Forward Guidance in Unconventional Times: The Euro-area Experience

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Abstract

I investigate the effect of forward guidance shocks on the Euro-area economy during the period 2009-2019, in which the effective lower bound on interest rates was binding. By isolating forward guidance surprises from high frequency interest rate movements around the European Central Bank's monetary policy announcements and using these as external instruments to identify forward guidance shocks in an SVAR framework, I show that unconventional monetary policy in the form of policy commitments was ineffective at stimulating output, prices and at easing financial conditions. I also show that these results are not driven by the presence of information effects by which announcements regarding future policy actions are contaminated with information regarding the future evolution of the economy.

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Declaration of Academic Integrity

I, Jesús María Argaña Espínola, hereby declare that the master's thesis entitled "Forward Guidance in Unconventional Times: The Euro-area Experience" is entirely my own work, and that I have employed no sources or aids other than the ones listed. I have clearly marked and acknowledged all ideas and illustrations that have been taken directly or indirectly from the works of others. I also confirm that this thesis has not been submitted in this form, or a similar form, to any other academic institution.

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1 Introduction

Central banks like the Federal Reserve and the European Central Bank (ECB) were swift to respond to the 2008 financial crisis and the ensuing European-sovereign debt crisis by lowering interest rates to historical lows (Rostagno et al., 2019). Conventional monetary policy, by which the monetary authority targets a short-term interest rate through open market operations, is crucially constrained by the lower bound on interest rates. At low interest rates, fiat currency and financial instruments like bonds become increasingly substitutable. Eventually, if interest rates reach a level known as the effective lower bound, in recognition of the possibility of negative rates, investors would rather hold their currency rather than accepting too low of a return (Rognlie, 2016). As a result, additional monetary stimulus is ineffective at further dampening economic fluctuations.

In the absence of alternative policies, the existence of this constraint implies large welfare losses in the form of unemployment, output losses and disinflation or deflation. In such environments, central banks resort to tools often referred to as unconventional policies. One of such policy is forward guidance, by which the central bank announces and commits, whether conditionally or unconditionally, to keeping interest low for a period of time in the future.

I study the causal response of aggregate macroeconomic and financial variables to forward guidance shocks in periods where the effective lower bound on interest rates binds. In doing so, I use market-based surprises around monetary policy announcements as external instruments to identify the underlying forward guidance shock in an SVAR framework. As opposed to prior studies, which have focused on non-crisis periods or which have merged data from both samples, I show that during crisis episodes forward guidance is ineffective at improving economic and financial conditions in the Euro-area (see, for example, Gertler and Karadi (2015), Miranda-Agrippino and Ricco (2018), and Andrade and Ferroni (2021)). There is also evidence of puzzling responses following an expansionary forward guidance shock with inflation expectations falling and financial conditions tightening. I explore whether these can be explained by the surprises used to identify the primitive shocks being contaminated with information regarding the evolution of the economy. Under this scenario, the surprises would be correlated with a policy shock and with an opposing information shock, leading to biased dynamics being estimated. Although I find evidence of this contamination, the results remain unchanged even with instruments devoid of these effects. This is unlike prior studies, which find that controlling for the private information of the central bank is important in better capturing the effect of monetary policy shocks (see, in particular, Miranda-Agrippino and Ricco (2016)).

I start by using the simple New Keynesian model together with fundamental results in monetary theory to illustrate the operation of forward guidance in a setting where it constitutes optimal monetary policy. In practice, these announcements exert downward pressure on long-term interest rates, as market participants trade to benefit from arbitrage profits in financial markets (Praet, 2013). Ultimately, the downward revision across the term structure spurs economic activity by many of the traditional channels.

Although simulation studies show the effectiveness of these policies, the empirical evidence of the effect of forward guidance on macroeconomic outcomes is inconclusive, particularly during crisis episodes. The major challenge in studying the effects of monetary policy empirically is that the central bank responds to current and anticipated economic developments. This makes it hard to distinguish the effect of monetary policy on economic fundamentals from changes in monetary policy that are due to the state of the economy. Identifying the causal effects of monetary policy requires instead isolating monetary decisions which are unrelated to the state of the economy, and tracing the resulting effects as they propagate (C. A. Sims, 1992; Kilian & Lütkepohl, 2017).

To isolate forward guidance surprises, I follow a large literature pioneered by Kuttner (2001) and greatly extended by Gürkaynak, Sack, and Swanson (2004). In particular, surprises are identified using high-frequency movements in asset prices around narrow intervals during ECB's monetary policy announcements. This strategy ensures the effect runs from monetary policy to asset prices, and not in reverse. To interpret these movements as stemming from forward guidance specifically requires decomposing the high-frequency movements into orthogonal components that admit economic interpretation. I follow E. T. Swanson (2015), who decomposes the high frequency price movements into three orthogonal dimensions of monetary policy: a target dimension (representing conventional monetary policy), a path dimension (forward guidance) and a dimension reflecting Quantitative Easing. In particular, after extracting the principal components of asset price movements around policy announcements, identification is achieved by rotating the axes that span the factor-space by imposing economic-type restrictions that allow their interpretation as distinct objects of monetary policy. Forward guidance is identified by orthogonality to the remaining monetary policy dimensions and to the one-month OIS rate movements (Altavilla, Brugnolini, Gürkaynak, Motto, & Ragusa, 2019b). The interpretation being that forward guidance triggers revisions in the term structure of interest rates that have not been captured by the first factor (Gürkaynak et al., 2004).

I model the dynamics of the economy using the vector autoregression (VAR) framework, as its conventional in the literature. To study the dynamic causal effects of forward guidance on the economy, I use methods that have been recently proposed in the literature. In particular, I follow the literature pioneered by Gertler and Karadi (2015), who use high-frequency surprises as external instruments to identify monetary policy shocks. These models, known as Proxy SVAR or SVAR identified by external instruments, circumvent the limitations of traditional restrictions used in studying monetary policy shocks and instead requires finding an instrument that is correlated with the shock of interest but is uncorrelated with all other contemporaneous shocks. Together with a normalisation assumption on an impact coefficient, these covariance restrictions allow to identify the causal dynamics following a realisation of the target shock (Stock & Watson, 2012; Mertens & Ravn, 2013).

In using the Proxy SVAR framework, I employ state of the art procedures to test for the instrument's strength and to perform inference on the estimated impulse responses. In the event of a weak instrument, one for which the covariance of the instrument and the shock converges to zero asymptotically, the Proxy SVAR estimator is inconsistent (Lunsford, 2015; Olea, Stock, & Watson, 2020). Lunsford (2015) shows that using the F-statistic from the IV literature is mistaken in the external instrument case, as the critical values themselves depend on the impact matrix estimate. Instead, Lunsford defines the weak proxy set as those instruments that result in an asymptotic bias larger than a user selected maximum bias tolerance. To test for the instrument's strength Lunsford proposes using an F-statistic based on a regression of the instrument on the VAR innovations. This test converges to a non-central χ^2 distribution with the non-centrality parameter being the signal-to-noise ratio of the instrument. For inference, I use the residual-based moving block bootstrap which Jentsch and Lunsford (2019) show is capable of reproducing the fourth-moment dependence between the external instrument and the reduced-form innovations, unlike the wild bootstrap commonly used in this setting.

Another strand of literature my work relates to is that which investigates the information contained in monetary policy announcements, beyond that of policy itself. In a widely cited study, Campbell et al. (2012) report that private forecasters revise their expectations following monetary policy announcements in the opposite direction to what theory would suggest. In particular, the forecasts for inflation and output were revised upwards following a contractionary policy shock. Despite the extensive research that followed, the current understanding of these effects is still poor (Jarocinski, 2020). More recently, Bauer and Swanson (2020) show that the problematic revisions in the US are a result of omitted variable bias. Indeed, they suggest that omitting information regarding economic developments between the time forecasters announce their expectations and the monetary policy announcement results in attributing forecasts revisions to monetary policy when both were in response to exogenous developments. In this regard, my contribution is showing that this is not the case for the Euro-area, at least during the effective lower bound period. Incorporating a simple proxy for news that measure the arrival of information prior to the monetary announcement fails to resolve the problematic revisions.

My findings are problematic as forward guidance is one of the tools central banks rely on to bypass the constraints imposed by the effective lower bound and raise aggregate welfare (Bernanke, 2020). The importance of unconventional policies cannot be overemphasised. Indeed, simulation studies for the US imply that the lower bound would bind for one-third of the time in the future were policy-rules of the past be used (Kiley & Roberts, 2017). Bernanke (2020) shows that unconventional policies could grant central banks with ample maneuvering space in an environment in which the natural rate is at 3%, by as much as if it were close to 6%.

The remaining parts are structured as follows. Section 2 introduces the theoretical underpinnings of forward guidance in a simple New Keynesian model. Sections 3 to 5 are devoted to discussing the empirical challenges of studying the effects of forward guidance on the wider economy and highlight the use of high-frequency asset price movements around policy announcements as a means of identifying forward guidance surprises. Section 6 provides a detailed overview of the Proxy-SVAR framework together with a brief description of the methods employed for testing the instrument's strength and for constructing valid confidence intervals for the estimated impulse responses. I discuss my main findings in section 8 and explore the possibility of these being driven by information effects in sections 9 and 10. Finally, I present some robustness checks in section 11 and conclude in section 12.

2 Forward Guidance as Optimal Monetary Policy in an ELB Environment

The point of departure is the canonical three-equation New-Keynesian model. The objective of this section is to provide a rich theoretical background to guide the interpretation of the empirical analysis and to introduce the fundamental underpinnings of forward guidance in periods in which the effective lower bound (ELB) constraint is binding. As such, I do not provide the full derivation of the model, these can be found in any graduate monetary economics textbook[1].

The economy is inhabited by a large number of identical, infinitely-lived households, a continuum of intermediate goods producers indexed along the unit interval, a representative final-good producer, a central bank and a government.

2.1 The Households

Households maximise expected life-time utility subject to a sequence of budget constraints for each period by choosing a stream of consumption, C_t, labour supply, N_t and nominal bond holdings paying one unit of account next period, B_{t+1}. Although it is possible to introduce money into the utility function in an additive separable fashion, doing so does not change the model predictions. Indeed, in this basic New Keynesian model, money serves only as a unit of account (Galí, 2015).

Households earn the nominal wage rate W_t for each unit of labour supplied, the price of the bonds paying one unit of account next period is given by Q_t. Finally, P_t represents the price level at date t and T_t represents any lump-sum transfers or deductions by the government. Formally their problem is given by:

[1] The particular version of the model I present here is adapted from Chris Edmond and Eric E. Sims' lecture material for Advanced Macroeconomics at the University of Melbourne and Graduate Macroeconomic Theory II at the University of Notre Dame, respectively.

$$
\begin{aligned}
\max_{\{C_t, N_t, B_{t+1}\}_{t=0}^{\infty}} \quad & \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\eta}}{1+\eta} \right], \quad \sigma, \eta > 0 \\
\text{s.t.} \quad & P_t C_t + Q_t B_{t+1} = B_t + W_t N_t - T_t, \\
& \lim_{T \to \infty} \mathbb{E}_t \, B_T \geq 0
\end{aligned}
$$

The second constraint, known as the no-Ponzi game condition, rules out planning solutions in which households are allowed to borrow increasingly large amounts to finance unbounded large consumption streams.

The key efficiency conditions resulting from the above problem are:

$$
C_t^{-\sigma} = \beta \, \mathbb{E}_t \left(C_{t+1}^{-\sigma} \frac{P_t}{P_{t+1}} \frac{1}{Q_t} \right)
$$

$$
C_t^{\sigma} N_t^{\eta} = \frac{W_t}{P_t}
$$

The first condition, known as the Euler equation, is a stochastic difference equation describing the optimal evolution of consumption. The second equation is an intratemporal behavioural condition which pins down the optimal labour supply to support a given consumption choice.

2.2 The Firms

There are two types of firms, a representative final-good producer and intermediate-good producers indexed along the unit interval. Households purchase consumption goods from the final-good producer, who operates in a perfectly competitive environment. The production technology of final-good producers is described by the Dixit-Stiglitz aggregator:

$$
Y_t = \left(\int_0^1 y_t(i)^{\frac{\varepsilon-1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \quad \varepsilon > 1
$$

The concavity of the production function, governed by ε, implies that intermediate goods are imperfect substitutes of each other, giving each intermediate producer a small amount of market power (Chugh, 2015).

Final-good producers maximise profits subject to their production technology:

$$
\begin{aligned}
\max_{y_t(i)} \quad & P_t Y_t - \int_0^1 p_t(i) y_t(i) di \\
\text{s.t.} \quad & Y_t = \left(\int_0^1 y_t(i)^{\frac{\varepsilon-1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}}
\end{aligned}
$$

The solution to the problem yields the demand function for any intermediate good:

$$
y_t(i) = \left(\frac{p_t(i)}{P_t} \right)^{-\varepsilon} Y_t
$$

Note that the demand for firm i's good, $y_t(i)$, is a function of its price, $p_t(i)$, relative to the price level of the economy and the overall measure of economic activity, given by P_t and Y_t, respectively. Indeed, relatively cheaper goods face a higher demand but their substitutability is limited by ε.

Intermediate-good producers take the demand for their goods as given. Since they have a small degree of market power, their problem is to choose a price, p_t^*, to maximise profits subject to their production technology and the demand for their goods. However, their ability to do so is constrained by a Calvo price setting mechanism where in each period only fraction $1-\theta$ of the firms get the opportunity update prices, where $\theta \in [0,1]$ denotes the degree of price rigidity. Taking into account the possibility of remaining with their price for subsequent periods, these firms must choose a price to maximise expected discounted profits subject to the constrains described above. Formally their problem is:

$$
\begin{aligned}
\max_{p_t^*(i)} \quad & \sum_{k=0}^{\infty} \theta^k \, \mathbb{E}_t \left[\mathbf{Q}_{t,t+k} (p_t^*(i) y_t(i) - W_t N_t(i)) \right] \\
\text{s.t.} \quad & y_t(i) = N_t(i) A_t, \\
& y_t(i) = \left(\frac{p_t^*(i)}{P_t} \right)^{-\varepsilon} Y_t
\end{aligned}
$$

Where $\mathbf{Q}_{t,t+k} = \beta^k \left(\frac{C_{t+k}}{C_t} \right)^{-\sigma} \frac{P_t}{P_{t+k}}$ is the stochastic discount factor. Notice that future discounted profits are weighted according to the probability of being unable to update their price at all future points in time. The first constraint describes the production technology faced by the intermediate-good producers and the second constraint describes the demand for their products. A_t denotes total factor productivity and $N_t(i)$ denotes the labour demanded by firm i. The solution to the problem, known as the optimal reset price, describes the optimal price a firm constrained by the Calvo mechanism would choose whenever it faces the opportunity to change its price. It is given by:

$$p_t^*(i) = \frac{\varepsilon}{\varepsilon - 1} \frac{\mathbb{E}_t\{\sum_{k=0}^{\infty}(\theta\beta)^k C_{t+k}^{-\sigma} P_{t+k}^{\varepsilon-1} \frac{W_{t+k}}{A_{t+k}} Y_{t+k}\}}{\mathbb{E}_t\{\sum_{k=0}^{\infty}(\theta\beta)^k C_{t+k}^{-\sigma} P_{t+k}^{\varepsilon-1} Y_{t+k}\}}$$

Note that it is a weighted average of future marginal costs, $\frac{W_{t+k}}{A_{t+k}}$. If firms anticipate rising marginal costs, then they will increase prices whenever they are given the chance to do so. In the absence of nominal rigidities, $\theta = 0$, the expression collapses to $p_t^* = \frac{\varepsilon}{\varepsilon-1}\frac{W_t}{A_t}$, with the optimal price being a constant above marginal costs. This implies that under the flexible-price equilibrium, intermediate producers would react to variations in marginal costs by choosing the same price and would do so at the same time. This implies that all intermediate firms would face identical demands and would themselves demand the same amount of labour inputs.

The staggered nominal adjustment implied by the Calvo mechanism results in a price dispersion among intermediate producers, with only some firms able to change prices in any given period. This dispersion distorts the pricing mechanism and results in an inefficient allocation of labour and an inefficient level of consumption. To see why, take the ratio between the amount produced by any two distinct intermediate-good producers:

$$\frac{y_t(j)}{y_t(i)} = \left(\frac{p_t(j)}{p_t(i)}\right)^{-\varepsilon}$$

Under the flexible price equilibrium, $p_t(i) = p_t(j)$, implying that both firms would produce the same quantity. However, under nominal rigidities, the price between any two firms need not be the same. This shifts production towards the cheaper good and given the concavity of the final good production technology, this substitution generates sub-optimal consumption relative to the flexible equilibrium allocation (Galí, 2015; Walsh, 2017).

2.3 Aggregation

Noticing that all firms who are given the opportunity to adjust their prices at any given time period would choose the same optimal price, the Calvo-pricing mechanism implies the linearised inflation dynamics in this economy is given by:

$$\hat{\pi}_t = (1-\theta)(\hat{p}_t^* - \hat{p}_{t-1})$$

Where π_t denotes inflation and where hats denote their log-deviation values around the point of approximation, at $\pi_t = 0$. Log-linearising the optimal reset price around the same point and combining it with the law of motion of inflation above yields:

$$\hat{\pi}_t = \frac{(1-\theta)(1-\theta\beta)}{\theta}(\hat{w}_t - \hat{A}_t) + \beta\,\mathbb{E}_t\{\hat{\pi}_{t+1}\}$$

Where $\hat{w}_t$ denotes the log deviation in the *real* wage, defined as $w_t = \frac{W_t}{P_t}$. This equation implies that inflation today is the result of the current and all expected future real marginal costs deviations (Walsh, 2017).

The evolution equation for output is given by rewritting the linearised households' Euler equation around $\pi_t = 0$ together with the goods market clearing condition, $C_t = Y_t$. Defining the real rate, r_t, as $r_t = i_t - \mathbb{E}_t\{\pi_{t+1}\}$, with $i_t = -\log(Q_t)$, $\rho = -\log(\beta)$, implies the linearised Euler equation can be written as:

$$r_t = \rho + \sigma\,\mathbb{E}_t\{\Delta\hat{y}_{t+1}\}$$

To derive the New Keynesian Phillips Curve and the Dynamic IS curve, the model is written in terms of an output gap, in which the natural level of output is given by the output which would have resulted under flexible prices. I provide further details in Appendix C, as this involves substantial algebraic manipulations and provides no further understanding of the operation of the model.

