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Information or Uncertainty Shocks?

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Information or Uncertainty Shocks?*

Martin Baumgärtner†

Abstract

This paper shows that uncertainty has an impact on the effectiveness of monetary policy shocks. As uncertainty increases, so does the risk that a restrictive forward guidance shock will increase rather than decrease stock prices. This effect can be seen not only in high-frequency variables, but also in VAR models with external instruments. The results suggest that uncertainty is an alternative approach to explain the phenomena previously known as "information shock" and should therefore receive more attention in monetary policy measures.

Keywords: Uncertainty, High-Frequency Identification, Structural VAR, ECB

JEL-codes: E44, E52, E58, G14

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1 Introduction

In economic crises, there is a recurring debate about whether and if so, how central bank decisions are suitable for sustaining economic activity and thus the ultimate target of price stability. However, it is found that the effect of monetary policy shocks is not always clear. Especially in crises there are situations in which financial market participants react untypically to monetary shocks. It can happen that stock prices do not rise in the case of an expansionary shock, but fall contrary to theory. This phenomenon is known in the literature as "delphic/information shock" (e.g. Campbell et al., 2012; Jarociński and Karadi, 2020). It was previously suspected that information on future economic development was responsible for this. However, since there is strong evidence against this theory, the question arises what causes the atypical reaction of financial market participants.

The current paper shows that uncertainty is an important viable in this respect but has been neglected so far. It is demonstrated that uncertainty can explain the atypical reaction of high-frequency variables, e.g. stock prices fall after an expansionary measure by the central bank. I use the Euro Area Monetary Policy Event-Study Database (EA-MPD) by Altavilla et al. (2019) to construct the ECB's monetary policy shocks and measure the reaction of financial market participants to the ECB decision. In a baseline model with stock prices and monetary policy shocks, a similar picture emerges as in studies for the US (Bauer and Swanson, 2020). A restrictive shock lowers stock prices. However, if uncertainty is added to the analysis, forward guidance shocks show a positive correlation, suggesting that a restrictive forward guidance shock can lead to rising stock prices if there is a high degree of uncertainty.

Moreover, it is shown that this effect of uncertainty is not only found in high-frequency data but also leads to different macroeconomic effects in VAR models. I use the poor-man sign restriction introduced by Jarociński and Karadi (2020), which allows me to identify the different shocks. The resulting pattern in the estimated impulse responses is similar to the phenomenon known as "information shock". Therefore, the influence of uncertainty is an alternative hypothesis for "information shocks".

The importance of uncertainty in the context of monetary policy is supported by the findings of Aastveit et al. (2013). They establish a simple theoretical model which, based on Dixit and Pindyck (1994), explains the role of uncertainty in the effectiveness of monetary policy and shows that monetary policy might be less effective under high uncertainty.

The paper builds on the large strand of literature that deals with how monetary policy shocks can be calculated from the reaction of financial markets directly around a central bank decision. For example, Gürkaynak et al. (2005), Brand et al. (2010), Swanson (2017), Andrade and Ferroni (2018), Cieslak and Schrimpf (2019), and Altavilla et al. (2019) use shocks identified by the change in high-frequency variables around central bank events.

My paper complements research that aims to explain the unusual reaction of the financial markets in the context of monetary policy shocks. Bernanke and Kuttner (2005) find that a restrictive monetary policy shock lead to a lower present value of stocks. Yet, some events can be identified where the reverse is true. A possible explanation for this is given by Campbell et al. (2012) and Nakamura and Steinsson (2018). The underlying idea is that the central bank provides market participants with information on future economic developments at the same time as a monetary policy shock. A restrictive monetary policy could thus also convey information about a robust economic situation. This additional "information shock" leads market participants to adjust their forecasts upwards (Campbell et al., 2012). These improved market prospects may lead to a reaction of the high-frequency variables that at first sight does not correspond to theory. The basis for this is usually that the central bank has better forecasts of the economy than other market participants.

Romer and Romer (2000) show that central banks have better forecasts of future economic developments than other market participants. In their view, this superiority is not due to private information but to the fact that central banks invest considerably more effort in forecasting. Rossi and Sekhposyan (2016) find similar results for the inflation forecast, but at the same time discover that the central bank and other market participants systematically over- or underestimate the forecasts in some periods. However, Faust et al. (2004), D'Agostino and Whelan (2008), and Hoesch et al. (2020) find evidence that the superiority of the central bank forecasts does not exist today, or at least does not occur in all periods.

This insight has frequently been used in the literature to refine the identification of monetary policy shocks in VAR models. In addition to monetary policy shocks, the theory of the central bank releasing information to the market has widely been used in the literature to refine the identification of monetary policy shocks in VAR models. Miranda-Agrippino and Ricco (2018) use an instrument that is robust to information shocks, while Andrade and Ferroni (2018), Kerssenfischer (2019), Baumgärtner and Klose (2019), and Jarociński and Karadi (2020) separate the shocks by sign restrictions on high frequency variables. All studies find strong differences between the shocks affecting output and inflation. Although information shocks have substantially different effects on the economy, theoretical models suggest that they are not suitable as concrete instruments for the work of a central bank. In a DSGE model, Fujiwara and Waki (2019) show that these deliberately induced shocks would be associated with a high degree of uncertainty, which in turn would contradict the intentions of the measures.

However, a study by Bauer and Swanson (2020) casts doubts on the theory of information shocks. They show that restrictive monetary shocks reduce stock prices around FED decisions. This also applies to periods that provide the strongest evidence of information shocks. The authors conclude that information effects are weak if they exist at all. Besides, the authors have surveyed several US blue-chip forecasters, with the result that they have never raised their forecasts in the past due to a restrictive shock, thus fundamentally contradicting the theory of information shocks. This raises the question of what other factors are responsible for the observed response in financial market variables.

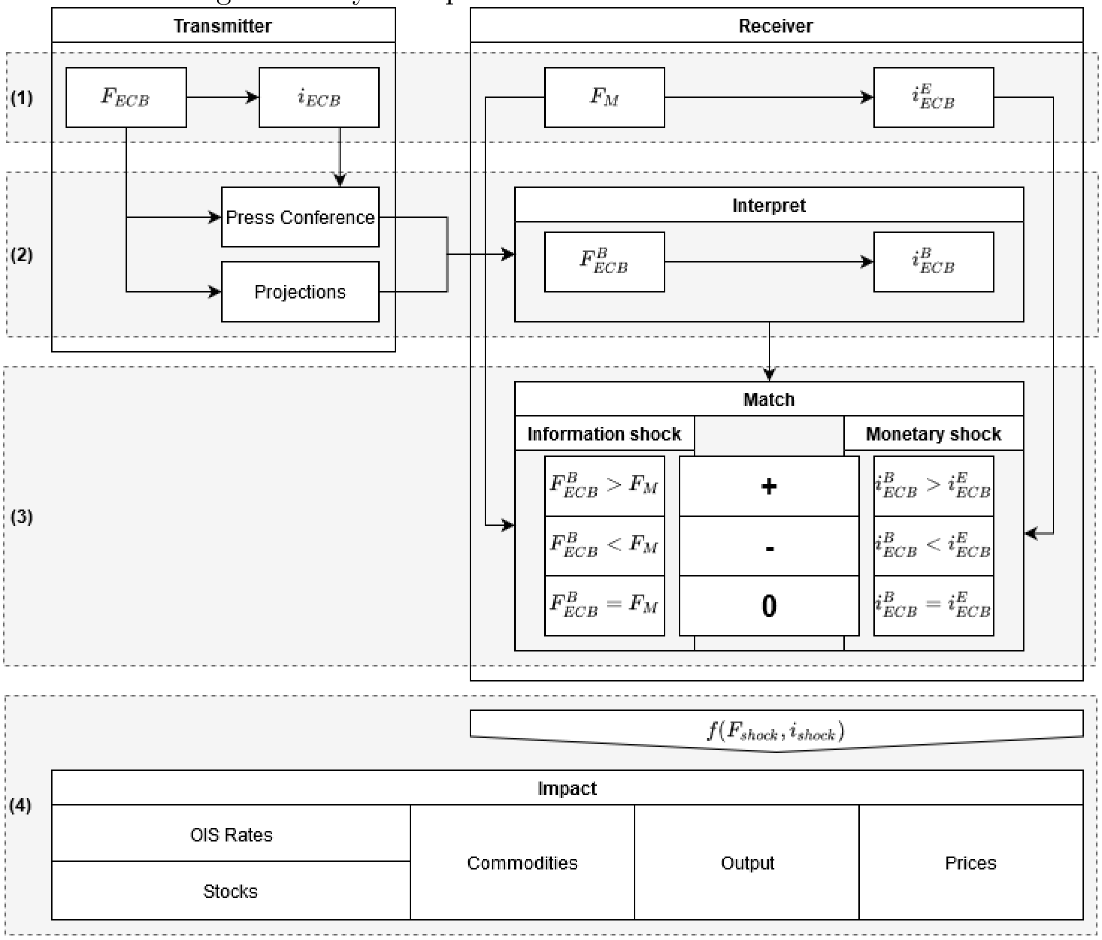
The remainder of the paper proceeds as follows: Section (2) describes the theoretical environment in which monetary policy and potential information shocks can occur. Furthermore, it is highlighted that the precondition for information shocks, i.e. the disclosure of information from the central bank to financial market participants, is fragile. Section (3) describes the methodology, the construction of the monetary policy surprises, the regression model and the variables included. Section (4) presents the estimation results, showing that uncertainty is an important omitted variable. In section (5) I show that the effects found are not only important in the short run but also influence the economic effectiveness of monetary policy. Finally, Section (6) concludes.

