 10 dates, and further distinguish between the two estimators (VAR-X and internal IV-VAR). Our results suggest that overall, both instruments are strong predictors of daily forecast errors in the corresponding 2 year interest rates, throughout the sample for and within both estimators.[8] For the EA, the largest Wald statistics are observed between 2013 and 2015, while for the UK around 2006. To maintain comparability, we set $t_b = 01/05/2006$ for the EEA and UK, where test statistics are above 50 for both estimators. Furthermore, we pre-multiply the IRFs by -0.05, effectively standardizing the monetary policy shock size to yield a 5bp point cut in May 2006. This corresponds to a shock size of about 1 standard deviation observed in the intraday surprise

[8]For the Euro Area, higher Wald test statistics are documented in general, which is not surprising given that for the UK we rely on government bond yields (Gilts) as opposed to OIS, which are thought to be cleaner measures of expectations about monetary policy.

series.

Table 1: Wald test statistics measuring local instrument strength

	11/04	05/06	11/07	05/09	11/10	05/12	11/13	05/15	11/16	05/18
UK (VAR-X)	24	52.1	41.7	23.7	18.3	11.4	19.9	29.7	30	30.8
UK (Internal IV-VAR)	23.6	53.6	37.8	22.3	15	11.1	21.3	28.5	32.6	31.6
Euro Area (VAR-X)	22.3	89.6	109	142.8	181.5	231.1	303.5	278.7	264.8	196.3
Euro Area (Internal IV-VAR)	22.2	84	118	148.4	184.7	234.9	282.6	287.3	237.5	170.3

The table reports Wald Test statistics $\xi_{1t} = H\hat{\Gamma}^2_{H,1t}/\hat{W}_{\Gamma_t,11}$ to test the null hypothesis that the instrument does not predict the 2 year rate at time t ($\Gamma_{1t} = 0$). Here, $\sqrt{H}(\hat{\Gamma}_{H,1t} - \Gamma_{1t}) \xrightarrow{d} N(0, W_{\Gamma_t,11})$. The corresponding 5% χ^2_1 critical value is given by 3.84.

3.2 Main Results

In the following, we discuss our main empirical results: time varying impulse response functions to an expansionary policy shock. For ease of exposition, we focus on estimates obtained under the VAR-X estimator. Results of the internal IV VAR estimator are broadly comparable, so we refer readers interested in the corresponding figures to Appendix X. Note that to visualize time variation in a digestible way, we choose to plot IRFs at three fixed horizons, that is on impact, after 1 week and after 3 weeks.

Our estimates for the Euro Area are given in Figure 2. With respect to the impact of monetary policy on interest rates, we can document a significant change in the pattern of transmission. Two key developments stand out. First, compared to the earlier sample, monetary policy nowadays transmits more through long term rates. While in the early part of the sample, the 10 year rate barely responded (around 1.5bps), the peak response recorded in 2016 stands at 5 times the initial ($8bp$). Most of the variation in the effects occur between 2010 and 2016, which corresponds to the period where the ECB introduced unconventional monetary policies including Forward Guidance (July 2013), Negative Interest Rates (June 2014) and Asset Purchase Programmes (January 2015). Second, towards the middle of the sample, both the 3 month OIS and (to a lesser extend) the 2 Year OIS rate show strong dynamic effects reinforcing the initial response. During that periods, the effect after 3 weeks can be 50% larger than on impact. Responses of financial variables also exhibit strong time variation. The bilat-

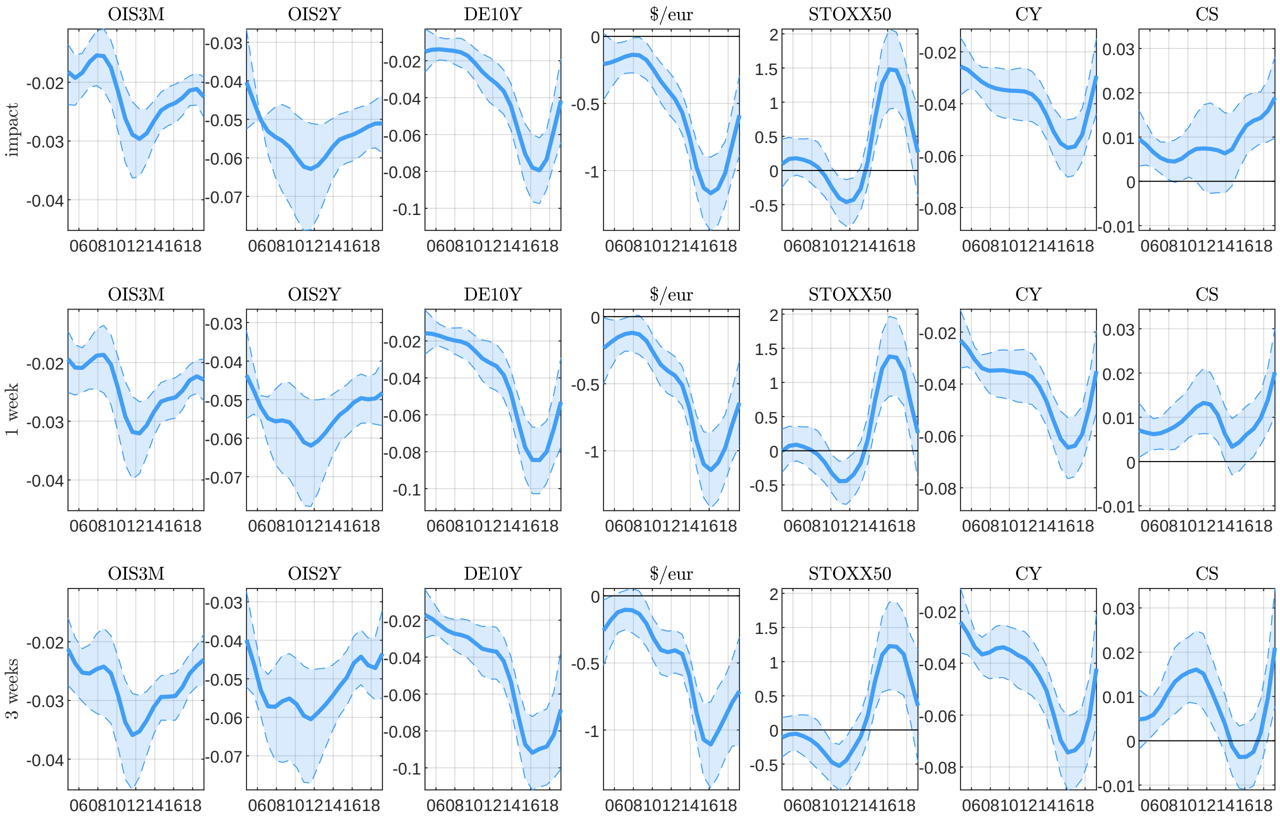

Figure 2: Euro Area: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in May 2006. Shaded areas give 90% confidence intervals.

eral exchange rate to USD depreciates throughout as predicted by economic theory, and time variation resembles that of the 10 year rate. A peak effect of more than 1 percent depreciation is documented around 2016, while in the early dates of our sample the exchange rate responded only minimally. The response of stock prices, measured by the STOXX50, is insignificant towards the beginning of the sample, while between 2014-2018, we can document a significant increase of about 1%. Somewhat counter-intuitive, estimates are significantly negative in the mid of our sample (between 2010 and 2014). This points towards the presence of information effects that dominate the stock price response around that time. Such effects can arise since central bank announcements reveal information not just about policy but also the economic outlook. Information about the latter can push interest rates and stock prices into the same direction (Jarocinski; 2021). Corporate financing conditions, measured by bond yields, broadly ease in line with expansionary monetary policy. Similar to the other financial variables, we find that the effect on yields has increased over time, with a peak effect around 2016. However, our estimates suggest that this effect has reverted towards the last years of the sample. Finally, Corporate spreads are found to increase, meaning that the decline in corporate bonds yields is slightly lower than that of government debt of the same maturities (see also Swanson (2021) for similar results). The evidence on time variation in spreads is less clear cut.

