EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Alexander Jung, Harald Uhlig

Monetary policy shocks and the health of banks

No 2303 / July 2019

Abstract

Based on high frequency identification and other econometric tools, we find that monetary policy shocks had a significant impact on the health of euro area banks. Information effects, which made the private sector more pessimistic about future prospects of the economy and the profitability of the banking sector, were strongly present in the post-crisis period. We show that ECB communications at the press conference were crucial for the market response and that bank health benefitted from surprises, which steepened the yield curve. We find that the effects of monetary policy shocks on banks displayed some persistence. Other bank characteristics, in particular bank size, leverage and NPL ratios, amplified the impact of monetary policy shocks on banks. After the OMT announcement, we detect that the response of bank stocks to monetary policy shocks normalised. We discover that, in the post-crisis episode, Fed monetary policy shocks influenced euro area bank stock valuations.

JEL Codes: E40, E52, G14, G21

Keywords: high-frequency identification, panel of individual banks, local projections, information effects.

NON-TECHNICAL SUMMARY

Although more than a decade has passed since the start of the global financial crisis, market valuations of euro area banks have not fully recovered and considerably lag behind those of US banks. This observation appears to be in stark contrast with the enormous efforts that have been made by central banks and governments to restore a normal transmission after the outbreak of the financial crisis. While popular explanations attribute the slow recovery of the European banking sector to its lower profitability, higher leverage and non-performing loan ratios than elsewhere, this development raises the wider issue of what has been the quantitative impact of monetary policy on the health of banks. A large literature has emphasised the important role for banks in the transmission of monetary policy and suggested that central banks affect the economy through the bank lending channel. Recent research has identified a risk-taking channel of monetary policy by which the riskiness of loans granted by banks increases in an environment of low interest rates. The transmission from policy rates to banks' net interest margins by which monetary policy may impact on banks' profitability is another relevant channel. Moreover, monetary policy surprises and forward-looking communications by central banks may impact on financial assets and valuations of bank assets via the signaling channel.

Acknowledging progress in understanding the transmission of monetary policy via banks, this study investigates whether monetary policy shocks had any quantitative effects on bank health. We empirically analyse the question with high-frequency identification (HFI). The method measures incremental changes in bank health indicators during short-time spans around policy announcements, when new information about monetary policy becomes publicly available. Monetary policy surprises and shocks are measures of unexpected movements in monetary policy and contain information about the future course of the central bank. We compute monetary policy surprises, as contained in changes of OIS rates (or Bund futures), on Governing Council meeting days in tight windows around policy announcements and consider three different proxies of monetary policy shocks. First, we apply principal components analysis to compute monetary policy shocks from monetary policy surprises at different maturities. Second, we decompose monetary policy surprises into three components, which have an economic interpretation: "jump surprises", "path surprises" and "slope surprises". Third, we decompose monetary policy shocks into "pure" monetary policy shocks and central bank "information shocks".

Measuring the transmission of monetary policy signals to banks requires an identification of the causal link between a monetary policy shock and bank variables. The HFI method implies that one should specifically look into bank indicators which are available at high frequency. In order to gain insights about how euro area banks responded to unexpected changes in monetary policy, we explain high frequency movements of bank health indicators by monetary policy shocks applying OLS regressions, local projections, and panel regressions. Our empirical analysis focuses on European banks, which operate in a predominantly bank-based system of financing and for which bank health indicators are available at high frequency. We look into classical market-based indicators such as banks' stock prices, banks' funding costs as well as bank health indicators, which are a mix between balance sheet and market-based indicators. We also use individual bank data on bank characteristics from an internal ECB dataset on banks individual balance sheet items (IBSI).

The existence of a zero lower bound (ZLB) problem has led many researchers to the conclusion that the ability of central banks to conduct monetary policy is constrained. At the lower bound, monetary accommodation cannot be provided through further reductions in policy rates and policy must become non-standard. Like other major central banks, the ECB embarked on a wide range of non-standard monetary policy measures including forward guidance starting in July 2013, a credit easing programme of June 2014, targeted longer-term refinancing operations (TLTROs) since September 2014, and a large-scale asset purchase programme since 2015, which was followed by a reinvestment strategy in 2019. The ECB hit the zero lower bound later than many other central banks. In June 2014, the ECB introduced negative interest rates (NIRP) and thereby created an effective lower bound (ELB) at negative rates. Moreover, short-term market interest rates became less sensitive to economic news in the aftermath of the financial crisis and anomalies in asset pricing may have been present. An advantage of using euro area data for the empirical assessment of the monetary policy influence on bank health is that the ELB problem did not affect most part of our sample, because the ECB hit the zero lower bound later than many other central banks.

Overall, we find that monetary policy shocks had a significant impact on bank health in the euro area. Information effects, which made the private sector more pessimistic about future prospects of the economy and the profitability of the banking sector, were strongly present in the post-crisis period. We show that ECB communications at the press conference were crucial for the market response and that bank health benefitted from surprises, which steepened the yield curve. We find that the effects of monetary policy shocks on banks displayed some persistence. Other bank characteristics, in particular bank size, leverage and NPL ratios, amplified the impact of monetary policy shocks on banks. After the OMT announcement, we detect that the response of bank stocks to monetary policy shocks normalised. We also discover that, in the post-crisis episode, Fed monetary policy shocks influenced euro area bank stock valuations.

1. Introduction

In a widely cited article Samuelson (1945) argued that the banking system as a whole is not affected by interest rate increases, but it would benefit from it. Conventional wisdom suggests that because banks engage in maturity transformation they profit from a steeper yield curve, since this may offer them higher net interest margins (English, van den Heuvel and Zakrajšek, 2018). The banking crisis resulting from the financial turmoil of 2008 created wide awareness about the importance of banks for the monetary policy transmission to the real economy. A large literature has emphasised the important role of banks in the transmission of monetary policy and emphasised that central banks affect the economy through the bank lending channel (Bernanke and Blinder, 1988; Bernanke and Gertler, 1995; Kashyap and Stein, 2000). Recent research has identified a risk-taking channel of monetary policy by which the riskiness of loans granted by banks increases in an environment of low interest rates (Maddaloni and Peydró, 2011; Altunbas, Gambacorta and Marques-Ibanez, 2014; Jiménez, Ongena, Peydró and Saurina, 2012 and 2014). The transmission from policy rates to banks' net interest margins by which monetary policy may impact on banks' profitability is another relevant channel (Altavilla, Boucinha and Peydró, 2018; Borio, Gambacorta and Hofmann, 2017). Moreover, monetary policy surprises and forward-looking communications by central banks may impact on financial assets and valuations of bank assets via the signaling channel (Kuttner, 2001; Bernanke and Kuttner, 2005; Gürkaynak, Sack and Swanson, 2005; Peek and Rosengren, 2013).

Acknowledging progress in understanding the transmission of monetary policy via banks, this study investigates whether monetary policy shocks had any quantitative effects on bank health. In order to gain insights about how euro area banks responded to unexpected changes in monetary policy, we employ a high frequency identification approach (HFI). We explain high frequency movements of bank health indicators by monetary policy shocks applying OLS regressions, local projections, and panel regressions. More precisely, we estimate a structural parameter β, which provides information on the extent to which monetary policy shocks impact on these bank variables. Our measurement of the transmission of monetary policy signals to banks requires an identification of the causal link between monetary policy shocks and bank variables. We combine data on monetary policy shocks with bank variables for the euro area covering the sample 1999 to 2017. To this end, we use classical market-based indicators on euro area banks such as stock prices and banks' funding costs as well as bank health data, which are a mix between balance sheet and market-based indicators and were obtained from market data services (e.g., KMV Moody's). We also use data on bank characteristics from an internal ECB dataset on individual bank balance sheet items (IBSI).

Although more than a decade has passed since the start of the global financial crisis, market valuations of euro area banks have not fully recovered and considerably lag behind those of US banks.

This observation appears to be in stark contrast with the enormous efforts that have been made by central banks and governments to restore a normal transmission after the outbreak of the financial crisis. The discrepancy in the pace of the recovery of euro area and US banks is visible from a wide range of indicators including price-to-book ratios, price-earnings-ratios, stock prices, profitability ratios, leverage ratios and non-performing loan (NPL) ratios (Bogdanova, Fender and Takáts, 2018). The post-crisis episode has highlighted the power of ECB communications in shaping market expectations. In this period, the ECB extensively used its communications in order to pre-announce policy actions and to influence market expectations. An important milestone for the recovery of the euro area economy and its banking sector was the introduction of the Outright Monetary Transactions (OMT) programme in 2012. In a speech on 26 July 2012 in London, President Draghi signaled the ECB‘s readiness to design new monetary policy measures with the words: "*Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough.*" The programme led to a reduction in risk premia and in the default risk of banks.[2]

The existence of a zero lower bound (ZLB) problem has led many researchers to the conclusion that the ability of central banks to conduct monetary policy is constrained. A recent survey by Swanson (2018), finds that other monetary policy tools such as forward guidance and large-scale asset purchases were still effective. Still, short-term market interest rates became less sensitive to economic news and anomalies in asset pricing may have been present against the background of the ZLB and the increased use of forward guidance (Moessner and Rungcharoenkitkul, 2019). An advantage of using euro area data for the empirical assessment of the monetary policy influence on bank health is that the ZLB problem did not affect most part of our sample, because the ECB hit the zero lower bound later than many other central banks. Like other major central banks, the ECB embarked on a wide range of non-standard monetary policy measures.[3] In June 2014, the ECB introduced negative interest rates (NIRP) and thereby created an effective lower bound (ELB) at negative rates (Praet, 2015). The NIRP negatively impacted on euro area banks' profitability through a compression of their net interest rate margins, but starting in September 2014 the ECB provided euro area banks with targeted longer-term refinancing operations (TLTROs), which lowered their funding costs and thereby provided compensation for it. Moreover, the stimulative effects of the non-standard measures for the euro area economy had positive (second round) effects on bank profitability.

[2] Altavilla, Giannone and Lenza (2016) show that reductions in bond yields due to the OMT announcements were associated with a significant increase in real activity, credit, and prices in Italy and Spain and some relatively muted spillovers in France and Germany.

[3] The measures have included a credit easing programme of June 2014, forward guidance started in July 2013, between 2015 and 2018 it conducted a large-scale asset purchase programme, which was followed by a reinvestment strategy.

Based on HFI and other econometric tools, we find that monetary policy shocks had a significant impact on bank health in the euro area. Information effects, which made the private sector more pessimistic about future prospects of the economy and the profitability of the banking sector, were strongly present in the post-crisis period. We show that ECB communications at the press conference were crucial for the market response and that bank health benefitted from surprises, which steepened the yield curve. We find that the effects of monetary policy shocks on banks displayed some persistence. Other bank characteristics, in particular bank size, leverage and NPL ratios, amplified the impact of monetary policy shocks on banks. After the OMT announcement, we detect that the response of bank stocks to monetary policy shocks normalised. We also discover that, in the post-crisis episode, Fed monetary policy shocks influenced euro area bank stock valuations.

Section 2 describes our empirical strategy. Section 3 explains the measurement of monetary policy shocks and banks' health. Section 4 provides the empirical results and Section 5 concludes.

2. Empirical strategy

The recent literature has highlighted the importance of central bank communications for understanding private expectations. A growing strand of the literature shows that financial variables are strongly influenced by both monetary policy actions and communications (including forward guidance). Monetary policy surprises and shocks are measures of unexpected movements in monetary policy and contain information about the future course of the central bank. Monetary policy surprises, as contained in changes of OIS rates (or Bund futures) in tight windows around policy announcements, respond quickly to new signals coming from the central bank. Building on the assumption that markets function in an efficient manner, they almost instantaneously price in new information on the monetary policy stance. This is because markets continuously process all kinds of information when forming expectations about the future monetary policy stance of a central bank. They monitor incoming data, which may give clues on the economic outlook and the implied monetary policy response. While surprises may also contain some noise about the policy signal, pure monetary policy shocks should only reflect those parts of a policy action by a central bank, which is owing to (accurate) information it has about future developments (Romer and Romer, 2004).

The literature has proposed several ways to extract monetary policy shocks from the data, and no measure is perfect. For example, researchers have used VAR models with a Cholesky decomposition (e.g. Christiano, Eichenbaum and Evans, 1996), the "narrative" approach (Romer and Romer, 2004), DSGE models that identify monetary policy shocks in the presence of a host of other shocks (Christiano, Eichenbaum and Evans, 2005) and VAR models with sign restrictions (Uhlig, 2005). The HFI of monetary policy shocks, which was pioneered by Cook and Hahn (1989), Kuttner

(2001) and Cochrane and Piazzesi (2002), has received particular attention in studies using financial asset prices.

The sample since the start of monetary union (1999 to 2017) is characterised by the possible presence of several regime changes: (i) the financial crisis in September 2008; (ii) the announcement of the OMT programme in July 2012; and (iii) the introduction of a large-scale asset purchase (APP) programme in March 2015.[4] The inclusion of a financial crisis dummy is strongly indicated given that it had a massive impact on financial asset prices and the transmission mechanism. The OMT programme lowered redenomination risk and thereby changed the impact of monetary policy on the euro area financial sector and, at the ELB, there was a more muted response of asset prices (de Santis, 2019; Moessner and Rungcharoenkitkul, 2019). The APP programme implied a stronger signaling channel, while a portfolio rebalancing channel made investors shift from government bonds to other potentially riskier assets (Altavilla, Carboni and Motto, 2015).

We study high-frequency monetary-policy shocks derived from monetary policy announcements. The method is to explain changes in bank health indicators by unexpected news about monetary policy as revealed on Governing Council days. Following Kuttner (2001) and Bernanke and Kuttner (2005), we compute monetary policy surprises on Governing Council meeting days in tight windows around policy announcements. We consider three different proxies of monetary policy shocks. First, we apply principal components analysis to compute monetary policy shocks from monetary policy surprises at different maturities (Nakamura and Steinsson, 2018). Second, we decompose monetary policy surprises into three components, which have an economic interpretation: "jump surprises", "path surprises" and "slope surprises" (Gürkaynak, 2005; Gürkaynak, Sack and Swanson, 2005 and 2007). Third, we decompose monetary policy shocks into "pure" monetary policy shocks and central bank "information shocks" (Jarociński and Karadi, 2018; Kerssenfischer, 2019). Recent papers (Swanson, 2016 and 2017; Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa, 2019) identify three factors, which can be interpreted as changes in the policy rate, forward guidance and changes in large-scale asset purchases (LSAP). Given the importance of the signaling channel, it cannot be excluded that APP announcements had forward guidance implications, which makes the distinction between the forward-guidance factor and the APP-factor difficult in practice. Within the HFI approach, we follow an alternative identification strategy by interacting jump, path and slope surprises with dummies for three corresponding regimes, namely the ELB, forward guidance and the

[4] Furthermore, a regime change could be owing to the introduction of forward guidance in July 2013 and the introduction of negative interest rates in June 2014. We also compute a dummy for the start of the ECB's forward guidance policy, which was in July 2013, and for the start of the ELB, which coincides with the start of the ECB's credit easing programme in June 2014.

APP, respectively. A significant slope-shifter for the APP regime would confirm that there was a measurable impact from slope surprises on bank health indicators.

Applying HFI, we estimate a bivariate regression explaining the daily change of a bank health indicator (Δd) on ECB's Governing Council decision days by the (high-frequency) monetary policy measure (Δps). We estimate (1) using OLS and heteroskedastic-and-autocorrelation consistent (HAC) corrected confidence bands applying Newey-West robust standard errors:

$$\Delta d_t = \alpha + \beta \Delta\, ps_t + \beta^{post} \Delta ps_t D_t + \gamma\, D_t + \varepsilon_t \qquad (1)$$

where the dummy D_t captures possible shifts in the parameter β owing to regime changes, "post" marks the regime after a structural break has occurred, and ε is an error term. In these regressions the parameter of interest is the coefficient β. A significant parameter β not only confirms that the monetary policy shock explains changes in the dependent variable. Its value also provides information about the strength of the relationship. In this respect, the slope shifter for β captures whether and to which extent the coefficient changed following a regime change. For regressions covering the full sample (1999-2017), we always include a financial crisis dummy, which is zero before September 2008 and 1 thereafter. For regressions starting in September 2008, we always include a dummy for the OMT programme, which is zero before July 2012 and 1 thereafter. In addition, for possible inclusion in the regressions, we compute a dummy to capture the APP programme, which is zero before March 2015 and 1 thereafter.

An important assumption of the high-frequency identification is that no other shock distorts our proxies for market expectations during the period of measurement. If non-monetary news is present, the dependent variable could respond to both monetary and non-monetary shocks, thereby distorting the high-frequency identification. Such other news would imply that the error term in equation (1) above will not be orthogonal to the monetary policy shock. In order to clean the measurement from the possible influence of other news, one can make the windows as tight as possible. An alternative approach followed in the literature is to use a heteroskedasticity-based estimator, which disentangles the monetary policy shock from the effect of other news ("background noise") based on their variance. By means of identification through heteroskedasticity (Rigobon, 2003; Rigobon and Sack, 2004),[5] we compare movements of dependent variables on Governing Council decision days with their (usual) movements during other, similar event windows which shall not coincide with Governing Council decision days. The identifying assumption is that the variance of monetary policy shocks increases on

[5] We apply the replication code provided by Nakamura and Steinsson (2018).