2 Theoretical Considerations

To illustrate what happens on the day of the announcement of a central bank decision, the theoretical considerations are presented below. Figure 1 explains how monetary and information shocks of a central bank arise and what their different effects are. Although this model contains information shocks, it also highlights where the difficulties lie in the reasoning for these shocks. However, they are not a prerequisite for the basic functioning of the model and may therefore not exist. The figure is adapted to the European Central Bank (ECB), but could easily be generalised.

Communication between the central bank and market participants takes place in a simple communication model based on Shannon and Weaver (1998). The model consists of a transmitter and a receiver, with the central bank acting as the transmitter and the market participants as the receivers. For the sake of simplicity, the

Figure 1: Styled representation of central bank shocks



Notes: F_{ECB} and F_M stand for the economic forecasts of the central bank (ECB) and market participants (M), i_{ECB} and i_M describe the overall monetary policy of both players. The superscript E indicates that these are expectations. In contrast, the superscript B describes the interpretation of the transmitter publication by the receiver.

market participants are grouped here as a single participant reflecting the median behaviour of all of them. In step (1), both players form forecasts about the future economic situation. F_{ECB} for the ECB and F_M for the markets, which include the future economic development. Based on the respective forecasts F_{ECB}, the Governing Council of the ECB decides on the monetary policy measures i_{ECB}. Here, i_{ECB} not only describes conventional interest rate policy but also includes other measures such as forward guidance or quantitative easing. In parallel, market participants form expectations about the actions of the central bank i_M^E based on their information F_M.

The ECB's decision, i_{ECB}, as well as the justification for it, F_{ECB}, will be communicated to market participants in a press conference after the Council meeting in step (2). Following a statement by the President of the ECB, journalists have the opportunity to ask questions to enhance understanding of ECB decisions. Also, the central bank publishes its forecasts every quarter, thereby further clarifying its predictions.[1] Market participants receive this information and interpret it. However, both i_{ECB} and F_{ECB} are not objectively observable and must, therefore, be interpreted based on central bank communication. Market participants form beliefs about what the central bank wants to communicate. These beliefs are i^B_{ECB} and F^B_{ECB}. It is important to understand that the beliefs of market participants may differ from the central bank's intention, but do not have to. On the one hand, e.g. a change in the policy rate can be observed relatively objectively and is therefore easy to interpret. Here $i_{ECB} = i^B_{ECB}$ should hold most of the time. Forward guidance, on the other hand, is more difficult to interpret, so that it is conceivable here that $i_{ECB} \neq i^B_{ECB}$. This is also true for a combination of different measures which were imposed at the same time.

The same applies to the forecasts of the central bank. In a regular press release and press conference, no concrete values are given. Therefore, there may be

[1] The ECB publishes its forecasts in March, June, September and December.

differences between F_{ECB} and F^B_{ECB}. If the central bank simultaneously discloses information on the forecasts, F_{ECB} is easily observable, so $F_{ECB} = F^B_{ECB}$ is more likely. In all other cases, it is not yet known to what extent the information from the press conference will be interpreted by the markets in line with the ECB's interpretation. It is also conceivable that the interpretation could be state-dependent, if one assumes that the participants are not entirely rational. For example, uncertainty in periods of crisis could change the interpretation of market participants because of animal spirits or changed risk preferences.[2]

In step (3) of the model, recipients compare the information received (i^B_{ECB}) with their expectations (i^E_M). The difference between these values corresponds to a monetary policy shock i_{shock}, i.e. information on monetary policy that has not yet been priced in. Possible information effects would be similar by comparing the information F^B_{ECB} and F_M, but with a small modification. In the literature, it is generally considered a prerequisite for possible information effects that the central bank has better forecasts than market participants (Faust et al., 2004; Bauer and Swanson, 2020; Hoesch et al., 2020). Here, this is not necessary. Rather, market participants must believe that the central bank has better information. If this condition holds, market participants will compare their convictions about the central bank's forecast, F^B_{ECB}, with the market forecasts F_M, similar to what happens with interest rates. The difference between the two would then induce an information shock.

[2]See Proaño and Lojak (2020) and Schildberg-Hörisch (2018).

Therefore, a monetary policy shock and an information shock would always occur and have an effect simultaneously. The impact on financial/real economic variables Δx_t in step (4), thus depends on the interaction of the two shocks. The simplest form of a relation would thus be:

$$\Delta x_t = \alpha + \beta_1 i_{shock,t} + \beta_2 F_{shock,t} + \epsilon_t \tag{1}$$

3 Methodology

In the this section, I discuss how the equation (1) can be reliably estimated for high-frequency variables. I will focus on overnight interest rate swaps (OIS) and stock prices, as these two are used in the literature to identify information shocks in VAR models (e.g. Altavilla et al., 2019; Jarociński and Karadi, 2020). The OIS rates are derivatives that show the market expectation for the evolution of overnight interest rates. Therefore, they are strongly linked to the actual central bank main refinancing rate in the future and are thus suitable for estimating the strength of the monetary policy shock. Of particular interest is which variables besides monetary policy shocks could also have an effect on OIS rates and stock prices and whether interactions between these variables are relevant. Bauer and Swanson (2020) have shown for the US that a simple estimate of (1) gives no evidence of information shocks. Also, the influence of information shocks on the forecasts of blue-chip companies seems to be small so that a variant with $\beta_2 = 0$ is possible. Therefore, I assume at first that there are no information shocks.

$$\Delta x_t = \alpha + \beta_1 i_{shock,t} + \epsilon_t \tag{2}$$

where x is any high-frequency variable. I will show in chapter (3.1) how the monetary policy shocks $i_{shock,t}$ for equation 2 can be calculated before in section (3.2) the estimation of the equation for high-frequency variables is described.

3.1 Monetary Policy Surprises

I use the Euro Area Monetary Policy Event Study Database (EA-MPD) by Altavilla et al. (2019) to measure the impact of monetary surprises on these financial market variables.[3] The database contains high-frequency deviations of financial variables around ECB press releases and around press conferences.

To calculate monetary policy surprises i_{shock} I apply the methodology of Altavilla et al. (2019). Based on Gürkaynak et al. (2005) and Swanson (2017) the authors use factor analysis with imposed restrictions:

$$X^w = F^w \Lambda^w + \epsilon^w \tag{3}$$

with w in {*press release, press conference*}

where X^w is the change of seven overnight OIS rates with maturities from 1 month to 10 years, F^w is a $(N \times T)$ matrix of latent factors, Λ are the factor loadings and ϵ^w is the idiosyncratic variation. I can estimate the latent factors F^w by using principal components on X^w. The matrix rank test of Cragg and Donald (1997) find one statistically significant factor for the press release window. For the conference window, two significant factors are found in the period before the financial crisis and three significant factors for the entire sample.[4] Therefore, for w=*press release* I use the first principal component and for w=*press conference* I use the first three principal components.

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[3] The database currently covers the observation period from 2002:01 to 2019:12, which is therefore also our observation period.

[4] See Altavilla et al. (2019) for detailed results, which I can reconstruct.

