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Working Papers in Economics and Statistics

2018-01

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University of Innsbruck
Working Papers in Economics and Statistics

The series is jointly edited and published by

- Department of Banking and Finance
- Department of Economics
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How does Monetary Policy Influence Bank Lending? Evidence from the Market for Banks' Wholesale Funding

Max Breitenlechner* Johann Scharler†

January 2018

Abstract

We study the transmission of monetary policy shocks to loan volumes using a structural VAR. To disentangle different transmission channels, we use aggregated data from the market for large certificates of deposits and apply a sign restrictions approach. We find that although the standard bank lending channel as well as the recently formulated risk-pricing channel (Disyatat, 2011; Kishan and Opiela, 2012) contribute to the transmission of policy shocks, the effects associated with the risk-pricing channel are quantitatively stronger. Our results also show that policy shocks give rise to non-negligible effects on loan demand.

Keywords: bank lending channel, risk-pricing channel, external finance premium, structural vector autoregression, sign restrictions.

JEL codes: C32, E44, E52

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1 Introduction

How does monetary policy influence the supply of bank loans? According to the standard bank lending channel (BLC), monetary policy manipulates the reserves in the banking system and, unless banks are able to fully off-set these fluctuations in reserves, they have to adjust the supply of loans (Bernanke and Blinder, 1988, 1992). More recently, financial frictions on the market for banks' funding and endogenous changes in banks' external finance premiums have been stressed as a complementary, and perhaps even more relevant, channel through which monetary policy influences loan supply (Disyatat, 2011; Kishan and Opiela, 2012). According to this risk-pricing channel (RPC), a contractionary policy shock, for instance, increases the default risk of banks. Due to the higher risk banks' external finance premiums increase, which leads to a reduction in the supply of bank loans (see also Bernanke, 2007).

Although a large empirical literature documents that banks adjust loan supply in response to monetary policy shocks,[1] relatively little is known about the precise transmission channels. In fact, Disyatat (2011) points out that most of the existing evidence in favor of the standard BLC is also consistent with a prominent role of banks' funding costs. The main objective of this paper is to evaluate the different transmission channels and to quantify their relative contributions to the dynamics of loan volumes in response to monetary policy shocks.

We estimate a vector autoregressive (VAR) model with quarterly U.S. data and identify shocks and transmission channels by combining a block-recursive identification scheme with sign restrictions on the impulse response functions (see e.g. Faust, 1998; Uhlig, 2005).[2] While the block-recursive identification of monetary policy shocks is well established (see e.g. Christiano et al., 1999), we propose a novel approach to distinguish between the different transmission channels, using data from the market for large certificates of deposits (jumbo CDs), which represents a common source for banks' wholesale funding (see e.g. Acharya and Mora, 2015; Kishan and Opiela, 2012).[3] Concretely, we use sign restrictions to identify supply and demand effects on the market for jumbo CDs in the aftermath of monetary policy shocks and argue that this distinction is informative about the channels through which the policy shock is transmitted. Consider for instance a contractionary monetary policy shock that is associated with a decline

[1] See e.g. Kashyap and Stein (1994, 1995, 2000), Kishan and Opiela (2000), Gambacorta (2005, 2008), and Gambacorta and Marques-Ibanez (2011), among many others.

[2] Combinations of zero and sign restrictions are also applied by e.g. Buch et al. (2014), Eickmeier and Hofmann (2013), Jarociński (2010), and Peersman (2011).

[3] In terms of magnitudes, jumbo CDs account on average for 14.06% of total deposits (the average is calculated for our sample across banks and time).

in the supply of funds available on the market for jumbo CDs. Such a *supply effect* is consistent with the interpretation that investors in jumbo CDs demand higher risk premiums as emphasized by the RPC. The standard BLC, in contrast, operates through the demand for funds. According to this channel banks respond to the monetary contraction by raising non-reservable types of funding. Thus, this *funding effect* should give rise to a shift of the demand for funds on the market for jumbo CDs. A similar funding effect may also arise if the demand for loans increases after a monetary contraction. Carpenter and Demiralp (2012) argue that firms respond to contractionary policy shocks by exhausting established credit lines to protect themselves against expected funding constraints (see also Sofianos et al., 1990; Morgan, 1998).[4] Hence, if banks raise funds on the market for jumbo CDs to accommodate fluctuations in the demand for loans in the aftermath of a contractionary policy shock, we should observe shifts in the demand for funds on the market for jumbo CDs. In our identification approach, we exploit this distinction between supply and funding effects on the jumbo CD market.