Governing Council decision days, while the variance of other shocks, i.e., the "background noise" is unchanged.

The traditional HFI approach has known limitations that need to be addressed in the empirical design. If indicators at lower frequency are included in the regressions, this may worsen identification and give rise to endogeneity concerns. This point is usually addressed by focusing on daily or intradaily indicators in the OLS regressions. Another point is that HFI does not provide information about how persistent the impact of monetary policy shocks on bank variables is. Several approaches have been pursued in the literature. One approach is to estimate impulse response functions from (daily) VARs (Altavilla et al., 2019) and to use high-frequency identified monetary policy shocks as external instruments in a traditional monetary vector autoregression (Gertler and Karadi, 2015). Local projections (LP) is another technique, which has gained popularity in the literature (Romer and Romer, 1989; Cesa-Bianchi, Thwaites and Vicondoa, 2016; Swanson, 2016; Jordà, Schularick and Taylor, 2016). We follow Jordà (2005) and generate (cumulative) impulse response functions from local projections involving bank variables, and regress the bank health variable k at date t+s on the monetary policy shock at date t as well as lags of the bank health variable and controls.[6] The lag length of the regression is determined using the AIC information criterion. The impulse response is given by the coefficient on the monetary policy shock (Δps), as one varies s from 0 to the horizon h:

$$\Delta d_{t+s,k} = \alpha_s + \psi_s(L) y_{t-1} + \beta_s \Delta ps_t \; + \gamma_s D_t \; + \varepsilon_{t+s} \quad for\ s = 0, 1, 2, \dots, h \qquad (2)$$

where α_s is a vector of constants, $\Delta d_{t,k}$ refers to a change in the bank health indicator k at time t, y_{t-1} is a vector of control variables - we include lags of monetary policy shocks, the level of the deposit facility rate and the (log of the) monetary base as control variables -, $\Psi_s(L)$ is a polynomial in the lag operator and coefficient β_s gives the response of $\Delta d_{t+s,k}$ to the monetary policy shock at horizon (t+s).[7] While the parameter of interest is again the coefficient β, we also evaluate the impulse response function. As before, we capture possible regime shifts in the slope by means of a dummy (D_t).

Previous studies imply that the response of bank health to monetary policy measures may depend on banks' business models. We therefore modify the setting of the high-frequency identification (1) and estimate a panel regression using bank-level data. This allows assessing the

[6] We generate local projections using both daily and quarterly data of bank variables, but report the results with quarterly data, which are smoother and allow extending the horizon of the impulse response functions.

[7] There could be also shocks in relation to other ECB communications (including speeches) within a given period, which are not captured by Δps. As shown by previous studies, with few exceptions such as OMT and APP announcements, surprises owing to speeches in the inter-meeting period were small.

impact of monetary policy shocks on the health of individual banks, while controlling for bank characteristics, the level of policy rates and the ECB's balance sheet expansion. The panel regression includes a (representative) sample of euro area banks, as reported in the IBSI dataset, bank characteristics, and two monetary policy instruments (the deposit facility rate and the monetary base), where the dependent variable $\Delta d_{i,t}$ is the daily change in the health of bank i in a one-day window around the Governing Council decision day at time t:

$$\Delta d_{i,t} = \alpha_i + \beta \Delta ps_t + \beta^{post} \Delta ps_t D_{1,t} + \sum_{j=1}^{n} \gamma_j \Delta ps_t X_{ji,t} + \tag{3}$$

$$+ \delta \Delta ps_t \, dfr_t + \delta^{post} \Delta ps_t \, dfr_t \, D_{2,t} + \varepsilon \Delta ps_t \, mb_t + \varepsilon^{post} \Delta ps_t \, mb_t \, D_{3,t} + \lambda \, D_{1,t} + \theta_t$$

where Δps refers to the monetary policy shock, dfr denotes the level of the deposit facility rate, mb is the log of the monetary base at time t, and $X_{ji,t}$ is a vector of explanatory variables comprising j bank-specific characteristics (at monthly frequency), the dummy $D_{l,t}$ (l=1,2,3) captures possible shifts in the parameters and "post" marks the regime after a structural break has occurred. The interactive specification exploits the cross-sectional aspect of the data by allowing the reaction of bank health to the monetary policy shock, the level of the deposit facility rate, the monetary base and other bank-specific characteristics. The specification includes a bank-specific fixed effect α_i, which controls for the fact that the average level of bank-specific variables may differ considerably in the cross section. While the parameter of interest is the coefficient β, the coefficient γ_j provides information on the influence of bank characteristics j on bank health, δ on that from the deposit facility rate and ε from the monetary base. By including a dummy for the OMT programme ($D_{1,t}$), we measure time-fixed effects and analyse whether shifts in the slope of the policy shocks on bank health may have occurred.

3. Measurement of monetary policy shocks and bank health

3.1 Monetary policy surprises and shocks

Expectations of policy actions by central banks are not directly observable, but it is possible to extract monetary policy surprises from movements in interest rate futures. We compute monetary policy surprises following the approach suggested by Kuttner (2001) and using OIS rates in tight windows around ECB Governing Council meetings in response to ECB announcements (Annex B provides further technical details). Since we also want to calculate surprise measures at different horizons, we collect daily OIS swap rates with maturities of two weeks, one, two, three, six, twelve, twenty-four months and ten years (source: Bloomberg) for the sample 1999 to 2017 as well as intradaily data for these indicators (source: Thomson Reuters), which were available to us for the shorter sample 2008 to 2017. Extracting monetary policy surprises from OIS rates has a number of advantages relative to other approaches: there is no issue of model selection, the vintage of the data used to produce the surprise measure is not an issue and there are no generated-regressor problems. Moreover, market surveys show that OIS rates are considered the market standard for swaps with maturities of up to one year. Despite the fact that these markets were hit by the financial crisis in 2008, the markets for these instruments remained highly liquid and credit risk of OIS rates was normally very small.

A change in monetary policy can have several dimensions. It can be understood as some unspecified average combination of a change in the policy rate (action) and a change in forward guidance (communication). Gürkaynak, Sack and Swanson (2005) distinguish between news related to the level of the ECB policy interest rate ("jump" news), news related to the "timing" of policy decisions between two Governing Council meetings, and news related to the "path" reflecting monetary policy signals pertaining to longer horizons. Since path surprises for the upcoming year may include policy announcements such as the ECB's forward guidance, their pattern has likely changed in a regime of forward guidance. Forward guidance may have led markets to economise on their resources in assessing the economic outlook by following suit its assessment, thus broadly ignoring any news contained in other communications. It also implied that other communication tools such as press conferences had a smaller influence on market expectations about forthcoming policy changes. In addition, we consider "slope surprises" (Gürkaynak, 2005), since certain non-standard measures had a direct influence on the slope of the yield curve. For example, large-scale asset purchases by the Eurosystem in the context of the APP directly influenced government bond yields at longer maturities.

We use measures for monetary policy surprises at different maturities to compute monetary policy shocks applying principal components analysis. More precisely, we proceed as follows. We construct the monetary policy shock as the first principal component of the change in four OIS interest rate swaps (1 month, 6 months, 1 year, 10 years) roughly proxying the term structure, while ignoring shorter-term "timing" surprises. The specific composite measure that we use as our benchmark policy indicator is the first principal component of the unanticipated change in these four OIS rates over a short window around Governing Council announcements.[8] The scale of the monetary policy shock is

[8] Using daily data, the first principal component accounts for 64.7% of variance, with the second principal component getting 23.1% and the third 10.1%. The eigenvalue for the first component is large, while for the second and third component they are below 1. Using intradaily data, the first principal component accounts for 57.7% of variance, with the second principal component getting 22.0% and the third 15.7%. The eigenvalues for

arbitrary. We rescale it so that its average effect on the change in the 2-year German government bond yield around Governing Council meeting days is equal to one throughout the full sample considered. Figure 1 shows that, while the interpreation is different, monetary policy shocks and monetary policy surprises mp1 (Kuttner, 2001) are largely similar in the euro area.

In the literature it is sometimes argued that it is difficult to interpret the results from principal components analysis. Fortunately, it has been shown that the first three principal components of a term structure respectively can be interpreted as level, slope, and curvature of it. By comparison with Nakamura and Steinsson (2018) who use principal components for HFI, we also include surprises from longer-term instruments such as the ten-year OIS rate so as to model the full term structure.[9] We contemplate that monetary policy surprises in the post-ELB episode were small and can be mostly found in the long end of the term structure. In the period after mid-2013, the ECB made use of non-standard measures, while monetary policy was gradually approaching the effective zero lower bound. The shock derived from the first principal component allows us to analyse non-standard measures such as "forward guidance" and "large-scale asset purchases", because it proxies the response of the whole yield curve to monetary policy announcements. At the same time, it treats loadings from the principal component analysis as constant over the entire sample, and neglects that relative contributions owing to action, forward guidance and asset purchases may have changed. In order to address this point we complement our analysis with a decomposition of monetary policy surprises into path, target and slope surprises. We explain daily changes of a bank health indicator (Δd) by means of three (independent) surprise components, which have an economic interpretation, and estimate (4) using OLS and heteroskedastic-and-autocorrelation consistent (HAC) corrected confidence bands applying Newey-West robust standard errors:

$$\Delta d_t = \alpha + \beta_1 \Delta\, jump_t + {\beta_1}^{post} \Delta jump_t * D_{1,t} + \beta_2 \Delta\, path_t + \\ + {\beta_2}^{post} \Delta path_t * D_{2,t} + \beta_3 \Delta\, slope_t + {\beta_3}^{post} \Delta slope_t * D_{3,t} + \varepsilon_t \quad (4)$$

where monetary policy surprises are decomposed into jump surprises (Δjump), path surprises (Δpath) and slope surprises (Δslope), the dummy $D_{l,t}$ captures the impact of regime shift l on parameter β_l (l=1,2,3), "post" marks the regime after a structural break has occurred, and ε is an error term.

the second and third component are again below 1.

[9] However, we do not include shorter-term eurodollar futures for which we could not obtain high-frequency data.

3.2 The window: size and information coverage

Comparing the market reaction from different windows can help to distinguish between the response of bank health to ECB actions and its communications. This may be important, since ECB press conferences provide substantial additional information to financial markets beyond that contained in its monetary policy decisions (Ehrmann and Fratzscher, 2009). On a Governing Council decision day, the choice is announced by means of a press release at 13:45 (CET). On the same day at 14:30 (CET), the President and the Vice-President of the ECB provide details about the decision in a press conference with a Q&A session, which normally takes about one hour. On that occasion, the President reads an Introductory Statement and gives a short rationale of the decision based on new information from the economic and monetary analysis. Subsequently, he gives further explanations of the policy decision by answering questions from journalists, thereby providing markets with further signals that are almost instantaneously priced into interest rate futures and exchange rates. In order to measure the market response, we define windows with different width around the Governing Council's announcements of its policy decision using intradaily (and daily) data. A narrow window of 30 minutes spans from 13:35 to 14.05 (CET) and covers news from the press release. A wide window of 120 minutes spans from 13:35 to 15:35 (CET) and includes news from the announcement of the policy decision and the press conference. A daily window covers one trading day from the end of the day before the press conference until the end of the day, when the monetary policy decision is published.

On Governing Council decision days other coinciding releases could also trigger a market reaction, thereby distorting the signal from ECB monetary policy announcements. Although Andersson (2010) reports that the number of macro news overlapping with Governing Council decision days was small, two examples serve to illustrate the argument. First, weekly reports of US initial jobless claims coincide with Governing Council days and their publication is at 14:30 (CET) during winter and 15:30 (CET) during summer (due to different daylight saving time periods between Europe and the US). Brand, Buncic and Turunen (2010), however, have shown that the impact of these releases on ECB monetary policy surprises is minor. Second, on several occasions the Bank of England's Monetary Policy Committee published its policy decision on Governing Council days at noon (London time), i.e., 45 minutes before the ECB's announcement, and implemented it immediately thereafter.[10] Consequently, in both examples the main market reaction to it would not overlap with news from the ECB monetary policy announcements, if a narrow window is used.

[10] From July 2016, the Bank of England reduced the number of MPC meetings from 12 to 8 and the governor has held a press conference at 13:30 (CET) on the same day, which lasted for about one hour.

Depending on the width of the window, the surprise measure may not only vary in size, but also in terms of information coverage. The 30 minute ("narrow") window measures the market response that only reflects information about the actual monetary policy decision, as reported in the press release. By means of a 120 minute ("wide") window it is possible to include the market response to ECB's communications at the press conference. A "daily" window may still be important, because the unprecedented increase in uncertainty in the aftermath of the crisis implied that markets took more time to digest policy signals from the ECB. While measures derived from the narrow window may be "clean" with regard to other news, they still may be noisy in the post-crisis regime because of volatile future contracts. Among the three measures, only those based on the "wide" and the "daily" window reflect possible changes in forward guidance, since they cover the market response to both the press release and ECB communications at the press conference.

In this respect, the scatterplots (Figure 2) illustrate that monetary policy shocks for the euro area from the wide and those from the daily window look fairly similar, though, as expected, they differ a bit from those obtained for the narrow window. More precisely, if we compare the shocks from the one-day and the wide 120-minutes window (Figure 2 RHS), discrepancies between both measures were small. By contrast, a comparison of monetary policy shocks obtained from the daily and the narrow 30-minutes window shows that some data points displayed larger deviations (i.e., the extreme points in Figure 2 LHS with the largest distance from the 45°-line). They can be related to known events, namely the collapse of Lehman Brothers (2008.9), the introduction of the first very long term refinancing operations (VLTROs) (end-2011), the OMT announcement (2012.7) and the start of credit easing (2014.9).

3.3 Information shocks

It is widely believed that central banks have an information advantage compared to markets when assessing the economic situation and the future course of monetary policy (Romer and Romer, 2000). Information effects of monetary policy announcements may play an important role in the overall causal effect of monetary policy shocks on the real economy. Several explanations for the central bank's information advantage have been proposed in the literature. Among them are the central bank's knowledge of its own probable policy actions, its comparative advantage in collecting detailed information about current and recent movements in the economy, and the expertise in forecasting macroeconomic variables. Given their involvement in banking supervision and their privileged access to confidential data, central banks may also have inside information about the health of the banking sector. For this reason, monetary policy shocks may not only reflect information about the economy, but also about bank health.

There is a growing literature demonstrating the relevance of the signaling channel as an additional channel of monetary policy (e.g., Cukierman and Meltzer, 1986; Melosi, 2017). This channel arises because changes in the policy rate convey information about the central bank's assessment of inflation and output to price setters. By signaling an improved economic outlook, information effects may positively affect the economy and this may eventually lead to improvements in bank health. A large information effect implies that the central bank has a great deal of power over private sector beliefs about economic fundamentals and stock market valuations. Under these circumstances, a tightening (easing) of monetary policy by the ECB may make the private sector more optimistic (pessimistic) about the future, and this will increase (lower) valuations of bank stocks.

Central bank "information shocks" can be extracted from the high-frequency co-movement of interest rate and stock market surprises (Jarociński and Karadi, 2018). It requires decomposing monetary policy shocks into "pure" monetary policy shocks and central bank "information shocks". Their identification exploits the property that information shocks and pure monetary policy shocks have different effects on financial assets. In response to a pure monetary policy shock, stock market valuations should always move in the opposite direction of the news about interest rates. Empirically this property cannot always be detected, since stock prices can be noisy and may react to other news. If stock markets and interest rates co-move positively, however, this can be taken as indication of the presence of a (contemporaneous) information shock.

In order to disentangle the information shock from a pure monetary policy shock, Jarociński and Karadi (2018) use monetary policy surprises (for the euro area they extract surprises from 3-month OIS rates) in a VAR model with sign-restrictions. The imposed restrictions identify a pure monetary policy shock that raises interest rates and lowers stock prices (for the euro area they use Euro Stoxx 50 futures), and an information shock that raises interest rates (by signaling an improved economic outlook) and increases stock prices. We use euro area data for these shocks from Kerssenfischer (2019), who broadly follows the approach by Jarociński and Karadi (2018) with two notable modifications. First, instead of the shorter 3-month OIS rate, he uses longer-term Bund futures of around 2 years. Second, he replaces the narrow window by a wide window around the ECB's press release that also includes the market reaction to the press conference. Conceptually, both modifications aim at better capturing ECB communications, including forward guidance, which could in principle affect the whole term structure.