Let the output gap be denoted by, $x_t = \hat{y}_t - \hat{y}_t^f$, where y_t^f stands for the flexible-price allocation. The stochastic evolution equation for inflation can be expressed as:

$$\hat{\pi}_t = \kappa x_t + \beta\,\mathbb{E}_t\{\hat{\pi}_{t+1}\} \tag{NKPC}$$

Where $\kappa = (\sigma+\eta)\frac{(1-\theta)(1-\theta\beta)}{\theta}$. This last equation is known as the New Keynesian Phillips Curve (NKPC). By forward iteration, note that the NKPC states that inflation today is a function of the current and all future expected output gaps (Walsh, 2017).

The evolution equation for the output gap, known as the Dynamic IS (DIS) curve, results from defining the natural rate of interest, r_t^n, as the real rate under the flexible equilibrium, $r_t^n = \rho + \sigma\,\mathbb{E}_t\{\Delta\hat{y}_{t+1}^f\}$. Combining it with the linearised Euler equation yields the DIS curve:

$$x_t = \mathbb{E}_t\{x_{t+1}\} - \frac{1}{\sigma}(r_t - r_t^n) \tag{DIS}$$

Note that it states that today's output gap is a function of the current and all expected future real interest rate gaps.

To complete the model, the central bank is given autonomy over the nominal interest rate, i_t. The implementation of monetary policy at every point in time is given by a monetary policy rule, for which a common functional form is given by:

$$i_t = r_t^n + \theta_\pi \hat{\pi}_t + \theta_x \hat{x}_t + e_t$$

θ_π and θ_x denote the central bank's reactivity to inflation and to the output gap, respectively, and e_t refers to the monetary policy shock. Importantly, notice that a contractionary monetary policy shock does not necessarily entail raising the interest. Instead, a contractionary shock refers to setting an interest rate above the one implied by the model given by the systematic components of the rule, $r_t^n + \theta_\pi \hat{\pi}_t + \theta_x \hat{x}_t$, above. Together with the dynamic IS curve and New Keynesian Phillips curve, these equations characterise the dynamics of this economy in a neighborhood around the point of approximation, $\pi_t = 0$.

2.4 Optimal Monetary Policy

In the absence of cost-push shocks and assuming that the real imperfections that result from the market power of intermediate-good producers are offset by a labour subsidy scheme, optimal monetary policy entails replicating the flexible price equilibrium (Galí, 2015). To see why recall that in this model inflation signals an inefficient dispersion of prices, which results in an inefficient allocation of consumption, production and labour relative to the efficient flexible-price equilibrium. It follows that in attaining the first-best allocation by replicating the natural level of output, the central bank must deter firms from changing prices.

Assume productivity follows a stochastic auto-regressive process given by $\hat{A}_t = \rho_a \hat{A}_{t-1} + v_t$ with shocks to productivity, v_t, being an identical and independent standard normal distributed process. Noting that it is possible to write natural output as $y_t^f = \frac{1+\eta}{\sigma+\eta}\hat{A}_t$, shocks to productivity result in movements in the natural rate[2]. Optimal monetary policy implies setting an nominal interest rate to trace movements in the natural rate such that, $r_t = r_t^n$ at every point in time. So long the central bank has sufficient space to maneuver, such policy is able to replicate the flexible price equilibrium.

Following Eggertsson and Woodford (2003), consider a situation in which a shock to technology drives the natural rate of interest below zero to an area in which the effective lower bound constraint on the interest rate, $i_t \geq 0$ binds. Let $r^{<0}$ denote the natural rate during this period and for simplicity, assume this is known to persist up to some period $\hat{T}$. After this period, the natural rate reverts to a positive value with certainty, denoted by $r^{>0}$.

$$r_t^n = \begin{cases} r^{<0} & t \in [0, \hat{T}) \\ r^{>0} & t \in [\hat{T}, \infty) \end{cases}$$

In pursuing the first-best allocation, the central bank is compelled to trace the natural rate of interest but is constrained by its inability to set i_t into negative territory. Absent effective policy, with $r_t > r_t^n$, the output gap falls, with output being inefficiently below its flexible equilibrium counterpart. Given the fall in marginal costs, firms start decreasing prices, creating disinflation or deflation. If agents know the situation will persist into the future, expectations regarding future output gaps and future inflation are also affected, triggering further desired savings by households and further downward price adjustment by firms (Walsh, 2017).

Eggertsson and Woodford (2003), building on Krugman (1998), recognise that the central bank can improve today's allocation by committing to future policy actions in the form of credibly announcing the path which nominal interest rate would take after the ELB contraint no longer binds. As best described by Krugman (1998) the constraint imposed by the ELB stems from a time-consistency problem. Indeed, once the ELB is no longer binding, the central bank faces the temptation to revert its decision and raise interest rates to close the output gap once again. If, on the other hand, the central bank can credibly commit to keeping interest rates low even after the crisis is over, then the

[2]See Appendix B for further details on how to rewrite the natural level of output as function of technology.

ELB constraint is much less detrimental.

To see this, forward iterate the Dynamic IS curve together with $\lim_{T\to\infty} \mathbb{E}_t\{x_T\} = 0$:

$$x_t = -\frac{1}{\sigma}\,\mathbb{E}_t \sum_{i=0}^{\infty}(r_{t+i} - r^n_{t+i}) = -\frac{1}{\sigma}\,\mathbb{E}_t \sum_{i=0}^{\infty}(i_{t+i} - \hat{\pi}_{t+i} - r^n_{t+i})$$

It is clear that today's output gap, and as a consequence, today's inflation are a function of all future expected real interest gaps and thus a function of the entire path of nominal interest rates (Walsh, 2017).

Optimal monetary policy during the ELB period consists of choosing the path of nominal interest rate to minimise welfare losses subject to the economy's dynamics as given by the NKPC and the Dynamic IS curve, subject to the effective lower bound, $i_t \geq 0$ and subject to the starting conditions. Werning (2012) shows that optimal monetary policy involves keeping the nominal interest at the effective lower bound for a period of time after the constraint is no longer binding. The interpretation of this result is that the central bank should commit itself to creating a boom after the crisis is over[3].

It is easy to see why such policy is optimal. The literature has traditionally used a second order approximation to the households utility function around the first best allocation to evaluate the welfare consequences:

$$L = \sum_{t=0}^{\infty} \beta^t(\hat{\pi}_t^2 + \lambda x_t^2)$$

In the absence of a credible promise by the central bank, today's deviation away from the optimal allocation is large and only slowly converges back towards the first-best as the crisis continues, resulting large welfare losses. On the other hand, under a credible commitment to creating a boom, the central bank is able to influence expectations favourably (Werning, 2012). In particular, anticipating the monetary easing beyond the ELB period, households increase consumption and their labour supply today, mitigating the fall in the output gap. Firms, also anticipating the boom, lower prices but by less than otherwise, easing disinflationary or deflationary pressures. By keeping interest rates lower beyond the binding effects of the effective lower bound, the economy remains away from the first-best for a longer period of time but smaller deviations away from it result.

[3] Krugman (1998) also emphasised the role of excessive accommodative monetary policy but in the sense of credibly committing to being irresponsible by creating inflation. Werning proves that the effects are most importantly being driven by the output boom, even if this entails inflationary pressures.

In turn, this mitigates the welfare losses under the ELB (Werning, 2012).

In practice, the central bank announcements of the future path of nominal interest rates is known as forward guidance (Walsh, 2017) and its effects in the Euro-area during the ELB period after the 2008 financial crisis is the primary focus of this paper. The next section provides a brief overview of the operation of forward guidance by the European Central Bank and the current state of the literature.

3 From Theory to Practice

The 2008 financial crisis and the European sovereign debt crisis that would eventually ensue saw the European Central Bank (ECB) lower their policy rate to historical lows. In response to the slack economic environment, together with the increasingly disinflationary pressures, the ECB resorted to a host of unconventional monetary policy actions, including the use of forward guidance (Rostagno et al., 2019).

Forward guidance as a policy tool is not limited to unconventional times, however. Central banks have used implicit forms of forward guidance through announcements that were interpreted as news regarding future policy actions and more explicitly through the use of published policy forecasts long before the crisis (den Haan, 2013; Barwell, Chadha, & den Haan, 2013). In fact, the first time the ECB openly acknowledged the use of such a policy was during the press conference following the 4$^{\text{th}}$ of July policy decision by announcing it expected rates to "*remain at present or lower levels for an extended period of time*[4]" (Praet, 2013).

According to the expectation hypothesis of the term structure, long term interest rates are a function of expected future short term rates. This implies that other than anchoring expectations regarding inflation and policy objectives, credible announcements regarding the path of future interest rates influences today's long term interest rates in the same direction by affecting expectations of future short rates (Praet, 2013; Charbonneau & Rennison, 2015). This triggers a spur in economic activity through many conventional channels monetary policy is believed to work through.

Moreover, unlike what the simple New Keynesian model suggests, forward guidance in practice does not entail an unconditional commitment. Instead, it is usually contingent

[4] `https://www.ecb.europa.eu/services/media/html/player.en.html?youtubeID=SG7wweqCY3c`

on the evolution of certain variables, known as state-contingent forward guidance (den Haan, 2013; Barwell et al., 2013).

Although, historically, there has been great interest by empirical macroeconomists in estimating the dynamic effects of monetary policy shocks, and while research on unconventional monetary policy is indeed flourishing, the literature focusing on forward guidance as a separate and distinct dimension of monetary policy is underwhelming. Most studies that have focused on forward guidance have done so using pre-crisis data, when the effects might differ compared to episodes in which the lower bound constraint binds. Gertler and Karadi (2015), for example, merge US data from pre and post-crisis periods to show that forward guidance shocks have a strong effect on prices and industrial production, with the peak effect for the latter being reached at 15 months post impact[5]. Similarly, Other (2018) uses data from both periods up to 2016 to show that although the effect on industrial production is significant and extends for around 20 periods after an initial delay of one year, there is no effect on prices in the US. On the other hand, Lakdawala (2019) finds small effects for both output and prices in the US using data up to 2011. Using data exclusively from the post-crisis era for the US, Kim, Laubach, and Wei (2020) show that while forward guidance exerts significant influence over output and prices, its effect peak only after 24-36 months post impact.

For the Euro-area, evidence is more scarce. Andrade and Ferroni (2021) use data from 2002 to 2016 to show that forward guidance devoid of information effects has no effect on industrial production and a delayed impact on prices. In a similar study, using data from 2008-2017 for the Euro-area, Kane, Roger, and Sun (2018) find perverse effects resulting from a forward guidance shock, even after controlling for information effects.

This thesis extends the empirical literature by estimating the effects of forward guidance post-2008 in the Euro-area. In doing so, I explore a nascent and growing area of research studying the effects of central bank communication on private agents' information regarding the future state of the economy, known as information effects. My findings are consistent with those of Kane et al. (2018), particularly given the puzzling responses I find in some variables following a forward guidance shock.

[5]Their results are robust to using only data from the pre-crisis period.

4 Empirical Overview

Estimating the causal effects of monetary policy on macroeconomic aggregates poses a number of empirical challenges. The most notable is the endogeneity of the monetary policy rule, by which most changes in the stance of monetary policy result from the policy maker's response to changes in the fundamentals of the economy. To establish the direction of causation as stemming from monetary policy to macroeconomic aggregates requires isolating actions by the monetary authority which are orthogonal to the state of the economy, generally referred to as monetary policy shocks (C. A. Sims, 1992; Kilian & Lütkepohl, 2017). Uncovering the effects on the wider economy requires then tracing the response of variables describing the economy after such episodes (Boivin & Ng, 2006).

Since most of the changes in monetary policy are endogenous and largely anticipated by the public, it is inappropriate to use raw changes in the policy instrument as a candidate measure. Relying on these raw changes would attenuate the estimated responses (Kuttner, 2001; Ramey, 2016). Kuttner (2001) proposes disentangling the anticipated and unanticipated effects of monetary policy on asset prices by measuring movements in future rates during the day of a monetary policy announcement. Since the future rate prior to a monetary announcement should have incorporated all expectations regarding monetary policy, its response just following the announcements should reflect the unanticipated component.

Identifying monetary policy shocks and its effects on the macroeconomy is usually carried out through so-called Structural Vector Autoregressions (SVARs), also referred to as identified VARs (Boivin, Kiley, & Mishkin, 2010; Walsh, 2017). In the VAR framework, the dynamics of the economy are assumed to be captured by a small set of jointly-dependent variables, modelled through a system of equations (Boivin et al., 2010). Identifying episodes of exogenous variation in policy requires imposing restrictions such that the dynamics embodied by the identified VAR following a realisation of these disturbances are economically interpretable (Boivin & Ng, 2006; Kilian & Lütkepohl, 2017).

The SVAR literature has traditionally identified the effects of monetary policy shocks through recursiveness identification schemes, in which constraints on impact effects are derived through an ordering establishing which variables can respond on impact to shocks (Ramey, 2016). For example, the policy block is usually allowed to respond on impact to shocks in output and inflation but inflation and output respond to monetary shocks with a delay. There are two problems with this scheme. The first problem concerns the well-known price puzzle in which inflation rises, rather than falling, in response to a contractionary monetary policy shock. C. A. Sims (1992) argues this can be understood as policy makers' endogenous response to future anticipated inflationary pressures but in such a way that is insufficient to curb the rise when it materialises (Balke, Emery, et al., 1994). Failing to account for such foresight in a VAR results in wrongfully attributing the rising inflation to a contractionary shock, when the former triggered the latter. Controlling for anticipatory policy requires adding a variable that contains information regarding expected inflation to the VAR (Balke et al., 1994). Christiano, Eichenbaum, and Evans (1994) show that the inclusion of commodity prices solved the price puzzle over their sample but other studies continued finding these responses even after including this variable. For example, Balke et al. (1994) show that including commodity prices does not solve the puzzle during the 1960-1979 period, arguing instead that the results were driven by the Federal Reserve reacting to cost push shocks but insufficiently so to avoid inflation.

The second problem under the traditional recursiveness assumption relates to the transmission mechanism from monetary policy to macroeconomic aggregates. Modelling the transmission mechanism involves incorporating financial variables into the VAR. Unlike macro aggregates, for which recursiveness assumptions at a monthly frequency may be well-suited, the response to and from monetary policy and the financial markets is not well adept for such identification scheme (Gertler & Karadi, 2015).

Many more restrictions have been used in identifying monetary policy shocks in the literature (see Ramey (2016) for a review). I follow Gertler and Karadi (2015), who use intra-daily asset price movements around monetary policy announcements to identify the underlying structural shocks in a framework known as the Proxy SVAR. This identification framework imposes covariance-type restrictions which under certain assumptions provide a credible mechanism by which to recover the shocks. In particular, high frequency movements are assumed to be correlated with the underlying monetary policy shock but uncorrelated to all other structural shocks. The former condition is known as *relevance*, while the latter is referred to as *exogeneity*.

Using high-frequency surprises as external instruments provides a convincing argument in favour of relevance and exogeneity. Indeed, under the rational expectations hypothesis, private agents know the full structure of the model, in particular of the monetary policy rule, and form their expectations based on full information. Under this assumption, high frequency asset price movements on narrow intervals around monetary announcements are a measure of monetary policy shocks up to a measurement error (Miranda-Agrippino, 2016). Moreover, the narrow intervals used reduce the likelihood of other shocks acting upon the system at the same time (Gürkaynak et al., 2004). In what follows, I first identify forward guidance surprises and then proceed to use these as instrument in the Proxy SVAR framework.

5 Monetary Policy Shocks and High Frequency Price Movements

Gürkaynak et al. (2004) follows Kuttner (2001) in measuring the effect of monetary policy on asset prices using futures price movements around policy announcement dates. Unlike Kuttner, who uses movements at a daily frequency, Gürkaynak et al. (2004) use intra-daily asset price movements around narrow intervals covering the Federal Open Market Committee (FOMC), further strengthening the direction of causality running from monetary policy to financial variables and not in reverse (Altavilla et al., 2019b).

Other than their intra-daily approach to asset price movements, Gürkaynak et al. (2004) show that monetary policy communication in the United States is best described by two dimensions, a target dimension and path dimension. The target dimension is interpreted as the unanticipated change in the Federal Funds rate. The path dimension, which is orthogonal to the first dimension and to changes in the current Federal Funds rate, is interpreted as the component of policy which influences future expected rates beyond any variation in the target dimension, naturally being interpreted as a forward guidance measure (E. T. Swanson, 2015). E. T. Swanson (2015) extends the analysis to incorporate much of the effective-lower bound period and establishes the presence of a third dimension during this period, interpreted as a Quantitative Easing measure after the Large Asset Purchase Program (LSAP) of the Federal Reserve following the financial crisis.

Altavilla et al. (2019b) follow in the footsteps of Gürkaynak et al. (2004) and develop the Euro Area Monetary Policy Event Study Database, henceforth EA-MPD. The database contains high-frequency price movements around *scheduled*[6] ECB announcements for overnight index swaps (OIS) for a range of maturities, for major European countries' bonds, for the EUROSTOXX 50 and the SX7E index and for the exchange rate with major trading partners. Unlike the Federal Reserve, the ECB communicates its decisions during two events, a brief press release communicating the policy decisions and a subsequent press conference in which the president explains the decisions taken and addresses questions from the press. Specifically, the press release is published at 13:45 CET, while the press conference begins 45 minutes later, at 14:30 CET. The EA-MPD contains the high frequency movement data for both windows and for the union of these, called the monetary policy event window (Altavilla et al., 2019b).

For the press release, the pre-quote is taken as the median price between 13:25 - 13:45 CET, whereas the post-quote is taken between 14:00 - 14:15 CET. For the press conference, the pre-quote and post-quote are taken from the intervals 14:15-14:25 CET and 15:40 - 15:50 CET, respectively. The monetary event window contains the pre-quote from the press release and the post-quote from the press conference (Altavilla et al., 2019b).

In the Euro-area, Altavilla et al. identify one dimension during the press release window and three dimensions during the conference window. The unique dimension in the press release window loads heavily on the one month OIS rates and so is interpreted as the Target dimension, as in Gürkaynak et al. (2004). The first two dimensions in the conference window receive the interpretation of a short-term and a longer-term forward guidance measure while the third one is interpreted as a Quantitative Easing policy measure.

I follow Gürkaynak et al. (2004) who model the effects of the central bank communication on asset prices as a factor model. Under this model, the observed asset price movements are seen as having been generated by N common unobserved factors representing different dimensions of monetary policy plus some non-cross correlated residual white noise (Gürkaynak et al., 2004; Shalizi, 2013).