Based on forecast error variance decompositions, we find that supply effects that are consistent with the RPC account for roughly 25% of the policy-induced variation in total loans, on average over a three year horizon. Funding effects, which are associated with shifts in the demand for funds on the market for jumbo CDs, account up to approximately 50% of the variation.[5] In an additional analysis, we further distinguish between shocks linked to funding effects depending on whether they are consistent with the standard BLC or with loan demand effects. Here we find that most of the variation associated with funding effects is in line with loan demand effects rather than with the standard BLC. In particular, shocks that give rise to dynamics consistent with the standard BLC account for approximately 16% of the policy shock induced variation in loan volumes, whereas loan demand effects account for around 57%. In this estimation, the contribution of the RPC is around 27%, which is of a similar order of magnitude as in our baseline specification.

Overall, we conclude that although the standard BLC as well as the RPC contribute to the transmission of policy shocks to loan volumes, the RPC is quantitatively more relevant. This finding supports the recent emphasis on banks' risk premiums as an important link between monetary policy and loan supply (see Disyatat, 2011; Kishan and Opiela, 2012). Our results also indicate that loan demand effects account for a large share of the variation in loan volumes

[4]Bernanke and Gertler (1995) note that firms may raise borrowing after a monetary tightening to keep the level of production constant and fund the build up of inventories.

[5]As we will discuss in Section 2, we also identify a residual channel of monetary transmission that captures the effects of policy shocks that relate to neither supply effects nor funding effects.

generated by policy shocks, which is in line with results presented in Carpenter and Demiralp (2012).

The paper is structured as follows: In Section 2 we present the empirical model and discuss our identification approach. Section 3 shows the main results and Section 4 provides a robustness analysis. Finally, section 5 concludes the paper.

2 Empirical Approach

2.1 Estimation and Data

Consider the VAR

$$Y_t = c + \sum_{j=1}^{p} A_j Y_{t-j} + e_t, \tag{1}$$

where Y_t is the vector of endogenous variables, A_j are matrices containing the reduced-form coefficients, c is the constant term and e_t is a vector of white noise reduced-form residuals with $E(e_t) = 0$ and $\Sigma_e = E(e_t e_t')$. We estimate the reduced-form model with Bayesian methods using an uninformative Normal-Inverse-Wishart prior for the coefficients and the variance-covariance matrix.[6] Therefore, we can analytically derive the posterior distribution, which is also a Normal-Wishart density, using the estimated A_j and Σ_e as location parameters (see Uhlig, 1994). According to the Bayesian (or Schwarz) information criterion we use $p = 2$ lags in our baseline estimation.[7]

The vector of endogenous variables Y_t includes real GDP (RGDP), the consumer price index (CPI), the Federal Funds rate (FFR), CD volumes (CDVOL), the CD rate (CDRATE), total loans (TOLN) and the volume of demand deposits (DDVOL). We use quarterly U.S. data over the period from 1984Q1 to 2007Q3, which is a rather stable period excluding the recent global financial crisis as well as the period before 1984. We also exclude the period after 2007 due to the almost zero interest rate in the aftermath of the financial crisis, which would complicate the identification of monetary policy shocks.[8]

Data for real GDP, consumer price index, Federal Funds rate, and demand deposits are

[6] Since we impose sign restrictions, the prior is only flat over the reduced form parameters and not over the structural parameters (see Baumeister and Hamilton, 2015).

[7] We show in a robustness analysis that our results are robust with respect to different lag lengths.

[8] Nevertheless, in our robustness checks we also estimate the model with an extended sample ranging up to 2015Q1.

obtained from the St. Louis Federal Reserve Economic Data (FRED). For total loans we use the data reported in the H.8 statistical release issued by the Board of Governors of the Federal Reserve System. Data for the jumbo CD market are obtained from the Consolidated Reports of Condition and Income (Call Reports), which contains income and balance sheet statements of all U.S. insured banks. We calculate the aggregate volume of jumbo CDs (CDVOL_t) from the data reported for individual banks as:

$$\text{CDVOL}_t = \sum_{i=1}^{N_t} \text{CDVOL}_{it},$$

where N_t is the number of banks in each quarter t. Although the CD rate is not directly available in the Call reports, it can be calculated as the quarterly interest expenses associated with jumbo CDs (INTEX_{it}) over the volume of jumbo CDs (see also Acharya and Mora, 2015; Kishan and Opiela, 2012):

$$\text{CDRATE}_t = 4 \frac{\sum_{i=1}^{N_t} \text{INTEX}_{it}}{\text{CDVOL}_t}.$$

We multiply the CD rate by four to obtain an annualized rate.