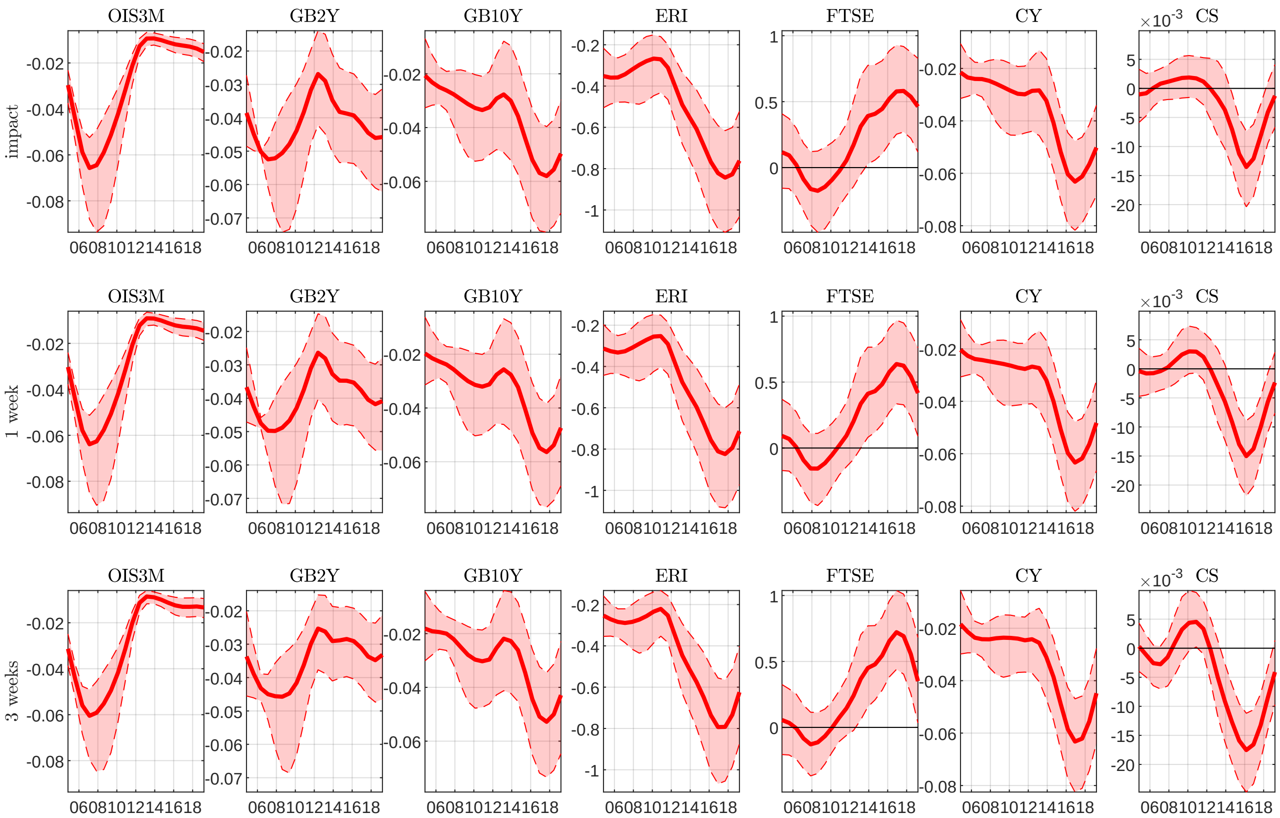

Figure 3: United Kingdom: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y Gilt rate by 5bp in May 2006. Shaded areas give 90% confidence intervals.

As for the UK, corresponding estimates are given in Figure 3. Broadly, size and time-variation in the impulse response functions is remarkably similar to the experience in the Euro Area. Policy transmits considerably less via short-term interest rates, and via 10 Year gilt rates. Little time-variation can be documented for the IRFs of 2 Year Gilt rates. Again, the timing of this shift roughly aligns with the BoE reaching near-zero interest rates (March 2009), and the introduction of unconventional monetary policies such as Forward Guidance (August 2013) and QE (March 2009). Note that the BoE did not introduce negative rates, which might explain why the IRF of the three year OIS rate remains near zero in the second half of the sample. The asset price response is qualitatively similar to what we document for the EA. The exchange rate index suggests a depreciation, and the magnitude of the depreciation doubles over time. A similar pattern is observed for the FTSE stock price index, suggesting an increase of up to 1% towards the end of the sample, while at the beginning the response is not significant. Unlike the EA, there is no evidence of central bank information effects dominating the stock price response at any time, since the IRFs are either insignificant or positive. The response of corporate bond yields also point towards stronger effects of monetary policy on corporate financing conditions, increasing from 2bp to between 6bp and 8bp depending on impulse response horizon. Unlike for the EA, the response of credit spreads declines over time reaching negative territory in the second half of the sample. This might be explained by the fact that QE by the Bank of England explicitly included purchases of sterling investment grade bonds, issued by private non-financial companies.[9]

3.3 Identification via heteroskedasticity

Our main empirical results are based on instruments constructed using intra-daily data. Here, a small 30 minute window around the policy announcement is used to measure the unexpected news in policy, minimizing the risk of contamination by other shocks. However, it is not completely unreasonable to think that part of the variation in z_t is driven by economic news unrelated to monetary policy, that is $z_t = \varepsilon_{1,t} + \sum_{j \neq 1} \varepsilon_{j,t} + \eta_t$, where $\varepsilon_{1,t}$ is the monetary policy shock and the $\varepsilon_{j,t}$ are other economic news. To assess the robustness of our results, we re-estimate the time-varying impulse response functions using an alternative identification strategy that allows for the presence of contaminating shocks. Following Rigobon and Sack (2004), Nakamura and Steinsson (2018) and Wright (2012), we make an assumption that on central bank announcement days, the variance of the monetary policy shock is considerably larger than on a set of chosen control dates. At the same time, the difference in variance of

[9] Specifically, this includes £10 billion bought in 2016–17, and a further £10 billion in 2020.

other structural shocks is assumed to negligible across those set of days. Note that this doesn't rule out that the conditional variance of other structural shocks varies over time, as long as the mean variance remains comparable on announcement and control days.

Formally, let us denote the monetary policy announcement days by $\mathcal{T}_1 = \{t_{a_1}, \ldots, t_{a_M}\}$, of which there are $T_1 < T$ in our sample, and denote control dates by $\mathcal{T}_2 = \{t_{a_2}, \ldots, t_{a_J}\}$ where $T_2 \leq (T - T_1)$. The covariance matrix of the reduced form errors is given by $E_(u_t u_t') = \Sigma_1, t \in \mathcal{T}_1$ at the announcement dates, and by $E_(u_t u_t') = \Sigma_2, t \in \mathcal{T}_2$ at control dates. We assume that the variance of monetary policy shock at announcement dates, $\mathrm{E}(\varepsilon_{1t}^2) = \sigma_1^2$, is much larger than on the control dates $\mathrm{E}(\varepsilon_{1t}^2) = \sigma_2^2$, that is $\sigma_1^2 > \sigma_2^2$. The variance of the other shocks remains constant, and for simplicity, is standardized to unity. Denote by b_i the ith column of the structural impact matrix B, then it holds that $\Sigma_1 = \sigma_1^2 b_1 b_1' + \sum_{i=2}^n b_i b_i'$ and $\Sigma_2 = \sigma_2^2 b_1 b_1' + \sum_{i=2}^n b_i b_i'$. Hence, the difference in the covariance matrices is given by $\Sigma_1 - \Sigma_2 = (\sigma_1^2 - \sigma_2^2) b_1 b_1'$, identifying the structural parameters of interest.