In principle, one could use high-frequency movements for all assets included in the EA-MPD but doing so may not give correct measures of unexpected changes in monetary policy. In this regard, overnight index swaps are a natural candidate since under the ex-

[6] This avoids the surprises being correlated with other contemporaneous shocks that the central bank may respond to (Miranda-Agrippino & Ricco, 2018)

pectation hypothesis of the yield curve, the fixed interest rate (referred to as the OIS rate) must equal the expectation of the floating overnight rate[7] (Lloyd, 2018). Indeed, Lloyd (2018) finds that OIS rates provide a good measure of current interest rate expectations for a period of up to two years, in which the term premium is small[8]. For periods further than two years, Lloyd suggests using government bond yields. This is problematic for the Euro-area following the sovereign-debt crisis where an increase in credit risk significantly affected the yield of government bonds (ECB, 2014). For these reasons, I opt to use OIS rates as in Altavilla et al. (2019b).

Furthermore, E. T. Swanson (2015) advocates for including only a subset of OIS contracts to avoid factors from arising from the common correlation generated by overlapping contracts rather than due to policy-mediated effects. Boivin and Ng (2006) find that increasing the number of series may also result in increased cross-correlation of the disturbances, thereby violating the assumptions inherit in the factor structure. Therefore, I choose to include OIS contracts for maturities of one, three, six months and one, two, five and ten years as in Altavilla et al. (2019b).

Let X be a $T \times 7$ matrix collecting the movement of the 7 choosen OIS rates for T monetary event dates as sourced through the EA-MPD. The factor model assumes that the observed price movements contained in X are the result of unobserved common components, $F\Lambda$, plus some asset-specific white noise, ε:

$$X = F\Lambda + \varepsilon$$

The latent component scores are captured by F, a matrix of dimension $T \times N$, where $N < K$. N refers to the number of latent factors, whereas K refers to the number of variables included in X, here 7. The impact of these unobserved factors on the asset prices are governed by Λ, a matrix dimension $N \times K$ referred to as the factor loading matrix (Gürkaynak et al., 2004; Shalizi, 2013; E. T. Swanson, 2015; Altavilla et al., 2019b).

While Gürkaynak et al. (2004) find two factors to be sufficient in explaining the variation of asset price movements on FOMC announcement dates prior to the financial

[7] An overnight index swap is an interest rate derivative based on the overnight rate, in which two parties agree to exchange interest rate payments based on an overnight floating rate and a fixed rate (Lloyd, 2018). For the Euro-area the floating overnight rate was the EONIA rate, though this is likely to change with the introduction of the new short term rate, the STR.

[8] On the other hand, OIS contracts have relatively low counter-party, liquidity and credit risk (Lloyd, 2018)

crisis, E. T. Swanson (2015) finds the emergence of a third factor for the post crisis period. Similarly, in the Euro-area, Altavilla et al. (2019b) find the emergence of a third factor during the conference window post financial crisis.

I repeat the test for the Euro-area under the expanded data set using all three windows: the press release, the conference and their union, the monetary policy event window. As in Altavilla et al. (2019b) the analysis begins in January 2002 and excludes the announcements on 8th of October and 6th of November of 2008. I extend the analysis to December 2019, testing the number of factors for the full sample, for the pre-crisis sample (January 2002 - August 2008) and for the pre-QE sample (January 2002 - December 2013). One could include dates post-2019 but doing so may compromise the analysis by introducing the unprecedented conditions that resulted from the Covid-19 pandemic (Nguyen & Lhuissier, 2020). I provide full details of the transformations to the raw data in Appendix A.

To test for the number of factors describing the observed price movements, the literature commonly uses the Cragg and Donald test (1997). Cragg and Donald (1997) propose testing for the rank of a matrix via minimising a distance measure between the variance of the data and the variance implied under a factor model with N_0 factors (Gürkaynak et al., 2004). The idea is to sequentially test for an increasing number of factors until it is no longer possible to reject the null of the data having been generated by more than N_0 factors. Further details on the test can be found in Appendix C[9].

Table 1 shows the results for all three window. Results for the conference and the press release window are similar. There are, however, some important results to highlight. Firstly, there is evidence of a third factor in the conference window prior to the introduction of Quantitative Easing measures (December 2013). This result highlights that these surprise are not be necessarily associated to a policy instrument. Rather, they represent policy measures as interpreted by the market. This is also true for forward guidance measures, with the ECB formally acknowledging the use of forward guidance measures for the first time in July 2013[10] but with path factor being detected during the pre-crisis period.

In 2016 the ECB shifted its communication regarding unconventional measures from the conference window to the press release window. This could explain why there is evi-

[9] I am grateful to Gürkaynak et al. for providing the MATLAB code to perform the test .

[10] `https://www.ecb.europa.eu/explainers/tell-me/html/what-is-forward_guidance.en.html`

		$N = 0$ $df = 21$	$N = 1$ $df = 14$	$N = 2$ $df = 8$	$N = 3$ $df = 3$
Conference Window	Full Sample	136.0528***	49.312***	21.0988***	4.7901
	Pre-Crisis	88.9795***	36.669***	7.7742	–
	Pre-QE	122.0747***	43.3018***	19.2974**	3.0867
Press Release Window	Full Sample	50.8692***	29.0493**	15.4728*	3.8572
	Pre-Crisis	69.8473***	21.9658	–	–
	Pre-QE	43.0567***	21.8678	–	–
Monetary Window	Full Sample	132.1148***	46.3722***	34.9938***	6.5035
	Pre-Crisis	76.7497***	36.5804***	14.5191	–
	Pre-QE	133.5971***	44.876***	19.7479**	9.559**

Table 1: Cragg and Donald Test for Number of Factors - Minimum Distance Estimates. N denotes the number of factor being tested for, df denotes the degrees of freedom. The full sample period encompasses January 2002 to December 2019. The Pre-Crisis period extends from January 2002 to August 2008 and the Pre-QE period runs from January 2002 to December 2013. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

dence for only one factor during the pre-crisis and pre-QE eras in the conference window but sufficient evidence for three factors for the full-sample[11]. In addition, this change in communication regarding unconventional measures presents additional challenges when identifying the forward guidance component. On the one hand, the conference window contains forward guidance announcements up to 2016. On the other hand, the press-release provides a measure of forward guidance only after this period. A natural alternative would be to use the monetary event window which incorporates both windows jointly. Using this window may come at a cost, however. It is not implausible for the ECB to alter its communication during the conference after having observed the markets' reaction to the information released during the press release[12]. Under this scenario, high frequency movements in asset prices taken over the monetary policy window might contain endogenous components of monetary policy. This would violate the very principle of using these price movements to measure monetary policy surprises. I opt, therefore, to use the conference window to identify the forward guidance surprises. In the appendix,

[11] One might have instead expected evidence of more than three factors during the full sample given the evidence for four factors when considering the conference window and the press release window during the pre-QE era.

[12] There are 45 minutes between the press release and the conference.

I show that the results from the factor extractions are remarkably similar across both of these windows. Moreover, the conference window also appears to capture more variation of the identified forward guidance factor.

Since there is evidence for three factors during the conference window for the entire sample, I proceed by extracting the first three principal components of the observed price movements. Principal components analysis, PCA, seeks to explains maximal variance for a set of variables with a reduced set of mutually uncorrelated components (Shalizi, 2013). It is straightforward to show that the principal components are eigenvectors asssociated with the N largest eigenvalues of the observed variables' variance covariance matrix. Let P be a matrix with columns containing the first N eigenvectors of the variance covariance matrix of the observed variables. The factor scores are found by forming linear combinations of the observed data with weights being determined by P, $F = XP$ (Wei, 2018).

It is well known that the common component, $F\Lambda$, suffers from indeterminacy (Shalizi, 2013). To see this, let Q be an orthogonal matrix ($Q'Q = I_N$) satisfying the dimension conditions for matrix multiplication. The original factor model is given by:

$$X = F\Lambda + \varepsilon$$

It is possible to rotate the factor score matrix, F, by Q and Λ by Q' without changing the features of the observed data matrix. Let $F^* = FQ$ and $\Lambda^* = Q'\Lambda$, rewriting the above as:

$$X = FQQ'\Lambda + \varepsilon$$

$$X = F^*\Lambda^* + \varepsilon$$

Since the residuals under the rotated model are the same as in the original model, the models are observationally equivalent (E. T. Swanson, 2015). This implies that one cannot interpret the extracted factors as corresponding to distinct monetary policy dimensions. In other words, under rotational indeterminacy, the principal components are merely a statistical device with no economic meaning attached (Gürkaynak et al., 2004; E. T. Swanson, 2015). Interpreting the observed price movements as having risen from distinct dimensions of monetary policy requires pinning down one rotation matrix by imposing a number of conditions that allow the rotated model to have an economic interpretation (E. T. Swanson, 2015).

5.1 Factor Model Identification

Since I seek to identify three factors, which implies Q is of dimensions 3×3, identification requires imposing 9 restrictions to uniquely pin down a Q matrix. The first six restrictions describe Q as being an orthogonal matrix, $QQ' = I$ (Altavilla, Brugnolini, Gürkaynak, Motto, & Ragusa, 2019a). The remaining three restrictions are derived from economic theory and lead to the structural interpretation of the factors as representing dimensions of monetary policy communication (Gürkaynak et al., 2004; E. T. Swanson, 2015)

Notice first that the rotated factors are linear combinations of the raw factors. For each rotated factor, F_i^*, for $i = 1, 2, 3$, it is the elements in the corresponding i-th column of Q that govern the weights assigned to each component. Similarly, the rotated loadings, Λ^*, are linear combinations of the original loadings with the elements in the rows of Q' (or equivalently the columns of Q) determining the weights given to each original loading. The natural way of thinking about this is that since the rotated factors are linear combinations of the original factors, their loadings are also determined by a linear combination of their original loadings, both governed by the appropriate column of the rotation matrix.

For the remaining three restrictions, E. T. Swanson (2015) builds on Gürkaynak et al. (2004) and proposes the following: First, the second and third factors, which we would like to interpret as forward guidance and Quantitative Easing, respectively, are not allowed to load on the one-month OIS contract. In terms of the rotation matrix these two restrictions can be expressed as:

$$Q_2'\Lambda_1 = 0$$

$$Q_3'\Lambda_1 = 0$$

Where Λ_1 denotes the first column of the loading matrix Λ, whose elements are the loads of the original factors on the one-month OIS rate.

The one remaining restriction is derived from the fact that the third factor, which is interpreted as Quantitative Easing, is not present prior to the financial crisis. Thus,

E. T. Swanson (2015) proposes minimising the variance of the third component over the pre-financial crisis period. Note that the variance of the Quantitative Easing factor is given by $(F_{pre}Q_3)'(F_{pre}Q_3)$, where F_{pre} contains the raw factors during prior to August 2008.

Mechanically, Altavilla et al. (2019b) imposes these restrictions through a constrained optimisation problem:

$$\begin{aligned} \min_{Q} \quad & (F_{pre}Q_3)'(F_{pre}Q_3) \\ \text{s.t.} \quad & QQ' = I_3, \\ & Q_2'\Lambda_1 = 0, \\ & Q_3'\Lambda_1 = 0 \end{aligned}$$

This identifies the rotation matrix, Q, up to a sign normalisation. To see why, notice that changing the sign of any column of Q will still be a solution to the above problem. To complete identification, I choose the signs such that the first rotated factor loads positively on the six-month OIS rate, the second rotated factor loads positively on the two-year OIS rate and the third one loads positively on the ten-year OIS rate, as in Altavilla et al. (2019b). Moreover, this allows to interpret these surprises as contractionary policy surprises (Altavilla et al., 2019b).

Table 2 show the estimated factor loadings on the different OIS contracts for the conference window. The forward guidance factor displays its characteristic hump-shape, with its influence on OIS rates first increasing across the term structure, peaking for the two-year OIS rate and decreasing thereafter. The Quantitative Easing factor, on the other hand, displays negative influence on the short term rates, possibly due to a substitution effect, rises thereafter and peaks at the ten-year OIS.

Altavilla et al. (2019b) finds that the first factor in the conference window only loads on the one-month OIS moderately. Indeed, Altavilla et al. name it ‘Timing’ as they interpret it as a type of forward guidance which acts on a shorter horizon. This interpretation does not seem to hold here, as I find it loads heavily on the one-month OIS rate. In fact, it acts much more as the ‘Target’ factor described by E. T. Swanson (2015) as its loads peaks for the asset with the shortest maturity and later decreases monotonically. For this reason I opt calling it ‘Target’. The difference with Altavilla et al. could be attributed to revisions in the EA-MPD database since it was first published.

	OIS_{1M}	OIS_{3M}	OIS_{6M}	OIS_{1Y}	OIS_{2Y}	OIS_{5Y}	OIS_{10Y}
TGT	1.00^{***}	0.68^{***}	0.59^{***}	0.50^{***}	0.36^{***}	0.31^{***}	0.22^{***}
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
FG	-0.00	0.65^{***}	0.79^{***}	0.86^{***}	0.88^{***}	0.79^{***}	0.62^{***}
	(0.02)	(0.04)	(0.02)	(0.01)	(0.04)	(0.02)	(0.03)
QE	0.00	-0.18^{***}	-0.09^{***}	0.03	0.23^{***}	0.49^{***}	0.72^{***}
	(0.01)	(0.04)	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)
Adj. R^2	0.99	0.92	0.98	0.98	0.95	0.96	0.95
Num. obs.	190	190	190	190	190	190	190

Table 2: Factor Loadings - Conference Window. Factor Loadings estimated through a regression of the form $OIS_t = \alpha + \beta F_t + u_t$ where OIS_t stands for the OIS high-frequency rate movements around Conference Window policy announcements and F_t stands for each of the three identified factors. TGT refers to the Target factor, FG to the forward guidance factor and QE to the Quantitative Easing factor. Newey-West standard errors reported in parenthesis, $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure 1 shows the identified forward guidance surprises. The largest contractionary surprise occurred in June 2008, whereas the largest expansionary surprise took place one month later, in July 2008. Large surprises are also identified in March and May 2011, with the former being contractionary and the latter being expansionary. This is consistent with ECB battling against the financial and economic turmoil resulting from the 2008 financial crisis and later on from the European sovereign debt crisis. In addition, variation in forward guidance surprises appear to diminish with time, with surprises after 2016 being small relative to early surprises.

To study the effect of forward guidance in aggregate variables, I proceed by using these surprises as external instruments for the underlying monetary policy shock in the SVAR framework, as done by Gertler and Karadi (2015).

6 Structural Vector Autoregressions

VARs and SVARs have become one of the main tools for applied macroeconomists ever since C. A. Sims (1980) famous critique of traditional structural dynamic simultaneous equation models (Kilian & Lütkepohl, 2017). In his seminal work, C. A. Sims argues that the exogeneity restrictions and the partial equilibrium approach used to model and estimate the then popular dynamic simultaneous equation models were often incredible. Instead, he advocated for estimating the joint dynamics of a small set of variables under

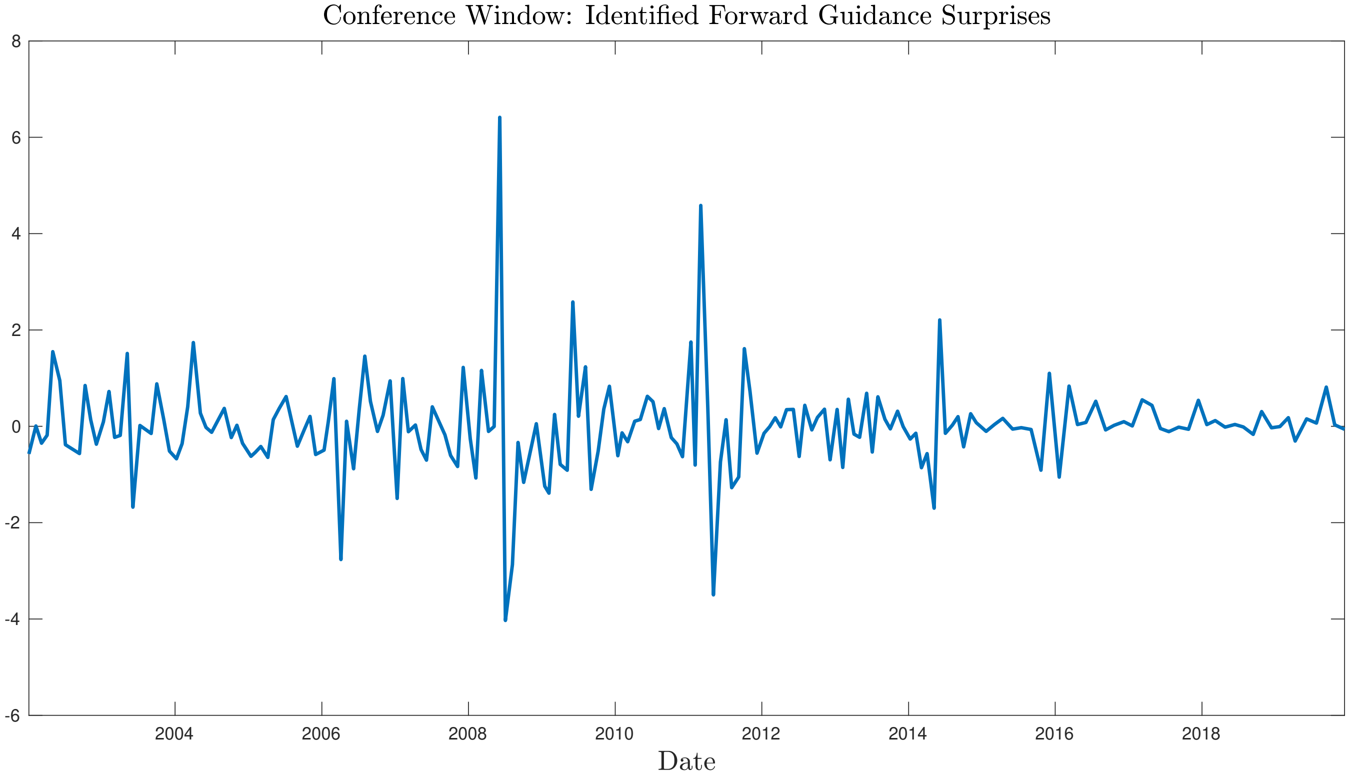

Figure 1: Identified Forward Guidance Surprises - Conference Window.

a system in which the evolution of every variable is allowed to be endogenously determined by itself and by every other included variable (Kilian & Lütkepohl, 2017). These models, known as vector autoregressions (VARs), or as reduced-form VARs, are seen as the estimable counterpart of the underlying mechanism assumed to have generated the observable data, known as the structural VAR (SVAR). 'Structural' refers here to the interpretation of this underlying mechanism as an economic model, or structure, as opposed to the micro-founded premise many modern theoretical models are based on (Fernández-Villaverde & Rubio-Ramírez, 2010).

In contrast to the reduced form, the structural VAR explicitly models the instantaneous response of the variables included in the system following the realisation of economically-interpretable mutually uncorrelated disturbances (Kilian & Lütkepohl, 2017). In this way, the dynamics embodied in the structural representation are seen as 'causal' in the sense of having been generated by distinct, identifiable economic shocks (Kilian & Lütkepohl, 2017). The results of these models are interpreted via (structural) impulse response functions (IRFs), which depict the joint evolution of the variables following a one-time realisation of a particular identified shock (Lütkepohl, 2010).