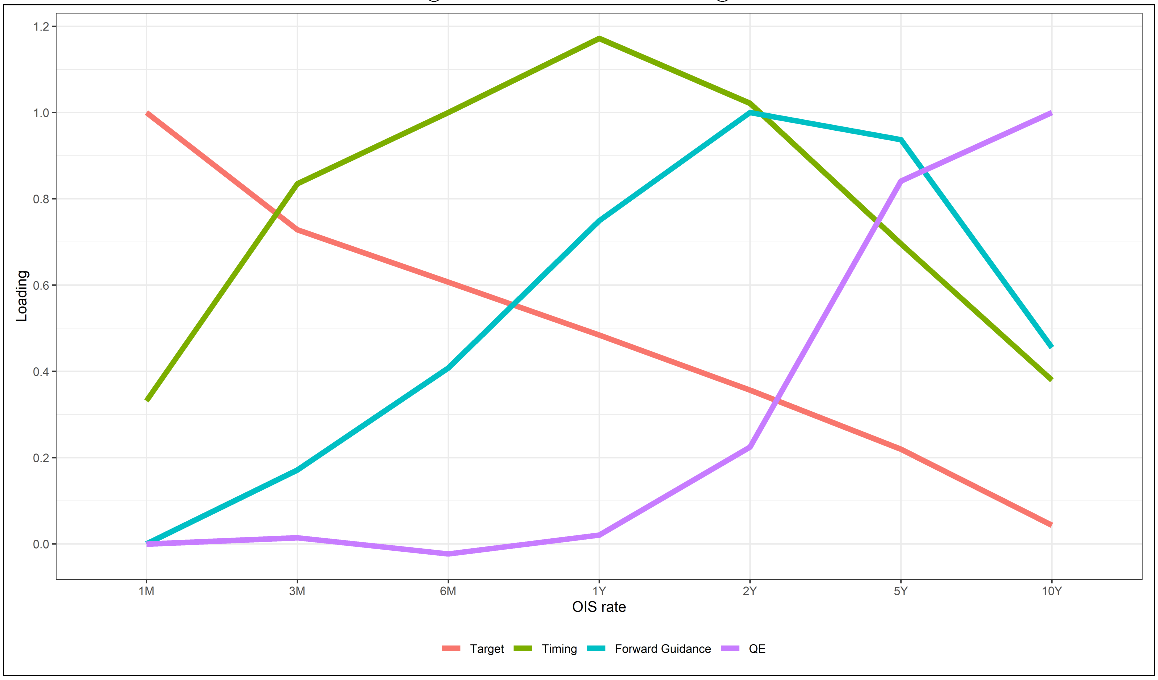
The factors F^w cannot be interpreted directly as each factor is usually correlated with all OIS futures:

$$X^w = \tilde{F}^w \tilde{\Lambda} + \epsilon^w \tag{4}$$

with $\tilde{F}^w = FU$, $\tilde{\Lambda} = U'\Lambda$ and where U is a 3×3 orthogonal matrix. Any combination of U that satisfies $UU' = I$ solves the equation.

I can create interpretable factors by identifying a unique matrix U^* with which I can rotate the factors $F^{w,*} = F^w U^*$. This is done by introducing restrictions on U as shown by Gürkaynak et al. (2005), Brand et al. (2010), Swanson (2017), and Altavilla et al. (2019). The resulting rotated factors $F^{w,*}$ can then be distinguished and named based on the introduced restrictions. From $UU' = I$ it follows that the resulting rotated factors are orthogonal to each other. The resulting factor loadings of the rotated factors are shown in figure 2.

Figure 2: Factor loadings



Notes: The figure shows the resulting factor loadings in basis points after rotation. All factors are scaled so that each has a unit effect on the corresponding OIS rate. Altavilla et al. (2019, Figure 3).

For the press release window, I find that the first factor loads heavily on the very short-term OIS rates. Since the conventional interest rate policy of the central bank affects this end of the scale, this factor is closely linked to it and I name it the *target factor*.

The loadings of the first factor in the press conference window show that this factor mainly influences the OIS rates under one year.[5] At the same time, the effect on the one-month OIS rates is small. Accordingly, it can be concluded that this factor surprisingly does not coincide with the target factor from the press release window, but is a kind of forward guidance with a short horizon. It is aimed at the next ECB decisions and is therefore called the *timing factor*.

The first additional restriction on U is based on the idea that forward guidance is future-oriented monetary policy. The immediate short-term end of the yield curve should not be affected by this policy. Accordingly, the first restriction is that this (second) factor should not load on the one-month OIS rates. The resulting factor loadings show that this factor mainly affects the medium term, i.e. two to five-year interest rates. In the following, this factor is referred to as *forward guidance factor*.[6]

For the identification of a *QE factor* it is assumed that quantitative easing does not influence the one-month OIS rates. Additionally, I rotate the (third) factor so that the variance in the pre-crises period is minimal (Swanson, 2017). This goes hand in hand with the idea that before the financial crisis purchase programmes based on a non-binding ZLB were not relevant. The resulting factor loadings show that this factor influences the long end of the yield curve, which is consistent with the expected effects of QE.

As the individual factors in the press conference window are orthogonal to each other by construction, the combination of the three press conference factors can be summed up. This is used to evaluate the impact of all measures that take effect during the press conference. As these do not affect the short end of the yield curve,

[5] Besides the orthoganality restrictions, the first factor in both windows is unrestricted.

[6] Overall, all loadings are similar to those of Altavilla et al. (2019). Detailed results are available from the authors upon request.

as shown above, I call this factor *unconventional factor*.

All surprises are scaled in a way that an increase of the respective value corresponds to an increase in OIS rate. Positive surprises, therefore, correspond to a monetary tightening.

3.2 High-Frequency Estimation

Of particular interest for my estimate are OIS rates and stock prices, as these two are used in the literature to identify information shocks in VAR models. To keep the results comparable, I use the change in the two-year OIS rates for all instruments and the change in the STOXX50 stock prices. Since the factors were calculated from different deviations, I also distinguish between the high frequency variables. The target factor describes the reaction of the OIS rates around the release of the ECB decision. The other surprises (timing, forward guidance and QE) are formed from the reactions of the OIS rates around the press conference. To clearly distinguish the effects, I consider both time windows separately. This leads to the following time periods: $\Delta x_{release}$ for the difference in the variable x before and after the release of the ECB decision, $\Delta x_{conference}$ for the difference in x before and after the press conference. This results in the following equations:

$$\Delta x_{release,t} = \alpha + \beta_2 target_t + \epsilon_t \tag{5}$$

$$\Delta x_{conference,t} = \alpha + \beta_2 unconventional_t + \epsilon_t \tag{6}$$

$$\Delta x_{conference,t} = \alpha + \beta_3 timing_t + \beta_4 FG_t + \beta_5 QE_t + \epsilon_t \tag{7}$$

where t indexes ECB announcements, $target_t$, $unconventional_t$, $timing_t$, FG_t and QE_t describes the monetary policy surprises for event t and $x_{w,t}$ describes the change of the high frequency variables during the announcement in the corresponding time window w at event t. Here, equations (5) and (6) are similar to those from

Bauer and Swanson (2020). However, equation (7) allows a finer distinction between the various unconventional monetary measures.

The OIS rates are directly linked to central bank policy through overnight interest rates. Therefore, if the central bank has a credible policy, then the change in the OIS rates should reflect only the monetary shock, regardless of the economic situation, since the central bank has committed itself to maintain this course. A restrictive central bank policy is expected to increase OIS rates, as this will raise expectations for main refinancing rates in the future. In contrast, stock prices are not exclusively linked to monetary policy but serve as a benchmark for the expectations of financial market participants. Without information shocks, a restrictive monetary policy is expected to lead to falling stock prices (Bernanke and Kuttner, 2005).

The next step is to extend equations (5)-(7) with possible omitted variables. Altogether four variables are added: Uncertainty at the time of the announcement, whether the central bank publishes a forecast, the publication of the US Initial Jobless Claims, and the current state of the economy.