3.4 Measurement of banks' health

Financial companies are special, since they may also make use of "off-balance sheet" items, valuations of non-performing loans may not be timely, while markets may price in information about how these activities affect the situation of banks. Because market-based measures may also reflect market perceptions of monetary policy effects on bank health, this could imply that their measurement tend to understate the actual effects of monetary policy on banks. Given the complexities involved in assessing the health of the banking sector, it may be preferable to look into a broad set of indicators including both accounting and bank-based measures. The present analysis goes beyond classical market-based indicators such as banks' stock prices and banks' funding costs, though we do not use accounting measures as in English, van den Heuvel and Zakrajšek (2018), since these were not available at the high frequency, which, as explained above, would be needed for HFI.

We select stock prices for the largest European banks from the Euro Stoxx banks index (source: Datastream) and proxy banks‘ funding costs by bond yields (source: iBoxx) for euro area banks, which include both high yield and investment grade debt. We also include bank health indicators, which are a mix between balance sheet and market-based indicators, namely the "distance-to-default" (DTD), the "expected default frequency" (EDF), and the "distance to insolvency" (DTI).[11] An increase (decline) in DTD and DTI as well as a decline (increase) in EDFs, would be indicative of a perceived improvement (deterioration) in banks' health. Annex C provides further details about the construction of these bank health measures. The DTD and EDF for euro area banks is obtained from KMV Moody's (for 1401 banks from 18 countries) and as a breakdown for the four largest euro area countries: Germany (432 banks), France (273 banks), Italy (152 banks), Spain (85 banks) both in terms of a median and an average, weighted by total assets. Furthermore, we collect daily DTDs for 50 individual banks from a representative sample of European banks (IBSI dataset, for details see Annex C) and match them with other bank characteristics. We compute the DTI of large euro area companies (including banks and insurance companies) from the (daily) volatility index of the VSTOXX.[12] For all these indicators daily data were collected. In line with conventional knowledge, our indicators show that after the collapse of Lehman Brothers in September 2008 the health of euro area banks deteriorated massively, while the recovery took considerable time (see Figure 3 to 5). Moreover, like it did for the Great Depression (see Atkeson, Eisfeldt and Weill, 2017), the DTI detected that an insolvency crisis in the euro area happened around mid-2008. This can be seen from the low level of the DTI indicator and the fact that the DTI for the 95 percentile of banks undershot the one for the 90 percentile.

[11] Note that daily changes in the DTD and the EDF are predominantly market-based measures since they mainly reflect (valuation) changes in assets and liabilities, as normalised by asset volatility.
[12] We also compute a monthly measure of the DTI for a representative sample of European banks (IBSI sample) as the k percentile of the sample of the euro area banks with k = {95, 90, 75, 50, 25, 10, 5}.

4. Empirical results

4.1 Evidence from high-frequency identification with monetary policy shocks

How have monetary policy shocks impacted on bank variables? We start by looking at the results from HFI for a sample that excludes the ELB episode (1999 to June 2014). We find that monetary policy shocks had a significant impact on a broad set of euro area bank variables (see Table 1). For the full sample, monetary policy shocks appear to have had a positive impact only on bank bond yields, while the impact on other bank indicators was insignificant. This assessment improves, if we control for background noise. The "Rigobon" estimates (identification through heteroskedasticity) suggest that the impact on bank health was significant for the full sample, i.e, it was positive on DTD and DTI and negative on EDF. In this respect, the results robustly show that reductions (increases) in government bond yields transmitted into lower (higher) bank bond yields. According to our estimates, a monetary policy shock that decreases German 2-year government bond yields by 100 basis points caused bank bond yields in the euro area to decrease by between 72 and 82 basis points. The parameter estimates of β, which are estimated with OLS (HAC), also show that the impact varied over time.[13] The transmission from monetary policy shocks to banks changed after the outbreak of the financial crisis. This is visible from the significant slope change for β measuring the monetary policy impact on the health of euro area banks (as measured by DTD, EDF and DTI) and the banks in the four main euro area countries (Germany, France, Italy and Spain) (see Table 1, third row). In this respect, we discover that the slope change of β is significant and positive for stock prices, which is puzzling. Theoretically, if bank stocks are used as dependent variable in the HFI the correct sign of β should be negative, since normally stocks and interest rates move in the opposite direction. A 'perverse' positive response of bank stocks may be related to a central bank information effect (Romer and Romer, 2000; Nakamura and Steinsson, 2018) to which we will turn below.

In the post-crisis regime the accommodative policy stance of the ECB implied that easing shocks were dominating (see Figure 1). Assessing the response of bank health to monetary policy shocks in particular depends on whether banks' assets or liabilities react stronger to them. A positive coefficient β for DTD and DTI (and a negative sign for EDF) can be expected, if bank health benefits from a higher level of interest rates, wider interest rate margins and a steeper yield curve (Borio,

[13] In appendix D, Table D1, we report results using a monetary policy shock for the press conference window. These regressions show basically no significant impact on bank variables, except the robust impact on bank bond yields and also no time variation. However, the R^2 in these regressions is much lower than what is reported in Table 1 suggesting that the identification of the regression may be worse.

Gambacorta and Hofmann, 2017). The opposite reaction may arise, if the banking system is under stress and there are impairments in the transmission mechanism by which tightening shocks may fail to steepen the yield curve. According to our estimates β is positive and implies that a monetary policy shock that decreases German 2-year government bond yields by 100 basis points on average caused the DTD to decrease by around 25 basis points (and between 47 and 79 basis points in the post-crisis sample), depending on the country. For the DTI, however, a reduction of up to 87 basis points (259 basis points post crisis) for the euro area is detected.[14] These results suggest that banks faced adverse consequences for their health, in particular during the ELB environment, when they were confronted with a considerable reduction of their net interest rate margin. This happened despite a positive impact of monetary policy (easing) shocks on euro area banks' funding costs.

Our results thus highlight the important role of ECB communications for the transmission of monetary signals to banks. We observe discrepancies in the response to monetary policy shocks and pure monetary policy shocks that may be particularly explained by the ECB's use of its communication tools. Through forward guidance, i.e. by providing systematic guidance on the expected path of future policy rates, central banks can exert a stronger influence on market expectations of future short term interest rates (Woodford, 2012). Forward guidance can take several forms (date-based, state-contingent), but does not always ensure that market expectations on future monetary policy are consistent with the policy intentions of the central bank.[15] As of 4 July 2013 the ECB provided markets with systematic forward guidance on the future path of its policy rates (ECB, 2013). This forward guidance signaled to markets an easing bias of the ECB. The ECB announced that it would expect the key ECB interest rates to remain at present or lower levels for an extended period of time conditional on the outlook for price stability (see ECB, 2014). Forward guidance provided markets with regular communications about the path of future policy rates, and, as has been shown, it strongly influenced asset prices in the euro area (Hubert and Labondance, 2018; Moessner and Rungcharoenkitkul, 2019). Since the ECB appears to have a great deal of power over private sector beliefs about economic fundamentals, the protracted easing of the monetary policy stance in the aftermath of the crisis likely made the private sector more pessimistic about future prospects of the economy and the profitability of the banking sector. This conjecture is confirmed in regressions that separate "pure monetary policy shocks" and "information shocks", where the sum of both shocks

[14] As suggested by the estimates with the Rigobon-method (identification through heteroskedasticity) "background noise" was present, implying that the size of the "true" coefficients was likely somewhat smaller, though their sign is robust. Note in this respect that the Rigobon coefficients are an average for the full sample.

[15] For example the code words, which were used in the Introductory Statement and in speeches in the first years of the ECB's existence, did not create full certainty to markets about forthcoming interest rates, but left ample scope for macroeconomic uncertainty to influence policy decisions.

equals the (aggregate) monetary policy shock.

Table 2 shows the HFI results for (1) distinguishing between both types of shocks. In these regressions, we use the monetary policy shock decomposition from Kerssenfischer (2019) for the wide window (including ECB press conferences) and report results for the sample 2002 to 2017. By contrast to the results for the aggregate policy shock (Table 1), we show that the impact of pure monetary policy shocks on bank health (DTD) may have been negative for the full sample, albeit small and the response for the two other measures (EDF, DTI) was insignificant. We find that information shocks, which are orthogonal to pure monetary policy shocks, were strongly present in particular in the post-crisis period (see seventh row). This shows more clearly that information effects explain why the response to aggregate monetary policy shocks was positive. Moreover, if we look at pure monetary policy shocks this also allows us to restore the expected negative effect on bank stocks. This is because information shocks led to a more muted response of bank stock prices to ECB announcements. According to our estimates, a (pure) monetary policy shock that decreased German 2-year government bond yields by 100 basis points caused the Euro Stoxx bank's share price index to increase by around 10 percent pre-crisis and by about 24 percent post-crisis. The quantitative impact of pure monetary policy shocks on bank bond yields was robust for the full sample and remained in the same ballpark as before, when using the aggregate shock. However, information effects linked to communications that interest rates would stay low for long appear to have amplified the effect on bank bond yields.

Another way to differentiate between the impact on bank health from ECB actions and its communications is to run the HFI using monetary policy shocks for the narrow and wide window. Communications at the press conference are an important element of monetary policy, as they can influence market expectations for the next meeting(s). The press release on Governing Council days announces the policy decision. Importantly, ECB communications at the press conference are excluded by monetary policy shocks constructed from the narrow window, but are included in the wide window. These post-meeting communications may offer markets important clues about the way the Governing Council assesses policy options conditional on its risk assessment, but also on forward guidance. Overall, our results confirm that ECB communications at the press conference were crucial for the market response. Table 3 reports the results concentrating on the post-crisis sample 2008 to 2017 and applying measures of the monetary policy shock for two windows: the narrow (30 minutes) and the wide (120 minutes) window. During that period, the ECB changed its deposit facility rate at 16 meetings. The results from the wide window confirm a positive impact of monetary policy shocks on bank bond yields, the DTD and the DTI, which broadly resemble those reported above for the post-crisis episode (Table 1). In this analysis, we also check that the impact of monetary policy shocks on banks may have changed after the OMT announcement. With the possible exception of the DTI for which the results point to a significant slope change, we find no evidence of a structural break, since the slope change related to the OMT dummy is insignificant. In addition, the results show that monetary policy shocks from the narrow window, which in particular reflect news about policy rate changes, had no significant impact on bank variables in the post-crisis sample. In these regressions, we observe a lower R^2 even though one would expect that the identification improves, if a narrower window is used in the HFI. This fits with the notion that in view of heightened uncertainty markets listened more to central bank communications than to actions.

4.2 Evidence from high-frequency identification based on policy surprises

A growing body of empirical studies makes the point that large-scale asset purchases had a sizeable and lasting impact on broad financing conditions in the euro area. In the case of the ECB separating the effects of forward guidance and large-scale asset purchases is, however, not straightforward, because the APP supported (rate) forward guidance via the signaling channel and both tools overlapped in terms of timing. The same may hold true for other instruments such as the adoption of negative interest rates. In order to identify the impact of the APP, we use a decomposition of monetary policy surprises in three factors (see Figure 6), which have an economic interpretation: jump surprises, path surprises and slope surprises (Gürkaynak, 2005). We distinguish between effects attributable to the ELB, forward guidance and the APP by interacting jump surprises with a ELB dummy (cedumpers), path surprises with a forward guidance dummy (forwarddumpers) and slope surprises with a APP dummy (appdumpers).[16] If there was a monetary policy impact related to either ELB or forward guidance or the ECB's large scale asset purchases on euro area banks, we should find a significant parameter of the slope change for β around these events.

We run HFI regressions (4) in which we explain daily changes in bank health variables around press conferences by three surprise components. The regressions shown in Table 4, which are well identified, have a higher R^2 than the above regressions using aggregate monetary policy shocks. Our results show that slope surprises had a significant influence on bank health, as measured by both the DTD and the EDF. This means that bank health benefitted from monetary policy surprises, which steepened the yield curve. As suggested by the significant slope change for β with respect to the APP dummy, the large-scale asset purchases strengthened the influence on the DTD and on bank bonds, while contributing to a normalisation of the response by bank stocks. The strengthening of the

[16] Note in these regressions we use unscaled surprise factors.

influence of slope surprises on bank funding costs during the APP episode is in line with the results from other studies on government bond yields (e.g., Altavilla, et al., 2019). Turning to the effects of path surprises, the results show that the introduction of a systematic approach to forward guidance by the ECB made a significant contribution to the normalisation of bank stock prices. While the impact of the ECB's forward guidance may have been broader than is detected, it cannot be excluded that some of this effect was captured by the slope factor. This is because the ECB's forward guidance aimed at lowering interest rates along the yield curve. If so, the results for the slope surprises would also reflect an impact of communications on bank health in the ELB environment. Turning to jump surprises, we discover that they potentially had strong supportive effects on banks' DTD and DTI in the ELB regime, although jump surprises were rare (see Figure 6). This result could therefore also reflect the positive effects from the TLTROs on banks' net interest rate margin since September 2014.

4.3 Time-variation and persistence of the effects

During the crisis the traditional transmission of monetary policy was impaired and other channels of the transmission mechanism became more important. Eventually the ECB hit the ELB in June 2014, introduced negative interest rates and provided further monetary accommodation through non-standard tools. It provided markets with systematic forward guidance since July 2013, started its credit easing programme in June 2014, and initiated a large-scale asset purchase programme since 2015. Against this background, we provide further analysis on time-variation of the coefficient β, in particular with a view to the ELB. Rolling regressions with a three-year window (Figure 7) show that this parameter changed its value coinciding with the ELB environment. These charts illustrate nicely that the impact of monetary policy shocks on bank bond and government bond yields strengthened coinciding with the ELB, an observation that has been related to the adoption of credit-easing and the large-scale asset purchase programme. Moreover, this analysis confirms that the normal transmission from monetary policy to bank stocks was eventually restored, as the sign of the coefficient β not only changed from positive to negative, but also became significant. In addition, this exercise suggests that, in the ELB environment, the effects from monetary policy shocks on bank health (DTD, DTI, EDF) were insignificant, as illustrated by the large confidence intervals.

An analysis of local projections provides additional information on the persistence of the response of bank variables to monetary policy shocks. We report (cumulative) impulse response functions for a length of 12 quarters based on estimates of (2) for the pre-ELB period (sample January 1999 end-May 2014). We estimate equation (2) for several indicators: DTD, EDF, DTI, bank stocks, bank bond yields, German government bond yields (10 years). The impulse responses with conditional error bands (see solid blue lines Figure 8) illustrate the effects from monetary policy shocks on these key indicators. Overall, monetary policy shocks affected these key indicators with some persistence, since the confidence intervals suggest that impulse responses are significantly different from zero for most horizons (up to 12 quarters). To better illustrate how bank variables respond to monetary policy shocks, we make a counterfactual experiment and decrease the shock initially by 25 basis points. We observe a persistent decrease of bank bond yields and government bond yields. While several studies find that monetary policy shocks had persistent effects on government bond yields, a recent study argues that the effect may have been transitory (Jarociński and Karadi, 2018). The impact on bank health (DTD, DTI, EDF) lasts for about 10 quarters. We detect a negative impact on bank stock prices that reverses after 11 quarters.[17] Linked to the presence of information effects, our results based on a pure monetary policy shock (see Figure D1 in annex D3) suggest that their impact on bank health tends to be somewhat less persistent.

4.4 Evidence from panel regressions

How does the reaction of bank health to monetary policy shocks vary across banks? Do bank-specific factors influence that link? What was the impact of negative interest rates and large-scale asset purchases on the banking system? In order to answer these questions, we estimate panel regressions (3) and include bank-level data for a representative sample of 317 banks included in the IBSI sample (see annex C.2). For around 50 of these banks individual balance sheet information and daily DTD data by individual banks from Moody's can be matched. In view of data availability we focus on estimates for the sample 2006 to 2017 using the decomposition into pure monetary policy shocks and information shocks for the wide window from Kerssenfischer (2019). We apply OLS with fixed effects and GLS with random effects,[18] and explain the KMV Moody's measure for the DTD, which takes the natural logarithm of the ratio of assets over debt for each bank, thereby taking into account that the distribution of the dependent variable may be highly skewed.[19] By including the deposit facility rate, we control for negative interest rates, while the monetary base is a control for the ECB's balance sheet expansion owing to the large-scale asset purchases.

Bank characteristics can influence the response of banks to monetary policy shocks (English,

[17] The wrong sign can be again related to the information effect (as is evident from Figure D1 in annex D3).

[18] The IV estimation could be indicated, since we include monthly (quarterly) bank characteristics in the HFI panel regression. We also estimated fixed effects regressions with IV, which are similar. Since the panel regressions are well identified, it may be argued that endogeneity is not an issue here.