To implement the identification strategy in our IV-SVAR, we make use of the fact that identification can be thought of as an instrumental variables regression (Rigobon and Sack; 2004). Specifically, let $\hat{u}_t^{2y}$ be daily forecast errors in the 2 year interest rate. Then, the contemporaneous impact matrix can be consistently estimated using the following instrument:

$$z_t = \left(\mathbf{1}(t \in \mathcal{T}_1) \frac{T}{T_1} - \mathbf{1}(t \in \mathcal{T}_2) \frac{T}{T_2} \right) \hat{u}_t^{2y}.$$

In Appendix 3, we show that under the assumptions above, the instrument is relevant and exogenous, specifically $\mathrm{E}[z_t \varepsilon_{1t}] = b_{11}^2(\sigma_1^2 - \sigma_2^2) = \alpha$ and $\mathrm{E}[z_t \varepsilon_{jt}] = 0, j \neq 1$. We also discuss more conditions general assumption under which the identification holds when the reduced form error variance is time varying. Even when this is the case, α does not vary over time provided the difference in volatilities remains constant over time, that is $(\sigma_{1t}^2 - \sigma_{2t}^2) = c$. To maintain comparability to our previous results, we assume this to hold in the following. This allows us to use the same shock size over time: an expansionary shock that cuts the 2Y OIS rate by $5bp$ in May 2006.

Figure 4 and 5 show the estimated impulse response functions for the Euro Area and UK respectively. For the Euro Area, the results are very similar, and point estimates almost coincide. Hence, we conclude that our results are robust in a sense that they arise under two different identification strategies. For the UK, some differences arise, and point estimates of our benchmark identification approach (black) are outside of the 90% confidence set of the heteroskedasticity based model in several occasions. However, it is fair to say that broadly, our the conclusions hold. Monetary policy conducted in the UK seems to act less via short term interest rates, but has become more effective at steering exchange rates, asset prices and corporate bond yields.

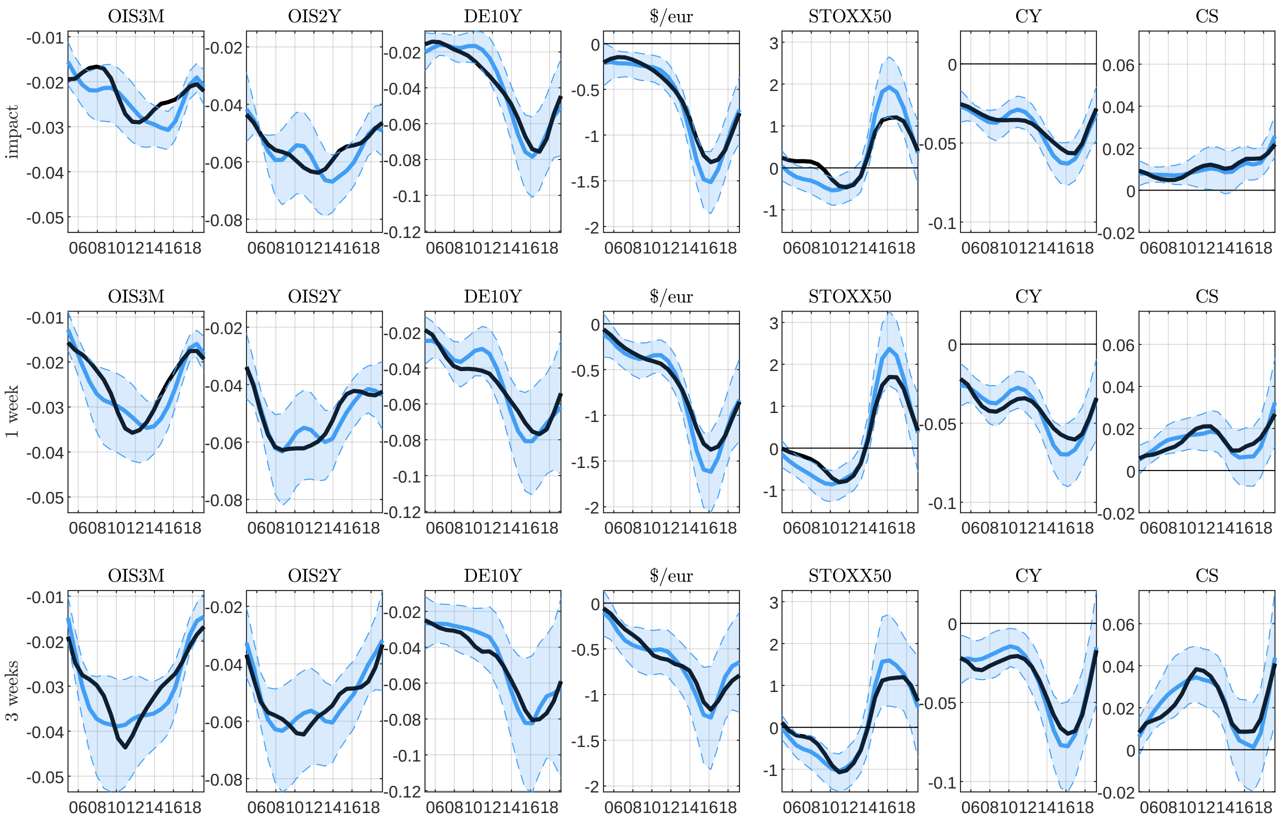

Figure 4: Euro Area: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in May 2006. Identification is obtained via Heteroskedasticity. Shaded areas give 90% confidence intervals. For comparison, point estimates under the high frequency IV are drawn in black.