Uncertainty is an important factor for monetary policy because it affects investments. In phases of high uncertainty, investment stimulating measures, such as monetary policy, have a smaller effect on investor decisions as there are more risks for investors (Aastveit et al., 2013). Similarly, the mechanism could have an effect on high-frequency variables: In phases of high uncertainty, financial market participants wait for the reaction of the central bank to guide them. They do not price in every shock immediately and postpone it until the central bank has announced its measures. Therefore, an effect is realized once the central bank announces its decision.[7] To account for the influence of uncertainty on the response of the financial markets to monetary policy decisions, I integrate this possible omitted variable into the equations (5)-(7). I use implied volatility as a measure of uncertainty at the time

[7] This would also explain the observation of Bauer and Swanson (2020) that financial markets consider economic news about central bank decisions only with a delay.

of the decision. This is approximated by the VSTOXX index closing price on the previous day of the decision labelled as $VSTOXX_{pd,t}$. To control the varying effectiveness of individual monetary policy measures with varying degrees of uncertainty, I also integrate the respective interaction terms.

As the second possible omitted variable, I review the impact of the ECB's publication of forecasts. These are published by the central bank every quarter and appear simultaneously with the press release. At these times it is easier for financial participants to get an intuition about the central bank's estimate of the future development. I expect $F_{ECB} = F^B_{ECB}$. Thus, if there are information effects, the central bank decisions that coincide with the publication of the projections are of particular interest. Therefore, I use a dummy to measure possible differences between the decisions. Similar to uncertainty, I also use interaction terms for the individual policy measures to allow for possible effects on each variable separately. The projections are published after the press conference. However, the most important results will already be announced at the press conference. Therefore the dummy is only used in the regressions (6)-(7) and not in (5).

Since US Initial Jobless Claims are released every week at 14:30 CEST, they are a potential omitted variable that could affect eurozone stock prices.[8] A high (low) change in the US unemployment rate could be a signal that the economic situation is deteriorating (improving). This would, therefore, be an explanation for a possible negative (positive) reaction of stock prices. US jobless claims are seasonally adjusted and used in logarithm. Likewise, the jobless claims are only used in the equations (6)-(7) and not in (5), because the US jobless claims are published after the ECB´s press releases.

A last potentially omitted variable is the current economic situation. It is conceivable that financial market participants react differently to central bank decisions,

[8] Brand et al. (2010) and Altavilla et al. (2019) review in their analysis of the OIS rates for this factor and find no significant impact.

depending on the market situation. I use the STOXX50 closing price on the previous evening of the decision as an additional control variable to monitor the real economic situation. The variable is abbreviated with $STOXX_{pd,t}$.

4 Results

The results of the estimates described in the previous chapter are shown below. I start with the simple estimates of equation (5)-(7) before turning to the results with control variables.

Table 1: Regression of $\Delta OIS/\Delta STOXX$ on monetary policy surprises

	release			conference		
	ΔOIS$_{2year}$	ΔSTOXX	ΔOIS$_{2year}$	ΔSTOXX	ΔOIS$_{2year}$	ΔSTOXX
Target	0.36^{***}	-0.04^{***}				
	(0.04)	(0.01)				
Unconventional			0.93^{***}	-0.02^{**}		
			(0.02)	(0.01)		
Timing					1.01^{***}	0.00
					(0.02)	(0.02)
FG					1.00^{***}	-0.02^{*}
					(0.01)	(0.01)
QE					0.26^{***}	-0.11^{***}
					(0.03)	(0.03)
Intercept	0.04	-0.02	-0.27^{***}	-0.10^{**}	-0.27^{***}	-0.10^{**}
	(0.08)	(0.02)	(0.07)	(0.04)	(0.04)	(0.04)
Adj. R^2	0.30	0.06	0.94	0.02	0.99	0.05
Num. obs.	196	196	191	191	191	191
F statistic	83.58	13.18	3192.07	5.38	4194.10	4.46

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The results for the baseline estimation in table (1) confirm the theoretical considerations. A restrictive monetary policy raises interest rates and vice versa. Since target surprises influence the short end of the yield curve, the effect on the two-year OIS rate is somewhat weaker than for the unconventional surprises.[9] At the same time, restrictive monetary policy lowers stock prices in the release window. A similar pattern can be seen in the conference window: Interest rates rise and stock

[9] For reasons of comparability between the measures, only the two-year OIS rate is given here. The results for shorter maturities than two years are available from the authors upon request.

prices fall in response to a restrictive shock. This is similar to the situation that Bauer and Swanson (2020) report for the US. However, if we look at unconventional surprises in a more detailed way, there are interesting differences: the influence of all surprises on OIS rates is positive. Yet, the effect is less clear for stock prices. Although the QE surprises still show a clear negative correlation, timing surprises are not significantly different from zero. This is not consistent with the results of Bernanke and Kuttner (2005). Forward guidance also differs significantly from zero only at the 10 per cent level. Therefore, the results of Bauer and Swanson (2020) need to be considered more differentiated, at least for the euro area: For communicative measures, in contrast to target and QE measures, evidence of behaviour can be found, which cannot be explained by pure monetary shocks alone.

This leads to the question of what the possible reasons are for why the two shocks do not have a clear impact on stock prices. Both instruments are communicative measures that aim to steer market expectations through announcements. A restrictive announcement does not seem to lead to a larger discounting of future profits by market participants over the entire data period, which in turn does not lower the present value, the stock prices. Of course "information effects" remain a possible explanation. However, the theoretical basis for this is doubtful. In the USA the forecasters do not seem to react to decisions of the FED with an unusual adjustment of their forecasts (Bauer and Swanson, 2020). Although there is no similar survey for Europe, it is possible that the situation is similar there.

Therefore, I present an alternative explanatory approach, which is based on my additional variables and can explain why stock prices rise as a result of an restrictive monetary policy. The results are illustrated in Table (2).

Again, we expect effective restrictive monetary policy to cause higher OIS rates and lower stock prices. The reaction of the OIS rates in the release window is similar to the previous results. However, due to the interaction terms, they must be interpreted with caution. The total effect of a target shock is now composed of two coef-

Table 2: Regression of $\Delta OIS/\Delta STOXX$ on monetary policy surprises including controls

	release		conference			
	ΔOIS_{2year}	$\Delta STOXX$	ΔOIS_{2year}	$\Delta STOXX$	ΔOIS_{2year}	$\Delta STOXX$
Target	0.6241***	0.0555				
	(0.1477)	(0.0376)				
Unconventional			0.8397***	−0.1323***		
			(0.0579)	(0.0360)		
Timing					1.1001***	−0.1147*
					(0.0578)	(0.0674)
FG					1.0562***	−0.1109**
					(0.0372)	(0.0434)
QE					0.2193*	−0.0253
					(0.1292)	(0.1505)
$\text{VSTOXX}_{\text{pd}}$	−0.0047	−0.0100***	0.0154	0.0007	0.0085	−0.0018
	(0.0112)	(0.0028)	(0.0102)	(0.0063)	(0.0055)	(0.0064)
$\text{VSTOXX}_{\text{pd}} *$ Target	−0.0070*	−0.0022**				
	(0.0037)	(0.0010)				
$\text{VSTOXX}_{\text{pd}} *$ Unconventional			0.0044**	0.0044***		
			(0.0021)	(0.0013)		
$\text{VSTOXX}_{\text{pd}} * Timing$					−0.0021	0.0048**
					(0.0018)	(0.0021)
$\text{VSTOXX}_{\text{pd}} *$ FG					−0.0026*	0.0034**
					(0.0014)	(0.0016)
$\text{VSTOXX}_{\text{pd}} *$ QE					0.0021	−0.0045
					(0.0060)	(0.0070)
projectionTRUE			0.2393	0.0548	0.1263	0.0527
			(0.1495)	(0.0930)	(0.0808)	(0.0941)
projectionTRUE*Unconventional			−0.0442	−0.0017		
			(0.0339)	(0.0211)		
projectionTRUE*Timing					−0.0941***	−0.0321
					(0.0344)	(0.0401)
projectionTRUE*FG					0.0221	0.0156
					(0.0247)	(0.0288)
projectionTRUE*QE					0.0005	0.0065
					(0.0653)	(0.0761)
US jobless claims			−0.5111	0.1485	−0.4566*	0.2235
			(0.4262)	(0.2652)	(0.2338)	(0.2724)
Stoxx_{pd}	−0.0006	−0.0003	−0.0004	0.0022**	−0.0012	0.0020*
	(0.0017)	(0.0004)	(0.0017)	(0.0011)	(0.0009)	(0.0011)
Intercept	0.3446	0.3150*	5.9383	−2.6759	5.6439*	−3.5415
	(0.6880)	(0.1751)	(5.6650)	(3.5242)	(3.1021)	(3.6145)
Adj. R^2	0.3001	0.1424	0.9525	0.0699	0.9865	0.0724
Num. obs.	196	196	182	182	182	182
F statistic	21.9008	9.0957	519.3571	2.9433	1017.8523	2.0865

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

ficients, one of which is dependent on another variable, for example $VSTOXX_{pd,t}$. Therefore, for the reaction of the OIS rates in the release window, the effect is positive, similar to table (1). There is a slightly negative correlation with increasing uncertainty, but this is small compared to the overall effect.