As opposed to the reduced from, the structural representation of the VAR is not estimable based solely on sample data. In particular, there are infinitely many candidate SVARs which could all have produced the same data. Following Gottschalk (2001) consider the structural form given by:

$$B_0 y_t = A_1^* y_{t-1} + A_2^* y_{t-2} + \ldots + A_p^* y_{t-p} + e_t$$

Where y_t is a $K \times 1$ vector, A_i^* and B_0 are a $K \times K$ matrices and e_t, the structural shocks vector, is of dimensions $K \times 1$. Furthermore, $\mathbb{E}(e_t) = 0$, $\mathbb{E}(e_t e_t') = D$, where D is diagonal. The estimable, reduced-form, is instead given by:

$$y_t = B_0^{-1} A_1^* y_{t-1} + B_0^{-1} A_2^* y_{t-2} + \ldots + B_0^{-1} A_p^* y_{t-p} + B_0^{-1} e_t$$

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t$$

Only the A_i parameter matrices, the residuals and reduced-form innovation's variance covariance matrix are estimable using sample data.

At the core of the SVAR framework is the assumption of *ivertbility*, which states the reduced form innovations, u_t, are non-singular transformations of the underlying structural shocks, e_t, encoded by B_0^{-1}. At a minimum, this requires that the VAR contains as many variables as there are shocks to the system (Stock & Watson, 2018).

Similar to the factor model, notice that it is possible to pre-multiply the original structural form by any comformable non-singular matrix Q. This alternative SVAR model would generate reduced-form estimates equivalent to original structural form and so it is not possible to distinguish one from the other.

$$QB_0 y_t = QA_1^* y_{t-1} + QA_2^* y_{t-2} + \ldots + QA_p^* y_{t-p} + Qe_t$$

$$y_t = B_0^{-1} Q^{-1} Q A_1^* y_{t-1} + B_0^{-1} Q^{-1} Q A_2^* y_{t-2} + + \ldots + B_0^{-1} Q^{-1} Q A_2^* y_{t-2} + B_0^{-1} Q^{-1} Q e_t$$

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t$$

Identifying the underlying structural form requires pinning down one and only one Q matrix, essentially excluding all but one structural representation (Christiano, Eichenbaum, & Evans, 1999; Gottschalk, 2001). Like the traditional structural dynamic simultaneous models, the restrictions used in the SVAR approach are based on out-of-sample information. Unlike traditional models, which usually restricted coefficients governing the effect of lagged values of the endogenous variables, C. A. Sims (1980) proposed restricting instead the coefficient matrix governing instantaneous responses, B_0, while emphasising the shocks be mutually uncorrelated (C. A. Sims, 2002; Kilian & Lütkepohl, 2017). As argued by C. A. Sims (2002) a structural interpretation is possible when the policy block can be changed without inducing changes to the joint distribution of the behavioural shocks. This would be implausible if structural disturbances were correlated across these blocks (C. A. Sims, 2002).

In practice, it is common to think about placing restrictions on the relationship $B_0^{-1}e_t$ rather than on $B_0 y_t$[13]. It is easy to note that restricting either B_0 or B_0^{-1} implies restrictions on the other quantity. As highlighted by Gottschalk (2001) restricting the instantaneous effects of shocks is often easier to impose on theoretical grounds.

6.1 Proxy SVAR

A large part of the empirical macroeconomics literature has been devoted to finding credible sets of restrictions to achieve identification (see Ramey (2016) and Kilian and Lütkepohl (2017) for a detailed overview). Stock and Watson (2012) and Mertens and Ravn (2013) build on the narrative identification approach introduced by Romer and Romer (1989) and propose instead using an external variable correlated with the shock of interest but uncorrelated to all other contemporary structural shocks[14], a framework now known as Proxy SVAR or SVAR identified by external instruments (Stock & Watson, 2018). Here, external refers to the instrument not being endogenously determined in the VAR. As a result its exclusion does not constitute a mis-specification of the model (Stock & Watson, 2018).

In terms of monetary policy, Gertler and Karadi (2015) use the high-frequency asset price movements as instruments to identify the underlying monetary policy shocks. This is in contrast to other studies which effectively used these high-frequency surprises as the

[13] Lütkepohl (2005) refers to these models as the B model and the A model, respectively. Other than thinking about restricting the impact effects of shocks rather than that of the variables themselves and some normalisation nuisances, there are very little differences among these models.

[14] By some accounts, Stock introduced the Proxy SVAR or SVAR-IV method in his lecture as part of the short courses series of NBER (Stock & Watson, 2018).

monetary policy shock in a constrained-VAR framework (see, for example, Jarociński and Karadi (2020)).

To understand how this approach results in identification, let $e_{1,t}$ be the structural shock of interest and without loss of generality consider a bivariate VAR that correctly models the dynamics of the system. In addition, let η denote the covariance between the target shock and the instrument. The moment conditions required by the Proxy SVAR framework are:

$$\mathbb{E}(z_t e_{1,t}) = \eta \tag{Relevance}$$

$$\mathbb{E}(z_t e_{2,t}) = 0 \tag{Exogeneity}$$

These imply covariance restrictions on the impact matrix B_0^{-1} (Mertens & Ravn, 2013). To see how, recall the reduced form innovations are non-singular linear combinations of the underlying structural shocks (Olea et al., 2020):

$$u_t = B_0^{-1}\varepsilon_t$$

$$\begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,1} \end{pmatrix}$$

Taking expectations and using the moment conditions above yields:

$$\begin{pmatrix} \mathbb{E}(z_t u_{1,t}) \\ \mathbb{E}(z_t u_{2,t}) \end{pmatrix} = \begin{bmatrix} b_{11}\,\mathbb{E}(z_t\varepsilon_{1,t}) + b_{12}\,\mathbb{E}(z_t\varepsilon_{2,t}) \\ b_{12}\,\mathbb{E}(z_t\varepsilon_{1,t}) + b_{22}\,\mathbb{E}(z_t\varepsilon_{2,t}) \end{bmatrix}$$

$$\begin{pmatrix} \mathbb{E}(z_t u_{1,t}) \\ \mathbb{E}(z_t u_{2,t}) \end{pmatrix} = \eta \begin{bmatrix} b_{11} \\ b_{12} \end{bmatrix}$$

Letting B_1 denote the column of the impact parameter matrix corresponding to the impact effects of the target shock, the above can be rewritten as:

$$\mathbb{E}(z_t u_t) = \eta B_1$$

The instrument identifies the impact coefficients of interest up to the covariance between the reduced form residuals and the external instrument. This implies that without an additional restriction on these quantities, it is not possible to disentangle the size of the shock from the size of variables' responses (Stock & Watson, 2016). To recover the on-impact coefficients I follow Stock and Watson (2012), who impose a unit-effect normalisation to complete identification. In particular, assume that the forward guidance shock, the shock of interest, has been scaled in such a way it produces a unit effect on impact in some variable. Without loss of generality, let this variable be ordered first in the system. This implies an additional restriction in the form of $b_{11} = 1$.

$$\begin{pmatrix} \mathbb{E}(z_t u_{1,t}) \\ \mathbb{E}(z_t u_{2,t}) \end{pmatrix} = \eta \begin{bmatrix} 1 \\ b_{12} \end{bmatrix}$$

It is then straightforward to recover the remaining parameters in a two step approach: After obtaining the reduced-form innovations, estimate the covariance between the external instrument and all innovations and then scale these quantities by the reciprocal of the covariance of the instrument and the pre-specified unit-effect normalised variable. Under the unit-effect normalisation, the latter estimated covariance recovers an estimate of η. It is then possible to derive a simple 'plug-in' estimator for B_1 (Kilian & Lütkepohl, 2017):

$$\hat{\eta} = \frac{1}{T}\sum_{t=1}^{T} z_t \hat{u}_{1,t}$$

$$\hat{B}_1 = \frac{1}{\hat{\eta}}\frac{1}{T}\sum_{t=1}^{T} z_t \hat{u}_t$$

To recover the shock sequence, Stock and Watson (2012) scale the population projection of the instrument on the VAR reduced-form residuals by the inverse of the ratio of η and the standard deviation of the target shock, $\frac{\eta}{\sigma_1}$. This identifies the shock up to a sign convention and up to the inverse of its standard deviation. Mechanically, this means the sequence can be recovered through the following:

$$\frac{e_{1,t}}{\sigma_1} = \frac{\mathbb{E}(z_t u_t')\,\mathbb{E}(u_t u_t')^{-1} u_t}{\sqrt{\mathbb{E}(z_t u_t')'\,\mathbb{E}(u_t u_t')^{-1}\,\mathbb{E}(z_t u_t')}}$$

To obtain a simple estimator of the history of shocks, the population moments conditions can be replaced by the sample moment conditions. I provide further details in the Appendix C.

6.2 Weak Proxy Problem

Olea et al. (2020) show that the external instrument estimafor for B_1 is inconsistent if the instrument is weak, a situation in which $\frac{\hat{\eta}}{\sqrt{T}}$ converges to zero asymptotically. Instead, the structural IRFs are biased by a ratio of Gaussian random variables in an additive separable fashion.

The external instrument literature has traditionally tested for weak proxies following the methods described in the IV literature, by computing the F-statistic of a regression of one innovation on the external instrument and comparing its value against the usual threshold critical value of 10 (Lunsford, 2015). Lunsford (2015) shows that this approach is mistaken in the external instrument case. Indeed, since in the external instrument case one does not observe the shocks, the distribution and therefore the critical values of the F-statistic used in the IV literature depend on the impact matrix B_0^{-1}. This implies not only that the critical values vary with the proxy being used but also that the estimated critical values may result in a mis-sized test if the proxy is weak and thus the estimate of B_1 is imprecise.

Lunsford (2015) models a weak external instrument under a local-to-zero assumption where the covariance between the external instrument and the structural shock converges to zero at rate $\sqrt{T}$. Under a weak proxy, the estimator for B_1 converges in distribution with parameter $\frac{C^2}{\sigma_\varepsilon^2}$ governing its shape. $\frac{C^2}{\sigma_\varepsilon^2}$ is interpreted as a signal-to-noise measure, that is, the strength of the proxy, C, relative to the variance of the underlying structural shock, σ_ε^2. As $\frac{C^2}{\sigma_\varepsilon^2} \to \infty$, the estimator of B_1 collapses to a degenerate distribution around its population value.

Following the IV literature, Lunsford (2015) measures the asymptotic bias generated under various signal-to-noise ratios and defines $\left(\frac{C^2}{\sigma_\varepsilon^2}\right)^*$ as the minimum noise-to-signal ratio needed for an asymptotic bias smaller than a user-defined maximum asymptotic bias tolerance, $1-b$, under a specific VAR dimension, K. The set of external instruments with $\frac{C^2}{\sigma_\varepsilon^2} \leq \left(\frac{C^2}{\sigma_\varepsilon^2}\right)^*$ belong to the weak proxy set. Lunsford then proposes testing whether the external instrument belongs to the weak proxy set through an F-statistic based on a regression of the instrument on the VAR innovations. Let $\hat{E}$ denote the residuals of this regression. Formally, the null and alternative hypothesis are:

$$\mathbb{H}_0 : \frac{C^2}{\sigma_\varepsilon^2} \in \left[0, \left(\frac{C^2}{\sigma_\varepsilon^2}\right)^*\right]$$

$$\mathbb{H}_1 : \frac{C^2}{\sigma_\varepsilon^2} \in \left(\left(\frac{C^2}{\sigma_\varepsilon^2}\right)^*, \infty\right)$$

The F-statistic is given by:

$$F_{Lunsford} = \frac{T-K}{K}\left[\frac{ZZ' - \hat{E}'\hat{E}}{\hat{E}'\hat{E}}\right]$$

Unlike the traditional IV approach, $F_{Lunsford}$ does not depend on estimates of B_0^{-1}. $kF_{Lunsford}$ converges in distribution to a non-central χ^2 distribution with non-cetrality parameter $\frac{C^2}{\sigma_\varepsilon^2}$. A large F-statistic implies that the probability of $\frac{C^2}{\sigma_\varepsilon^2} > \left(\frac{C^2}{\sigma_\varepsilon^2}\right)^*$ is sufficiently large to reject the weak instrument hypothesis, meaning there is sufficient evidence to reject an asymptotic bias larger or equal than $1-b$ at a given confidence level.

In practice, the computation of the F-statistic is simple. Lunsford (2015) provides threshold values, $\left(\frac{C^2}{\sigma_\varepsilon^2}\right)^*$, for a combination of VAR dimensions and asymptotic biases. Standard software can then compute the implied p-value, where this quantity is derived from a non-central χ^2 distribution with k degrees of freedom and the scaled F-statistic, $kF_{Lunsford}$.

6.3 Inference

I adopt the moving block bootstrap suggested by Jentsch and Lunsford (2019) to construct confidence intervals for the impulse response functions estimated via external instruments. Jentsch and Lunsford build upon the contributions made by Brüggemann, Jentsch, and Trenkler (2016) and show that the wild-recursive bootstrap commonly used in the external instrument literature is invalid as it fails to reproduce the fourth-moment dependence between the model's residuals and the external instrument. They instead suggest a simple modification to the residual-based moving block bootstrap procedure, in which blocks of the proxy variable are bootstrapped along with blocks of the innovations[15]

Nonetheless, there are several reasons why this approach might result in missized confidence intervals for my estimated SVAR. Firstly, the results found by Jentsch and Lunsford (2019) are based on a stable VAR process. This condition is unlikely to be satisfied in my empirical specification as some variables, like HICP, are usually modelled as integrated processes[16]. As such, their results do not necessarily carry over to my setting. In a related issue, being non-linear functions of the parameter matrices, impulse response functions may inherit the degenerate distribution of the estimated coefficients in integrated or cointegrated systems (Benkwitz, Neumann, & Lütekpohl, 2000). This is a possibility even in a stationary setting but it is aggravated in integrated and cointegrated systems. Bootstrap methods, which are based on asymptotic theory, are equally affected by these singularities (Lütkepohl, 2000). Finally, in the simulations performed by Brüggemann et al. (2016), the moving block bootstrapped required large sample sizes for correctly sized intervals (Lütkepohl & Schlaak, 2021). In light of these observations, I advice caution when interpreting confidence bands.

The degenerate limiting distribution of the estimated parameter matrices, could, in principle, be dealt with via the lag-augmentation technique first proposed by Dolado and Lütkepohl (1996). I, however, find that lag-augmentation too often results in either explosive estimates or explosive bootstrapped impulse responses, making inference invalid. To the best of my knowledge, these seemingly puzzling results have not been described in the literature and thus would be important to explore in coming years.

A final point I would like to make in regards to inference concerns the different estimation procedures available for Proxy SVARs. Mertens and Ravn (2013), Stock and Watson (2012) and Lunsford (2015) all provide different estimators for B_1. Unlike Lunsford and Mertens and Ravn, who base their estimation approaches on a unit-standard deviation normalisation, the estimation approach suggested by Stock and Watson (2012), which I adopt here, relies on a unit-effect normalisation. This difference has important implications for inference. Stock and Watson (2016) argue that the additional uncertainty

[15]Some lines of code for the bootstrap were built upon using Cesa-Bianchi, Thwaites, and Vicondoa's (2020) replication files and Trenkler's code for the class Multiple Time Series Analysis at the University of Mannheim. Further details can be found in the code file.

[16]Indeed, the ADF test also suggests this is the case in my setting.

introduced by the normalization is unaccounted for under a unit standard deviation normalisation, meaning that confidence intervals based on this normalisation are mis-sized. In general, this also means that confidence intervals produced under a unit-effect normalisation will be larger than those produced under the alternative.

7 Empirical Specification

Identifying and modelling the dynamic effects of monetary policy requires correctly approximating the data generating process. Although VARs model the joint dynamics by treating all variables as endogenous, the number of parameters grows quickly with the inclusion of each additional variable, often resulting in imprecise parameter estimates (Nicholson, Wilms, Bien, & Matteson, 2014). On the other hand, failure to include all relevant variables in the VAR results in model mis-specification and possibly a failure of the invertibility assumption, biasing the estimated impulse responses even with a strong proxy (Stock & Watson, 2018; Caldara & Herbst, 2019).

Following much of the literature I estimate a monthly VAR with six variables. In particular, I include the natural logarithm of the industrial production index; the natural logarithm of the harmonised index of consumer prices (HICP); the European non-financial corporate bond spread as constructed by Gilchrist and Mojon (2018); the two-year German bond yield as policy indicator; a market-based measure of 3-year inflation expectations and the spread between the Italian and the German sovereign bond yield with maturity of 10 years. As discussed in the robustness section, my results are robust to the inclusion of variables like the EUROSTOXX index and the exchange rate. Further details on the data and transformations employed can be found in Appendix A.

The inclusion of the industrial production index and the HICP as measures for output and prices, respectively, is standard in literature. The two-year German bond yield serves as policy indicator following Gertler and Karadi (2015) who suggest using a longer-term government bond yield as policy indicator for forward guidance. Indeed, under the expectation hypothesis today's long term yield is an average of expected future short-term rates. It follows that movements in the long term rate incorporates revisions to the expected path of future interest rate (Praet, 2013). I use the German government bond yield, in particular, as it incorporates less risk premia and has remained sensitive during the ELB period (ECB, 2014; Kerssenfischer, 2019).

The New Keynesian model makes it clear that inflation expectations is key in determining the real rate of interest and therefore households' intertemporal consumption-saving decision. Moreover, optimal monetary policy in a liquidity trap involves being able to influence inflation and output expectations favourably (Eggertsson & Woodford, 2003; Werning, 2012). Therefore, I include a market based measure of inflation expectations derived from inflation-linked swaps with three years to maturity. Note, however, that such market-based approaches to infer inflation expectations are likely contaminated with inflation risk premia (Grothe & Meyler, 2015; De Santis, 2016).

Gilchrist and Mojon (2018) construct the non-financial corporate spread for the Euro-area as the difference between the average corporate bond yields for non-financial companies and the German government bond yields of matching maturity (Gilchrist & Mojon, 2018). The non-financial corporate credit spreads have been shown to be able to predict the evolution of the real economy, which is of special importance in potentially information-deficient VARs. (Miranda-Agrippino, 2016; Miranda-Agrippino & Ricco, 2018). In addition, Caldara and Herbst (2019) show that omitting credit spreads attenuates impulse responses of real activity to monetary policy shocks, possibly by failing to capture the endogenous response of the central bank to future anticipated financial conditions.