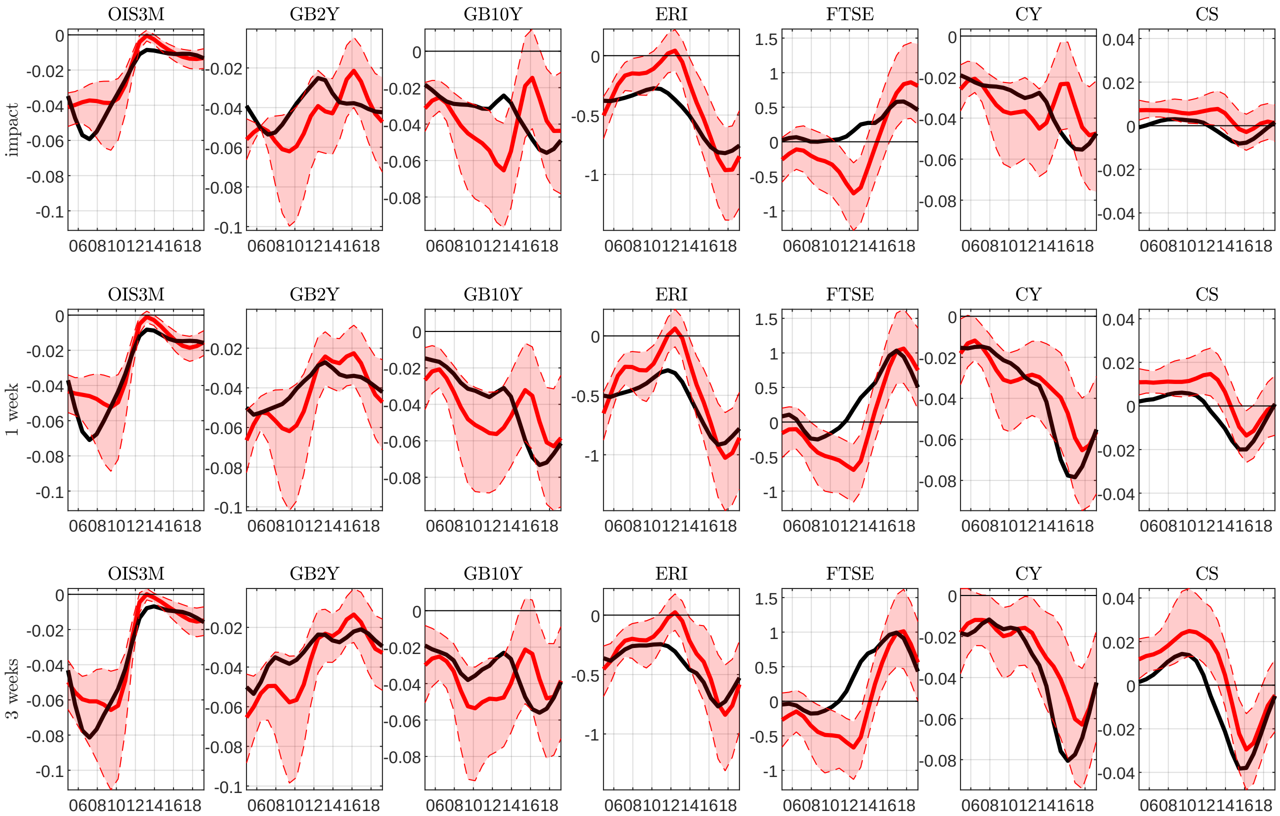

Figure 5: United Kingdom: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in May 2006. Identification is obtained via Heteroskedasticity. Shaded areas give 90% confidence intervals. For comparison, point estimates under the high frequency IV are drawn in black.

3.4 The role of information effects

The stock price response in the Euro Area suggests that some of the results may not reflect response to genuine monetary policy surprises, but instead information effects (Jarocinski; 2021; Miranda-Agrippino and Ricco; 2021). This information channel is a channel of policy announcements that may arise if the central bank is believed to possess superior information about the economic outlook. In that case, the high frequency surprise can reflect a mix of two shocks: a genuine policy shock, that is an unexpected deviation from the monetary policy rule or an information shock, which captures the endogenous component of policy to news in expected fundamentals.

To construct an instrument that is robust to such information frictions, we follow Jarocinski (2021) and Kerssenfischer (2019) in exploiting the high frequency surprise of stock prices to construct an instrument that is robust to such information frictions. Specifically, for the Euro Area we separate policy from information shocks via a simple sign-restricted model:

$$\begin{pmatrix} \Delta\text{OIS2Y}_t \\ \Delta\text{STOXX50}_t \end{pmatrix} = \begin{pmatrix} + & + \\ - & + \end{pmatrix} \begin{pmatrix} \varepsilon_t^p \\ \varepsilon_t^i \end{pmatrix}$$

where ΔOIS2Y_t and $\Delta\text{STOXX50}_t$ are the high frequency surprises in the two year OIS rate and the STOXX50 index respectively. For the UK, the model is based on surprises in the 2 year Gilt and FTSE index. Effectively, the model assumes that genuine monetary policy shocks induce a negative co-movement between interest rates and stock prices, while information shocks are assumed to push them into the same direction. Following Kerssenfischer (2019), we use the median target model of Fry and Pagan (2011) to define the informational robust instrument as $z_t^{policy} = \hat{\varepsilon}_t^p$. Note that for the EA, the policy shock explains about 57% of the variation in the interest rate surprise, while for the UK the number stands at a substantially larger value of 70%. In line with our previous findings, this suggests a smaller role of information effects in the UK.

In Figure 6 we provide estimated impulse response functions for the Euro Area, obtained using the informationally robust series z_t^{policy} as instrumental variable. To facilitate comparison, we also draw in point estimates from our benchmark instrument. Broadly, we document significant difference in the estimates once information shocks are purged out of the high frequency surprise series. Short (3m) and medium term (2Y) rates are less sensitive to monetary policy in recent periods, while at the same time, the increase in effects through the 10 Year rate is less pronounced and only significant on impact. The documented time-variation pattern in the IRFs for exchange rates and stock prices are robust to excluding information shocks. Importantly, the impact response of a monetary policy easing is now positive throughout the sample, suggesting that information shocks play no role throughout the sample. Corporate bond yields are estimated to decline, and little evidence remains for time variation. In turn, the response of corporate bond spreads declines over time and becomes insignificant, suggesting

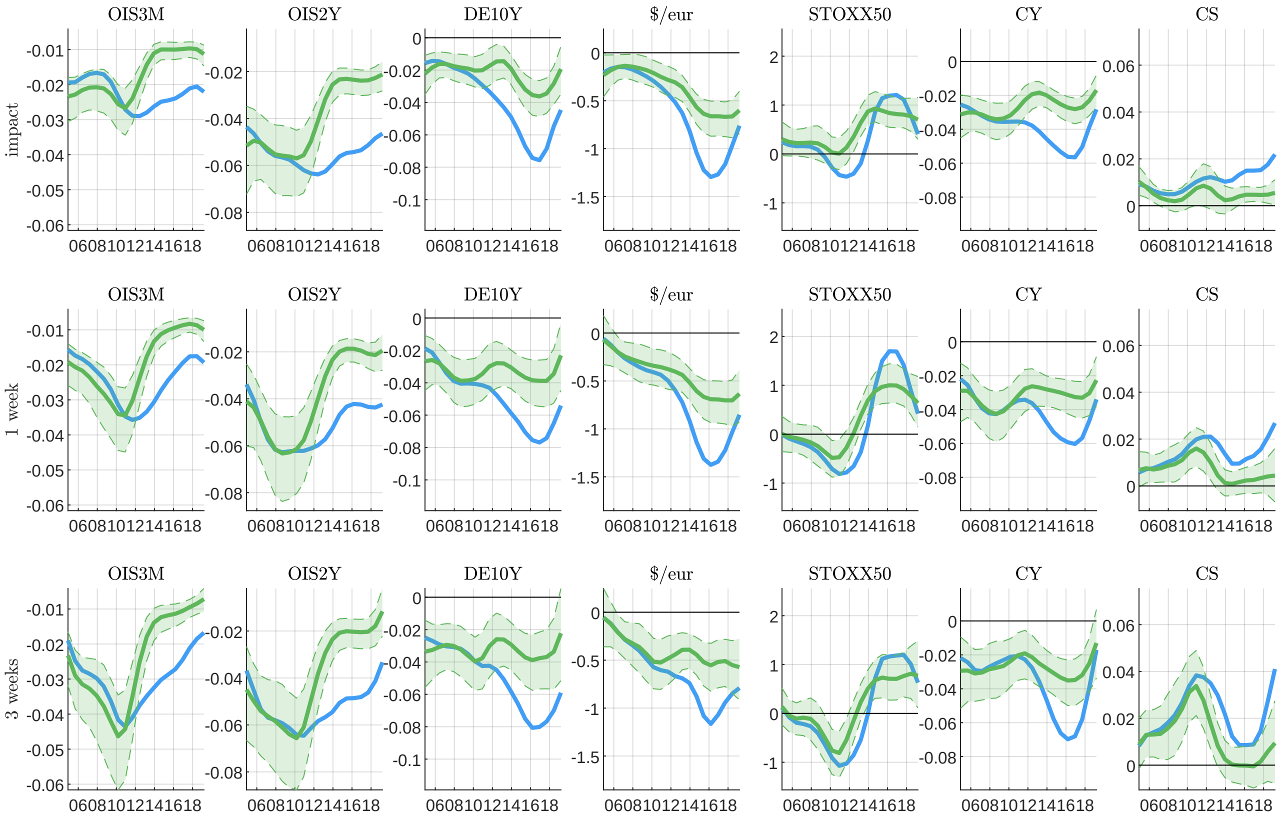

Figure 6: Euro Area: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in May 2006. Green line with shaded areas give point estimates and 90% confidence intervals of the informationally robust instrument obtained from the sign-restriction model. For comparison, the blue line adds the point estimates from the benchmark instrument.

that nowadays corporate financing conditions move along with the respective risk free rates.