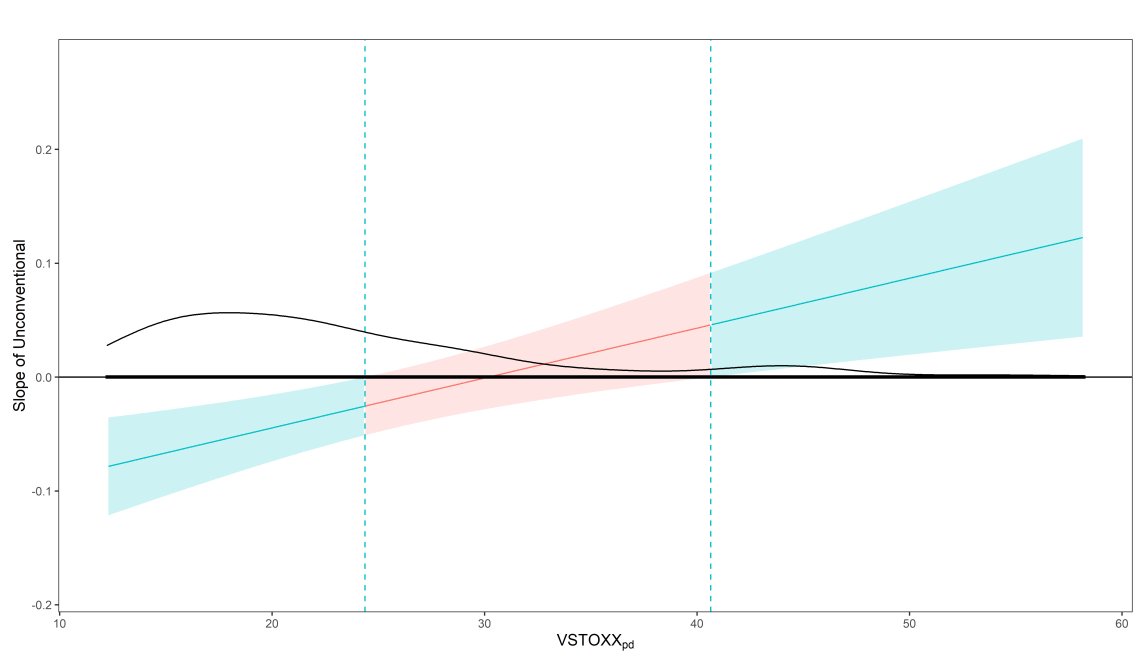
The effect of stock prices is determined by the level of uncertainty. The higher the level of uncertainty at the time of publication, the more negative the reaction of stock prices. Additionally, the interaction term of $VSTOXX_{pd,t} * Target_t$ is significant. The higher the uncertainty, the stronger the effect of the target surprises on the stock prices. Monetary policy via the target factor appears to be particularly effective in phases of high uncertainty.

If we look at the conference window, we see that the basic effect of unconventional monetary policy is still in line with expected behaviour. Without uncertainty, unconventional monetary policy increases overnight interest rates and lowers stock prices. However, the interaction terms with uncertainty show that this is not fully valid. While the positive effect on OIS rates increases with increasing uncertainty, it is becoming less and less effective for stock prices. If uncertainty increases, the total coefficient becomes less negative. Figure (3) illustrates the change of the parameter with increasing uncertainty. The confidence intervals presented describe the 95% Johnson-Neyman intervals according to Johnson and Fay (1950) and Bauer and Curran (2005). They indicate at which uncertainty values the parameters deviate significantly from zero. At low uncertainty the coefficient of unconventional surprises together with the interaction term is clearly negative. With increasing uncertainty, the overall coefficient also increases, so that, from an index value of 30, it is positive overall.

In addition, there is a significantly positive effect in connection with the previous day's stock prices. Stock prices tend to rise during the ECB conference when the economic outlook is positive.

The picture is similar when looking at the individual measures in detail in the

Figure 3: Change in the effect of unconventional monetary policy with varying uncertainty



Notes: The confidence interval describes the "Johnson-Neyman" intervals at the 95% significance level. The distribution of uncertainty is shown by the thin black line.

conference window. Without the influence of uncertainty, all restrictive measures increase OIS rates and lower stock prices. Interestingly, the effect of a timing shock on OIS rates is dependent on whether the central bank discloses its forecasts and forward guidance is negatively influenced by the level of uncertainty. However, the effects are not particularly large compared to the baseline effects of timing and forward guidance. The overall effect of uncertainty in the previously observed data would never been high enough that the sign for OIS rates would change to positive. This is an indication that the ECB is considered credible to consistently implement the policies it announces.

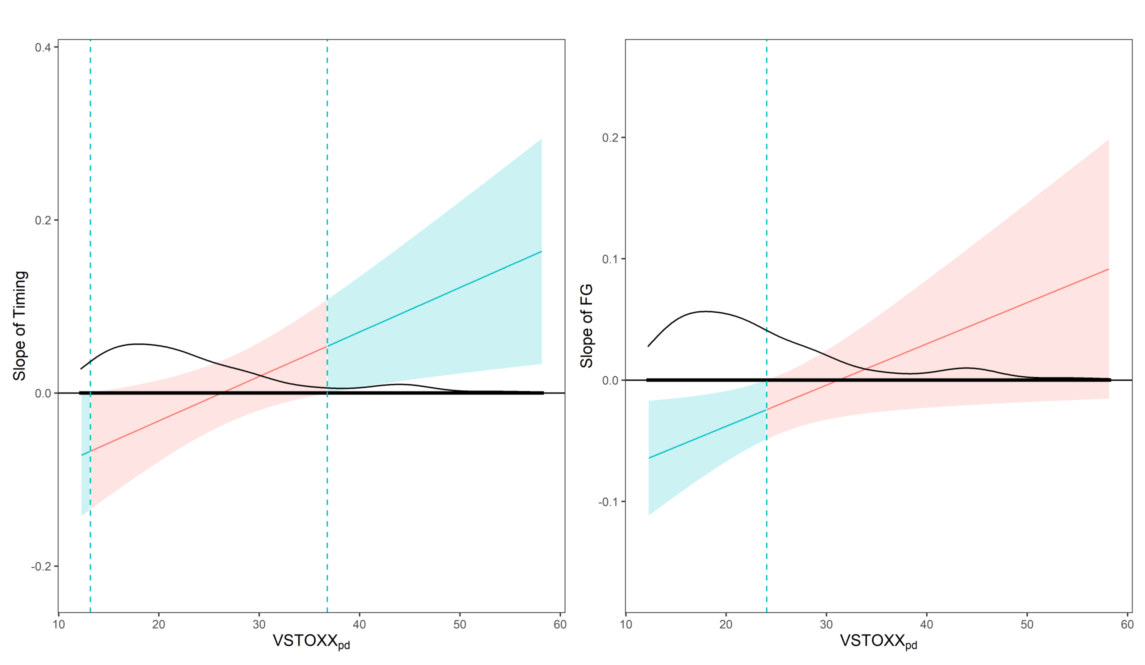
However, in the case of stock prices, it is apparent that uncertainty plays a significant role. The coefficient of timing and forward guidance is, without uncertainty, significantly negative. With increasing uncertainty, however, the coefficient moves into the positive range. In addition, the level of the stock prices before the ECB announcement, i.e. the state of the economy, has a positive influence on the development of stock prices in the considered press conference window.

The publication of the ECB projections does not appear to have a systematic impact on stock prices. Neither the individual coefficient nor the interaction terms with monetary policy surprises are significantly different from zero. Thus, there is no indication that releases or press conferences at these points in time provide a particularly large amount of information to the stock markets. The impact of the publication of the US unemployment also appears to be negligible for the stock market. An F-test also does not show any joint significance.