Finally, the Italian-German 10-year government bond yield spread is incorporated to capture the debt-fragmentation of the Euro-area to which the ECB might have been responding to, in a similar fashion to Kane et al. (2018). Although being rooted on the poor fiscal condition of member states, the sovereign debt crisis threatened the integrity of the entire Monetary Union and its financial stability as well as the homogeneous transmission of monetary policy (Rostagno et al., 2019).

To obtain a monthly measure of the forward guidance surprises, I opt to follow Miranda-Agrippino and Ricco (2016), who simply take the sum of all surprises in a month. For months with only one announcement, the monthly surprise equals the value for this announcement. For months with no announcements then the monthly value equals zero[17].

[17] A common alternative is to use the method proposed by Gertler and Karadi (2015). However, several authors have found that this method induces autocorrelation in the surprises (Ramey, 2016; Miranda-Agrippino & Ricco, 2018)

In the baseline specification I begin the analysis in April 2009, following Ehrmann, Gaballo, Hoffmann, and Strasser (2019), who suggest the effective lower bound period is reached once the short term policy rate indicator, EONIA in the case of the Euro-area, is below 1%. Indeed, restricting the sample to periods in which the ELB constraint binds limits the possibility of regime changes triggering a mis-specification in the monetary policy rule (Bagliano & Favero, 1998).

Consider a K-dimensional reduced form VAR(p) model, where all deterministic terms have been omitted for simplicity:

$$y_t = A_1 y_{t-1} + A_2 y_{t-1} + ... + A_p y_{t-p} + u_t, \quad u_t \sim WN(0, \Sigma_u)$$

The model can be rewritten as a VAR(1) through the companion form representation:

$$\mathbf{Y_t} = \mathbf{A Y_{t-1}} + \mathbf{U_t}$$

Where $\mathbf{Y_t}$, $\mathbf{U_t}$ are $Kp \times 1$ vectors and $\mathbf{A}$ is a $Kp \times Kp$ matrix. The first equation of the system recovers the original VAR(p) process, while the remaining equations are identities. The model is said to be stable if all eigenvalues of the companion form matrix $\mathbf{A}$ are less than unity in absolute value.

Under the stability condition, the VAR system can be expressed in the canonical MA representation, which expresses the current value of the system in terms of a weighted average of the current and past innovations:

$$y_t = \sum_{j=0}^{\infty} \Phi_j u_{t-j} \tag{1}$$

Where $\Phi_j = \mathbf{J A^i J'}$ with $\mathbf{J}$ being a matrix of dimensions $K \times Kp$ equaling $\mathbf{J} = [I_K, 0, \ldots, 0]$ or more generally $\Phi_j = \sum_{i=1}^{i} \Phi_{j-i} A_j$. In particular, under the canonical representation $\Phi_0 = I_K$ and u_t is a vector white noise process. Moreover, under this representation the MA parameter matrices are square summable, $\sum_{j=0}^{\infty} \Phi_j < \infty$[18]. The structural MA representation is found by recognising that the reduced form innovations are linear combinations of the structural shocks:

[18] The Wold Representation Theorem establishes that every covariance-stationary process has a canonical representation of this form. In addition, under stability, the MA coefficients are absolutely summable (Lütkepohl, 2005).

$$y_t = \sum_{j=0}^{\infty} \Theta_j \varepsilon_{t-j} \tag{2}$$

where $\Theta_j = \Phi_j B_0^{-1}$ (Lütkepohl, 2005).

VARs are interpreted through so called impulse response functions which depict the dynamics of the system following a one time realisation of one element of the innovation vector, $u_{t,i}$, where i indicates the element in question. It is straightforward to see that the response of the system to an innovation to $u_{t,i}$ h periods in the past is given by the i-th column of Θ_h (Lütkepohl, 2005, 2010).

Integrated or cointegrated systems do not possess a fundamental representation as given by (2) since at least one eigenvalue in $\mathbf{A}$ equals unity. Indeed, in this case the systems' initial conditions do not dissipate as $t \to \infty$. Nevertheless, the impulse response functions can be computed as above. In particular, under integration or cointegration the system can be re-expressed as:

$$y_t = \sum_{j=0}^{t-1} \Phi_j u_{t-j} + \mathbf{J}\mathbf{A}^t Y_0 \tag{3}$$

Where Y_0 is a vector of initial conditions (Kilian & Lütkepohl, 2017).The Φ_j in (3) are not the MA coefficient matrices of the canonical representation as they are no longer square summable, and the effects of shocks or innovations may not decay to zero in the limit (Lütkepohl & Reimers, 1992).

I specify the model in levels, ignoring possible cointegrating relationships. Indeed, if the variables are cointegrated, these relationships will be implicitly estimated by the VAR in levels, whereas first-differencing would result in a model mis-specification and in the OLS estimator being inconsistent[19](Naka & Tufte, 1997; Kilian & Lütkepohl, 2017) . Indeed, it is straightforward to show that fitting a VECM model, which explicitly models cointegrating relationships, is just a re-parametarisation of the VAR in levels (Naka & Tufte, 1997).

With or without cointegration, the OLS estimator for a VAR in levels remains consistent. Moreover, as long as $p > 1$ and a constant is included, the marginal distribution of the VAR parameter matrices retain their asymptotic normality, even if cointegration

[19]In small samples, the OLS estimator is biased (Kilian & Lütkepohl, 2017). I, however, do not apply any bias correction since the system is already near explosive.

is present. However, the joint distribution of the VAR parameter matrices is degenerate under cointegration. This creates complications when testing for joint restrictions, for example, when testing for the joint significance of impulse responses (Kilian & Lütkepohl, 2017), which is something I do not pursue here.

The information criteria suggests lag orders ranging from one to four[20]. I test for residual autocorrelation by applying the Lagrange multiplier test (otherwise known as the Breusch-Godfrey test) and the F-Rao test sequentially to differing lag orders[21]. Both tests indicate the presence of residual auto-correlation for all lags considered by the information criteria and for lags beyond these. This is not entirely unexpected as Edgerton and Shukur (1999) show both tests perform poorly for large systems and for systems with strongly autocorrelated variables. Instead, I choose a specification that retains model parsimony and that result in acceptable levels residual autocorrelations as given by the autocorrelation plots. In particular, I fit a VAR(4) with a constant. This specification results in acceptable levels of residual autocorrelation at low lags but with some significant autocorrelation at very long lags[22]. In the robustness section I show that my results are incentive to lag order specification. Last, I define the weak proxy set as those proxy variables which generate an asymptotic bias larger than 20%. Testing for the strength of forward guidance surprises using Lunsford's F-test leads to rejection of the null hypothesis at the 5% level, meaning there is sufficient evidence to indicate these surprises are in the strong proxy set.

[20]I am grateful to my supervisor, Professor Dr. Carsten Trenkler, for providing the code for the computation of the lag order as suggested by the information criteria. The code has been written part of his Multiple Time Series Class at the University of Mannheim.

[21]The Portmanteau test performs poorly in level VARs with integrated or cointegrated variables, whereas the LM test displays acceptable size provided the system and the lags being tested for are small (Brüggemann, Lütkepohl, & Saikkonen, 2006).

[22]I provide the residual autocorrelation plots in Appendix B.

8 Baseline Results

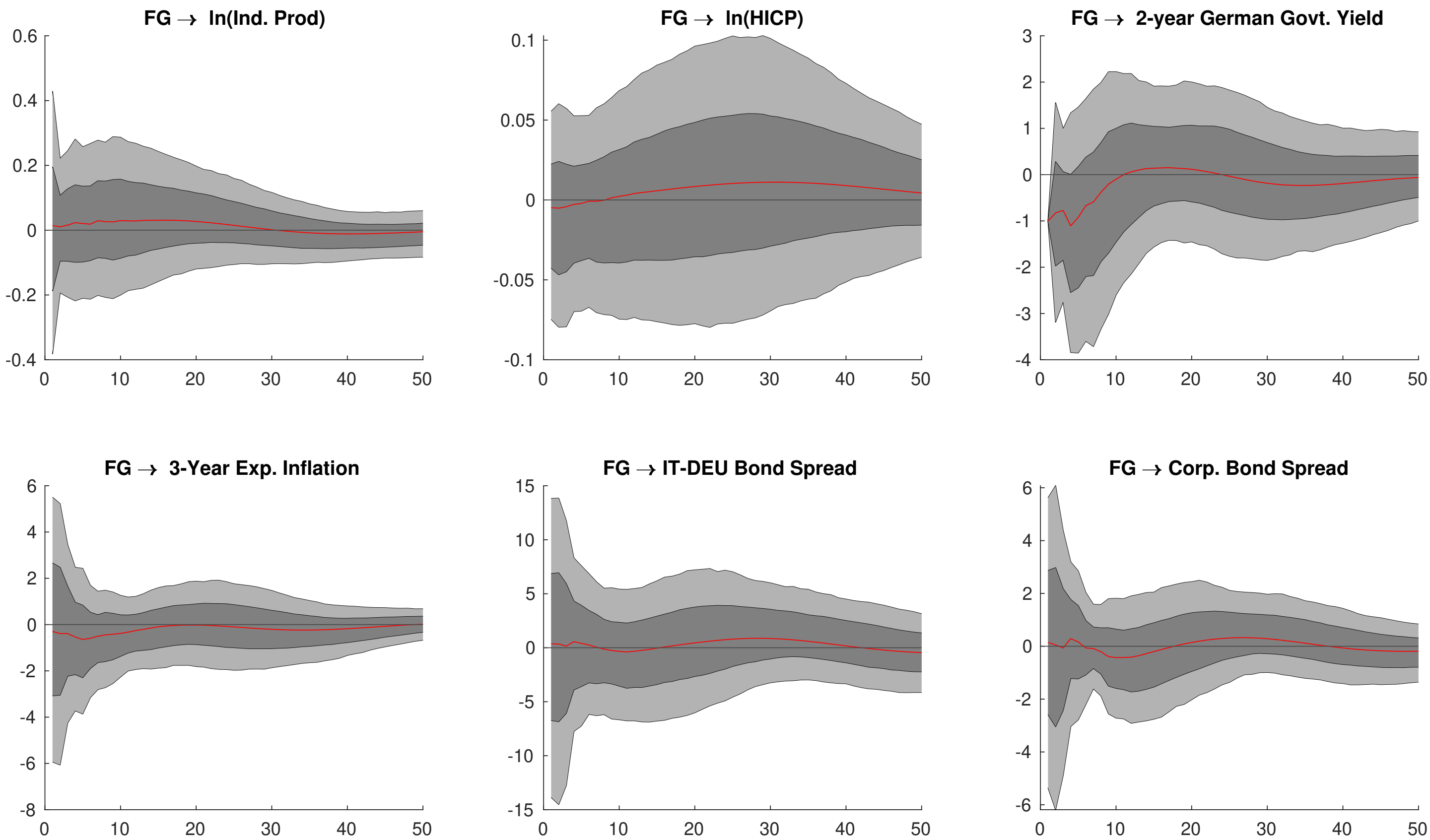

Figure 2: IRFs following a one time negative forward guidance shock, identified via external instruments. Light grey areas and dark grey areas indicate 90% and 80% confidence intervals, as estimated via the moving block bootstrap with 9999 bootstrap samples.

Figure 2 displays the results to a one time *expansionary*[23] forward guidance shock that lowers the German 2 year government bond yield by 1 percentage point on impact. The light and dark grey bands depict the bootstrapped confidence intervals at the 90% and 80% significance levels, respectively, constructed via 9999 bootstrap samples.

It is worth noting that the confidence intervals around the point estimate IRFs are large. Indeed, at the 90% level no variable displays significant responses. At the 80% confidence level, only the 2-year German yield displays significant responses at some short

[23]It is traditional in the literature to display IRFs to a positive shock realisation. I opt for a negative shock realisation since expansionary monetary policy is the concern during crises. Note, however, that due to the linearity of the VAR model this is without loss of generality. Indeed, the IRFs to a one time positive shock realisation are just the reflection of those depicted in figure 2 along the x-axis.

horizons. Other than possibly being a consequence of the objects outlined above, this might also indicate conditional heterokedasticity that has not been accounted for in the estimation (Lütkepohl & Schlaak, 2021).

By construction, the shock lowers the 2-year German government bond yield by 1 percentage point on impact. The effect reaches its peak effect at 4 months post impact, with the yield falling by an additional 10 basis points. Subsequently, the effect gradually dissipates and reaches insignificance once again by five months post impact.

The confidence intervals around the point IRFs for industrial production and the HICP suggest forward guidance is ineffective in stimulating output and prices. The point estimates indicate a modest effect at best. Recall that these effects are relative to a shock that induced a large, 1 percentage point, decline in the policy indicator. The peak effect for industrial production is reached 17 months post impact with it rising by 3 basis points. For HICP, the peak effect is reached by month 31 post impact with it rising by only 1 basis point. The shape of the IRFs are consistent with the prior literature describing hump-shaped effects on output and prices.

The point IRF for inflation expectations displays puzzling, albeit insignificant effects. Indeed, the estimate suggests inflation expectations decrease after an expansionary forward guidance policy shock. The effect is also persistent, with expectations falling by 64 basis points by month five and remaining negative for all considered horizons. This cannot be explained by the measure of expectations being contaminated with inflation risk premia, as I would expect the premia to also rise following an expansionary shock.

The responses of the Italian-German 10 year government bond yield spread and the non-financial corporate bond spread are also insignificant. The point estimates for both variables are similar and suggest that both rise slightly on impact. These responses are also problematic given that expansionary forward guidance should be associated with easing financial conditions. Nevertheless, the subsequent rather rapid oscillatory behaviour also hints towards the response being minimal and only imprecisely estimated.

Figure 3 displays the identified forward guidance shocks. The most noticeable shocks occurred during the 2011-2014 period, consistent with ECB grappling against the European sovereign debt crisis which at the time threatened to break-up the Euro-area. The largest *contractionary*, positive, shocks occurred during January and March 2011 and January 2013, whereas the largest *expansionary* shocks were realised during February

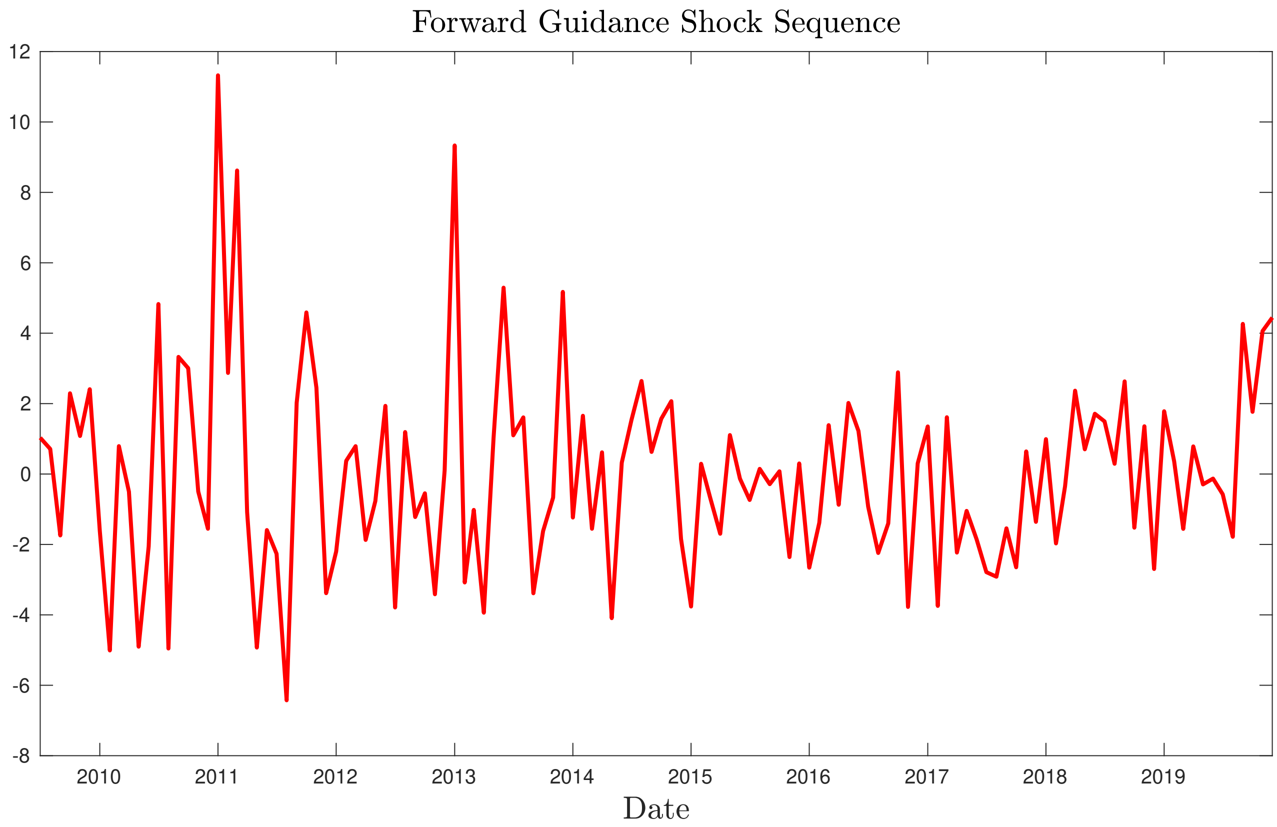

Figure 3: Identified sequence of Forward Guidance Shocks via external instruments.

and August 2010, and May and August of 2011. I urge caution in interpreting positive shock realisations as contractionary policy. Recall that in the New Keynesian model, a monetary policy shock entails setting an interest rate higher or lower than the interest rate implied by the model. Similarly, the shocks being identified here result from using high-frequency surprises around monetary policy announcements as external instruments. In this way, these high-frequency surprises could be interpreted as a higher or lower response by the ECB as perceived by market participants. Thus, a contractionary shock can still be consistent with overall easing policy.

Taken together, my results suggest that forward guidance was ineffective at stimulating output and inflation as well as unsuccessful at easing financial conditions and debt fragmentation in the Euro-area during the ELB period. It is possible, however, that my results are biased. Several authors have suggested that monetary announcements do not only reveal information regarding current and future policy actions but also relay information regarding the future state of the economy. In this case, the forward guidance surprises would be correlated not only with the monetary policy shock but also with a shock regarding the state of the economy, violating the exogeneity condition required by the Proxy-SVAR framework. In this way, a monetary policy shock labelled as contractionary would be accompanied by a positive information shock with the market interpreting unanticipated contractionary decisions as the central bank foreseeing favourable conditions in the future. Note, however, that the identification of forward guidance *surprises* is not attenuated even in the presence of these effects. Indeed, the impact of the information effect is predicted to move OIS rates in the same direction as the monetary component (Altavilla et al., 2019b).