For the UK, there is little evidence of information effects confounding our impulse response functions. Readers interested in the corresponding estimates are referred to Appendix B.2.

3.5 The role of unconventional policies

Much of the time variation in the impulse response functions is either gradual (e.g. IRF of exchange rate) or tightly aligned with the introduction of unconventional policies (e.g. IRF of interest rates). Hence, it is perfectly possible that time-variation is less important once we conditioning on the different dimensions of monetary policy, namely standard rate cuts, forward guidance and Asset Purchasing programmes. After all, it is perfectly possible that a shift away from convention towards unconventional policy shocks explains much of the time-varying effectiveness we observe.

In the following, we aim to shed light on this question by conditioning on different policy dimensions, each distinct in their effects on short-, medium- and long term interest rates. To do so, we follow standard approaches in the literature using high frequency surprises of the entire term structure of risk free rates (between 1m and 10Y). For the short end, we proxy these by either OIS (EA) or short term sterling futures (UK), while at the long end we use government bond yields. Following Swanson (2021), Gürkaynak et al. (2005) and Altavilla et al. (2019), we proceed identifying a "target" factor which resembles conventional monetary policy, a forward guidance factor and a large scale asset purchasing (LASP) factor. To obtain these, we first estimate three orthogonal factors driving a large fraction of the variation in the term structure around policy announcements. Then, identifying restrictions are leveraged to rotate the factors in a way the can be interpreted economically. Specifically, only the target factor is allowed to affect the short end of the term-structure. Furthermore, forward guidance and LASP shocks are disentangled assuming that the LASP factor is not important prior the onset of the financial crisis (August 2008). This is operationalized by minimizing the variance of the LASP factor in the first half of the sample. More details on the method are available in Swanson (2021), and a plot of the factors along estimated loadings on the term structure is given in Appendix B.3.

With these factors at hand, we use them as external instruments in our daily VARs. To keep the results comparable, we standardize the shock size to yield a 5bp decrease in the 2 Year rate at a fixed date. Recomputing the Wald statistics of Table 1 for each instrument suggest that we need to shift the date of standardization towards the second half the sample (Dec 2016), as the LASP factor is only weakly correlated with the 2 Year rate in the first half of the sample.

For the Euro Area, Figure 7 shows estimated impact impulse response functions for the different policy dimensions. For comparison, the chart also draws in the (impact) IRFs obtained as our main results, which is based on using the high frequency surprise in the 2 year rate. A

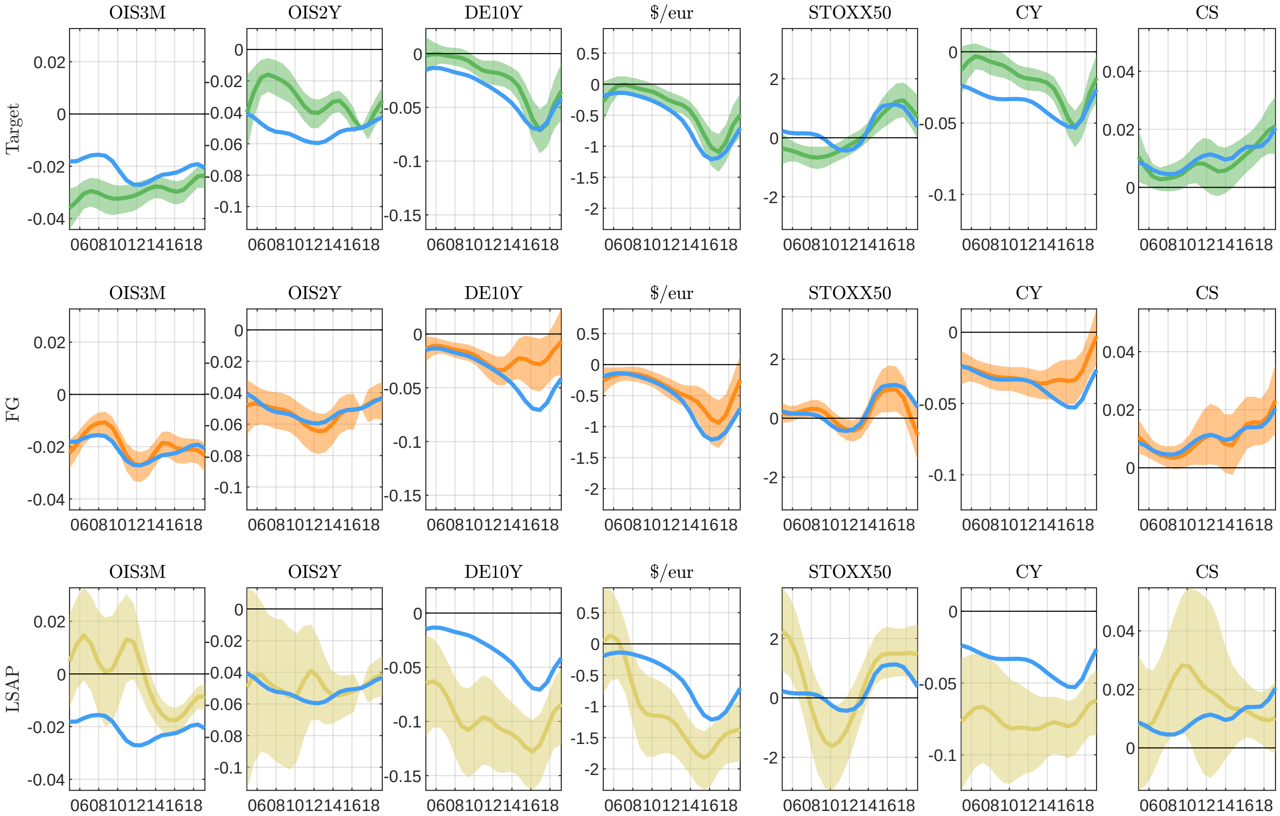

Figure 7: Euro Area: Impact impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in December 2016. Shaded areas give 90% confidence intervals. Each row reports IRFs to either a standard rate cut (target), Forward Guidance (FG) or Large Scale Asset Purchasing (LASP) shock.

few things stand out from these results. First, further conditioning on Target, FG, and LASP factor can account for most of the time variation in the 3 Month, 2 Year and 10 Year interest rates. By that, we mean that there is no strong evidence for time variation in the effect of Target shocks on the 3 month rate, FG shocks on the 2Y rate and LASP shocks on the 10 Year rate. However, the time variation in other interest rates and financial variables remains substantial. Exchange rates and Stock Prices are still estimated to be affected more strongly over time. There is less evidence for time variation of FG and LSAP shocks on corporate credit conditions, however, strong time variation remains when using the target factor as instrument. For the UK, we obtained broadly similar results, so refer to Appendix B.3 for the interested reader.

Overall, we conclude that a simple decomposition of monetary policy into the three most prominent factors is not sufficient to explain the time variation we document in our main empirical results (section 3.1).

4 Conclusion

In this paper, we develop kernel based estimators for time varying impulse response functions of structural VAR models identified by external instruments. Compared to prominent Bayesian approaches, our frequentist estimators are very simple to implement, computationally trivial and require no choice for the law of motion and corresponding priors. Unlike Bayesian state-of-the art methods, the kernel based esitmators can handle very long datasets and variables expressed in (log) levels. Importantly, inference can be reliably conducted even if identification is only weak.

We illustrate the methodology estimating time-varying effects of monetary policy on financial variables. In a model involving more than 4000 daily observations (and variables expressed in levels), we use high-frequency surprises around monetary events to identify monetary policy shocks. Our results suggest that the conduct of policy has become more effective at steering financial variables such as stock prices, the exchange rate and corporate financing conditions. Importantly, these findings are robust to using a different identification strategy that relies on heteroskedasticity (Rigobon and Sack; 2004), a more subtle identification scheme teasing out information shocks, and to the identification via factors that aim to capture unconventional policies designed to steer medium to long run interest rates.