[19] We checked that the results are similar, if an approximation of the DTD formula is employed that does not use the logs of assets over debt.

van den Heuvel and Zakrajšek, 2018). In general, larger banks and more cost-efficient banks may be associated with lower default risk. Market leverage is a key state variable for determining the effects of financial frictions on the economy and may explain differences in bank profitability. Moreover, banks with higher profitability may have a lower probability-of-default. NPL ratios, which are very diverse across euro area banks, could be important since they impact on the ability of banks to provide loans and NPLs are widely considered to be one of the main reasons behind the low aggregate profitability of European banks.[20] We therefore include bank size (logarithm of total assets), a leverage ratio (equity-to-asset ratio), an efficiency measure (cost-to-income ratio), a liquidity measure (liquid asset ratio), an asset quality measure (non-performing loan ratio), a measure for income diversification (non-interest income relative to total revenue), cost efficiency (cost-to-income ratio), profitability (return on assets).

From the cross-section several interesting findings emerge. In a panel of individual banks we show that high-frequency monetary policy shocks (Δps) (i.e., pure monetary policy shocks and information shocks) had a statistically significant impact on bank health (see Table 5).[21] The effect of pure monetary policy shocks on the DTD was positive, but we find that it became smaller after the OMT announcement. Information shocks had the opposite impact on the DTD and this influence strengthened in the post-OMT regime. Figure 9 shows that pure monetary policy shocks and information shocks typically went into opposite directions implying that both shocks were reinforcing each other with regard to bank health. Moreover, for both shocks bank fixed effects are confirmed by the significant estimate of α (and the Hausman test). Time fixed effects since the adoption of the OMT programme, which are captured by a dummy (omtdumpers), are found to be present in these regressions. Other bank characteristics, in particular bank size, leverage and NPL ratios, amplified the impact of monetary policy shocks on banks. Fixed-effect and random-effects regressions provide indications that bank size and leverage amplified the effect of pure monetary policy shocks on banks, while only bank size and NPL ratios amplified the effect of the information shock on banks. Otherwise bank profitability, as measured by the return on assets, and NPL ratios were typically insignificant. Still, these effects may be present and fully absorbed by fixed-effects.

Turning to the effect of the deposit facility rate, by lowering the rate into negative territory the ECB helped euro area banks to reduce their costs through deposit funding at the ELB. The sustained low level of interest rates posed, however, a challenge to banks who engage in maturity

[20] NPLs are usually defined as loans that are either more than 90 days past-due or that are unlikely to be repaid in full.
[21] Diagnostic tests indicate that the residuals in these regressions are homoscedastic with no autocorrelation.

transformation. As highlighted by the bank lending survey (see e.g., ECB, 2018), the negative deposit facility rate led to a compression of banks' net interest rate margins, because of a dampening impact of the measure on bank lending rates. From mid-2014, the ECB gave some compensation by providing banks with targeted longer-term operations (TLTROs), which eased funding conditions for all euro area banks for a prolonged period of time. As shown in Table 5, the amplifying impact of the deposit facility rate on bank health did not change at the ELB. This result holds both for pure monetary policy shocks and information shocks. Since the parameter estimates of β have the same sign for both shocks, but the parameter for the pure monetary policy shock was larger, the overall effect was negative, though small.

Large-scale asset purchases implied a massive expansion of the ECB's balance sheet, since they work through expanding money supply, thereby raising asset prices, lowering bond yields and reducing long-term interest rates. Between 2015 and 2017, there was a strong increase in the ECB's balance sheet and its monetary base. Asset purchases can empower the signaling channel based on the central bank's commitment to maintain an accommodative policy for a prolonged period of time to achieve its price stability objective. Moreover, asset purchases also had positive side-effects for banks' asset quality and liquidity, thus helping them to improve their balance sheets. Using the monetary base as proxy for money supply, we find that in normal times the amplifying effect from the monetary base was very small. However, we find that with the introduction of the APP this effect became very sizeable, as suggested by the slope change of β. Since pure monetary policy shocks and information shocks moved in the opposite direction and the parameter estimates of β had the same sign, but were larger for information shocks than for pure monetary policy shocks, the total effect was on balance dominated by the information shock. [22]

4.5 Asymmetries in the transmission mechanism and international spillovers[23]

Asymmetric behaviour of bank interest rates in the case of a monetary tightening or easing could affect the speed by which monetary policy shocks transmit to the banking sector and the real economy. The empirical literature has documented that lending and deposit rates respond sluggishly to money market rate changes (Apergis and Cooray, 2015; De Bondt, 2005; Dedola and Lippi, 2005; Gambacorta and Iannotti, 2007; Hofmann and Mizen, 2004). Even before the ELB there could be non-

[22] For pure monetary policy shocks it is likely that the fixed-effect captures part of the response in relation to the monetary base expansion, since the parameter estimate of β is significant in the random-effects regression.
[23] For comparison with the previous literature, we also provide results on monetary policy shocks and financial asset prices (see Annex D). These results show that earlier results can be reproduced with the monetary policy shocks used in this study.

linearities and banks may transmit tightening signals faster than easing signals, whenever faced with a compression of their net interest rate margins. In order to analyse asymmetries in the monetary policy transmission, we modify equation (1):

$$\Delta d_t = \begin{cases} \alpha + \beta_{tight}\Delta ps_t + \beta_{tight}^{post}\Delta ps_t\, D_t + \gamma\, D_t + \varepsilon_t & if\ \Delta ps \geq 0 \\ \alpha + \beta_{ease}\Delta ps_t + \beta_{ease}^{post}\Delta ps_t\, D_t + \gamma\, D_t + \varepsilon_t & if\ \Delta ps < 0 \end{cases} \quad (1a)$$

where D_t denotes a dummy for the financial crisis. We explain bank variables distinguishing between tightening ("tight") and easing ("ease") monetary policy shocks (one-day window) and run the regression for the pre-ELB episode. Our results show that asymmetries in the transmission of monetary policy shocks were present for bank health (DTD, EDF), in the post-crisis regime (see Table 6). Prior to the financial crisis the impact of easing shocks and tightening shocks on these indicators had opposite sign and approximately the same magnitude. Post-crisis, easing shocks became more pronounced, while the sign for β became identical for tightening and easing shocks. Furthermore, the results for DTI suggest that the magnitude of the response of tightening and easing shocks was different. Table 6 confirms that, in the post-crisis episode, there was a 'perverse' stock market reaction of banks in response to easing shocks.

For several reasons international linkages have become more important over recent decades. Most importantly, central banks no longer decide on policy rates in an independent way (Taylor, 2013), but even in a system of flexible exchange rates there could be spillovers from US monetary policy via its influence on financial conditions to euro area banks. Moreover, Belke and Gros (2005) provide evidence that the ECB followed the Fed in its interest rate decisions. To assess whether banks in the euro area benefitted from the response of the Fed, we modify our high frequency approach and check whether there was an influence from the Fed's monetary policy measures on European banks resulting in international spillovers. Meetings of the FOMC and the ECB Governing Council were normally on different days. Therefore, the possible influence from the Fed on euro area bank health has to be measured on FOMC meeting days. We check for international spillovers from US monetary policy shocks on euro area bank health and explain (daily) changes of euro area bank variables around meeting days of the Fed's FOMC and replace the domestic monetary policy shock by a foreign one:

$$\Delta d_t = \alpha + \beta \Delta ps_t^{US} + \beta^{post}\Delta ps_t^{US}\, D_t + \gamma\, D_t + \varepsilon_t \quad (1b)$$

where D_t denotes a dummy for the financial crisis. We run regression (1b) for which we use a monetary policy news shock series for the US, as reported in Nakamura and Steinsson (2018). The series is computed as a first principal component from five futures from a narrow 30-minutes window around FOMC announcements.[24] The sample for this regression is the period 2000.2 to 2014.2.

We show that US monetary policy was causal for some improvements in euro area bank stock prices and contributed to reducing the risk of an insolvency crisis. During 2007-2008, the Fed lowered its funds rate by 525 basis points and reached the lower bound. To mitigate the effects of the financial crisis, policy rates were kept unusually low for an unusually long time and the Fed embarked on three tranches of its QE programme. Given the accommodative monetary policy stance, the largest US monetary policy shocks post-crisis can be found on the easing side. As Table 7 shows, US monetary policy shocks had in general no impact on euro area banks. In the post-crisis episode, however, they are found to have exerted a sizeable impact on stock prices of euro area banks (and possibly contributed to improvements to euro area EDFs). According to our estimates, a US monetary policy shock that decreased the one-year US Treasury bond yields by 25 basis points during this period caused Euro Stoxx bank's share prices to increase by around 13 percent on average.

5. Conclusions

Popular explanations attribute the slow recovery of the European banking sector to its lower profitability, higher leverage and non-performing loan ratios than elsewhere. What has been the contribution of monetary policy shocks on the health of banks? By means of high-frequency identification and other econometric tools, we assess the link between monetary policy shocks and the health of euro area banks. The HFI method measures incremental changes in bank health indicators during short-time spans around policy announcements, when new information about monetary policy becomes publicly available. Monetary policy surprises and shocks are measures of unexpected movements in monetary policy and contain information about the future course of the central bank. We compute monetary policy surprises on Governing Council meeting days from OIS rates (and Bund futures) in tight windows around policy announcements and consider different proxies of monetary policy shocks. First, we apply principal components analysis to compute monetary policy shocks from monetary policy surprises at different maturities. Second, we decompose monetary policy surprises into three components, which have an economic interpretation: "jump surprises", "path surprises" and "slope surprises". Third, we decompose monetary policy shocks into "pure" monetary policy shocks

[24] The monetary policy news shock is scaled such that its effect on the one-year Treasury yield is 100 basis points.

and central bank "information shocks".

Overall, we find that monetary policy shocks had a significant impact on bank health in the euro area. Information effects, which made the private sector more pessimistic about future prospects of the economy and the profitability of the banking sector, were strongly present in the post-crisis period. We show that ECB communications at the press conference were crucial for the market response and that bank health benefitted from surprises, which steepened the yield curve. We find that the effects of monetary policy shocks on banks displayed some persistence. Other bank characteristics, in particular bank size, leverage and NPL ratios, amplified the impact of monetary policy shocks on banks. After the OMT announcement, we detect that the response of bank stocks to monetary policy shocks normalised. We also discover that, in the post-crisis episode, Fed monetary policy shocks influenced euro area bank stock valuations.

REFERENCES

Altavilla, C., Boucinha, M., Peydró, J.-L., 2018. Monetary policy and bank profitability in a low rate environment. *Economic Policy*, 33(96), 531-586.

Altavilla, C., Brugnolini, L., Gürkaynak, R., Motto, R., Ragusa, R., 2019. Measuring euro area monetary policy. ECB Working Paper No. 2281.

Altavilla, C., Carboni, G., Motto, R., 2015. Asset purchase programmes and financial markets: lessons from the euro area. ECB Working Paper No. 1864.

Altavilla, C., Giannone, D., Lenza, M., 2016. The financial and macroeconomic effects of the OMT announcements. *International Journal of Central Banking*, 12(3), 29-57.

Altunbas, Y., Gambacorta, L., Marques-Ibanez, D., 2014. Does monetary policy affect bank risk?, *International Journal of Central Banking*, 10(1), 95-135.

Andersson, M., 2010. Using intraday data to gauge financial market responses to Federal Reserve and ECB monetary policy decisions. *International Journal of Central Banking*, 6, 117-146.

Apergis, N., Cooray, A., 2015. Asymmetric interest rate pass-through in the U.S., the U.K. and Australia: new evidence from selected individual banks, *Journal of Macroeconomics*, 45, 155-172.

Atkeson, A., Eisfeldt, A., Weill, P.-O., 2017. Measuring the financial soundness of US firms 1926-2012. *Research in Economics*, 3, 613-635.

Begenau, J., Piazzesi, M., Schneider, M., 2015. Banks' risk exposures. NBER Working Paper No. 21334.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of Political Economy*, 81, 637-654.

Belke, A., Gros, D., 2005. Asymmetries in Transatlantic monetary policy making: Does the ECB follow the Fed? *Journal of Common Market Studies*, 43, 921-946.

Bernanke, B., Blinder, A., 1988. Credit, money, and aggregate demand. *American Economic Review*, 78(2), 901-921.

Bernanke, B., Gertler, M., 1995. Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4), 27-48.

Bernanke, B., Kuttner, K., 2005. What explains the stock market's reaction to Federal Reserve policy? *Journal of Finance*, 60(3), 1221-1257.

Bogdanova, B., Fender, I., Takáts, E., 2018. The ABCs of bank PBRs. *BIS Quarterly Review*, March 2018, 81-95.

Bojaruniec, P., Morandi, G., 2015. Setting-up the transmission of individual MFI statistics on balance sheet items and interest rates across the Eurosystem, paper available from the BIS website:

https://www.bis.org/ifc/events/ws_micro_macro/morandi_paper.pdf.

Borio, C., Gambacorta, L., Hofmann, B., 2017. The influence of monetary policy on bank profitability. *International Finance*, 20, 48-63.

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

Cesa-Bianchi, A., Thwaites, G., Vicondoa, A., 2016. Monetary policy transmission in an open economy: new data and evidence from the United Kingdom. Bank of England Working Paper No. 615.

Chan Lau, J., Sy, A., 2006. Distance-to-Default in Banking: A Bridge Too Far? IMF Working Paper WP/06/215 (Washington: International Monetary Fund).

Christiano, L., Eichenbaum, M., Evans, C., 1996. The effects of monetary policy shocks: evidence from the flow of funds. *Review of Economics and Statistics*, 78(1), 16-34.

Christiano, L., Eichenbaum, M., Evans, C., 2005. Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1), 1-45.

Cook, T., Hahn, T., 1989. The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics*, 24(3), 331-351.

Cochrane, J., Piazzesi, M., 2002. The Fed and interest rates: a high-frequency identification. *American Economic Review*, 92(2), 90-95.

Cukierman, A., Meltzer, A., 1986. A theory of ambiguity, credibility, and inflation under discretion and asymmetric Information. *Econometrica*, 54(5), 1099-1128.

De Bondt, G., 2005. Interest rate pass-through: empirical results for the euro area. *German Economic Review*, 6, 37-78.

De Santis, R.A., 2019. Redenomination risk. *Journal of Money, Credit and Banking, forthcoming*.

Dedola, L., Lippi, F., 2005. The monetary transmission mechanism: Evidence from the industries of five OECD countries. *European Economic Review*, 49, 1543-1569.

ECB, 2014. The ECB's forward guidance. *Monthly Bulletin*, April, 65-73.

ECB, 2016. Financial Stability Review, Section C, ECB: Frankfurt.

ECB, 2018. Euro Area Bank Lending Survey, ECB: Frankfurt.

Ehrmann, M., Fratzscher, M., 2009. Explaining monetary policy in press conferences. *International Journal of Central Banking*, 5(2), 41-84.

English, W., van den Heuvel, S., Zakrajšek, E., 2018. Interest rate risk and bank equity valuations. *Journal of Monetary Economics*, 98, 80-97.

Faust, J., Rogers, J., Swanson, E., Wright, J., 2003. Identifying the effects of monetary policy shocks on exchange rates using high frequency data. *Journal of the European Economic Association*, 1(5), 1031-1057.

Gambacorta, L., Iannotti, S., 2007. Are there asymmetries in the response of bank interest rates to monetary shocks? *Applied Economics*, 39, 2503-2517.

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

Gürkaynak, R., 2005. Using federal funds futures contracts for monetary policy analysis. Finance and Economics Discussion Series 2005-29, Board of Governors of the Federal Reserve System (U.S.).

Gürkaynak, R., Sack, B., Swanson, E., 2005. Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking*, 1(1), 55-93.

Gürkaynak, R., Sack, B., Swanson, E., 2007. Market-based measures of monetary policy expectations. *Journal of Business and Economic Statistics*, 25(2), 201-212.

Hofmann, B., Mizen, P., 2004. Interest rate pass-through and monetary transmission: evidence from individual financial institutions' retail rates. *Economica*, 71, 99-123.

Hubert, P., Labondance, F., 2018. The effect of ECB forward guidance on the term structure of interest rates. *International Journal of Central Banking*, 14(5), 193-222.

Jarociński, M., Karadi, P., 2018. Deconstructing monetary policy surprises: the role of information shocks. ECB Working Paper No. 2133.

Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1), 161-182.

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J., 2012. Credit supply and monetary policy: identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5), 2301-2326.

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J., 2014. Hazardous times for monetary policy: what do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2), 463-505.

Jordà, O., Schularick, M., Taylor, A., 2016. Sovereigns versus banks: credit, crises, and consequences. *Journal of the European Economic Association*, 14(1), 45-79.

Kashyap, A., Stein, J., 2000. What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3), 407-428.

Kerssenfischer, M, 2019. Information effects of euro area monetary policy: New evidence from high-frequency futures data. Deutsche Bundesbank Discussion Paper No. 07/2019.

Kuttner, K., 2001. Monetary policy surprises and interest rates: evidence from the Fed funds futures markets. *Journal of Monetary Economics*, 47, 523-544.