This could also be understood through the New Keynesian model. Optimal monetary policy calls the central bank to commit to keeping interest rates low for a period of time even after the ELB constraint no longer binds. In the model, private agents are assumed to understand the structure of the economy, so they interpret this policy as purely monetary. However, if agents are not perfectly informed, then forward guidance announcements can also act to inform agents regarding the path of the natural rate. Since according to the NKPC, inflation today is the result of today's and all future expected real interest rate gaps, the simultaneous release of information may fail to bring the real rate closer to the natural rate. As a consequence forward guidance would be less effective (Nakamura & Steinsson, 2018).

9 Information Shocks

Under the standard premise of rational expectations, agents are assumed to know the model and to understand the systematic behaviour of monetary policy. Under this assumption, high-frequency surprises around policy announcements are a measure of monetary policy shocks up to a measurement error (Miranda-Agrippino, 2016). Since monetary policy actions are frequently taken in anticipation of future events, it is possible that in announcing monetary policy actions, the central bank also transfers knowledge regarding the future state of the economy.

Romer and Romer (2004), for example, show that much of the conventional wisdom of aggregate responses to monetary policy shocks is restored after their narrative series is orthogonalised with respect to the Federal Reserve's forecasts. They argue that failing to do so would result in a measure of monetary policy shocks contaminated with the endogenous variation in response to the policy maker's anticipation of future events. Miranda-Agrippino (2016) suggests that using high-frequency surprises does not circumvent the policy maker's anticipation of future events if agents differ on information sets or forecast model. Such differences may result in incorrectly labelling market reactions around policy announcements as a measure of monetary policy shocks when it may have resulted from the unanticipated but systematic component of the monetary policy rule. Indeed, Miranda-Agrippino finds evidence that high-frequency surprises during policy announcements in the United States are predictable by macro-financial factors. Not only does this provide evidence for imperfect information (Miranda-Agrippino & Ricco, 2018), but according to Miranda-Agrippino (2016) this type of predictability also implies the surprises are correlated with a shock to the premia required by investors.

Bauer and Swanson (2020) and Cieslak (2018) argue against Miranda-Agrippino's (2016) interpretation of the predictability of monetary surprises as time-varying risk premium. Instead they argue that the ex-post predictability of surprises is due to a failure of market participants to recognise useful information when making their forecast. While the econometrician can uncover these relationships by looking at the data ex-post, doing so ex-ante would be much harder. Bauer and Swanson (2020) suggest that the ex-post predictability could be reconciled with agents learning about the monetary policy rule. In such environment, forecasts are optimal and rational but subjected to the current understanding of the operation of monetary policy. Such ex-post predictability caused by imperfect information on the conduct of monetary policy can also result in a failure of the exogenetiy condition. Suppose the central bank reaction function specifies the path of nominal interest rates solely as a function of output and inflation. If market participants are learning how the central bank operates through their announcements, then the surprises could be the result from the systematic but unknown component of the rule. Since the surprises are now correlated with systematic component of monetary policy, then shocks to inflation and output would also be correlated with the surprises (Bauer & Swanson, 2020). If such situation arises, Bauer and Swanson (2020) suggest simply projecting the surprises on all predictive variables and using the residuals as the new external instrument.

Campbell et al. (2012) present evidence of information transfer beyond that concerning monetary policy actions during announcements. In particular they show that the forward guidance factor as identified by Gürkaynak et al. (2004) is associated with private forecast revisions of the opposite sign to that predicted by theory. They coin the terms "Odyssean" and "Delphic" forward guidance to refer to information regarding policy commitments and to information regarding the fundamentals of the economy, respectively. The latter is ultimately responsible for the counter-intuitive forecast revisions. Nakamura and Steinsson (2018) find evidence consistent with that of Campbell et al. (2012). They suggest that the weak adjustment of break-even inflation to monetary surprises as identified by high frequency asset price movements could be attributed to revisions in both the real rate (triggered by the pure policy surprise) and in the natural rate (triggered by information revelation about the state of the economy), leaving the gap unchanged.

Other authors have identified information components based on the co-movement of OIS rates and other asset prices. Jarociński and Karadi (2020) identify the information component of monetary announcements as the positive co-movement between the three-year Federal Fund rate and the S&P500 index, arguing that a pure contractionary policy shock should induce a negative reaction in the stock market according to 'standard' asset pricing theory. Andrade and Ferroni (2021) use instead inflation-linked swap rates, identifying the information component of monetary announcements as the positive co-movement between the 5-year ILS rate and the one-year OIS rate. Cieslak and Schrimpf (2019) use similar sign restrictions but exploit monotonicity-type restrictions on the term structure to identify a third shock which they name financial risk premia shock.

More recently, Bauer and Swanson (2020) challenge the existence of information shocks. They show that the problematic revisions found by Campbell et al. (2012) disappear once a measure of economic developments is incorporated into the forecast revision regressions. They argue Campbell et al.'s regressions fail to include information regarding economic developments between the day private forecasts are made and the subsequent monetary policy announcement. Ultimately, both the central bank and the private forecasters are responding to these. Failing to account for economic developments results in omitted variable bias, wrongly attributing the forecast revisions to monetary policy actions rather than to the these exogenous economic developments.

Their evidence is compelling. Indeed, not only do they show that Macroeconomics

Advisers' GDP nowcast[24] is unresponsive to the Federal Reserve's announcements, but also that 36 private forecasters involved with the Blue-Chip forecasts report to seldom revise their expectations in response to the Federal Reserve's announcements. When they do so, they do it in line with standard theory. In fact, they do not find evidence to suggest the Federal Reserve has any advantage over the Blue-Chip forecasts, implying that there could not be any information transfer through these announcements. Lastly, they question using stock market movements around policy announcements as a measure of information effects. They find the response of the S&P500 index to be, on average, strongly negative in response to contractionary policy surprises. Thus, they argue that if counter-intuitive stock price movements do reflect the information effect, then these are likely small.

The existence of predictability and information effects would lead to a violation of the exogeneity requirement. Under both scenarios, the instrument would fail to disentangle the partial effect of each shock and so the estimated impulse responses would not be interpretable as being the effect of monetary policy (Miranda-Agrippino, 2016; Miranda-Agrippino & Ricco, 2018)

These shocks may also result in invalidating the assumption of invertbility. Recall that the standard premise in the SVAR literature is that the reduced-form VAR innovations are invertible linear combinations of the underlying structural shocks. Hence, having identified the space spanned by the reduced form innovations, one can recover the structural shock via the rotation matrix, B_0. Under non-invertibility, however, the space spanned by the structural shocks and that spanned by the reduced form innovations do not coincide and so its generally not possible to recover the underlying shocks from the VAR residuals (Stock & Watson, 2018; Miranda-Agrippino & Ricco, 2019).

E. R. Sims (2012) uses a DSGE framework to show that the presence of shocks that relay information about the future state of the economy to the agents generates a missing state problem. In terms of fitting the VAR, the variables included fail to capture the full state of the economy, resulting in the innovations being combinations of the structural shocks plus forecasting errors. While the biases generated in impulse responses are small and more prevalent at long horizons, the addition of observable variables which help forecast the future state are helpful in ameliorating these. Intuitively, non-invertibility is an

[24] The current quarter nowcast is revised with every major news release.

information insufficiency problem which can be mitigated by expanding the information of the VAR (Stock & Watson, 2018). Indeed, as discussed by Miranda-Agrippino (2016) the inclusion of the excess bond premium into the VAR may also act as a good predictor of the future state, thereby reducing biases in the impulse responses stemming from the information effects possibly present in the central bank's communication.

Since the existence of predictability or information effects would invalidate the estimated impulse responses found in the previous section, I proceed to re-evaluate the evidence for these in the Euro-area during the ELB period. In doing this I use a combination of the methods used in the literature.

9.1 Predictability

I start by examining the predictability of the forward guidance surprises during the effective lower bound period. Unlike Miranda-Agrippino (2016) and Andrade and Ferroni (2021), I do no have access to factors derived from large dynamic factor models. Instead, I opt for a more rudimentary approach testing the predictability of the surprises using a small set of variables intended to replicate the variables that Miranda-Agrippino (2016) found to be predictive of surprises in the UK and the US.

In the following, all variables other than government yield spreads are taken in first difference. Moreover, surprises at month t are regressed against predictors at month $t-1$ to ensure these were available prior to the announcements, as done by Miranda-Agrippino (2016). Table 3 displays the results for variables included in the baseline VAR specification, the full set of results can be found in the Appendix B. There is little evidence to indicate surprises were predictable with this set of variables. Indeed, the statistical fit of all models is poor in terms of the F-statistic and the adjusted R^2. The best evidence for predictability is given by the corporate bond spread but the overall fit is still poor, particularly when comparing to the results obtained by Miranda-Agrippino (2016), whose F-statistics went up to a of 26.

This does not mean there are no financial or macroeconomic variables out there which could predict the surprises, but it does indicate that these variables would be different to the ones found in the US and the UK by Miranda-Agrippino (2016). My results are consistent with Andrade and Ferroni (2021), who find no evidence of predictability using factors extracted from a macro-financial dynamic factor model with around 40 variables for the Euro-area. The results, thus, provide evidence in favour of the surprises not being contaminated with neither time-varying risk premia nor with endogenous monetary responses.

	R^2	F statistic
3-year expected inflation	0.00154	0.19479
IT-DEU 10 year spread	0.00023	0.02927
HICP	0.0012	0.15091
Industrial Porduction	0.00143	0.17994
Corporate Bond spread	0.00815	1.03499
2-year German Govt. yield	0.00418	0.5287

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3. Goodness of Fit measures from separate regressions of month t surprises on month $t-1$ variables, $FG_T^M = \alpha + \beta X_{t-1} + u_t$. Note, all variables are in monthly frequency as in Miranda-Agrippino (2016). All variables other than spreads are in first differences. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

9.2 Information Effects

In this section I assess the presence of the information shocks during policy announcements. In particular, I regress monthly forecast revisions for GDP and HICP on forward guidance surprises with and without a proxy for economic developments. I source the survey data from Thomson Reuters through the Reikon terminal. While the Nowcast refers to forecasts for the current year, forecasts refers to the one year ahead forecast. With some exceptions, surveys are carried out once per month, normally at the beginning of each month, before the monetary policy announcement[25].

Table 4 shows the results. There is indeed some evidence of information effects with the nowcasts for HICP being revised *upwards* in response to contractionary forward guidance surprises. Although the evidence is less strong for the GDP nowcast and for the one step ahead HICP revision, the positive signs are still problematic. It is also surprising that monetary surprises embodied in the forward guidance surprises exert a larger influence on nowcasts relative to the one step ahead forecast. Moreover, the evidence for information shocks is stronger for HICP. Indeed, although the point estimate for the GDP nowcast revision is positive, it is statistically insignificant. The forecast response for GDP displays a theory-consistent sign, albeit it is also insignificant. It is also worth

[25]Check Appendix A for further details.

noting that except for the HICP nowcast revisions, the statistical fit of the other models is poor.

	HICP Nowcast Revision	GDP Nowcast Revision	HICP Forecast Revision	GDP Forecast Revision
Intercept	-0.0028	0.0316	-0.0080	0.0069
	(0.0240)	(0.0550)	(0.0092)	(0.0177)
FG_t	0.0471^{*}	0.0684	0.0053	-0.0166
	(0.0211)	(0.0648)	(0.0070)	(0.0241)
Adj. R^2	0.0231	0.0000	-0.0068	-0.0046
Num. obs.	101	101	105	105
F statistic	3.3678	1.0002	0.2937	0.5277

Table 4. Results from regressions of the form $\Delta y_t^f = \alpha + \beta FG_t + u_t$. FG_t refers to the high-frequency forward guidance factor and Δy_t^f represent the monthly forecast or nowcast revisions for HICP and GDP. Newey-West standard errors reported in parenthesis. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table 5 shows how results change when incorporating a variable intended to capture economic developments prior to the monetary policy announcement. In a similar fashion as Bauer and Swanson (2020), I compute the change in the log value of a stock market index one day prior to the policy announcement relative to its value 45 days prior[26]. Bauer and Swanson (2020) find that using changes in the S&P500 over 13-weeks to capture economic news is comparable to using more sophisticated measures[27]. My results are mostly insensitive to incorporating this variable, suggesting that for the Euro-area the arrival of news and subsequent omitted variable problem does not explain the problematic revision of nowcasts/forecasts of macro-aggregates. Indeed, point estimates are largely unchanged and the point estimate for HICP nowcast revisions remains statistically significant. Interestingly, the fit of all models other than the HICP nowcast revision regression improved with the addition of the news proxy, albeit only slightly.

The point estimates for the change in the log value of the EUROSTOXX index are larger for the forecast revisions relative to the nowcast revisions, and highly significant for HICP. This is consistent with theory. Indeed, one way forward guidance is thought to operate is by making financial markets less sensitive to the arrival of news (Charbonneau & Rennison, 2015). In principle, this could explain why nowcasts are affected by forward

[26]The change is taken between the value of the log EUROSTOXX50 value one to three days prior to the announcements and its value 45 days earlier. For the most part, results are unchanged to sensitive changes in the number of days used in computing the log differences.

[27]I choose to use 45 days as I find using 13 weeks, or 65 days, results in too noisy measurements.

guidance surprises but not by news vice-versa.

	HICP Nowcast Revision	GDP Nowcast Revision	HICP Forecast Revision	GDP Forecast Revision
Intercept	-0.0049	0.0220	-0.0099	-0.0000
	(0.0229)	(0.0486)	(0.0094)	(0.0133)
FG_t	0.0455^{*}	0.0608	0.0034	-0.0234
	(0.0213)	(0.0596)	(0.0069)	(0.0231)
$\Delta \ln EUROSTOXX_t$	0.1824	0.8568	0.2012^{*}	0.7271^{**}
	(0.3317)	(0.7797)	(0.1015)	(0.2642)
Adj. R^2	0.0168	0.0015	0.0147	0.0599
Num. obs.	101	101	105	105
F statistic	1.8557	1.0732	1.7733	4.3134

Table 5. Results from regressions of the form $\Delta y_t^f = \alpha + \beta FG_t + \gamma \Delta \ln EUROSTOXX_t + u_t$. FG_t refers to the high frequency forward guidance factor; $\Delta \ln EUROSTOXX_t$ reflects the change in the natural logarithm of the EUROSTOXX index between the day prior to the announcement and its value 45 days earlier; Δy_t^f represent the monthly forecast or nowcast revisions for HICP and GDP. Newey-West standard errors reported in parenthesis. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Last, I explore whether incorporating the EUROSTOXX high frequency movements around the conference window can control for the information effects. Recall that according to Jarociński and Karadi (2020), counterintuitive movements in the EUROSTOXX index reflect the information component of monetary surprises. Table 6 displays the results of a regression of forecasts and nowcast revisions on the high frequency forward guidance surprises and the EUROSTOXX movement around policy announcements. Though it appears that incorporating the movement in the EUROSTOXX index is important in explaining revisions for HICP, its inclusion leads to an increased point estimate for the forward guidance surprises on HICP revisions. These results casts doubt on Jarociński and Karadi (2020) interpretation of counter-intuitive stock market movements around policy announcements as indicator of information effects.

10 Information-Robust Surprises and IRFs

The results above indicate that the forward guidance surprises are contaminated with information effects, especially in the case of HICP. This also indicates that using the forward guidance surprises as external instruments without purging the information contained in them would violate the exogeneity condition required by the Proxy-SVAR

	HICP Nowcast Revision	GDP Nowcast Revision	HICP Forecast Revision	GDP Forecast Revision
Intercept	0.0016	0.0382	-0.0045	0.0080
	(0.0236)	(0.0559)	(0.0086)	(0.0168)
FG_t	0.0487^{*}	0.0707	0.0062	-0.0163
	(0.0217)	(0.0633)	(0.0083)	(0.0261)
$EUROSTOXX_t$	0.0406	0.0610	0.0301^{**}	0.0093
	(0.0257)	(0.0538)	(0.0109)	(0.0244)
Adj. R^2	0.0291	-0.0050	0.0456	-0.0133
Num. obs.	101	101	105	105
F statistic	2.5009	0.7505	3.4842	0.3158

Table 6. Results from regressions of the form $\Delta y_t^f = \alpha + \beta FG_t + \gamma EUROSTOXX_t + u_t$. FG_t refers to the high frequency forward guidance factor; $EUROSTOXX_t$ captures high frequency price movements in the EUROSTOXX50 index around policy announcements; Δy_t^f represent the monthly forecast or nowcast revisions for HICP and GDP. Newey-West standard errors reported in parenthesis. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

methodology. In this section I orthogonalise these surprises with respect to the information contained in them and proceed to re-estimate the impulse response functions. In particular, I project the forward guidance surprises at intradaily frequency on the HICP nowcast revisions, and use the residuals as the new proxy for forward guidance shocks in the Proxy SVAR framework.

Figure 4 shows the identified forward guidance shocks under the baseline VAR using the raw and the orthgonalised external instruments. The shocks using the non-informational robust instrument are depicted in red, whereas those identified by the information robust instrument are shown as dashed black lines. Note that using the orthogonalised surprises does not affect the instrument's strength, as it is still possible to reject the null hypothesis of Lunsford's test at the 5% confidence level for an asymptotic bias larger than 20%. The difference between both shock series is imperceptible. Likewise, the structural impulse responses are nearly identical for both instruments[28]. In particular, this means that accounting for the information effect does not lead to stronger effects on HICP, industrial production or financial indicators and does not solve the problematic response of inflation expectations.

[28] I report the IRFs in the Appendix B.