References

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.

Arias, J. E., Rubio-Ramirez, J. F. and Waggoner, D. F. (2021). Inference in bayesian proxy-svars, *Journal of Econometrics* .

Caldara, D. and Herbst, E. (2019). Monetary policy, real activity, and credit spreads: Evidence from Bayesian Proxy SVARs, *American Economic Journal: Macroeconomics* **11**(1): 157–92.

Cochrane, J. H. and Piazzesi, M. (2002). The fed and interest rates-a high-frequency identification, *American economic review* **92**(2): 90–95.

Fry, R. and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: a critical review, *Journal of Economic Literature* **49**: 938–960.

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

Giacomini, R., Kitagawa, T. and Read, M. (2021). Robust bayesian inference in proxy svars, *Journal of Econometrics* .

Giraitis, L., Kapetanios, G. and Marcellino, M. (2021). Time-varying instrumental variable estimation, *Journal of Econometrics* **224**(2): 394–415.

Giraitis, L., Kapetanios, G. and Yates, T. (2014). Inference on stochastic time-varying coefficient models, *Journal of Econometrics* **179**(1): 46–65.

Giraitis, L., Kapetanios, G. and Yates, T. (2018). Inference on multivariate heteroscedastic time varying random coefficient models, *Journal of Time Series Analysis* **39**(2): 129–149.

Gürkaynak, R. S., Sack, B. and Swanson, E. (2005). The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models, *American economic review* **95**(1): 425–436.

Jarocinski, M. (2021). Estimating fed's unconventional policy shocks.

Jentsch, C. and Lunsford, K. G. (2021). Asymptotically valid bootstrap inference for proxy svars, *Journal of Business & Economic Statistics* pp. 1–16.

Kapetanios, G., Marcellino, M. and Venditti, F. (2019). Large time-varying parameter vars: A nonparametric approach, *Journal of Applied Econometrics* **34**(7): 1027–1049.

Kerssenfischer, M. (2019). The puzzling effects of monetary policy in VARs: Invalid identification or missing information?, *Journal of Applied Econometrics* **34**(1): 18–25.

Koop, G., Pesaran, M. H. and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models, *Journal of econometrics* **74**(1): 119–147.

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.

Lakdawala, A. (2019). Decomposing the effects of monetary policy using an external instruments svar, *Journal of Applied Econometrics* **34**(6): 934–950.

Lütkepohl, H. (1990). Asymptotic distributions of impulse response functions and forecast error variance decompositions of vector autoregressive models, *The review of economics and statistics* pp. 116–125.

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

Miranda-Agrippino, S. and Ricco, G. (2018). The transmission of monetary policy shocks.

Miranda-Agrippino, S. and Ricco, G. (2019). Identification with external instruments in structural vars under partial invertibility.

Miranda-Agrippino, S. and Ricco, G. (2021). The transmission of monetary policy shocks, *American Economic Journal: Macroeconomics* **13**(3): 74–107.
URL: *https://www.aeaweb.org/articles?id=10.1257/mac.20180124*

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

Noh, E. (2017). Impulse-response analysis with proxy variables, *Available at SSRN 3070401* .

Olea, J. L. M., Stock, J. H. and Watson, M. W. (2021). Inference in structural vector autoregressions identified with an external instrument, *Journal of Econometrics* **225**(1): 74–87.

Paul, P. (2020). The time-varying effect of monetary policy on asset prices, *Review of Economics and Statistics* **102**(4): 690–704.

Plagborg-Møller, M. and Wolf, C. K. (2021). Local projections and vars estimate the same impulse responses, *Econometrica* **89**(2): 955–980.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy, *Review of Economic Studies* **72**(3): 821–852.

Rigobon, R. (2003). Identification through heteroskedasticity, *Review of Economics and Statistics* **85**(4): 777–792.

Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices, *Journal of monetary economics* **51**(8): 1553–1575.

Stock, J. H. and Watson, M. W. (2012). Disentangling the channels of the 2007-09 recession, *Brookings Papers on Economic Activity* **43**(1): 81–156.

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

Wright, J. H. (2012). What does monetary policy do to long-term interest rates at the zero lower bound?, *The Economic Journal* **122**(564): 447–466.

Appendix A Proofs

A.1 Proof of Theorem 1

The results of the Theorem follow directly from Theorem 2.2 of Giraitis et al. (2018) (GKY18) once we account for the presence of the exogenous variable, z_t (Extension 1 (E1)) and the introduction of a lag order greater than 1 (Extension 2 (E2)). The only other difference between the analysis of GKY18 and ours is that GKY18 allow for stochastic parameter processes. We choose to restrict ourselves to deterministic sequences for the parameter processes, to simplify the presentation of our asymptotic results.

We consider each extension in turn, starting with E1. There are two matters relating to proving E1. The first relates to extending Theorem 2.1 of GKY18 to this case (Result E11, (RE11)), and the second is to establish asymptotic normality as in (2.15) of GKY18 (Result E12, (RE12)). . RE11 follows immediately by 2 and (6.2)-(6.3) of GKY18.

RE12 relates to showing normality of term $T_{n,t;1}$ (the first term of $T_{n,t}$) in page 41 of the online appendix of GKY18. Normality follows immediately by Lemma 6.2 (ii) of GKY18 using Assumption 3(ii).

Next, consider E2. The result here follows immediately by considering the companion form of (**??**), given by

$$\tilde{y}_t = \tilde{A}_t \tilde{y}_{t-1} + \nu_t, \tag{12}$$

where $\tilde{y}_t = (y_t', y_{t-1}', ..., y_{t-p+1}')'$, $\tilde{A}_t = \begin{pmatrix} A_{1t} & A_{1t} & ... & A_{pt} \\ I & 0 & ... & 0 \\ 0 & ... & ... & ... \\ ... & ... & I & 0 \end{pmatrix}$, $\nu_t = \left((B_t \varepsilon_t)', 0, ..., 0 \right)'$ and applying Theorem 2.2 of GKY18.

A.2 Proof of Theorem 3

All but one of the results of this Theorem follow directly from the proof of Theorem 1. The only result that needs to be proven is the indepenence of $\hat{\tilde{\beta}}_t$ and $\hat{\tilde{\sigma}}_t$. We revisit the proof of Theorem 2.2 of GKY18. THe asymptotically relevant terms of $\sqrt{H}\left(\hat{\tilde{\beta}}_t - \tilde{\beta}_t\right)$ and $\sqrt{H}\left(\hat{\tilde{\sigma}}_t - \tilde{\sigma}_t\right)$ are given by $T_{n,t;1}$ and $q_{n,t}$ which are both defined in page 41 of the online appendix of GKY18. The expectation of their cross product involves the third moments of ε_t which are zero by the symmetry assumption of Theorem 3 proving the result.