For the calculation of CDVOL and CDRATE, we follow Den Haan et al. (2002) and use only insured banks which are located in the US (1,040,066 bank quarters). Interest expenses of jumbo CDs are reported for 1,001,764 bank quarters.

We drop observations associated with negative interest expenses (5,043 observations). Volumes of jumbo CDs are available for each of the finally 996,721 bank quarters. To calculate the aggregate CD volume and the CD rate, we use data only from banks which report volumes as well as interest expenses. The remaining data preparation follows Carpenter and Demiralp (2012) and Uhlig (2005): We deflate nominal variables (total loans, CD volumes and demand deposits) by the consumer price index. All variables (except the Federal Funds rate and the CD rate) enter the VAR in logs and are seasonally adjusted. Table 1 provides a detailed description of the data.

2.2 Identification

To identify shocks and disentangle different transmission channels, we impose combinations of zero and sign restrictions on the impulse response functions. Table 2 summarizes our identification approach. The zero restrictions preserve the standard block-recursive ordering frequently applied to identify monetary policy shocks (see e.g. Christiano et al., 1999): Monetary policy responds contemporaneously to changes in output and prices and with a one period lag to changes in total loans or demand deposits (see also Den Haan et al., 2007; Eickmeier and Hofmann, 2013).[9] We impose no causal ordering between the Federal Funds rate and the jumbo CD market variables (volumes and prices). Hence, monetary policy shocks are not exactly identified and we are able to impose sign restrictions to disentangle dynamics on the market for jumbo CDs.

To distinguish between monetary policy transmission channels, we impose sign restrictions based on the idea that the channels give rise to distinct dynamics on the market for jumbo CDs. Consider first a contractionary monetary policy shock that is transmitted through the RPC to bank loan supply. As emphasized by the RPC, the monetary tightening should induce investors to demand higher compensation for risk. In other words, they are only willing to supply funds on the market for jumbo CDs if they are compensated by a higher risk premium, resulting in a shift in the supply of funds. Consequently, interest rates should increase and volumes should decline on the market for jumbo CDs. Thus, we interpret policy shocks that are associated with supply effects on the market for jumbo CDs as being transmitted through the RPC. We identify these supply effects on the jumbo CD market by imposing opposite signs on the responses of the interest rate and volumes of jumbo CDs.

In contrast, alternative channels, unrelated to risk-pricing considerations, operate through the demand side of the market of jumbo CDs. According to the standard BLC, a monetary contraction induces banks to substitute away from reservable deposits to non-reservable sources of funding. Hence, the demand for wholesale funding in general, and also the demand for funds on the market for jumbo CDs, should increase, leading to a shift in the demand for funds on the market for jumbo CDs. In case of such a funding effect, policy shocks should move interest rates and volumes in the same direction on the market for jumbo CDs. Therefore, to identify monetary policy shocks that are associated with funding effects, we require that the responses of both jumbo CD market variables are positive along with the increase in the Federal Funds rate.

While the standard formulation of the BLC emphasizes the direct effects of monetary policy on the amount of reserves in the banking system, alternative versions have been proposed that rely less strongly on these quantity effects. Monetary policy may, for instance, influence the

[9]In Section 4 we consider alternative orderings.

opportunity cost of holding bank deposits inducing depositors to rebalance their portfolios after a monetary shock (see Kishan and Opiela, 2000; Disyatat, 2011). Alternatively, banks may respond to a policy shock by substituting away from deposits to funding sources with longer maturities because they are viewed as a more stable source of funding.[10] In these cases, we should still observe adjustments in the funding structure of banks. Note that this argument also implies that funding effects on the market for jumbo CDs should occur even if monetary policy is implemented primarily through credible announcements (Guthrie and Wright, 2000), rather than through quantity adjustments on the market for bank reserves.