Leland, H., 1994. Corporate debt value, bond covenants, and optimal capital structure. *Journal of Finance*, 49(4), 1213-1252.
Maddaloni, A., Peydró, J.-L., 2011. Bank risk-taking, securitization, supervision, and low interest rates: evidence from the euro-area and the U.S. lending standards. *Review of Financial Studies*, 24(6), 2121-2165.

Melosi, L, 2017. Signaling effects of monetary policy. *Review of Economic Studies*, 84(2), 853- 884.

Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2), 449-470.

Moessner, R., Rungcharoenkitkul, P., 2019. The zero lower bound, forward guidance and how markets respond to news. *BIS Quarterly Bulletin*, March 2019, 83-94.

Nakamura, E., Steinsson, J., 2018. High frequency identification of monetary non-neutrality: the information effect. *Quarterly Journal of Economics*, 133(3), 1283-1330.

Peek, J., Rosengren, E., 2013. The Role of Banks in the Transmission of Monetary Policy. Federal Reserve Bank of Boston Research Department Public Policy Discussion Papers No. 13-5.

Praet, P., 2015. Monetary Policy Lessons from the Financial Crisis - Some Remarks. Speech at the SNB Research Conference, organised by the Swiss National Bank, Zurich, 24 September 2015.

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

Rigobon, R., Sack, B., 2004. The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51, 1553-1575.

Romer, C., Romer, D., 1989. Does monetary policy matter? A new test in the spirit of Friedman and Schwartz. NBER Macroeconomics Annual 4, 121-170.

Romer, C., Romer, D., 2000. Federal Reserve information and the behavior of interest rates. *American Economic Review*, 90(3), 429–457.

Romer, C., Romer, D., 2004. A new measure of monetary shocks: derivation and implications. *American Economic Review*, 94(4), 1055-1084.

Samuelson, P., 1945. The effect of interest rate increases on the banking system. *American Economic Review*, 35(1), 16-27.

Swanson, E., 2016. Measuring the effects of unconventional monetary policy on asset prices. in: Albagli, E., Saravia, D., Woodford, M. (eds.), Monetary Policy through Asset Markets: Lessons from Unconventional Measures and Implications for an Integrated World, edition 1, volume 24, chapter 4, 105-130, Central Bank of Chile: Santiago de Chile.

Swanson, E., 2017. Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets. NBER Working Paper No. 23311.

Swanson, E., 2018. The Federal Reserve is not very constrained by the Lower Bound on Nominal Interest Rates. NBER Working Paper No. 25123.

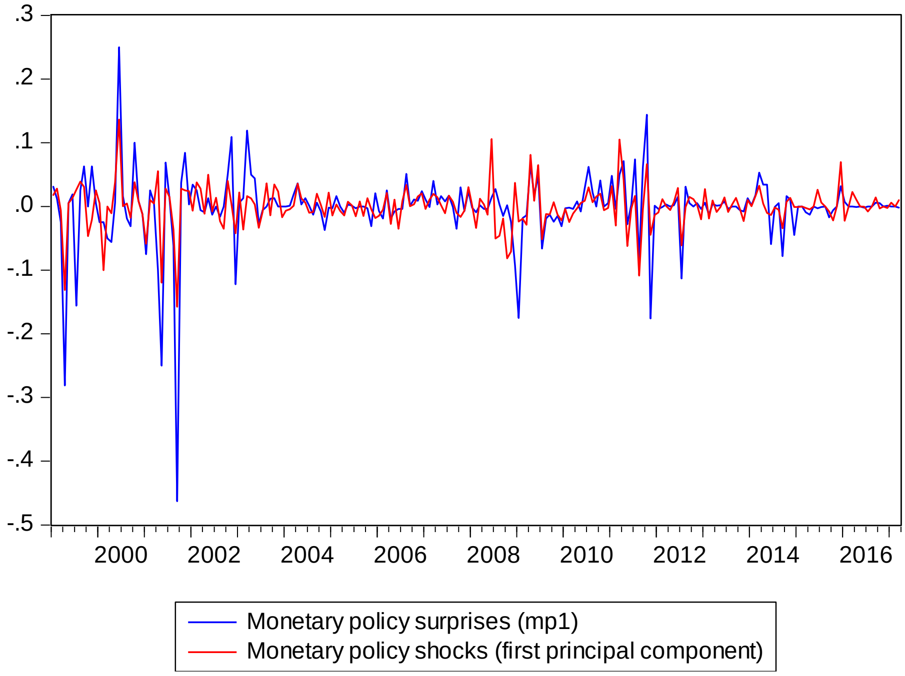
Taylor, J., 2013. International monetary coordination and the great deviation. *Journal of Policy Modeling*, 35(3), 463-472.

Uhlig, H., 2005. What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2), 381-419.

Woodford, M., 2012. Methods of policy accommodation at the interest-rate lower bound. Federal Reserve Bank of Kansas City Jackson Hole Symposium Conference Volume, The Changing Policy Landscape, August, 185-288.

ANNEX A: Figures and Tables

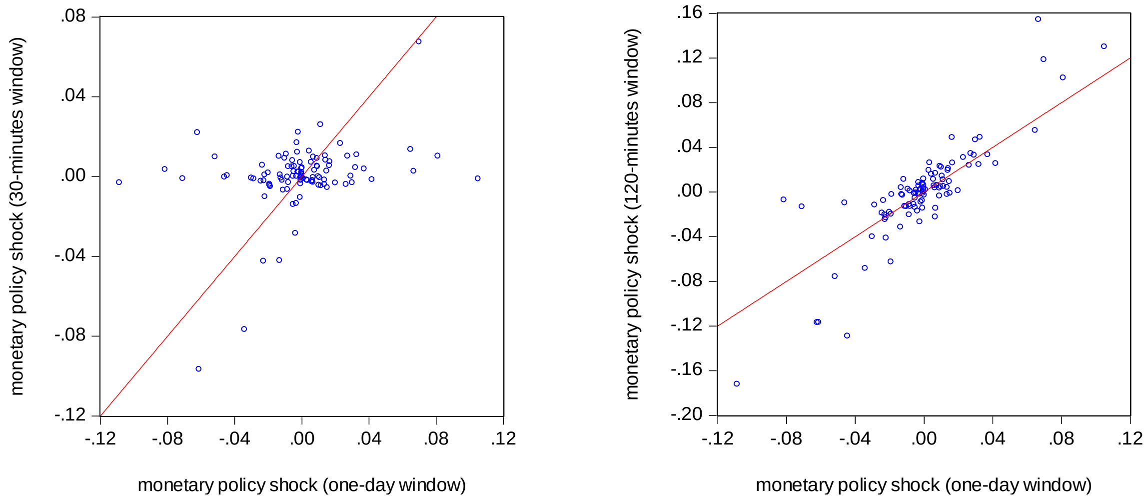
Figure 1: Monetary policy surprises and shocks for the euro area



Note: Based on daily data for euro area OIS rates.

Source: Bloomberg, own calculations.

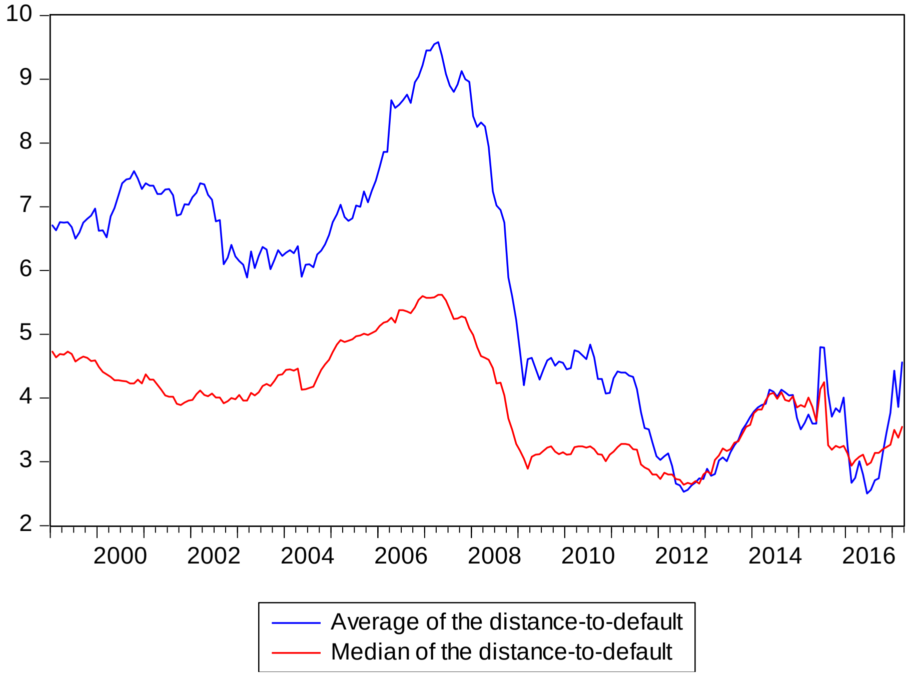
Figure 2: A comparison of intradaily and daily monetary policy shocks



Note: Δps has been calculated from the first principal component of the change in four OIS interest rate swaps (1 month, 6 months, 1 year, 10 years). The scale of the policy news shock is arbitrary. We rescale it so that its average effect on the change in the 2-year German government bond yield around Governing Council meeting days is equal to one. The line in Figure 2 shows a 45°-line.

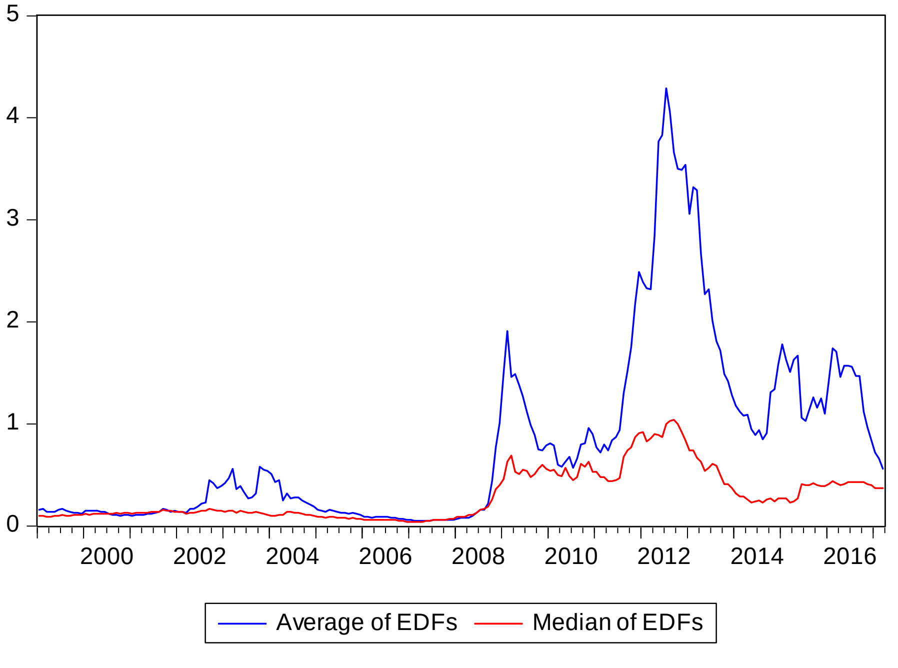
Source: Bloomberg, Thomson Reuters, own calculations.

Figure 3: Distance-to-default for euro area banks (levels)



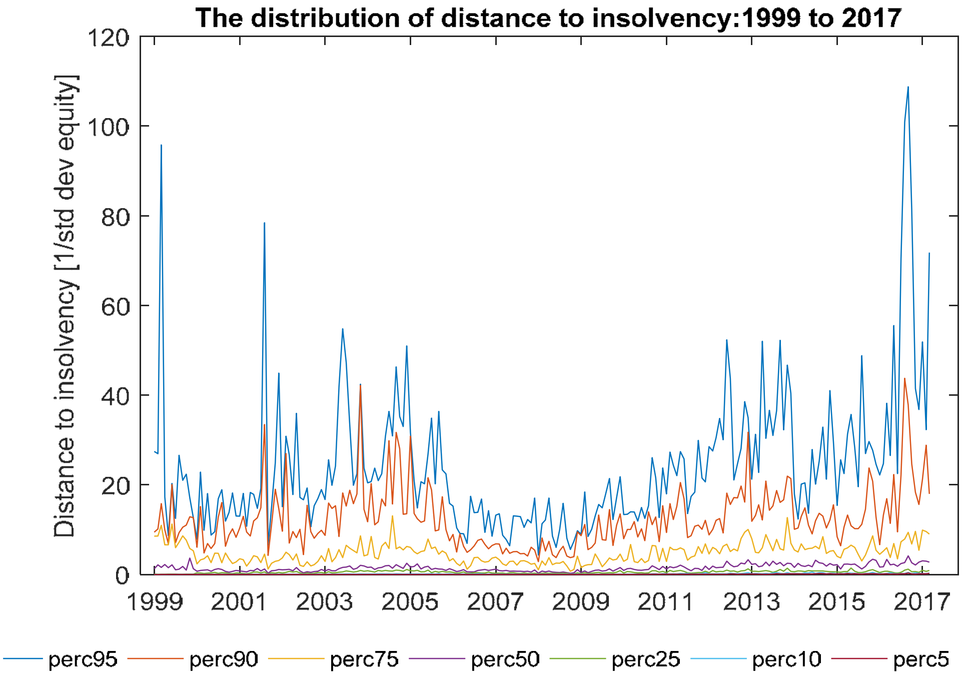
Note: Moody's credit edged derived distance-to-default indicator. Source: KMV Moody's.

Figure 4: Expected default frequencies for euro area banks (probabilities)



Note: Expected default frequency (EDF) within one year. Source: KMV Moody's.

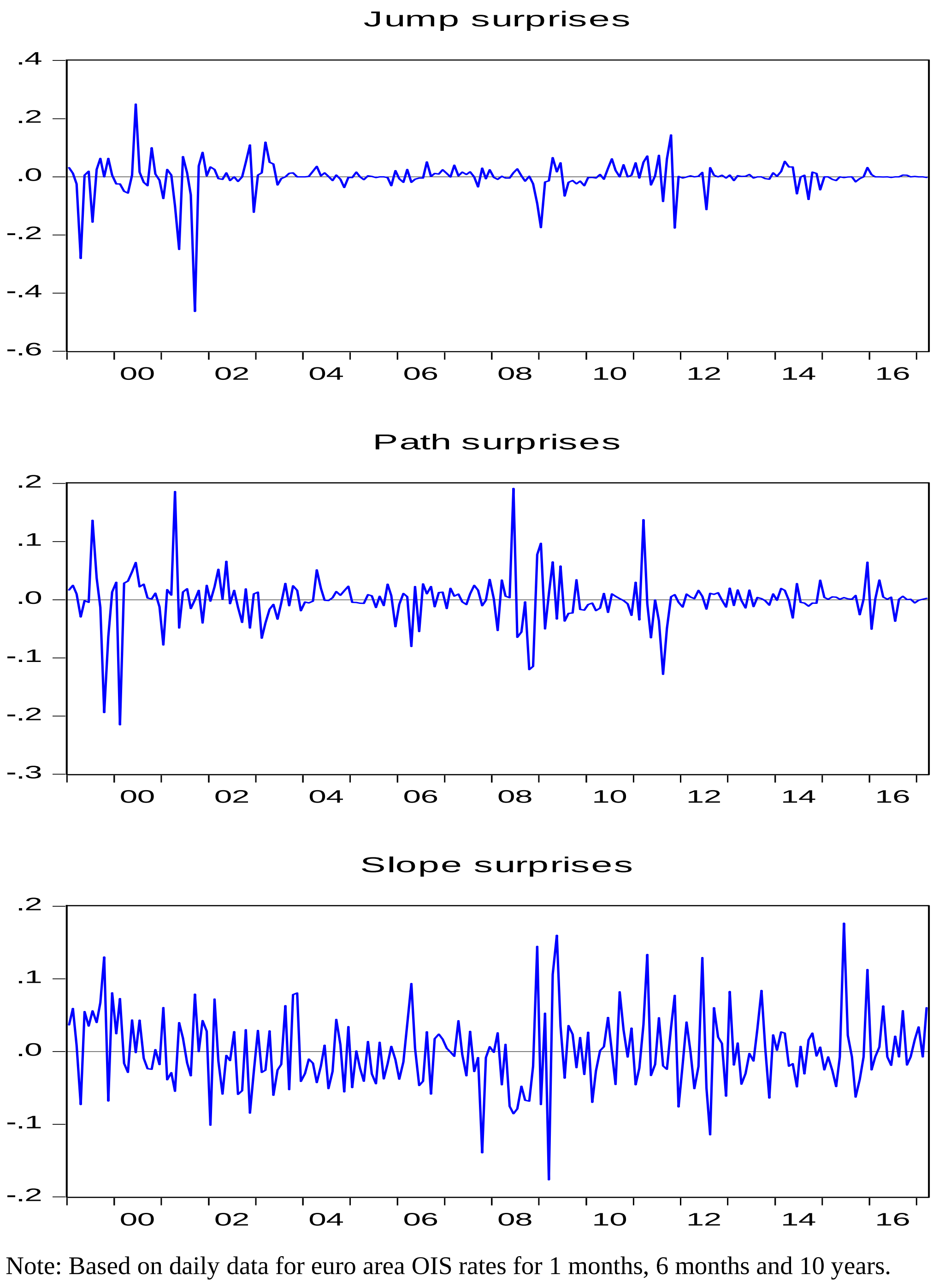
Figure 5: Distance-to-insolvency for euro area banks (in terms of percentiles)



Note: measure has been calculated from daily stock prices of the banks covered in the IBSI dataset.