Appendix B Supplementary results

B.1 Benchmark results using the internal IV approach

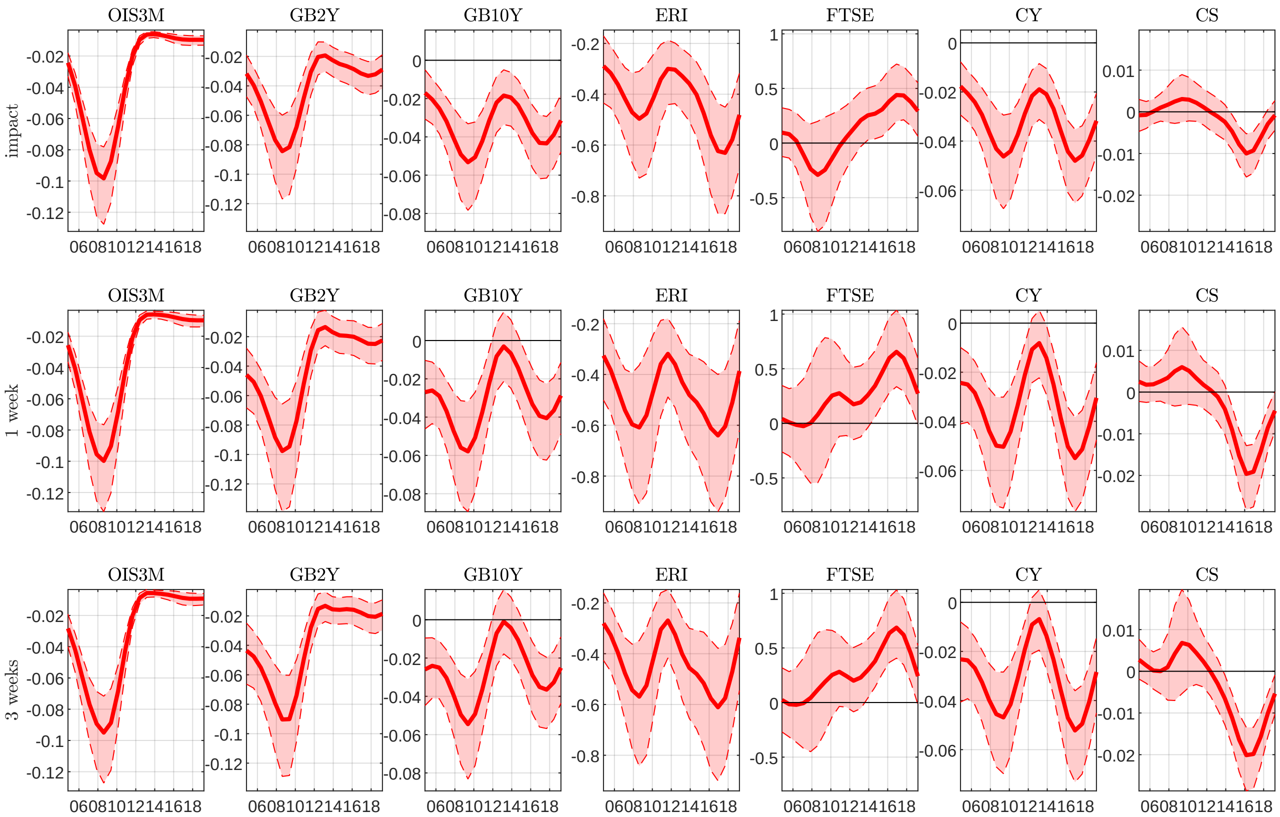

Figure B.8: United Kingdom: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y Gilt rate by 5bp in May 2006. Shaded areas give 90% confidence intervals. Estimator based on the internal-IV VAR (Plagborg-Møller and Wolf; 2021).

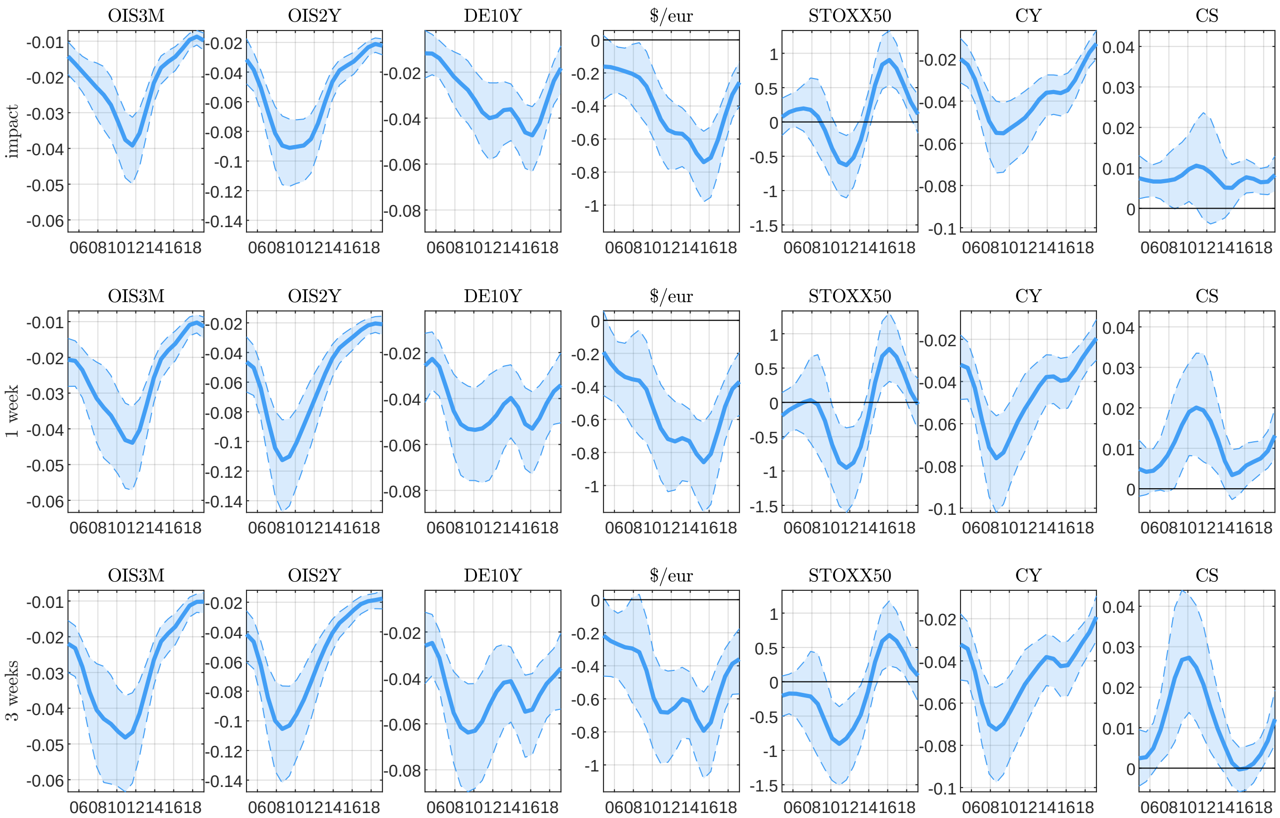

Figure B.9: Euro Area: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in May 2006. Shaded areas give 90% confidence intervals. Estimator based on the internal-IV VAR (Plagborg-Møller and Wolf; 2021).