Figure (4) shows the heterogeneity between timing and forward guidance surprises. While the timing coefficient is significantly negative with very low uncertainty, the values turn positive for high uncertainty. A similar pattern is apparent for forward guidance. There is a significant negative effect at low uncertainty, which cannot be distinguished from zero with increasing uncertainty. In principle, a restrictive monetary policy has a dampening effect on stock prices. However, as soon as there is a high level of uncertainty, this is no longer the case. Above a certain level of implied uncertainty in an economy, an uncertainty index value of 26.2 for timing and 31.2 for forward guidance, the overall coefficient becomes positive. In such cases, restrictive monetary policy can lead to an increase in stock prices, which is consistent with the observations in the information shock literature.

Therefore, uncertainty could be a possible explanation for the pattern observed by Bauer and Swanson (2020), who claim that financial market participants price in past market events with a delay at the time of the central bank decision. Similar to the incentive for firms to postpone investment decisions for some time when uncertainty is high, it may be reasonable for financial market participants without sufficient benchmarks to wait for the reaction of the central bank and postpone the pricing of bad news until then. If the central bank responds to a crisis with conventional measures such as interest rate policy, this calms the markets. The negative effect of economic news is (over)compensated by the positive monetary

Figure 4: Change in the effect of timing and forward guidance with varying uncertainty



Notes: The confidence interval describes the "Johnson-Neyman" intervals at the 95% significance level. The distribution of uncertainty is shown by the thin black line.

policy shock. This results in a textbook reaction as long as the monetary policy shock is big enough. However, if the central bank opts for softer measures, the central bank will not be able to dampen the uncertainty in the market, because timing and forward guidance become less effective while uncertainty increases. Here, too, the markets evaluate the previous economic news and monetary policy together, but the monetary policy does not succeed in balancing the economic news. Accordingly, the stock price reacts in an unusal way.

5 VAR Approach

Uncertainty at the time of the ECB decision may explain why financial market participants react atypically and why a restrictive monetary policy leads to rising stock prices. The question, therefore, arises whether this finding in the high-frequency data is a short-term anomaly or whether this behaviour has an influence on longer-term macroeconomic variables. To investigate this, I rely on the approach of Jarociński and Karadi (2020). The authors use a *VAR model with external instruments and poor-man sign restriction* to identify monetary policy shocks. They divide a shock series into either monetary or information shocks. I adapt this procedure here: For timing and forward guidance surprises, I divide the time series into two sub-series each: one with surprises at low uncertainty and one with high uncertainty based on the level of the VSTOXX index on the day before the ECB decision. Therefore, it is possible to compare the effectiveness of timing and forward guidance surprises in different situations.

5.1 Economic Model

The econometric model used here is based on the work of Stock and Watson (2012), Mertens and Ravn (2013), and Gertler and Karadi (2015). It is identical with the model in Baumgärtner and Klose (2019). Let Y_t be a $(N \times T)$ matrix of N economic variables with T observations. Consider a VAR in general structural form:

$$AY_t = C + \sum_{j=1}^{J} C_j Y_{t-j} + \epsilon_t \tag{8}$$

where C represents a vector of constants, while A and C_j form the coefficient matrices including J lags. Premultiplying both sides with the inverse of A leads to

$$Y_t = SC + \sum_{j=1}^{J} SC_j Y_{t-j} + v_t \tag{9}$$

with v_t denoting the reduced form residuals and $S = A^{-1}$. They are connected to the structural shocks ϵ_t by

$$v_t = S\epsilon_t \tag{10}$$

because they are a linear combination of structural shocks. Inserting (10) in (9) gives:

$$Y_t = SC + \sum_{j=1}^{J} SC_j Y_{t-j} + S\epsilon_t \tag{11}$$

I am especially interested in estimating one column of S. The column s^p indicates how the reduced form residuals v_t changes in response to a unit increase in the structural shock ϵ_t^p. I follow Gertler and Karadi (2015) and focus our analysis on column $s^{mp} = S_{\cdot,mp}$, which reflects the reaction of our variables to a monetary policy shock. All other columns are represented by $s^q = S_{\cdot,q}$. Together with (10) it follows:

$$v_t^{mp} = s^{mp}\epsilon_t^{mp} \tag{12a}$$

$$v_t^q = s^q\epsilon_t^{mp} \tag{12b}$$

These can be solved for v_t^q by

$$v_t^q = \frac{s^q}{s^{mp}} * v_t^{mp}. \tag{13}$$

The fraction represents a unit effect normalization. A unit shock in ϵ_t^{mp} increases v_t^{mp} by the very same amount. All other effects on variables are expressed in proportion. If we seek to solve this equation, we face an endogeneity problem. To circumvent it, I use a two-step approach with an instrument Z. According to Stock and Watson (2018), a good instrument requires the following characteristics to obtain consistent estimates:

$$E[\epsilon_t^{mp} Z'] = \alpha \neq 0 \qquad \text{(relevance)} \tag{14a}$$

$$E[\epsilon_t^q Z'] = 0 \qquad \text{(exogeneity w.r.t. other current shocks)} \tag{14b}$$

Therefore, an instrument is needed which is highly correlated with the monetary policy shock ϵ_t^{mp} but not correlated with any other shock ϵ_t^q at the same time. With a feasible instrument and the reduced form variance-covariance matrix Σ I get a consistent estimate of s by using a two-stage approach. In the first stage I regress v_t^{mp} on Z to estimate the fitted value $\hat{v}_t^{mp}$. The result is the part of the variation in v_t^{mp} which relies on the structural shock ϵ_t^{mp}. Inserting this in (13) gives

$$v_t^q = \frac{s^q}{s^{mp}} * \hat{v}_t^{mp} + \xi_t. \tag{15}$$

The second stage regression (15) leads to a consistent estimation of $\frac{s^q}{s^{mp}}$. With Σ I can then determine all components of s^{mp}, which in turn allows us to estimate impulse responses from our partially identified structural VAR model (16):[10]

$$Y_t = SC + \sum_{j=1}^{J} SC_j Y_{t-j} + s\epsilon_t^{mp} \tag{16}$$

5.2 Data

The endogenous variables Y_t in our model consist of a proxy for Output (ECB industrial production excluding construction), Prices (ECB harmonized index of consumer prices), Commodities (IMF Primary Commodity Price index), Stock prices (Euro Stoxx 50), Uncertainty (ECB Composite Indicator of Systemic Stress (CISS)) and 2-year German government bonds (DE2Y).[11] The monetary policy surprises shown above must be transformed into a monthly frequency. Following Gertler and Karadi (2015) I use monthly average surprises: The shock values of the elapsed 31 days are added up and then the arithmetic mean of all accumulated values in each month is formed. This gives surprises at the beginning of the month a higher weight within that month than surprises at the end of the month, thus balancing the effect

[10] See Gertler and Karadi (2015) for a detailed derivation.

[11] Output, Prices, Commodities, and Stock prices are used in logarithms. All four variables are seasonally adjusted.

of variable meeting dates. The Akaike information criteria suggest a maximum lag of $J = 5$. My observations cover the period from 2002:01 to 2019:12, which is based on the availability of the high-frequency data in the EA-MPD.

5.3 Poor-Man Sign Restriction

This research aims to find out how expectation-forming monetary policy affects the economy in different states of uncertainty. The idea to identify the different shocks is based on the methodology of Jarociński and Karadi (2020). For the two surprise series, timing and forward guidance, I consider the level of the index of the implied volatility of the euro area and divide the series into two regimes: one with a high degree of uncertainty and one with low uncertainty. The results of the previous chapter serve as reference values. With an index value of $crit_{Timing} = 27$ for timing and a value of $crit_{FG} = 31$ for forward guidance, there is a positive overall effect of the corresponding surprise on stock prices in the high-frequency period in section (4). Therefore, all monetary policy surprises announced in an environment above these values are classified as high uncertainty states, all below them as low uncertainty states.