Source: Datastream, own calculations.

Figure 6: Jump, path and slope surprises in the euro area

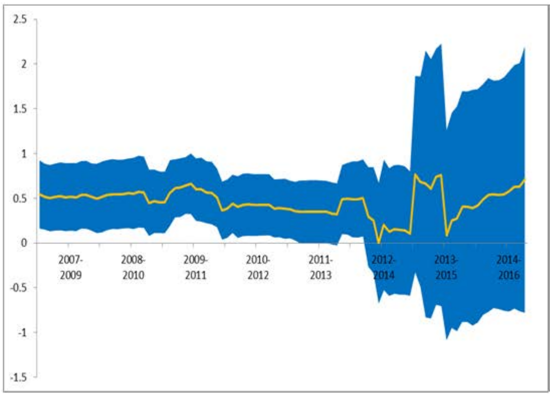


Note: Based on daily data for euro area OIS rates for 1 months, 6 months and 10 years.

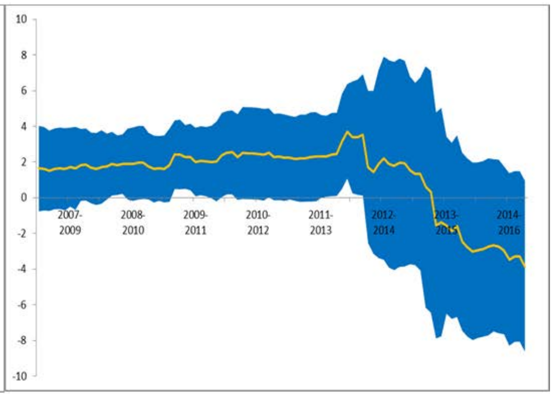
Source: Bloomberg, own calculations.

Figure 7: Estimates of time-varying coefficients in the HFI regressions

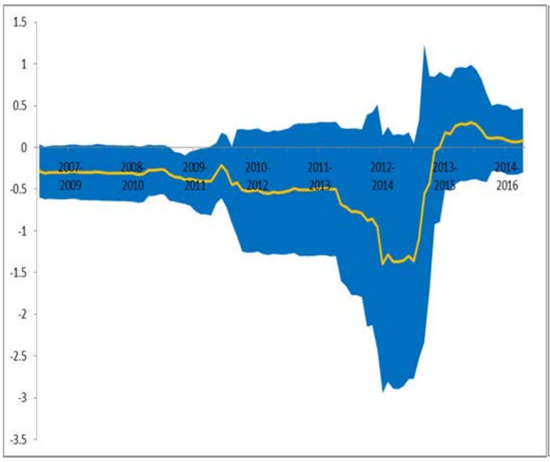
Distance-to-default for the euro area



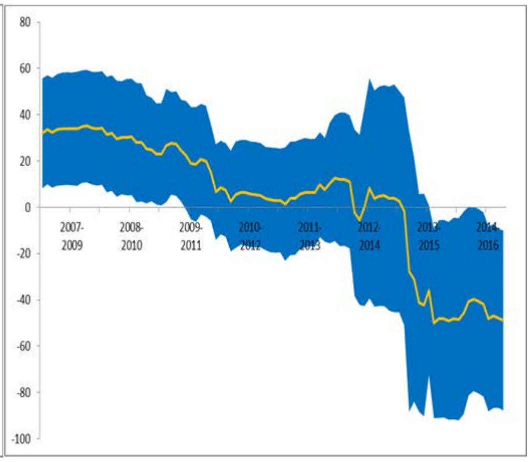
Distance-to-insolvency for the euro area



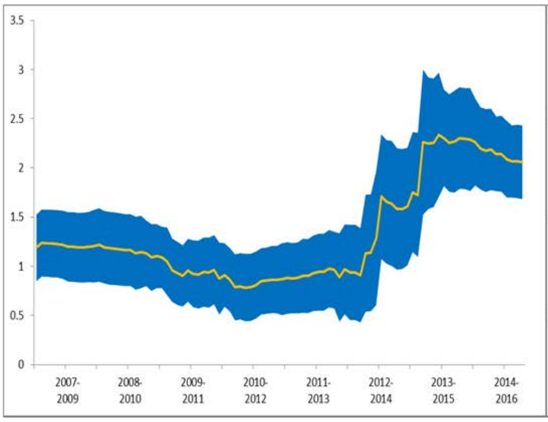
Expected default frequency for the euro area



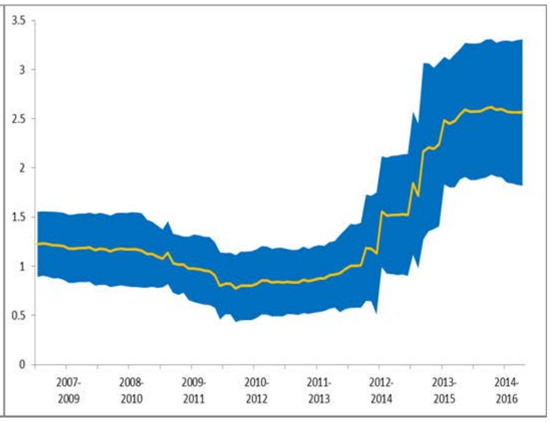
Bank Stocks (Euro Stoxx banks)



Bank bond yields for the euro area



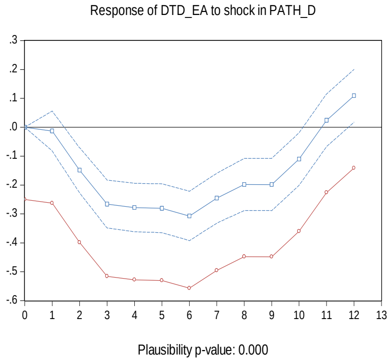
Government bond yields (10years) for Germany



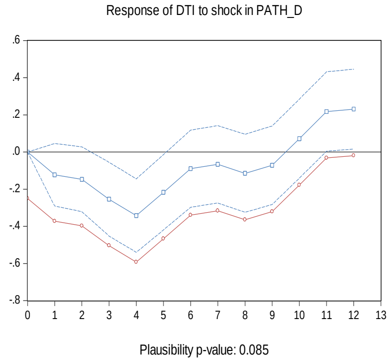
Note: Sample 2006 to 2017. Monetary policy shock is calculated from the one-day window. Coefficients are obtained from rolling regressions of equation (1) with a rolling three-years window and no dummy is included. The solid yellow lines show the coefficients of the respective bank indicator and the blue shaded area shows the confidence interval at 5%-level drawn around the coefficient estimates.

Figure 8: Local projections and counterfactual policy simulations with monetary policy shocks

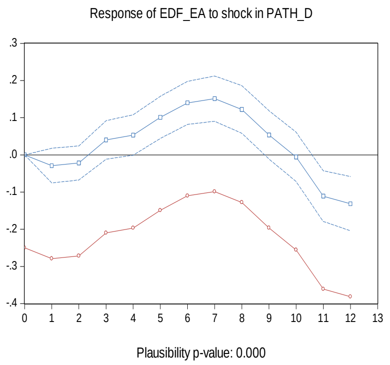
Distance-to-default (DTD)



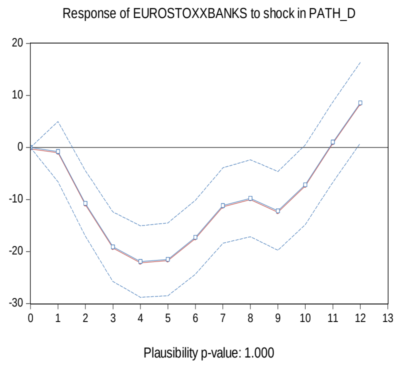
Distance-to-insolvency (DTI)



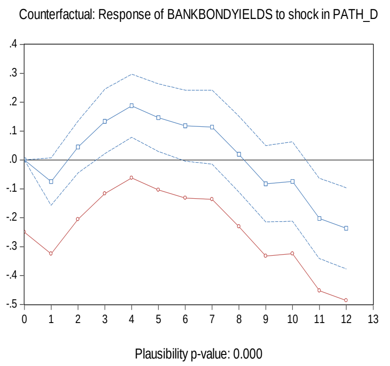
Expected default frequencies (EDF)



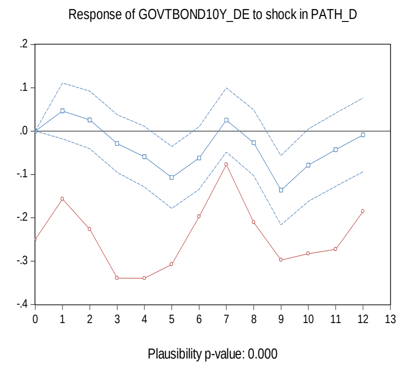
Bank stocks (Euro Stoxx banks)



Bank bond yields for the euro area

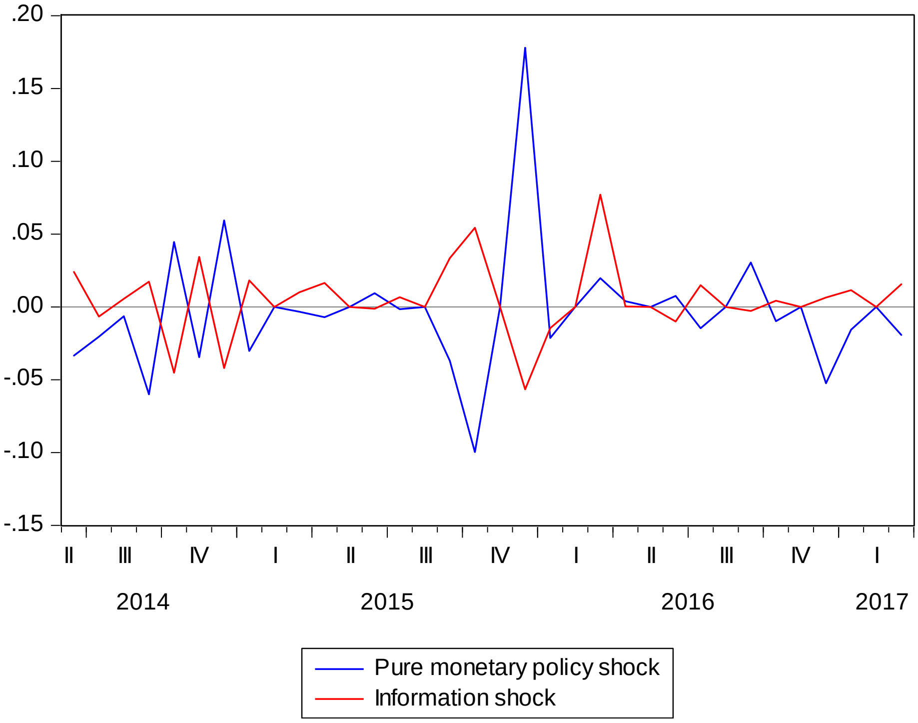


German bond yields (10 years)



Note: Sample: 1999.1-2014.5. Quarterly data, monetary policy shock with daily window. Solid (blue) lines with squares and associated dashed (blue) lines are the impulse responses with conditional error bands. The solid (red) line with circles is the counterfactual response, given an initial decrease in the monetary policy shock by 25 basis points in the first quarter. The p-value (from an F-test) at the bottom of each graph is a test result measuring the distance between the conditioning event and the sample estimates. The regressions include a dummy (findumpers) for the financial crisis.

Figure 9: Pure monetary policy shocks and information shocks in the ELB episode



Note: Sample 2014 to 2017. The decomposition into a pure monetary policy shock and an information shock is computed from a 135 minutes window (13:35 to 15:50) using 2-year Bund futures and Euro Stoxx 50 futures (see Kerssenfischer, 2019).

TABLE 1: Monetary policy shocks and bank health indicators

	one-day window			
Dependent variable	c	Δps	Δps*D	R squared
Distance-to-default				
Euro area OLS	0 (-0.69)	0.04 (0.67)	0.55*** (2.96)	0.13
Rigobon		0.24** (2.42)		
DE OLS	0 (-0.20)	0.04 (0.64)	0.47*** (3.27)	0.13
Rigobon		0.20** (2.36)		
FR OLS	0 (0.37)	0.05 (0.41)	0.62*** (3.12)	0.10
Rigobon		0.26** (2.16)		
IT OLS	0 (-1.26)	0.13* (1.84)	0.48** (2.39)	0.10
Rigobon		0.30*** (3.36)		
ES OLS	0 (-0.47)	-0.02 (-0.17)	0.79*** (3.23)	0.10
Rigobon		0.26* (1.92)		
Expected default frequencies				
Euro area OLS	0 (0.65)	0 (0.01)	-0.50** (-2.36)	0.06
Rigobon		-0.17** (-2.44)		
DE OLS	0 (0.31)	0 (0.26)	-0.54** (-2.36)	0.05
Rigobon		-0.18** (-2.42)		
FR OLS	0 (1.04)	0.01 (0.87)	-0.37** (-2.33)	0.04
Rigobon		-0.12** (-2.17)		
IT OLS	0 -1.05	-0.01 (-1.17)	-0.44* (-1.94)	0.04
Rigobon		-0.17** (-2.31)		
ES OLS	0 (0.92)	0 (-0.09)	-0.29** (-2.01)	0.07
Rigobon		-0.10* (-1.80)		
Distance-to-insolvency				
Euro area OLS	0.01 (0.58)	-0.02 (-0.05)	2.59*** (3.30)	0.04
Rigobon		0.87* (1.76)		
Bank bond yields				
Euro area OLS	0.01* (1.79)	0.72*** (3.39)	0.24 (0.89)	0.35
Rigobon		0.82*** (4.95)		
EUROSTOXX banks				
Euro area OLS	-0.21 (-1.44)	-5.26 (-0.61)	28.42* (1.97)	0.05
Rigobon		4.78 (0.64)		

Note: Sample: 1999.1-2014.5. Regression of equation (1) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10 significance level. Δps refers to the monetary policy shock for the one-day window derived as first principal component of the change in four OIS interest rate swaps (1 month, 6 months, 1 year, 10 years). “Rigobon” reports the identification through heteroskedasticity estimates, where control days are 1 week after Governing Council days. DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the financial crisis (findumpers).

TABLE 2: Pure monetary policy shocks, information shocks and bank health indicators

	pure monetary policy shock				information shock			
Dependent variable	c	Δps	Δps*D	R squared	c	Δps	Δps*D	R squared
Distance-to-default								
Euro area	-0.01*	-0.19**	-0.10	0.06	-0.01*	0.15	0.53**	0.15
	(-1.83)	(-2.35)	(-0.64)		(-1.80)	-0.84	(2.50)	
DE	0	-0.11	-0.11	0.03	0	0.24*	0.26	0.09
	(-0.73)	(-1.34)	(-0.69)		(-0.78)	(1.72)	(1.57)	
FR	0	-0.29***	0.09	0.04	0	0.14	0.62**	0.11
	(-1.16)	(-2.69)	(0.49)		(-1.05)	(0.53)	(2.01)	
IT	-0.01*	-0.15*	-0.30*	0.09	-0.01	0.23	0.63**	0.19
	(-1.77)	(-1.71)	(-1.74)		(-1.81)	(1.08)	(2.36)	
ES	-0.01	-0.30***	-0.15	0.08	-0.01	-0.14	1.09***	0.17
	(-1.53)	(-3.12)	(-0.75)		(-1.52)	(-0.53)	(3.67)	
Expected default frequencies								
Euro area	0	0.04	0.39	0.08	0	-0.03	-0.80**	0.20
	(0.89)	(1.36)	(1.65)		(0.84)	(-1.08)	(-2.49)	
DE	0	0.07	0.47	0.09	0	-0.09	-0.84**	0.17
	(0.36)	(1.20)	(1.56)		(0.34)	(-1.22)	(-2.05)	
FR	0*	0.02	0.36	0.08	0*	-0.03	-0.70**	0.18
	(1.74)	(1.21)	(1.53)		(1.82)	(-1.52)	(-2.26)	
IT	0	0.02	0.55*	0.10	0	-0.07	-0.87**	0.17
	(0.79)	(1.05)	(1.79)		(0.84)	(-1.46)	(-1.98)	
ES	0	0.05	0.16	0.07	0	-0.06	-0.47**	0.28
	(1.53)	(1.00)	(1.16)		(1.55)	(-0.87)	(-2.39)	
Distance-to-insolvency								
Euro area	-0.01	-1.62	-0.26	0.07	-0.01	-0.05	3.13	0.08
	(-0.26)	(-1.38)	(-0.19)		(-0.19)	(-0.03)	(1.58)	
Bank bond yields								
Euro area	0	0.80***	-0.35	0.17	0	0.96***	-0.50	0.14
	(0.16)	(6.53)	(-1.25)		(-0.19)	(4.81)	(-1.52)	
EUROSTOXX banks								
Euro area	-0.41**	-10.38**	-13.88*	0.10	-0.40**	19.88**	9.87	0.11
	(-2.28)	(-2.12)	(-1.69)		(-2.34)	(2.16)	(0.79)	

Note: Sample: 2002.3-2017.3. Regression of equation (1) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δps refers to the pure monetary policy shock and the information shock respectively computed from a 135 minutes window (13:35 to 15:50) using 2-year Bund futures and Euro Stoxx 50 futures (see Kerssenfischer, 2019). DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the financial crisis (findumpers).