B.2 Information effects in the UK

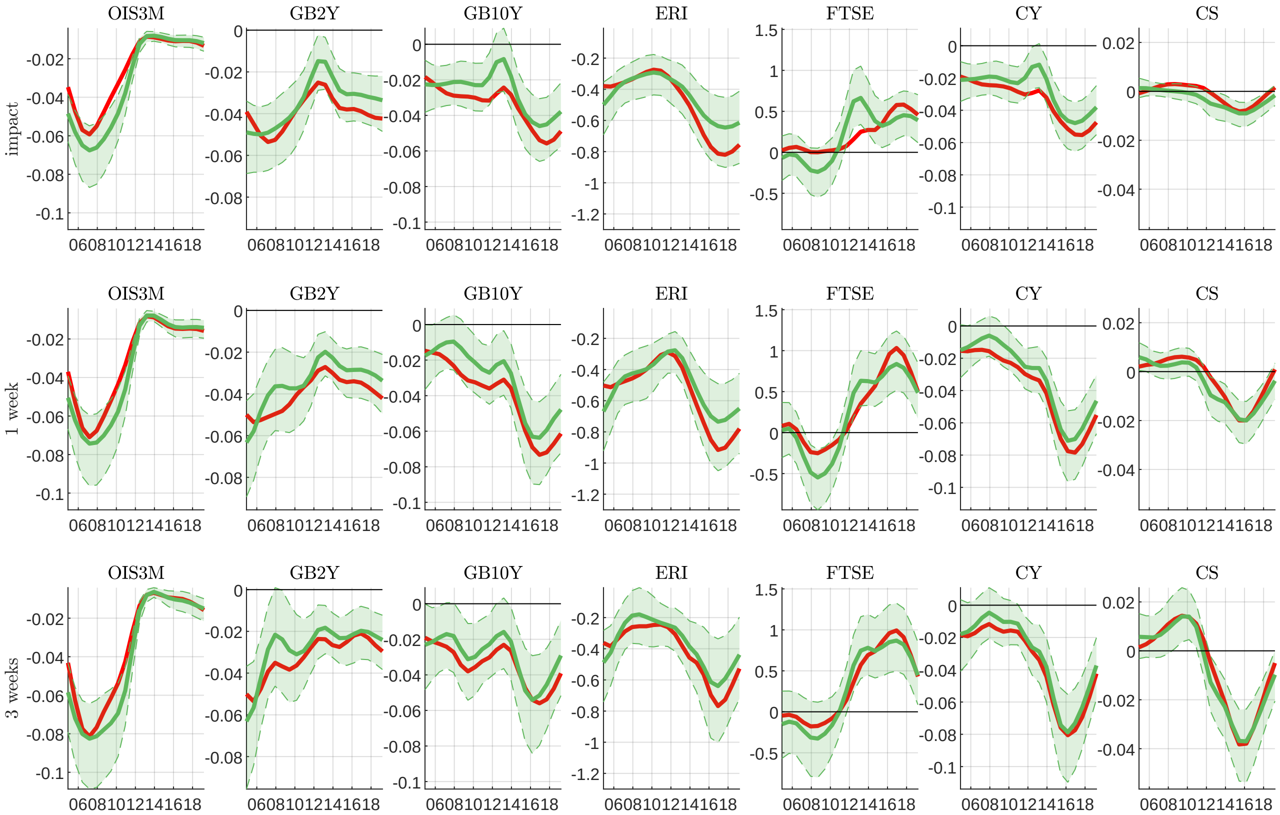

Figure B.10: United Kingdom: Impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 10bp in May 2006. Shaded areas give 90% confidence intervals.

B.3 Policy Factors

Table 2: Factor loadings on high frequency surprises in the Euro Area

	OIS 1M	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 5Y	DE 10Y
Target Factor	**1**	0.86	0.73	0.63	0.5	0.29	0.09
S.E.	0.02	0.02	0.02	0.01	0.01	0.01	0.01
FG Factor	0	0.4	0.66	**1**	1.08	0.89	0.41
S.E.	0.03	0.03	0.03	0.01	0.03	0.02	0.03
LASP Factor	0	-0.03	0.05	0.17	0.48	0.94	**1**
S.E.	0.02	0.02	0.02	0.03	0.02	0.03	0.03

The table reports estimated factor loadings alongside standard errors for the Target Factor, Forward Guidance (FG) Factor, and Large Scale Asset Purchases (LASP) Factor. Database as made available by Altavilla et al. (2019), involving either surprises in the OIS or if not available, German government bond yields.

Table 3: Factor loadings on high frequency surprises in the United Kingdom

	FSScm1	FSScm2	FSScm3	FSScm4	GB2YT	GB5YT	GB10YT
Target Factor	**1**	1.1	1.03	0.9	0.65	0.51	0.3
S.E.	0.01	0.03	0.02	0.01	0.03	0.02	0.02
FG Factor	0	0.52	0.85	**1**	0.5	0.28	0.11
S.E.	0.01	0.02	0.02	0.02	0.04	0.01	0.02
LASP Factor	0	0.16	0.37	0.53	0.7	0.96	**1**
S.E.	0.01	0.03	0.02	0.02	0.06	0.02	0.03

The table reports estimated factor loadings alongside standard errors for the Target Factor, Forward Guidance (FG) Factor, and Large Scale Asset Purchases (LASP) Factor. FSScm1, FSScm2, FSScm3 and FSScm4 are synthetic series computed by Thomson Reuters which track the short-term sterling future contracts expiring within the next four quarters. Hence, they measure expectations about the 3-month Libor rate up to one year. GB2YT, GB5YT and GB10YT are the surprises based on Gilt Years with maturity at 2, 5 and 10 Years respectively.

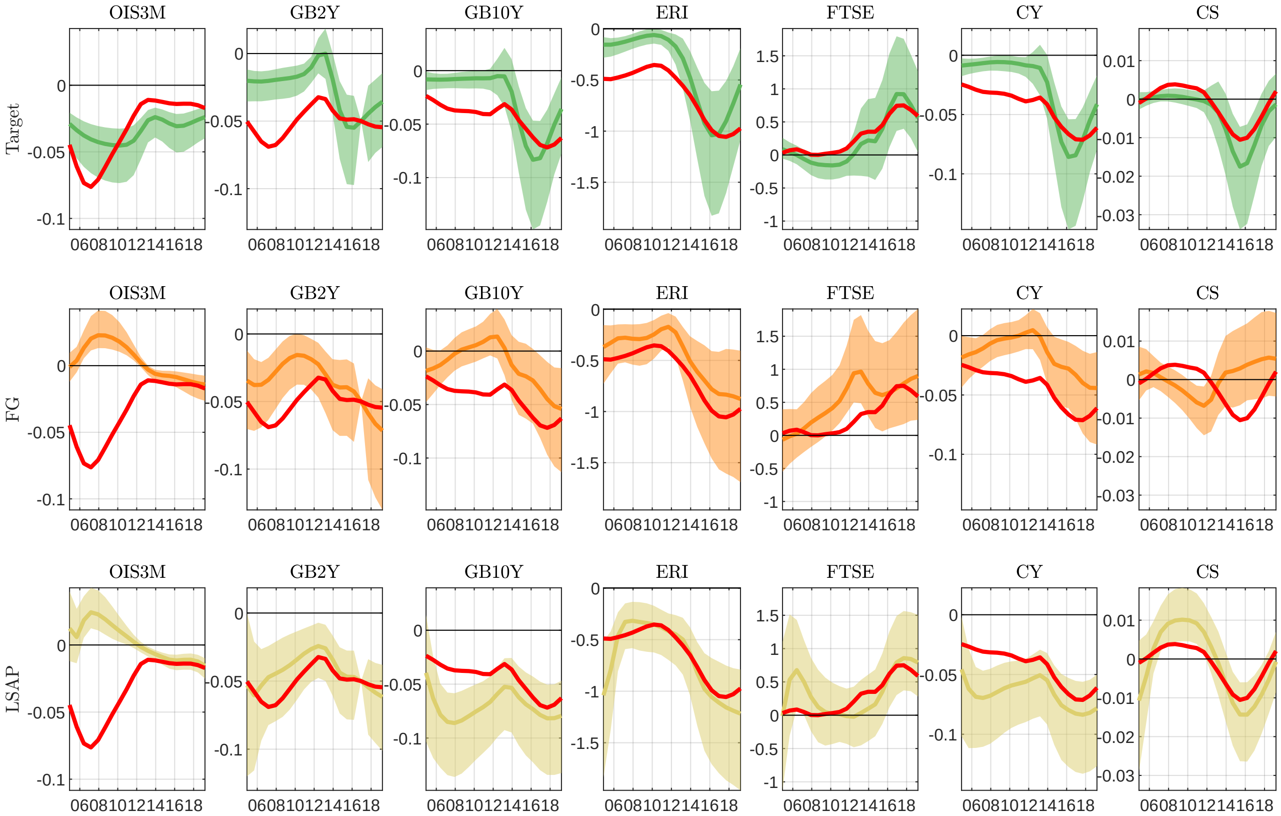

Figure B.11: United Kingdom: Impact impulse response functions of an expansionary monetary policy shocks normalized to decrease the 2Y OIS rate by 5bp in January 2016. Shaded areas give 90% confidence intervals. Each row reports IRFs to either a standard rate cut (Target), Forward Guidance (FG) or Large Scale Asset Purchasing (LASP) shock.