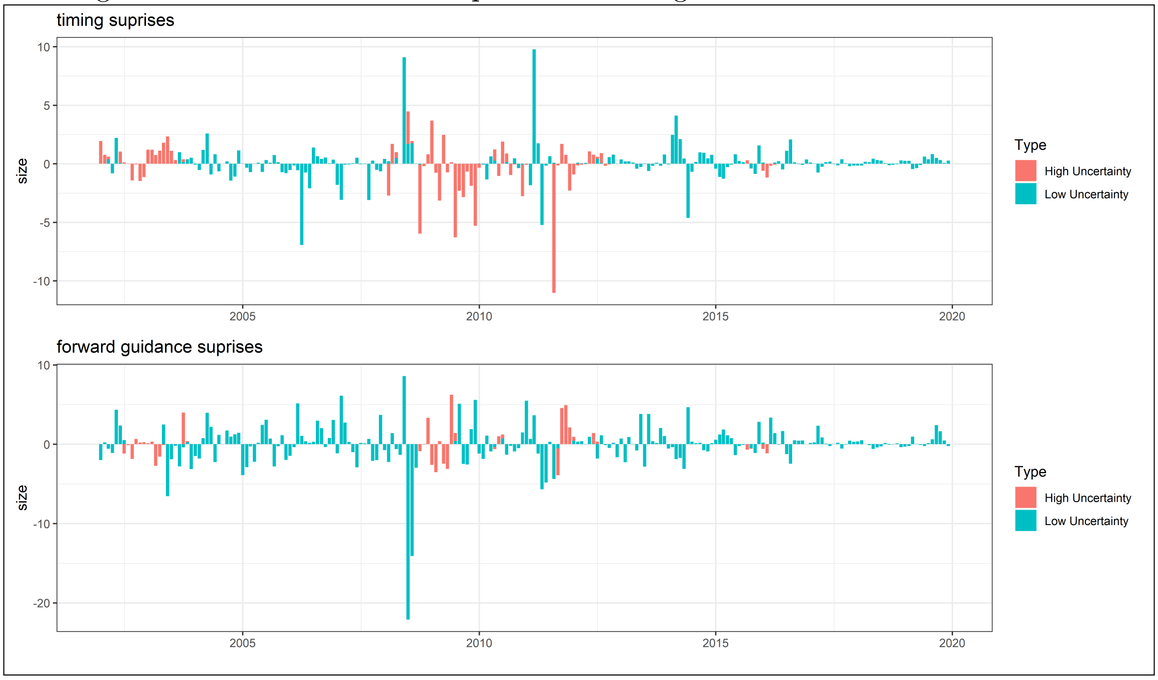
$$c_{t,j} = \begin{cases} crit_j > VSTOXX_{pd,t} & \rightarrow \text{low uncertainty} \\ crit_j < VSTOXX_{pd,t} & \rightarrow \text{high uncertainty} \end{cases} \tag{17}$$

Here $c_{t,j}$ describes the event classification for monetary policy event t and measure j, $VSTOXX_{pd,t}$ the implied volatility from the day before the ECB decision and $crit_j$ as critical cut-off value for the surprise series $j =$ timing, forward guidance. The resulting shock series are displayed in Figure (5).[12]

Uncertainty is particularly high during periods of crisis such as the financial crisis and the euro crisis. Accordingly, surprises are concentrated in these periods.

[12]Since I first classify the events and then convert them into monthly data using the average monthly surprises described above, it follows that both shocks can occur in the same month.

Figure 5: Classification of surprises according to the Poor-man restriction



Accordingly, monetary shocks with low uncertainty are the normal case and shocks with high uncertainty are the exception. The different values for $crit_j$ have the consequence that the number of surprises under high uncertainty is lower for forward guidance than for timing surprises.

5.4 Instrument Validity

In the next step, the surprises are used as instruments to identify the VAR model. In order for the model to be reliably estimated with the constructed instruments, two conditions must be met: According to (14b) it must not be correlated with other shocks. This can be considered fulfilled here, as the surprises observed are from a tight time frame around the ECB's announcement (Kuttner, 2001). There are no indications that other events had a notable influence during this period (Brand et al., 2010; Altavilla et al., 2019).

Furthermore, the instruments must be highly correlated with monetary policy shock (14a) and therefore have explanatory power. To test whether my instruments are suitable, I regress the DE2Y residual ($\hat{v}_t^{mp}$) on my factors separately. Table (3) reports the regression results for each shock. I use heteroscedasticity and autocorrelation consistent (HAC) covariance matrix for the F-statistic.

Table 3: Regression of Residuals on Z

	Dependent variable:			
	residual DE2Y			
	High Uncertainty	Low Uncertainty	High Uncertainty	Low Uncertainty
$Timing_{high}$	0.029^{***} (0.007)			
$Timing_{low}$		0.015^{**} (0.007)		
FG_{high}			0.014^{*} (0.008)	
FG_{low}				0.013^{***} (0.003)
Constant	0.004 (0.008)	−0.001 (0.008)	−0.0004 (0.008)	0.0004 (0.008)
R-squared	0.085	0.026	0.012	0.071
robust F-statistic	15.734	4.447	2.992	17.832
Note:				*p<0.1; **p<0.05; ***p<0.01

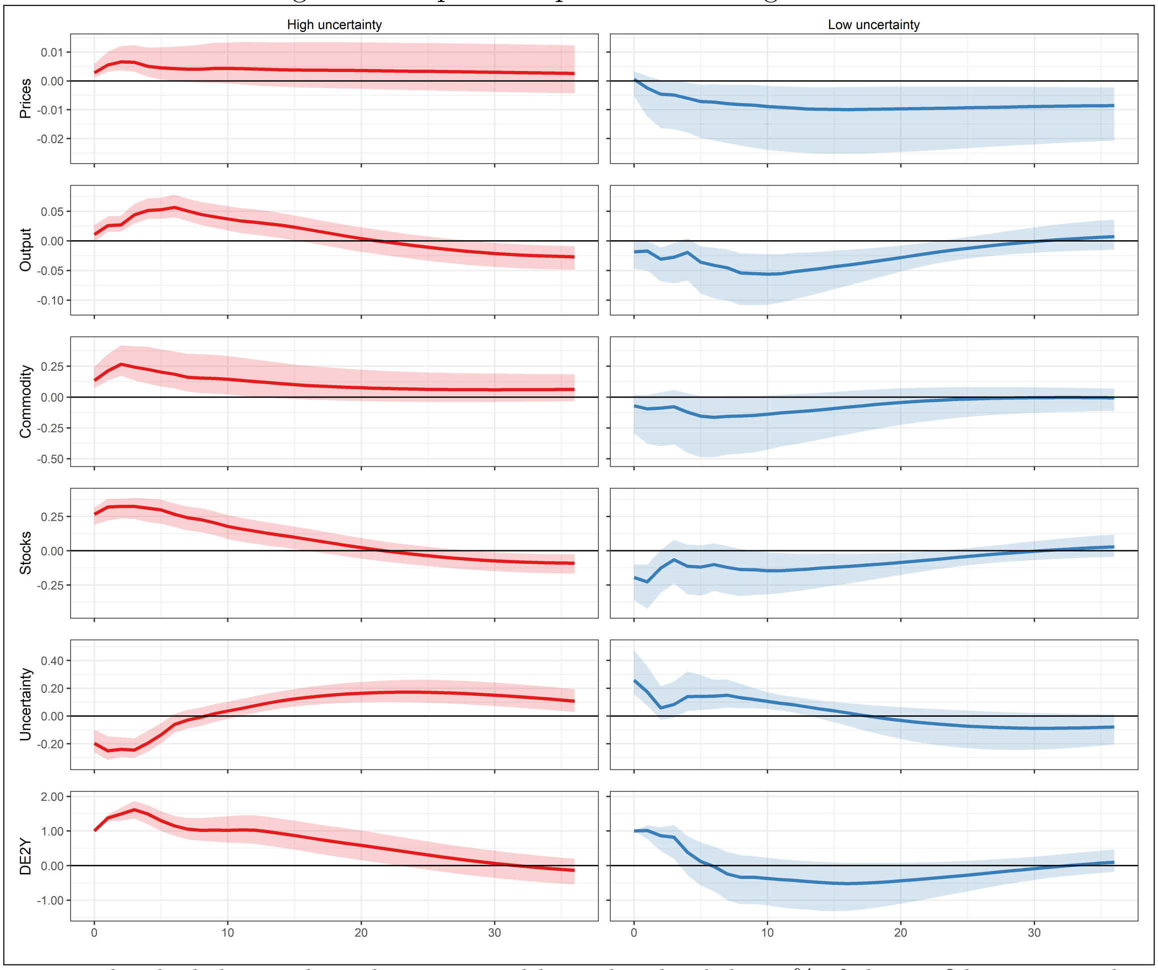
In the literature, an F-statistic of 10 is commonly considered the critical limit for the admissibility of the instrument (Stock and Watson, 2018). For all values above this, the confidence intervals have the correct size. All values below this limit are at risk of the confidence intervals being too small and the estimate being distorted. The results in table (3) show parallels to Figure (4). Based on the F-statistic, there are no objections to an instrument estimate for timing shocks with high uncertainty and forward guidance shocks with low uncertainty. In Figure (4) these are the areas where parameter differs significantly from zero. In the other two cases, there are concerns about weak instruments. Here the coefficient of the shocks is not different from zero.