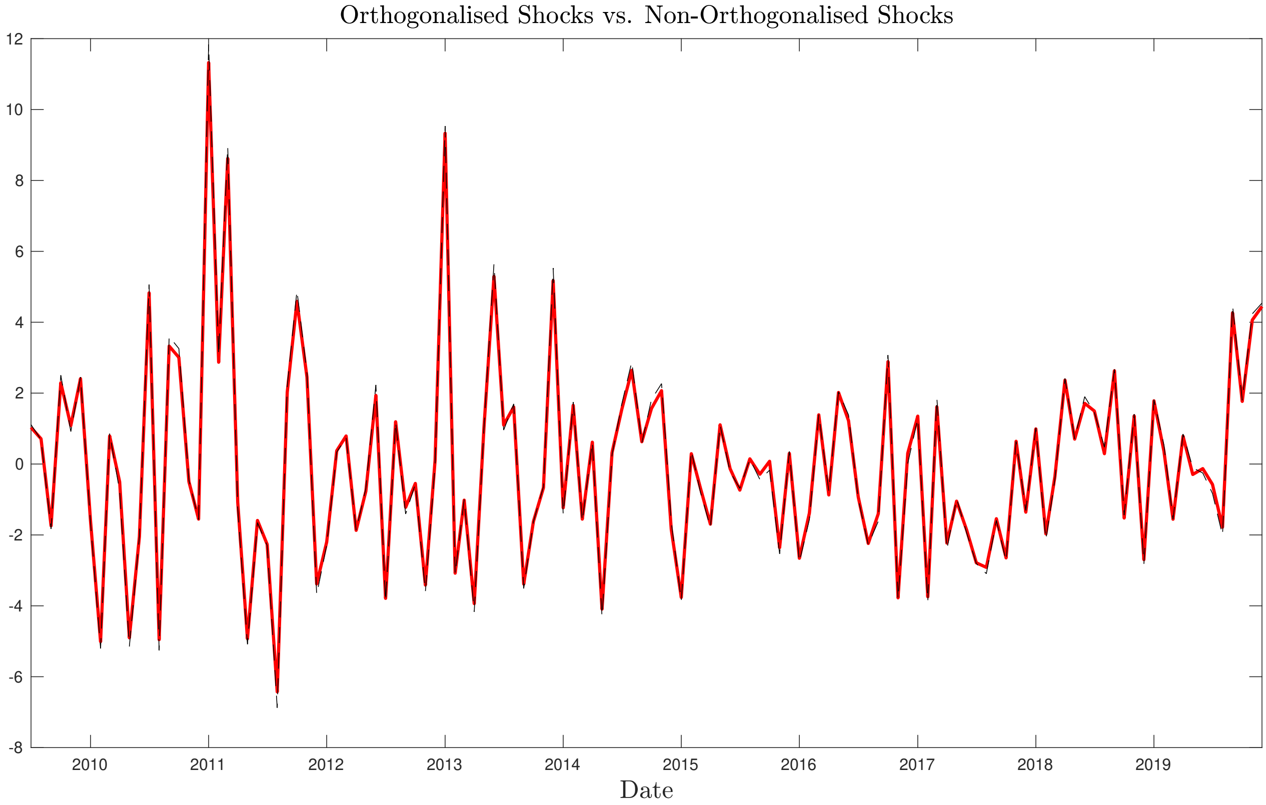

Figure 4: Identified Shock Sequence: Raw vs. Orthogonalised Instrument Raw shocks in red and information-robust shocks in dashed black.

My results also highlight that the bias in impulse responses induced by forward guidance surprises contaminated with information effects is small, at least during the ELB period. This is in stark contrast to the results presented in the literature as in Andrade and Ferroni (2021), Other (2018) and Miranda-Agrippino (2016).

In principle the differences could be attributed to a variety of factors. As discussed by Miranda-Agrippino and Ricco (2018), results hinge on the variables included in the VAR, the sample period and identification strategy employed. It could also be that the information effects lost its importance during the effective lower bound period. This would be consistent with the findings of Hoesch, Rossi, and Sekhposyan (2020) who suggest this is the case for the US after the mid 2000s.

Other factors could account for the difference, however. As suggested by Bu, Rogers, and Wu (2021), using the entire yield curve in constructing the surprise components of monetary policy shocks may attenuate the information content of the announcements. Authors like Jarociński and Karadi (2020) and Miranda-Agrippino (2016), who find strong biases induced by the information effects, have relied on raw surprises as measured by using high-frequency movements for a *single* short-term future, which may be more susceptible to information shocks.

Moreover, while authors like Miranda-Agrippino and Ricco (2018) and Jarociński and Karadi (2020) focus on monetary policy shocks without disentangling its different components, I work specifically with forward guidance surprises. In this regard Cieslak and Schrimpf (2019) show that explicit forward guidance announcements act mostly as a monetary shock. This is of significant importance as explicit forward guidance announcements are most common in periods in which the effective lower bound binds.

Finally, the differences that resulted may be due to the orthogonalisation procedure I use. While Miranda-Agrippino and Ricco (2018) and Lakdawala (2019) are able to explicitly account for differences in the information set of the central bank and the public, I am only able to do so implicitly. In particular, both set of authors orthgonalise their monetary surprises using the difference between market forecasts and the Federal Reserve's forecasts. Accounting for the ECB's information set at a monthly frequency is hard as they publish their forecasts on a quarterly basis. The Federal Reserve, on the other hand, releases the so-called Greensbook forecasts monthly although with a four year delay. I do not expect this difference to be driving the effects, however. If such discrepancies in information sets exists and if the market incorporates them through policy announcements, then orthogonalising monetary surprises with respect to forecast revisions should also control for this. A limitation of this approach is that it also orthogonalises monetary surprises with respect to changes in forecasts that do occur purely from the monetary component of the announcement. While this is indeed a possibility, I find that the instrument retains its strength even after being orthgonalised.

My results are most related to those of Andrade and Ferroni (2021) and Kane et al. (2018). Andrade and Ferroni (2021) find strong effects in the ECB's forward guidance after accounting for information effects. There are two fundamental differences, however. While I explore forward guidance in crisis times exclusively, Andrade and Ferroni do so for the period of 2002-2016. Second, in a similar fashion to Jarociński and Karadi (2020), their identifications strategy relies on sign restrictions on high-frequency movements between OIS and inflation-linked swaps, which movements relative to the those of the OIS rate are assumed to embody the information effects. While I am not able to incorporate their data on inflation linked swaps, Altavilla et al. (2019b) show that using either Jarociński and Karadi (2020) or Andrade and Ferroni (2021) methods yield similar results. In this regard, I do not find evidence for that high frequency EUROSTOXX price movements around policy announcements are useful in explaining problematic forecast revisions.

On the other hand, my results do confirm the findings of Kane et al. (2018). While the authors find evidence of information effects in high-frequency movements around policy announcements, the impulse response functions estimated using an informational robust instrument fails to solve the puzzling responses of credit spreads, the exchange rate and the price level.

11 Robustness

11.1 Different Lag Orders

Given the relatively small lag order selected for the baseline specification, I re-estimate the baseline model allowing for longer lag orders. The Lagrange multiplier test is unable to reject the null hypothesis, even at long lags. For lags larger than 12, the system becomes explosive. Including further lags gradually decreases the strength of the instrument, perhaps by straining the power of Lunsford's F-test. In particular, it is no longer possible to reject the null for lags orders greater than 9 at significance levels lower or equal than 10%. However, conclusions for these lag orders are unchanged.

11.2 Different Time Periods

Beginning the sample period in January 2008 results in much stronger responses, particularly for industrial production, which increases by 5.6 basis points at month 14, and for the 2-year German yield which response remains significant for up to 7 months post-impact. This also highlights the importance of forward guidance announcements early on during the crisis, even prior to the ELB period. Moreover, the response of industrial production is significant between month 11 and 21 post impact, whereas the response of HICP remains insignificant but the point IRF indicates increased persistency. The puzzling responses of expected inflation and the financial indicators remain, however. In addition, the information-robust surprises result once again in very similar IRFs.

Beginning in late 2010, the instrument loses its strength.

11.3 Different Endogenous Regressors

The inclusion of additional regressors into the VAR does not result in significant differences. In particular, controlling for the EONIA rate, the Euro effective nominal exchange rate, the EUROSTOXX index or the VSTOXX index leave most results unchanged, though the confidence intervals are slightly larger. Moreover, the additional variables respond to the forward guidance shock in line with theory. Of particular importance are the responses of the EONIA rate and on the exchange rate. The EONIA rate keeps unchanged for up to three months post impact and subsequently declines, decreasing by 0.25 percentage points by seven months post impact and converging towards zero in dampened oscillations. The Euro exchange rate, on the other hand, experiences a depreciation of around 5 basis points on impact and continues to decline slightly for five additional months after which the effects slowly dissipate.

12 Conclusion

I assess whether the ECB's forward guidance has been effective in stimulating the Euro-area economy during the effective lower bound period which resulted from the 2008 financial crisis. Forward guidance surprises are identified by high-frequency movements of OIS rates for a range of maturities during policy announcements. By using these surprises as external instruments for the underlying forward guidance shock in an SVAR framework, my main contribution is showing that forward guidance has been ineffective at decreasing economic slack and at improving financial conditions during this period. Moreover, I show that these results hold even after cleansing the external instruments from the information they contain regarding the future evolution of the economy.

If forward guidance is to remain in the toolbox of the central bank during crises, then my results highlight the need of adjusting the ECB's communication style when announcing the path of short term interest rates. In this regard, future research should consider addressing whether the underwhelming effect of forward guidance in the Euro-area economy is due to the style of communication used, from a poor understanding of forward guidance operations by market participants or stem from an inability to commit to future policy actions.

As a second contribution, I show that the problematic revisions of HICP nowcasts following monetary policy announcements are not explained by an omission of economic events that the ECB and ultimately the private forecasts respond to. To the best of my knowledge this is the first time this result has been described for the Euro-area. This also highlights differences between the operation of the Federal Reserve's communication and that of the European Central Bank. Exploring what factors could account for these differences is also a valuable avenue for future research.

My study is not without its limitations, however. Of utmost importance is that OIS rates are themselves constrained during lower bound episodes (Andrade & Ferroni, 2021). This could have biased the surprises identified through high-frequency movements of OIS rates and later attenuated the impulse response functions. Overcoming this is challenging, however. Not only are other candidate financial instruments scarce, but they are also potentially contaminated with risk premia. A second limitation arises in regards to using the change in the EUROSTOXX value over a 45-day period prior to monetary announcements as the only measure of economic events. Future studies should incorporate less noisy measures in order to confirm my results.

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Appendix A - Data Appendix

High Frequency Data

Both, the high frequency OIS rates movements and the EUROSTOXX50 index movements are sourced from Euro-area Monetary Policy Event Database (EA-MPD) as in Altavilla et al. (2019b). For the extraction of the principal components and for the identification of the monetary policy communication dimensions, the OIS rates are standardised to mean zero and variance of one.

The EUROSTOXX50 movements are not transformed further for the forecast/nowcast regressions.

EA-MPD Raw Data Handling

As in Altavilla et al. (2019b):

1. Prior to August 2011, the OIS rates for maturities equaling 2, 5 and 10 years are not available. Instead, the German sovereign bond yields for matching maturities are used for this time period.

2. Whenever NANs are reported, the entries for these days are deleted. This is not a major limitation since this occurs only 6 times post 2002, which is when the analysis begins.

3. Known outliers are deleted. These include: the announcements after the September 11 2011 attacks on the USA (17/09/2011), 08/10/2008 with the planned bank rate cuts of 50% and 06/11/2008.

VAR Baseline Specification

- Industrial production index: sourced from the ECB's Statistical Data Warehouse at monthly frequency. This index excludes the construction sector. Seasonally and working-day adjusted. Transformation: natural logarithm.

- HICP: sourced from the ECB's Statistical Data Warehouse at monthly frequency. Seasonally and working-day adjusted. Transformation: natural logarithm.

- Euro-area non-financial corporate bond spread (with respect to Bund): as in Gilchrist and Mojon (2018). Sourced from Banque de France at a monthly frequency.

- 3-year inflation expectations: Market implied inflation expectation from inflation linked swaps. Sourced from Bloomberg at a daily frequency and aggregated to a monthly frequency by taking the unweighted average of all observations within a month.

- IT-DEU 10-year bond yield spread: individual countries' series taken from Bloomberg at a daily frequency. The aggregation into monthly frequency is done taking a simple unweighted average of all observations within a month. To construct the spread I take the difference between the Italian monthly yield and the German one.

- German 2-year bond yield: sourced from the Deutsche Bundesbank's term structure of listed Federal Securities at a daily frequency and using the Svensson method. Aggregated into monthly frequency by taking the unweighted average of observations within a month.

- Miranda-Agrippino and Ricco (2018), who simply take the cumulative sum of all announcements within the month. For months in which there was no announcement, then the monthly announcement equals zero.

VAR (Main) Robustness Checks

- Effective Nominal Exchange Rate: the exchange rate of the Euro against Euro-area major trading partners. Sourced from the ECB's Statistical Data Warehouse at monthly. Transformation: natural logarithm.

- EONIA rate: sourced from the ECB's Statistical Data Warehouse at a monthly frequency.

- EUROSTOXX 50 index: sourced at a daily frequency from Bloomberg and aggregated into monthly observations by taking the unwegihted average of all observations in a month. Transformation: natural logarithm.

- VSTOXX index: sourced at a daily frequency from Bloomberg and aggregated into monthly observations by taking the unwegihted average of all observations in a month. Transformation: natural logarithm.

Information Effect Variables

Thomson Reuters Surveys

With some exceptions, surveys are carried out once per month, normally at the beginning of each month. There are some exceptions, however. In regards to the next year forecasts, the poll of December 2017 is unavailable. Instead, Reuters conducted two interviews in November, one on the 17th and one on the 30th. I use the November 17th forecast as the November forecast and the forecast of the 30th as the December forecast. Similarly, the GDP nowcast for the polls conducted in August and October 2014 December 2017 are unavailable. For the December observation, I take the values from the November 30th poll instead. For the August and October 2014 forecasts, I take the mean forecast between the two adjacent months. Finally, the are two polls conducted in April and July 2020, I take the mean value of the observations (this occurs only in the nowcast polls). The HICP nowcast series for August and September 2014 are unavailable. This means I cannot apply the method used in GDP. Instead, I take the nowcast observation of the month that is available and closest to these months: for August, the July nowcast and for September, the October Nowcast. Finally, I take the mean observation between the two polls conducted in July 2020.

Revisions

Ideally, to measure the extent upon which revisions of private forecast are associated to monetary policy announcements, we would want the series to unfold in the following manner: private forecasters move first, the central bank to then announce their monetary decisions and the private forecasters updating their forecasts afterwards.

For most of the data I gathered from the Reuters survey and the monetary surprises from the monetary surprise event database, it is possible to replicate such timeline. Indeed, for most months, it is the private forecasters who move first.

There are, however, many exceptions to this ideal:

- No monetary event announcements: in many occasions there were no announcements made explicitly by the ECB during the windows measured by the EA-MPD.

In this case I assume there were no forward guidance type shocks, i.e. I assume a value of zero for that month. I also assume that this zero surprise occurred on the same date but after the forecasts were made.

- Simultaneous releases: the survey data doesn't state the time of the survey release. I drop observations for dates in which the survey results and announcements by the ECB were released simultaneously. This also means that I cannot compute the forecast revisions between the previous month and the current one.

- Finally, there are dates for which the announcement occurred first. Depending on the subsequent events (whether this is followed by a survey or another monetary policy shock), it is still possible to use forecasts revisions using the latest monetary surprise as the effective surprise.

Regressions

For the regressions of nowcasts and forecasts revisions:

- Nowcasts/Forecasts Revisions: sourced from Reikon.

- FG_t, high-frequency forward guidance surprises: as identified using the OIS rates from the Euro-area Monetary Policy Event Database.

- $EUROSOTXX_t$, high-frequency EUROSTOXX movements: sourced from the Euro-area Monetary Policy Event Database.

- $\Delta \ln EUROSTOXX_t$, the change in the EUROSTOXX index over the 45-day period: daily EUROSTOXX data sourced from Bloomberg. Transformation: natural logarithm and first differences.

Anticipation Regressions

All variables other than spreads in first differences as in Miranda-Agrippino (2016).

- 3-year EURIBOR: daily data sourced from Bloomberg. Aggregation into monthly frequency is done by taking the unweighted average over monthly observations.

- EONIA rate: sourced from the ECB's Statistical Data Warehouse at a monthly frequency.

- Industrial Confidence Indicator: part of the European Commission's business indicators. Sourced from Bloomberg at monthly frequency.

- 3-year expected inflation: Market implied inflation expectation from inflation linked swaps. Sourced from Bloomberg at a daily frequency and aggregated to a monthly frequency by taking the unweighted average of all observations within a month.

- 1-year expected inflation: Market implied inflation expectation from inflation linked swaps. Sourced from Bloomberg at a daily frequency and aggregated to a monthly frequency by taking the unweighted average of all observations within a month.

- IT-DEU 10 year spread: individual countries' series taken from Bloomberg at a daily frequency. The aggregation into monthly frequency is done by taking a simple weighted average of all observations within a month. To construct the spread I take the difference between the Italian monthly yield and the German one.

- SP-DEU 10 year spread: individual countries' series taken from Bloomberg at a daily frequency. The aggregation into monthly frequency is done taking a simple weighted average of all observations within a month. To construct the spread I take the difference between the Spanish monthly yield and the German one.

- EUROSTOXX index: sourced at a daily frequency from Bloomberg and aggregated into monthly observations by taking the unweighted average of all observation in a month.

- VSTOXX: sourced at a daily frequency from Bloomberg and aggregated into monthly observations by taking the unweighted average of all observation in a month.

- HICP: sourced from the ECB's Statistical Data Warehouse. Monthly frequency. Seasonally and working-day adjusted.

- Unemployment Rate: sourced from the ECB's Statistical Data Warehouse at monthly frequency. Seasonally adjusted.

- Industrial Production Index: sourced from the ECB's Statistical Data Warehouse. This index excludes the construction sector. Monthly frequency and seasonally and working-day adjusted.

- Non-financial Corporate Spread (with respect to Bund): as in Gilchrist and Mojon (2018). Sourced from Banque de France at a monthly frequency.

- 2-year German Govt. yield: Sourced from the Deutsche Bundesbank's term structure of listed Federal Securities at a daily frequency and using the Svensson method. Aggregated into monthly frequency by taking the unweighted average of observations within a month.

- CISS (Composite Index of Systemic Stress): sourced from the ECB's Statistical Data Ware-house at weekly frequency. Aggregation to monthly frequency done through unweighted average of all observations within a month.

- Exchange Rate (Effective Nominal Exchange Rate): the exchange rate of the Euro against Euro-area major trading partners. Sourced from the ECB's Statistical Data Warehouse at monthly.

Appendix B: Further Results

Monetary Policy Window

Table 10 shows the factor loadings from the identified factors in the monetary window. The loadings are remarkably similar to those of the conference window.

The identified forward guidance factors for both windows are depicted in figure 6. It is clear that their patterns are similar but it is also clear that some differences do remain. Surprisingly, the conference window's identified forward guidance factor does seem to pick up more variation post the communication changes in 2016. In general, the spikes across the conference window factor are more pronounced. This is especially evident for the mid-2014 spikes, which seems to not have been picked up as much in the monetary window.