TABLE 3: Monetary policy shocks and bank health indicators (financial crisis episode)

	narrow window				wide window			
Dependent variable	c	Δps	Δps*D	R squared	c	Δps	Δps*D	R squared
Distance-to-default								
Euro area	0	0.62	-0.67	0.03	0	0.30**	-0.16	0.07
	(-0.29)	(1.12)	(-1.05)		(-0.13)	(2.34)	(-0.63)	
DE	0	0.57	-0.71	0.03	0	0.26**	-0.07	0.06
	(-0.78)	(1.17)	(-1.29)		(-0.65)	(2.53)	(-0.28)	
FR	0	0.59	-0.65	0.02	0	0.36***	-0.06	0.06
	(0.24)	(0.90)	(-0.87)		(0.45)	(2.71)	(-0.19)	
IT	-0.01	0.69	-0.57	0.05	-0.01	0.22**	-0.14	0.07
	(-1.17)	(0.81)	(-0.59)		(-1.10)	(2.02)	(-0.49)	
ES	0	0.60	-0.44	0.03	0	0.40**	-0.34	0.09
	(-0.57)	(1.08)	(-0.63)		(-0.41)	(2.29)	(-1.08)	
Expected default frequencies								
Euro area	0	-1.06	0.49	0.04	0	-0.17	-0.08	0.03
	(0.13)	(-1.25)	(0.49)		(-0.02)	(-1.50)	(-0.25)	
DE	0	-1.19	0.78	0.03	0	-0.19*	-0.01	0.02
	(-0.00)	(-1.27)	(0.70)		(-0.18)	(-1.77)	(-0.03)	
FR	0	-0.46	0.02	0.02	0	-0.13*	-0.1	0.02
	(-0.64)	(-0.78)	(0.03)		(-0.79)	(-1.76)	(-0.40)	
IT	0	-2.04	1.12	0.08	0	-0.12	-0.17	0.01
	(0.14)	(-1.34)	(0.67)		(-0.03)	(-1.64)	(-0.37)	
ES	0	-0.21	-0.34	0.08	0	-0.11*	-0.25	0.08
	(-0.70)	(-1.16)	(-0.79)		(-0.90)	(-1.82)	(-1.05)	
Distance-to-insolvency								
Euro area	0	-2.85	3.34	0.08	0.01	1.22***	-1.99**	0.10
	(0.11)	(-0.76)	(0.86)		(0.17)	(2.94)	(-1.98)	
Bank bond yields								
Euro area	0	0.79	0.17	0.09	0	0.56***	0.63	0.37
	(0.15)	(1.26)	(0.21)		(0.65)	(2.70)	(1.61)	
EUROSTOXX banks								
Euro area	-0.76**	53.67	-45.3	0.08	-0.71**	10.04	-18.09	0.08
	(-2.17)	(1.47)	(-1.15)		(-2.07)	(1.04)	(-1.19)	

Note: Sample: 2008.9-2017.3. Regression of equation (1) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δps refers respectively to the monetary policy shock for the narrow (30 minutes) window and the wide (120 minutes) window derived as first principal component of the change in four OIS interest rate swaps (1 month, 6 months, 1 year, 10 years). DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the OMT programme (omtdumpers).

TABLE 4: Monetary policy surprise factors and bank health indicators

Dependent variable	c	Δjump	Δjump*D	Δpath	Δpath*D	Δslope	Δslope*D	R squared
Distance-to-default								
Euro area	0	0.23**	-1.23**	0.11	-0.46	0.34**	0.65*	0.37
	(-0.06)	(2.16)	(-2.34)	(1.08)	(-0.82)	(4.17)	(1.79)	
DE	0	0.19*	-1.03*	0.15*	-0.44	0.25***	0.84*	0.37
	(-1.17)	(1.72)	(-1.66)	(1.86)	(-0.79)	(3.19)	(1.84)	
FR	0	0.20**	-1.25*	0.21*	-0.33	0.34***	0.98**	0.33
	(0.79)	(2.00)	(-1.82)	(1.93)	(-0.46)	(3.47)	(2.16)	
IT	-0.01	0.33**	-1.63**	-0.04	-0.45	0.42***	0.27	0.37
	(-1.49)	(2.03)	(-3.83)	(-0.35)	(-0.82)	(4.06)	(0.98)	
ES	0	0.30***	-1.22***	0.23	-0.93*	0.35***	0.29	0.32
	(-0.66)	(3.18)	(-3.07)	(1.34)	(-1.87)	(3.08)	(1.30)	
Expected default frequencies								
Euro area	0	-0.05	0.36*	0.06	0.25	-0.61***	0.49**	0.27
	(0.05)	(-0.54)	(1.94)	(0.56)	(1.11)	(-2.70)	(2.13)	
DE	0	-0.10	0.44**	0.06	0.47*	-0.60**	0.34	0.20
	(0.10)	(-0.84)	(2.43)	(0.56)	(1.74)	(-2.13)	(1.16)	
FR	-0.01	-0.02	0.29	0.01	0.08	-0.41*	0.21	0.14
	(-0.89)	(-0.24)	(1.62)	(0.14)	(0.33)	(-1.76)	(0.88)	
IT	0.01	-0.04	0.47	0.14	0.96**	-0.65**	0.55*	0.25
	(0.81)	(-0.38)	(1.61)	(1.12)	(2.51)	(-2.18)	(1.78)	
ES	0	-0.10	0.27**	0	-0.02	-0.24**	0.15	0.22
	(0.42)	(-1.49)	(2.11)	(0.03)	(-0.09)	(-1.98)	(1.15)	
Distance-to-insolvency								
Euro area	0.06*	1.05**	-6.79***	1.31***	-1.67	0.51	-1.00*	0.15
	(1.85)	(2.47)	(-3.24)	(2.65)	(-1.30)	(1.07)	(-1.70)	
Bank bond yields								
Euro area	0	0.16*	0.01	0.63***	0.36	0.26*	0.73***	0.61
	(-0.37)	(1.83)	(0.04)	(3.39)	(1.54)	(1.79)	(4.85)	
EUROSTOXX banks								
Euro area	-0.36	-4.73	-11.19	19.46***	-63.93***	13.79*	-20.85**	0.25
	(-1.14)	(-1.00)	(-0.77)	(2.81)	(-3.64)	(1.93)	(-2.54)	

Note: Sample: 2008.9-2017.3. Regression of equation (4) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δjump refers to jump surprises, Δpath refers to path surprises, Δslope refers to slope surprises as in Gürkaynak (2005). These factors have been computed from OIS rates at different maturities (one-day window). DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the ELB (cedumpers), forward guidance (forwarddumpers) and the APP programme (appdumpers).

TABLE 5: Monetary policy shocks and banks' distance-to-default (panel regressions)

Distance-to-default (DTD)	pure monetary policy shock		information shock	
	(1)	(2)	(1)	(2)
Variables	Fixed Effects	GLS	Fixed Effects	GLS
Δps	0.624**	0.606*	-1.509***	-1.497***
	(0.292)	(0.358)	(0.465)	(0.429)
omtdumpers*Δps	-0.364***	-0.372***	-0.112	-0.108
	(0.122)	(0.119)	(0.122)	(0.114)
deposit facility rate*Δps	-0.486***	-0.484***	-0.352***	-0.350***
	(0.0690)	(0.0615)	(0.0545)	(0.0524)
deposit facility rate*Δps*cedumpers	-10.03	-9.136	55.31	57.37
	(42.24)	(45.24)	(46.44)	(45.58)
log of monetary base*Δps	0.0373***	0.0370***	-0.00833**	-0.00812*
	(0.00496)	(0.00366)	(0.00375)	(0.00434)
log of monetary base*Δps*appdumpers	-79.19	-79.43**	-94.42*	-94.46**
	(47.59)	(39.09)	(52.00)	(44.88)
leverage*Δps	-2.948**	-2.964***	0.985	0.896
	(1.270)	(1.089)	(1.214)	(1.106)
return on assets*Δps	-0.00826	-0.00508	-0.0313	-0.0314*
	(0.00557)	(0.0127)	(0.0344)	(0.0166)
size*Δps	-0.0744***	-0.0722**	0.199***	0.198***
	(0.0226)	(0.0284)	(0.0382)	(0.0353)
NPL ratio*Δps	-0.00423	-0.00332	-0.0192	-0.0197***
	(0.00524)	(0.00521)	(0.0118)	(0.00688)
omtdumpers	0.00578***	0.00604**	0.00484**	0.00515*
	(0.00194)	(0.00290)	(0.00181)	(0.00290)
Constant	0.00316***	0.00302	0.00453***	0.00436**
	(0.00108)	(0.00206)	(0.000891)	(0.00206)
Observations	3,934	3,934	3,934	3,934
R-squared	0.079	0.079	0.085	0.085
Number of groups	51	51	51	51
Bank FE	yes	no	yes	no

Notes: Sample: 2008.9-2017.3. Regression of equation (3). Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; omtdumpers is a dummy for the regime shift following the announcement of the ECB's OMT programme in July 2012; cedumpers for the start of the ELB in June 2014 and appdumpers for the APP programme starting in March 2015, Δps denotes a monetary policy shock, which can be either a pure monetary policy shock or an information shock. Both are for a 135 minutes window (13:35 to 15:50) using 2-year Bund futures and Euro Stoxx 50 futures (see Kerssenfischer, 2019).

TABLE 6: Monetary policy shocks and bank health indicators: tightening versus easing shocks

	tightening shocks				easing shocks			
Dependent variable	c	Δps	Δps*D	R squared	c	Δps	Δps*D	R squared
Distance-to-default								
Euro area	-0.01	0.28*	0.15	0.12	-0.01**	-0.18**	0.84***	0.11
	(-1.20)	(1.92)	(0.38)		(-2.41)	(-2.28)	(3.66)	
DE	0	0.23*	0.34	0.13	-0.01	-0.12	0.65***	0.11
	(-0.89)	(1.88)	(1.21)		(-1.47)	(-1.57)	(3.14)	
FR	0	0.31	0.24	0.09	-0.01**	-0.31**	1.04***	0.11
	(-0.25)	(1.42)	(0.49)		(-2.20)	(-2.39)	(3.66)	
IT	0	0.08	0.31	0.04	-0.01***	-0.09	0.87**	0.09
	(0.34)	(0.72)	(0.84)		(-2.81)	(-0.84)	(2.50)	
ES	-0.01	0.36	0.21	0.07	-0.01	-0.18	1.25***	0.16
	(-0.99)	(1.21)	(0.33)		(-0.87)	(-1.44)	(4.19)	
Expected default frequencies								
Euro area	0**	-0.06	-0.11	0.09	0	0	-0.33	0.04
	(2.19)	(-1.58)	(-0.43)		(-0.16)	(0.25)	(-1.12)	
DE	0	-0.09	-0.27	0.06	0	-0.04	-0.21	0.03
	(1.46)	(-1.40)	(-0.87)		(-0.84)	(-1.00)	(-0.63)	
FR	0	-0.02**	-0.01	0.09	0	0.02**	-0.21	0.01
	(1.89)	(-2.00)	(-0.03)		(1.64)	(2.26)	(-0.73)	
IT	0	-0.01	-0.34	0.05	0	-0.01	-0.15	0.02
	(0.35)	(-0.42)	(-1.25)		-1.16	(-0.44)	(-0.47)	
ES	0	-0.09	0.05	0.06	0*	0.07	-0.43**	0.07
	(1.26)	(-1.52)	(0.29)		(1.76)	(1.28)	(-2.33)	
Distance-to-insolvency								
Euro area	-0.03	1.63**	-2.58**	0.07	0.01	-0.59	5.59***	0.06
	(-0.80)	(2.11)	(-2.46)		(0.12)	(-0.65)	(3.34)	
Bank bond yields								
Euro area	0.01	1.12***	0.02	0.37	-0.03***	-0.15	0.56*	0.04
	(1.17)	(3.69)	(0.06)		(-4.75)	(-0.89)	(1.84)	
EUROSTOXX banks								
Euro area	-0.39*	7.20	0.82	0.02	-0.67	-17.82	57.29***	0.10
	(-1.87)	(1.03)	(0.03)		(-1.45)	(-1.27)	(2.73)	

Notes: Sample: 1999.1-2014.5. Regression of equation (1a) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δps refers to the monetary policy shock computed from the one-day window. DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the financial crisis episode (findumpers).

TABLE 7: Fed monetary policy shocks and euro area bank health indicators

	narrow window			
Dependent variable	c	Δps	Δps*D	R squared
Distance-to-default				
Euro area	0.01*	-0.12	-0.17	0.04
	(1.79)	(-0.98)	(-0.40)	
DE	0.01**	-0.12	-0.23	0.03
	(2.61)	(-1.45)	(-0.43)	
FR	0.01**	-0.23	0.01	0.06
	(2.03)	(-1.50)	-0.02	
IT	0.01	-0.1	-0.23	0.06
	(1.11)	(-0.62)	(-0.59)	
ES	0.01	-0.21	-0.12	0.07
	(1.57)	(-1.16)	(-0.30)	
Expected default frequencies				
Euro area	0**	0.01	1.30*	0.07
	(-2.04)	(0.56)	(1.71)	
DE	0	0	1.76*	0.06
	(-1.99)	(0.22)	(1.95)	
FR	0	0.01**	1.16	0.06
	(-2.46)	(2.21)	(1.64)	
IT	0	0	1.07	0.06
	(-1.34)	(-0.40)	(1.56)	
ES	0	0.02	0.29	0.04
	(-2.14)	(1.03)	(1.13)	
Distance-to-insolvency				
Euro area	0.08***	-1.38*	1.53	0.03
	(2.75)	(-1.89)	(0.46)	
Bank bond yields				
Euro area	0	-0.01	-0.24	0.01
	(-0.33)	(-0.15)	(-0.34)	
Euro Stoxx banks				
Euro area	0.73	0.30	-52.28**	0.03
	(3.31)	(0.05)	(-2.27)	

Notes: Sample: 2000.2-2014.2. Regression of equation (1b) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δps refers to the monetary policy shock computed from a 30 minutes window (see Nakamura and Steinsson, 2018). DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the financial crisis episode (findumpers).

ANNEX B: Construction of monetary policy surprises

An overnight swap (OIS) is a financial contract between two counterparties to exchange a fixed interest rate against a geometric average of overnight interest rates over the contractual life of the swap. For European OIS contracts, the Euro overnight index average (EONIA) is the underlying floating (rate) leg of the contract. EONIA is the 1-day interbank interest rate for the euro area. The EONIA rate is the rate targeted by the ECB.

Suppose that the ECB currently targets a (known) rate $r_s = r^A$ for the remaining $D(t)$ days of the current maintenance period, and will then switch to a (yet possibly unknown) target rate $r_s = r^B$ afterwards. The one-month OIS swap rate can then be written as:

$$OIS(30)_t = \frac{D(t)}{30} r^A + \frac{30-D(t)}{30} E_t r^B + \rho_t \qquad \text{(B1)}$$

where ρ_t is a risk premium and E_t denotes the market expectation conditional on information available in t. We compute the monetary policy surprise (ff1) in the 1-month OIS contract as the expected change in interest rates during a small window with length $\mu+\tau$, where t is the time of the announcement of the decision, $(t-\mu)$ refers to the start and $(t+\tau)$ to the end of the window (for the narrow (wide) window we take 10 minutes before the announcement from the press release and 20 (110) minutes after it):

$$ff1_t = E_{t+\tau} r^B - E_{t-\tau} r^B = \left(OIS(30)_{t+\tau} - OIS(30)_{t-\mu}\right) \frac{30}{30-D(t)} \qquad \text{(B2)}$$

We make the standard assumption that the risk premium remains unchanged during the small window. We compute monetary policy surprises for longer horizons (ff{k}) similar to (B2), but replace the 1-month contract by the k-month OIS contract (e.g., k=3, 6, 12, 24, 120). In the case of the 1-month contract, we adjust for the remaining days of the current maintenance period, since in the case of the ECB the policy rate change becomes effective with the settlement of the next MRO, usually after six (sometimes five) days after the Governing Council decision and we therefore set D(t)=6 for Governing Council decision days t, while for longer contracts of 6 months and beyond the correction is close to zero. Usually, Governing Council decision days were once a month. Between January 1999 and October 2001 the ECB Governing Council took policy decisions twice a month, whereas its monthly press conference was held at the first meeting of the month. When coding the high-frequency data for monetary policy surprises, in this study we always refer to monetary policy surprises observed coinciding with press conferences. Moreover, effective January 2015 the ECB reduced the number of Governing Council decision dates from 12 to 8 per year. Therefore, we code no policy surprises in intermeeting months for which there was no Governing Council decision day.