To take into account the uncertainty caused by weak instruments, the impulse response functions use the confidence bands of Montiel Olea et al. (2020). These are not influenced by instrument strength and are, therefore, robust in the weak instrument case.

5.5 VAR Results

Figure (6) and (7) show the impulse responses of a restrictive monetary policy shock in the estimated VAR models. The impulse responses of the shock series sometimes differ considerably from one another.

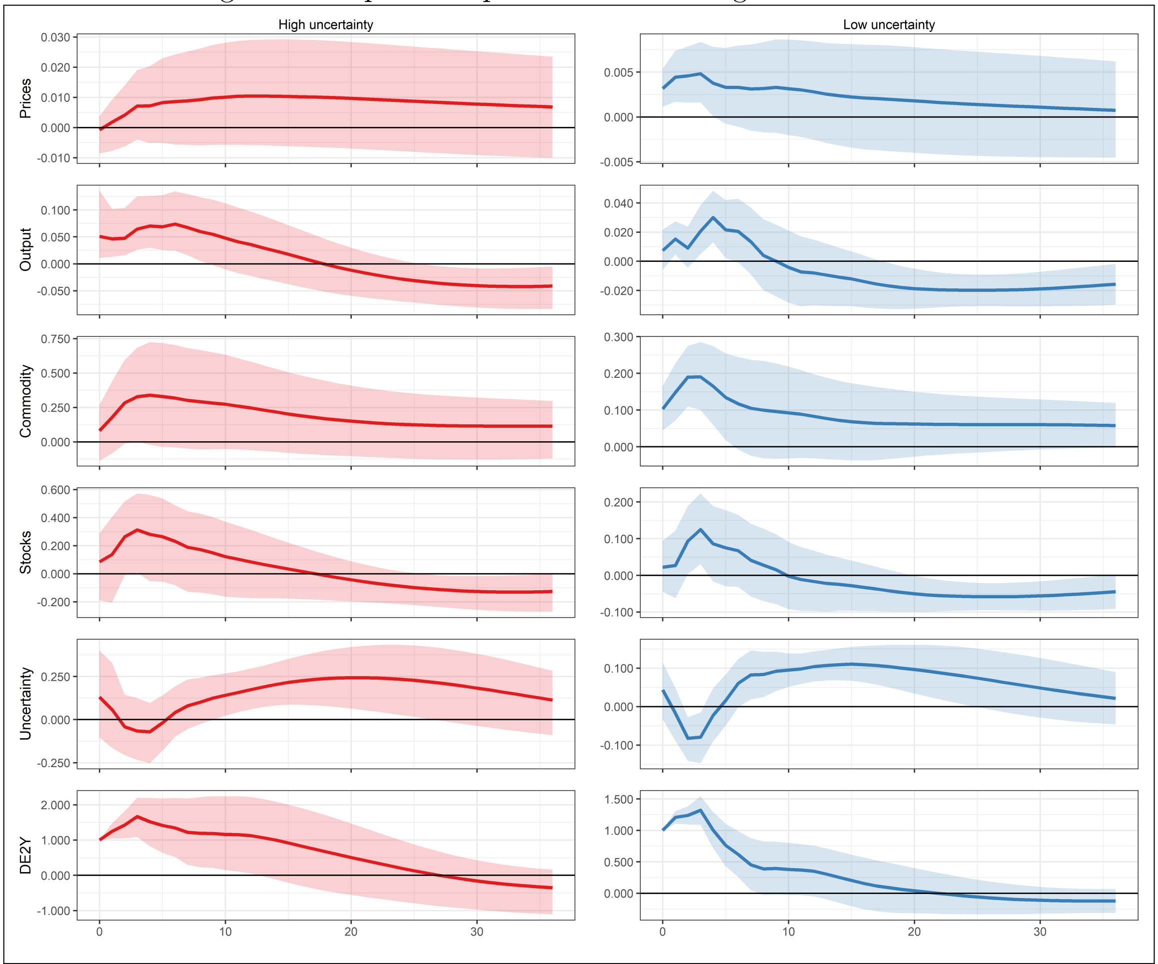
Figure 6: Impulse responses of timing shocks



Notes: The shaded area show the upper and lower bands of the 68% of the confidence intervals. The intervals shown are robust for weak instruments (Montiel Olea et al., 2020).

It is evident from Figure (6) that the estimated impulse response functions have the expected textbook behaviour after a timing shock with low uncertainty: a restrictive monetary policy lowers stock prices, reduces output and leads to a decrease in prices. In contrast, a timing shock at high uncertainty produces different reactions. Interest rates rise, but uncertainty decreases and stock prices rise, as do commodity prices. The impact on the output is clearly positive. Contrary to the theory, prices do not fall but rather rise.

Figure 7: Impulse responses of forward guidance shocks



Notes: The shaded area show the upper and lower bands of the 68% of the confidence intervals. The intervals shown are robust for weak instruments (Montiel Olea et al., 2020).

With forward guidance, the picture is less clear. The pattern of timing shocks at low uncertainty, which is consistent with theory, is not repeated: The output level initially improves but significantly decreases in the medium term. As a result of the short-term growth, the price level also rises. When uncertainty is high, due to the weak correlation between the shock and our policy variable, the confidence intervals are wide, so that no reliable conclusions can be drawn about the response. These results could be explained by the generally lower effectiveness of forward guidance with a long horizon, both in theory and empirically (McKay et al., 2016; Baumgärtner and Klose, 2019).

Overall, the results of the VAR model fit well with the observations in the high-frequency data. The pattern of timing impulse response functions is similar to what is known from the literature as information shock (Jarociński and Karadi, 2020). However, the shocks were identified in different ways, using information already known before the ECB's announcement. In the instantaneous response of the impulse responses, similar behaviour can be found as with the high-frequency variables. A restrictive timing or forward guidance shock in the presence of high uncertainty raise stock prices and has significantly different macroeconomic effects on output and prices. This suggests that it is not information from the central bank that is responsible for the unusual reaction of stock prices, but the changed behaviour of market participants due to uncertainty.

6 Conclusion

In this paper, I show that uncertainty at the time of central bank decision-making is of considerable importance for the impact of the ECB's expectation-building measures. On the one hand, uncertainty can explain the pattern found in the information shock literature: It explains why at some points the reaction of stock prices does not correspond to the theory. On the other hand, it can be shown that uncertainty does not only have short-term effects but is of particular importance for the macroeconomic impact of monetary timing shocks.

Moreover, I show that the analysis of the high-frequency variable for the Fed presented by Bauer and Swanson (2020) also holds for the euro area. However, it is evident that with a finer distinction between unconventional measures in terms of timing, forward guidance and QE, the coefficients of expectation-forming measures are not significantly positive, as might be expected.

To investigate this anomaly I integrate several, potentially omitted, variables into the estimation. The results suggest that uncertainty has an impact on the response of stock prices after a timing or forward guidance shock. In periods of high uncertainty, a positive stock price response occurs significantly more often than in normal periods. In phases of high uncertainty, it is worthwhile for both financial investors and companies to wait and postpone decisions until the coming central bank decision. The markets have an incentive to wait because they know that the central bank will act, but not how and to what extent. The markets wait for the evaluation of the crisis by the central bank and then include this information. If the central bank responds to a crisis with target or QE surprises, this calms the markets. The negative effect of economic news is (over)compensated by the expansive monetary policy surprises. However, if the central bank opts for timing or forward guidance, the central bank will not be able to dampen the uncertainty in the market, because timing and forward guidance become less effective as uncertainty increases. A mere announcement by the central bank is not capable of triggering an expansive shock in times of crisis.

Therefore, future research should consider the potential effects of uncertainty more carefully, for example, when evaluating the effectiveness of central bank measures. At the same time, the central bank must be aware of the fact that its measures do not have the same effects at all times. It is important to understand in detail why uncertainty influences monetary policy. This would be an interesting starting point for future research.

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