	OIS_{1M}	OIS_{3M}	OIS_{6M}	OIS_{1Y}	OIS_{2Y}	OIS_{5Y}	OIS_{10Y}
TGT	0.99^{***}	0.83^{***}	0.66^{***}	0.47^{***}	0.34^{***}	0.27^{***}	0.16^{***}
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
FG	-0.00	0.50^{***}	0.73^{***}	0.87^{***}	0.91^{***}	0.85^{***}	0.65^{***}
	(0.03)	(0.03)	(0.03)	(0.01)	(0.04)	(0.01)	(0.02)
QE	0.00	-0.11^{***}	-0.08^{***}	-0.00	0.17^{***}	0.44^{***}	0.72^{***}
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Adj. R^2	0.98	0.96	0.97	0.98	0.96	0.98	0.98
Num. obs.	197	197	197	197	197	197	197

Table B.1. Factor Loadings for the monetary window estimated through a regression of the form $OIS_t = \alpha + \beta F_t + u_t$ where OIS_t stands for the OIS high-frequency rate movements around the Monetary Event window and F_t stands for the three identified factors. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

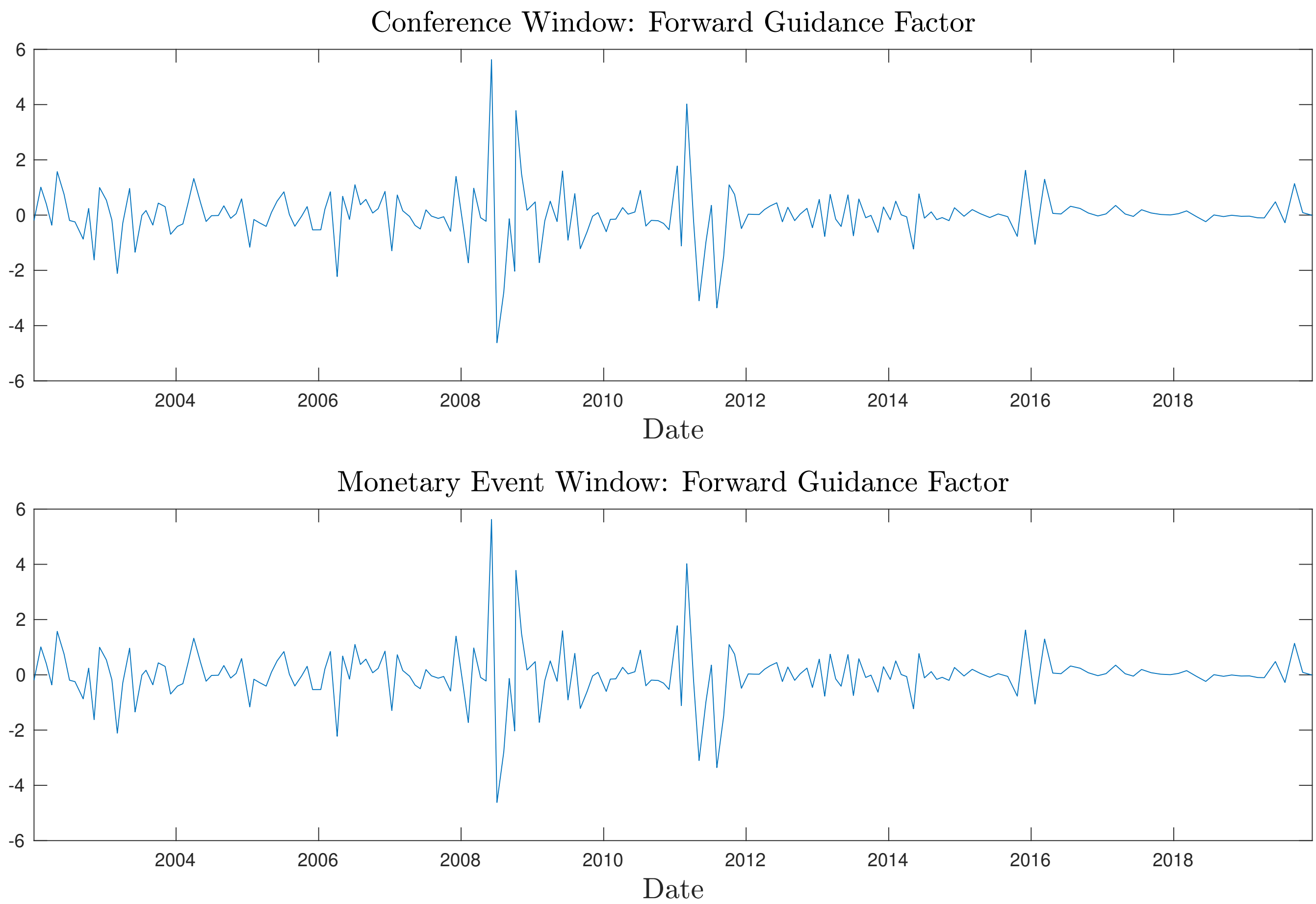

Figure B.1: Comparison of forward guidance factor scores identified in the Conference Window and the Monetary Event window. Top panel shows estimates for Conference Window and bottom panel for Monetary Event Window.

Residual Autocorrelation Plots for Baseline VAR

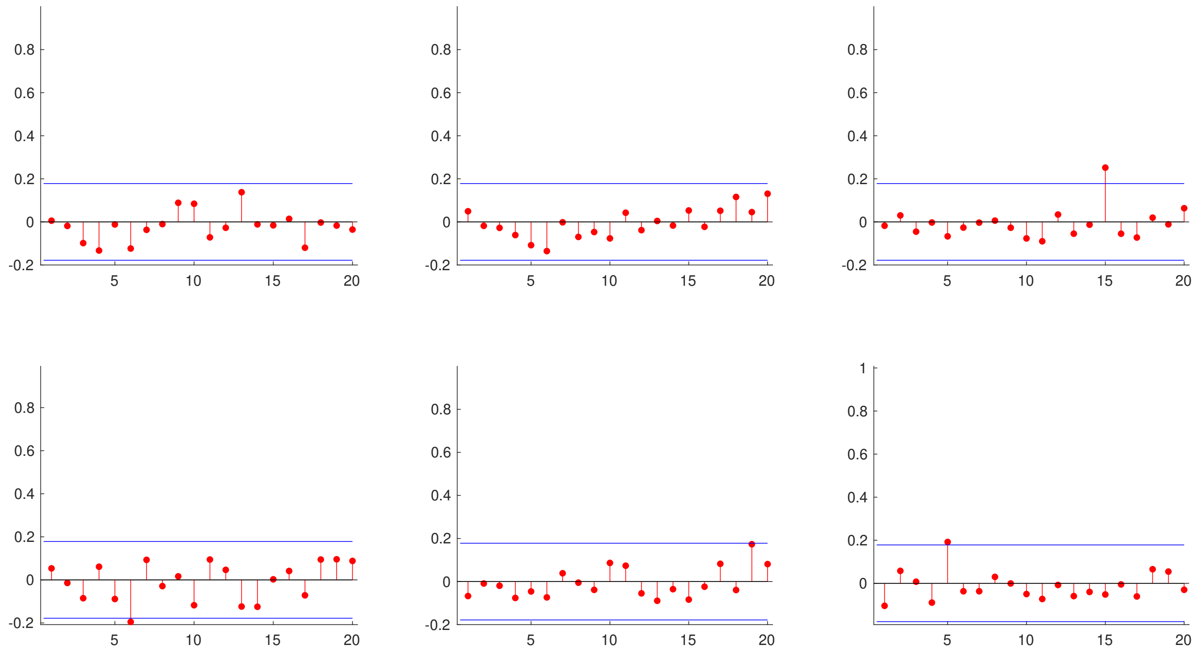

Figure B.2: Residual Autocorrelation Plots for Baseline VAR

IRFs Comparison

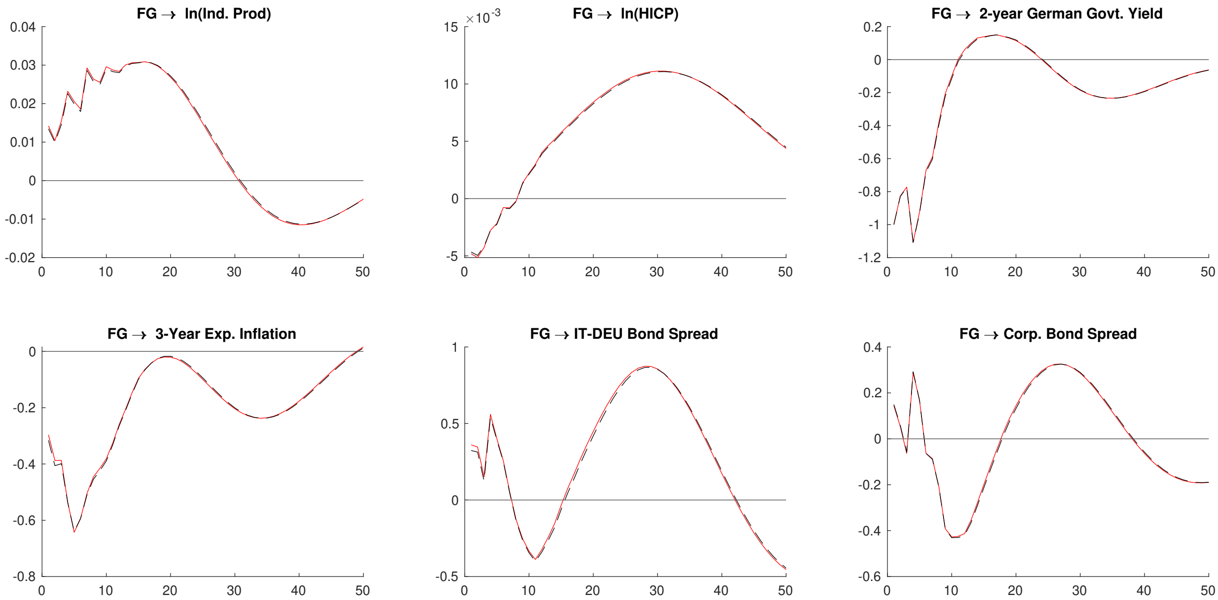

Figure B.3: Baseline VAR specification point IRFs as identified by orthgonalised and non-orthgonalised forward guidance surprises with respect to HICP nowcasts revisions. Red curves depict non-informational robust IRFs and dashed black lines depict informational robust ones.

Predictability

	R^2	F statistic
3-year EURIBOR	0.01698	2.17708
EONIA	0.00567	0.71911
Industrial Confidence	0.0051	0.64589
3-year expected inflation	0.00154	0.19479
1-year expected inflation	0.00033	0.19479
IT-DEU 10 year spread	0.00023	0.02927
SP-DEI 10 year spread	0.00024	0.03099
EUROSTOXX	0.00107	0.13512
VSTOXX	0.00007	0.00908
HICP	0.0012	0.15091
Unemployment Rate	0.00014	0.01716
Industrial Production	0.00143	0.17994
Corporate Spread	0.00815	1.03499
2-year German Govt. yield	0.00418	0.5287
CISS	0.00658	0.83431
Exchange Rate	0.00291	0.36775

Table B.2: Results from separate regressions of month t surprises on month $t-1$ variables, $FG_T^M = \alpha + \beta X_{t-1} + u_t$. Note, all variables are at a monthly frequency and with the exception of spreads are in first differences, as in Miranda-Agrippino (2016). $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Appendix C: Further Details

New Keynesian Model: Details on Aggregation

Using the households' optimal labour supply decision, the market clearing condition, $Y_t = C_t$ and the intermediate good production function in aggregate form, $N_t = \frac{Y_t}{A_t}\int_0^1 \left(\frac{p_t(i)}{P_t}\right)^{-\sigma} di$ (Walsh, 2017) and taking log-deviations imply that the log deviation of real marginal costs can be written as:

$$\hat{w}_t - \hat{A}_t = (\sigma + \eta)\hat{y}_t - (1 + \eta)\hat{A}_t$$

Under the flexible price equilibrium the aggregate price level is given by $P_t^* = \frac{\varepsilon}{\varepsilon - 1}\frac{W_t}{A_t}$, This implies that the log devitation in real wages under flexible prices is directly proportional to deviations in technology, $\hat{w}_t = \hat{A}_t$. Together with the goods market clearing condition, $C_t = Y_t$, the intermediate good production function in aggregate form, $Y_t = A_t N_t$[29], and the households optimal labour supply, the flexible price equilibrium in deviation form is given by: $\hat{y}_t^f = \frac{1+\eta}{\sigma+\eta}\hat{A}_t$, where $\hat{y}_t^f$ denotes the natural level of output.

Using this last result, it is then possible to write the log deviation in real marginal costs under rigid prices in terms of the output gap:

$$\hat{w}_t - \hat{A}_t = (\sigma + \eta)(\hat{y}_t - \hat{y}_t^f)$$

With this, it is easy to complete the derivation of the NKPC using the law of motion for inflation: $\hat{\pi}_t = \frac{(1-\theta)(1-\theta\beta)}{\theta}(\hat{w}_t - \hat{A}_t) + \beta\,\mathbb{E}_t\{\hat{\pi}_{t+1}\}$.

Cragg and Donald Test

Cragg and Donald (1997) propose testing for the number of factors via computing the distance between the variance matrix of the observed data, Σ_X, and the variance matrix of the factor model under N_0 factors (Gürkaynak et al., 2004).

Recall the factor model structure:

$$X = F\Lambda + \varepsilon$$

[29]Notice that this simple form is implied by the fact that under the flexible price equilibrium $p_t(i) = P_t$

Under the assumption that the common factors are uncorrelated with the errors and that $\mathbb{E}(F'F) = I_N$ the variance matrix of the observed variables, Σ_X, can be decomposed into the variance attributed to the latent factors, $\Lambda'\Lambda$, and the variance attributed to the idiosyncratic component, Ψ.

$$\mathbb{E}(X'X) = \mathbb{E}(F\Lambda + \varepsilon)'(F\Lambda + \varepsilon)$$

$$\Sigma_X = \Lambda'\Lambda + \mathbb{E}(\varepsilon'\varepsilon)$$

$$\Sigma_X = \Lambda'\Lambda + \Psi$$

In particular, Cragg and Donald (1997) consider the following test statistic:

$$W = \min_{\Gamma(N)}\{\text{vech}(\Sigma_X - \Lambda'\Lambda + \Psi)'V^{-1}\text{vech}(\Sigma_X - \Lambda'\Lambda + \Psi)\}$$

where $V = \text{cov}(\text{vech}(\Sigma_X)$. The minimisation is over the set of covariance matrices implied by the factor model $\Lambda'\Lambda + \Psi$ such that $\Lambda'\Lambda v = 0$ with $v'v = I_{K-N}$, $(\Sigma_X - \Lambda'\Lambda + \Psi)' = (\Sigma_X - \Lambda'\Lambda + \Psi)$ and where the parameters governing Ψ belong to a compact set.

To implement the test I follow Gürkaynak et al. (2004), whose authors kindly provide the MATLAB code. Formally the null and alternative hypothesis are:

$$\mathbb{H}_0 : N = N_0$$

$$\mathbb{H}_1 : N > N_0$$

The test statistic is given by:

$$W = \text{vech}(\Sigma_X - \Lambda'\Lambda + \Psi)'V^{-1}\text{vech}(\Sigma_X - \Lambda'\Lambda + \Psi)$$

where $V = \text{cov}(\text{vech}(\Sigma_X)$. To compute the test, W is minimised over all possible implied variance under a factor model with N_0 factors, $\Lambda'\Lambda + \Psi$.

The idea is to sequentially test for an increasing number of factors until one fails to reject the null for a chosen significance level. The test statistic converges asymptotically to a χ^2 distribution with degrees of freedom equal to $\frac{K(K+1)}{2} - (KN_0 + K) + \frac{N_0(N_0-1)}{2}$. Rejection of the null hypothesis in favour of the alternative implies there is sufficient evidence to believe the data has been generated by more factors than under the null.

Shock Sequence Identification

Following Olea et al. (2020) and Stock and Watson (2012). Using the moment conditions:

$$\mathbb{E}(z_t e_{1,t}) = \eta \tag{4}$$

$$\mathbb{E}(z_t e_{2,t}) = 0 \tag{5}$$

Together with the standard VAR assumption of uncorrelated shocks, implying a diagonal variance matrix for the shocks:

$$\mathbb{E}(e_t e_t') = \Sigma_{ee} = D$$

The shock of interest can be identified up to a sign and scale via:

$$\frac{e_{1,t}}{\sigma_1} = \frac{\mathbb{E}(z_t u_t')\,\mathbb{E}(u_t u_t')^{-1} u_t}{\sqrt{\mathbb{E}(z_t u_t')'\,\mathbb{E}(u_t u_t')^{-1}\,\mathbb{E}(z_t u_t')}}$$

'Proof':

Notice first that the assumption that reduced form innovations are linear combinations of structural shocks, $u_t = B_0^{-1} e_t$ implies an innovation variance matrix of the form:

$$\mathbb{E}(u_t u_t') = \Sigma_{uu} = B_0^{-1} D B_0^{-1'}$$

Let σ_1^2 denote the target shock's variance and once again let B_1 denote the column vector of B_0^{-1} describing the impact effect of the shock of interest, in this case ordered first, and recalling the moment conditions of relevance and exogeneity imply:

$$\mathbb{E}(z_t u_t') = \mathbb{E}(z_t (B_0^{-1} e_t)') = \eta B_1'$$

The main result follows from projecting the instrument on the reduced form innovations. This projection identifies the history of shocks up to $\frac{\eta}{\sigma_1^2}$. To see this note that the population projection is defined as follows:

$$\mathbb{E}(z_t u_t')\,\mathbb{E}(u_t u_t')^{-1} u_t$$

Using the the prior results, $\mathbb{E}(z_t u_t') = \eta B_1'$ and $\mathbb{E}(u_t u_t') = \Sigma_{uu} = B_0^{-1} D B_0^{-1'}$ implies the linear projection can be rewritten as:

$$\eta B_1'(B_0^{-1} D B_0^{-1'})^{-1} u_t$$

Note that:

$$B_0 B_1 = h_1$$

Where h_1 is a column vector of dimension $K \times 1$ with its first element equaling to one and all remaining equaling zero. Then it is easy to see that the linear projection recovers the shocks up to a scale determined by the covariance between the shock and the instrument and the inverse of the shock's variance.

$$\eta B_1'(B_0^{-1} D B_0^{-1'})^{-1} u_t = \frac{\eta}{\sigma_1^2} e_{1,t}$$

Finally, to recover $\frac{e_{1,t}}{\sigma_1}$ up to a sign it is necessary to divide the linear projection by $\frac{\eta}{\sigma_1}$, which is itself recovered via $\sqrt{\mathbb{E}(z_t u_t')' \, \mathbb{E}(u_t u_t')^{-1} \, \mathbb{E}(z_t u_t')}$. The latter can be re-written in terms of the impact coefficients using results similar to the ones above. In particular:

$$\sqrt{\mathbb{E}(z_t u_t')' \, \mathbb{E}(u_t u_t')^{-1} \, \mathbb{E}(z_t u_t')} = \sqrt{B_1'(B_0^{-1} D B_0^{-1'})^{-1} B_1}$$