ANNEX C: Technical details on bank health indicators

C1. Distance-to-default, expected default frequency and distance-to-insolvency

The distance-to-default (DTD) measure, which is based on Black and Scholes (1973) and the Merton (1974) model, is a widely used measure of corporate default risk in the finance literature. Conceptually, it is assumed that, if a default of a firm happens, the value of its assets falls below the default point, which is determined by the value of the firm's debt. The DTD indicator for a firm measures the distance between the expected value of the asset and the default point:

$$DTD_t = \frac{\log\left(\frac{A_t}{D_t}\right) + \left(r_t - \frac{1}{2}\sigma_{A_t}^2\right)(T-t)}{\sigma_{A_t}\sqrt{T-t}} \tag{C1}$$

with A is (the market value of) total assets of a firm, D is (the market value of) debt and r denotes the risk-free rate of interest (Euribor) and σ_A denotes a standard deviation that measures the volatility of asset returns and T-t is usually set to 1 year. In the empirical analysis, we employ the DTD for banks as reported by Moody's KMV Credit Edge model. In order to avoid the instability caused by an imprecise estimate of the risk-free rate, their version of the DTD uses a modified formula of (C1):

$$DTD_t = \frac{\log\left(\frac{A_t}{D_t}\right)}{\sigma_{A_t}\sqrt{T-t}} \tag{C2}$$

The standard deviation refers to the annual change in the market value of the assets in percentage terms (i.e., the annualized standard deviation of the log returns). When applying the DTD to banks, a known limitation is that it may not account for regulatory actions by bank supervisors.[25] Therefore, and given that regulators may intervene ahead of a bank default, this measure may understate the likelihood that a bank becomes subject to corrective actions.

We also examine expected default frequencies (EDFs) of banks, which is a forward-looking measure of actual probability of default and is closely related to the DTD. Moody‘s EDF is a measure of the probability that a firm will default over a specified period of time (i.e., one year). "Default" is defined as failure to make scheduled principal or interest payments. According to Moody's KMV Credit Edge model, a firm defaults when the market value of its assets (the value of the ongoing business) falls below its liabilities payable (the default point). The market information contained in the firm's stock price and balance sheet are translated into an implied risk of default. Probabilities of default are derived from the distance-to-default using the Merton model (equation C2). The probability of default (EDF) is

[25] Note that the distance-to-capital measure (DTC), which takes into account capital requirements from the Basel Capital Accord I, is obtained from a linear transformation of the DTD. While it would imply different levels of the thresholds, paths look similar to those from the DTD.

then given by:

$$EDF_t = 1 - N(DTD) = N(-DTD) \quad \text{(C3)}$$

while the EDF from KMV computes the probability based on the DTD of a firm and matches this value with known default probabilities from a large sample of firms, including firms with and without default. DTDs and EDFs have broadly simlar information content, since they differ only in terms of the known default distribution of firms, while moving in opposite direction.

The distance-to-insolvency (DTI) is another indicator of firms' bond default and bankruptcy risk. Conceptually, the DTI aims to measure by how much the asset value of a firm can drop before it becomes insolvent (measured in units of the firm's asset standard deviation). In general, a firm's DTI at a point in time t is defined as the ratio of a measure of leverage to a measure of asset volatility:

$$DTI_t = (\frac{A_t - L_t}{A_t})\frac{1}{\sigma_{A_t}} \quad \text{(C4)}$$

with the notations as above, L is (the market value of) total liabilities by banks and σ_A denotes the volatility of the assets. The (percentage) gap between the value of a firm's assets (A) and its liabilities (L) can be referred to as a leverage ratio. More precisely, as shown by Atkeson, Eisfeldt and Weill (2017), equation (C4) can be simplified:

$$DTI_t = \frac{1}{\sigma_{E_t}} \quad \text{(C5)}$$

where E denotes the (daily) stock price of a bank and DTI is a variable with monthly frequency. The DTI measure (C5) requires the validity of the Leland (1994) structural model of credit risk. The above derivation is only valid, if DTI and DTD are close to one another. While the Leland model and the Merton model are largely similar,[26] the Leland model explicitly introduces taxes and bankruptcy costs and derives not only the endogenous default boundary, but also the value-maximizing leverage decision.

C.2 The IBSI dataset

The ECB internal dataset on individual balance sheet items (IBSI) covers 317 euro area banks and includes balance sheet data as of August 2007 at the monthly frequency. It provides information on the balance sheet of MFIs, both on the asset and liabilities side (Bojaruniec and Morandi, 2015). The asset

[26] The Leland model relaxes the assumption of the Modigliani-Miller theorem that the value of the firm is invariant to its capital structure.

side indicators inter alia include cash, loans to households, NFCs and governments, debt securities, money market fund (MMF) shares/units, equity and non-MMF investment fund shares/units, non-financial assets (including fixed assets) and remaining assets. On the liabilities side, time series are collected for deposits included and not included in the broad money aggregate M3, debt securities issued, capital and reserves and remaining liabilities. In addition, we also include data with quarterly information on banks' other characteristics (e.g. return on assets, leverage ratios, NPL ratios, cost to income ratios, etc.) from SNL.

ANNEX D: Additional results

D1. Monetary policy shocks and bank health: wide window

Table D1 below reports results of the HFI approach (1) based on the aggregate monetary policy shock for the wide (intradaily) window using the series from Kerssenfischer (2019).

TABLE D1: Monetary policy shocks and bank health

	wide window			
Dependent variable	c	Δps	Δps*D	R squared
Distance-to-default				
Euro area	-0.01*	-0.04	0.14	0.02
	(-1.76)	(-0.53)	(0.88)	
DE	0	0.02	0.03	0
	(-0.68)	(0.32)	(0.21)	
FR	0	-0.09	0.25	0.03
	(-1.05)	(-0.79)	(1.41)	
IT	-0.01	0	0.08	0
	(-1.71)	(0.01)	(0.57)	
ES	-0.01	-0.16*	0.34	0.03
	(-1.51)	(-1.70)	(1.47)	
Expected default frequencies				
Euro area	0	0.01	-0.11	0.01
	(0.84)	(1.05)	(-1.04)	
DE	0	0.01	-0.09	0
	(0.33)	(0.45)	(-0.70)	
FR	0*	0	-0.06	0.01
	(1.66)	(-0.33)	(-0.71)	
IT	0	-0.01	-0.08	0
	(0.75)	(-0.97)	(-0.63)	
ES	0	0	-0.10	0.02
	(1.50)	(0.12)	(-1.29)	
Distance-to-insolvency				
Euro area	-0.01	-0.69	1.26	0.02
	(-0.21)	(-1.00)	(1.39)	
Bank bond yields				
Euro area	0	0.58***	-0.10	0.28
	(0.04)	(8.34)	(-0.50)	
Euro Stoxx banks				
Euro area	-0.40**	0.92	-1.74	0
	(-2.14)	(0.27)	(-0.22)	

Note: Sample: 2002.3-2017.3. Regression of equation (1) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δps refers to the information shock computed from a 135 minutes window (13:35 to 15:50) using 2-year Bund futures and Euro Stoxx 50 futures (see Kerssenfischer, 2019). DE: Germany, FR: France, IT: Italy, ES: Spain. The regressions contain an intercept and slope dummy D for the financial crisis episode (findumpers).

D.2 Monetary policy shocks and financial asset prices

We apply the HFI approach to the link between monetary policy shocks and financial asset prices. This serves as a consistency check with the previous literature (e.g., Gürkaynak, Sack and Swanson, 2005; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2018). In equation (1) we replace bank variables with other financial asset prices as explanatory variable. Table D2 below provides the results for a daily and an intradaily monetary policy shock and for government bond yields for Germany and France for different maturities (2, 5 and 10 years; source Datastream), stock prices (Euro Stoxx 50) and exchange rates (bilateral USD/EUR and EUR nominal effective exchange rate) as dependent variable (d).[27] First, the results for the daily and intradaily monetary policy shock are broadly similar both in terms of significance and magnitude and with the exception of the German government bonds, for which the daily window suggests that the monetary policy impact became stronger during the financial crisis. Second, we confirm the finding that the parameter β in equation (1) is positive and significant, if yields on government bonds are used. Moreover, the results show that monetary policy shocks had a decreasing influence along the maturity spectrum (i.e., the impact is stronger on the 2-years horizon as compared with the 10-years horizon). Third, we detect no significant impact of monetary policy shocks on stock prices and find that this puzzling result is, as in the case of bank stocks, related to the information effect. Finally, we show that monetary policy shocks have an impact on the euro exchange rate (both bilateral vis-à-vis the US dollar and in effective terms). The results indicate that the transmission to the exchange rate became stronger in the post-crisis regime, which can be explained by the ECB's large-scale asset purchases (APP programme).

[27] We include the ECB reference exchange rate between the US dollar and the Euro, which is fixed every working day at 2:15 pm (C.E.T.) following a concertation procedure between central banks across Europe (source: ECB) as well as the nominal effective exchange rate of the Euro (source: ECB), which is computed against the rates of a group of 19 trading partners.

TABLE D2: Monetary policy shocks and asset prices

	one-day window				wide window			
Dependent variable	c	Δps	Δps*D	R squared	c	Δps	Δps*D	R squared
Government bond yields								
2 year DE	0	0.58**	1.16***	0.43	0	0.59***	0.35	0.38
	(-0.13)	(2.23)	(3.83)		(-0.59)	(2.98)	(1.30)	
2 year FR	0.01	1.53***	0.35	0.63	0	0.99***	0.06	0.48
	(1.30)	(6.68)	(1.36)		(0.10)	(11.02)	(0.25)	
5 year DE	0	0.40**	1.06***	0.35	-0.01	0.43***	0.34	0.31
	(-0.69)	(2.10)	(4.21)		(-1.57)	(2.71)	(1.29)	
5 year FR	0	1.26***	0.31	0.47	-0.01*	0.85***	-0.03	0.35
	(0.46)	(4.92)	(1.04)		(-1.68)	(10.60)	(-0.12)	
10 year DE	0	0.40**	0.82***	0.34	0	0.44***	0.16	0.27
	(0.95)	(2.27)	(3.12)		(-0.06)	(10.13)	(0.96)	
10 year FR	0	0.77***	0.44	0.35	-0.01	0.46***	0.09	0.2
	(0.69)	(3.77)	(1.50)		(-1.18)	(8.84)	(0.46)	
Stock prices and exchange rates								
Eurostoxx 50	-0.07	-5.55	20.08	0.02	-0.39**	0.19	-3.77	0.01
	(-0.38)	(-0.49)	(1.30)		(-2.06)	(0.06)	(-0.61)	
USD/EUR	0	-0.01	0.10***	0.08	0	-0.02***	0.05**	0.04
	(1.29)	(-0.65)	(3.48)		(1.50)	(-2.77)	(2.60)	
EUR nominal effective	0.03	-0.47	3.77**	0.05	0.04	-0.69*	2.34**	0.05
	(1.02)	(-0.40)	(2.40)		(1.31)	(-1.81)	(2.90)	

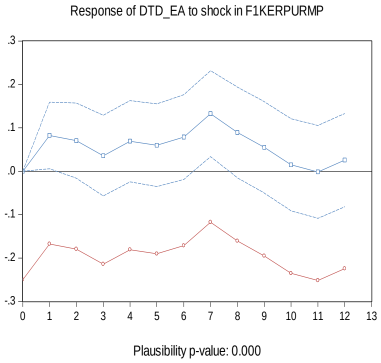
Note: LHS sample: 1999.1-2017.3; RHS sample: 2002.3-2017.3. Regression of equation (1) with OLS and HAC standard errors; t-statistics in parenthesis; *** refers to the 1% significance level, ** refers to the 5% significance level, * refers to the 10% significance level. Δps refers to the monetary policy shock for the daily window and the wide (135 minutes) window respectively. While the first series is derived as first principal component of the change in four OIS interest rate swaps (1 month, 6 months, 1 year, 10 years), the latter is obtained from Kerssenfischer (2019). DE: Germany, FR: France. The regressions contain a slope dummy D for the financial crisis (findumpers).

D3. Local projections

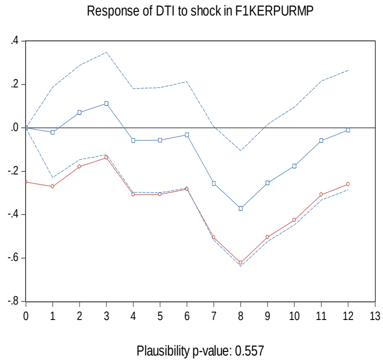
Figure D1 below reports the results from the local projections (Figure 8), if the monetary policy shock is replaced by a pure monetary policy shock.

Figure D1: Local projections and counterfactual policy simulations with monetary policy shocks

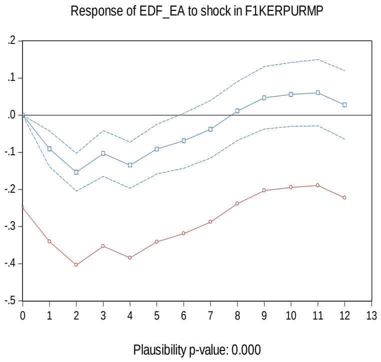
Distance-to-default (DTD)



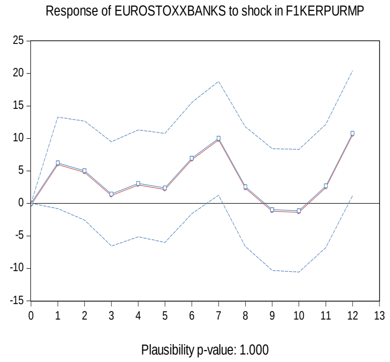
Distance-to-insolvency (DTI)



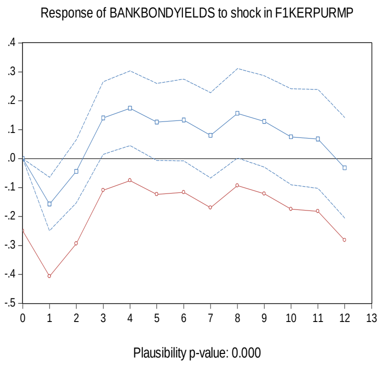
Expected default frequencies (EDF)



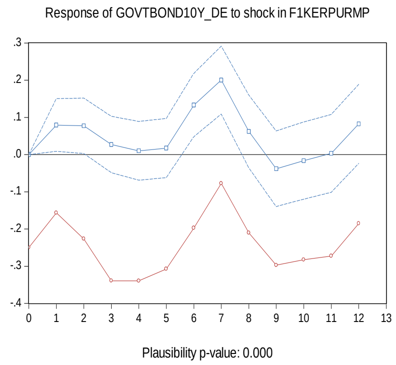
Bank stocks (Euro Stoxx banks)



Bank bond yields for the euro area



German bond yields (10 years)



Note: Sample: 1999.1-2014.5. Quarterly data, pure monetary policy shock with wide window (Kerssenfischer, 2019). Solid (blue) lines with squares and associated dashed (blue) lines are the impulse responses with conditional error bands. The solid (red) line with circles is the counterfactual response, given an initial decrease in the monetary policy shock by 25 basis points in the first quarter. The p-value (from an F-test) at the bottom of each graph is a test result measuring the distance between the conditioning event and the sample estimates. The regressions include the dummy (findumpers) for the financial crisis.

Acknowledgements

The authors thank an anonymous referee, M. Kerssenfischer, A. Cukierman, E. Nakamura, J.-L. Peydró, D. Georgarakos, M. Boucinha, R. Cristea for useful comments and discussion, E. Ocakverdi for the programme to run local projections, A. Rendina and D. Mari for research assistance. We also thank session participants at conferences of the European Economic Association (Cologne), the Royal Economic Society (Brighton), and the European Public Choice Society (Rome) for discussion and comments. The authors remain responsible for any errors or omissions.

Alexander Jung
European Central Bank, Frankfurt am Main, Germany; email: alexander.jung@ecb.europa.eu

Harald Uhlig
University of Chicago, Chicago, United States; email: huhlig@uchicago.edu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-3565-4 ISSN 1725-2806 doi:10.2866/620258 QB-AR-19-084-EN-N