The transmission channels discussed so far should lead to changes in the supply of bank loans. However, funding effects may also arise due to changes in the demand for loans. If firms' exhaust existing loan commitments in response to a monetary tightening (Carpenter and Demiralp, 2012; Peersman, 2011; Sofianos et al., 1990), banks may require additional funding to accommodate the higher demand for loans, also resulting in demand shifts on the market for jumbo CDs.[11]

We also identify an additional, residual transmission channel by restricting the response of the CD rate to be negative in response to a contractionary policy shock. These residual effects capture, for instance, a decline in banks' demand for jumbo CDs in response to a restrictive policy shock. These dynamics may arise if banks decrease their demand for wholesale funding in response to firms and households demanding fewer loans. This mechanism corresponds to the standard interest rate channel, where a monetary tightening dampens economic activity and ultimately reduces the demand of bank loans. The residual effects also capture situations where a contractionary policy shock gives rise to an increase in the supply of funds on the jumbo CD market. This may occur if investors perceive banks as relatively safe borrowers due to e.g. too-big-to-fail considerations. In this case, prices of jumbo CDs decline while volumes increase.

In short, we distinguish between monetary policy shocks according to whether they are associated with (i) supply effects, (ii) funding effects, or (iii) residual effects that are related to neither (i) or (ii).

Although the imposed restrictions allow us to identify funding effects on the market for jumbo CDs, these effects are consistent with the standard BLC as well as with the dynamics induced by

[10]Drechsler et al. (2016) show that banks set deposit rates such that the opportunity cost of holding deposits increases after a monetary contraction, resulting in a decline in deposits.

[11]Similarly, Den Haan et al. (2007) and Giannone et al. (2012) document that loans to non-financial corporations (commercial and industrial loans) increase after a tightening of monetary policy.

higher loan demand, as discussed above. Thus, while we are able to isolate dynamics consistent with the RPC using our baseline identification scheme, we are not able to disentangle the individual channels comprised by funding effects on the market for jumbo CDs. Nevertheless, the implications of the standard BLC and higher loan demand effects differ with respect to the dynamics of loan volumes. While the BLC predicts that loan supply, and ultimately loan volumes, decline, firms' increasing use of credit lines should result in higher loan volumes after a policy shock. Therefore, we also consider an augmented identification scheme where we explicitly identify policy shocks associated with higher loan demand by restricting the response of total loans. Table 3 summarizes this additional identification scheme. Note, however, that we are no longer able to identify a residual channel and may therefore not be able to capture the overall influence of monetary policy, in this case.

Also note that in contrast to the large strand of literature that evaluates the bank lending channel using micro-level data (see e.g. Kashyap and Stein, 1995, 2000; Kishan and Opiela, 2000), we do not require bank-specific information, since our approach relies on aggregated data and the overall dynamics on the market for jumbo CDs.

We implement the identification approach using the algorithm proposed by Arias et al. (2014). Specifically, we draw 5,000 models, where each model is a set of coefficient matrices and a variance-covariance matrix, from the posterior distribution and sequentially work through the models as follows:

(i) We apply a Cholesky decomposition to the variance-covariance matrix to obtain orthogonal shocks, u_t, that are related to the reduced form residuals through the linear mapping: $u_t = P^{-1}e_t$, where $PP' = \Sigma_e$. Using a random orthogonal matrix Q, with $Q'Q = I$, Σ_e can also be decomposed as $PQQ'P'$. Hence, by premultiplying the reduced-form system (1) by $(PQ)^{-1}$, we obtain a transformed set of orthogonal shocks, $\tilde{u}_t = (PQ)^{-1}e_t$. Since, our identification scheme relies on zero restriction, in addition to the sign restrictions, we follow Arias et al. (2014) and obtain a random matrix Q recursively using the Gram-Schmidt process.

(ii) We obtain the impulse responses generated by the transformed model and check whether the imposed sign restrictions are fulfilled (zero restrictions hold by construction). We impose sign restrictions on impact and in the first period. If the restrictions are fulfilled, $\tilde{u}_t$ bears a structural interpretation and the transformed model is saved as part of the restricted posterior distribution, which we finally use for inference. If not, we draw a new random matrix Q, obtain a new set of transformed, orthogonal shocks and check the sign restrictions.

(iii) We proceed to the next model if we find a transformation that satisfies the imposed sign restrictions, or if a maximum of 10,000 transformations are checked, and work through steps (i) and (ii). Applying this algorithm, we found a transformation for each model satisfying our set of baseline restrictions.

A potential concern with our identification strategy could be that we do not take compositional effects into account.[12] Consider for instance a monetary tightening that leads to higher rates of return in the economy and thereby reduces the incentives for investors to search for yield. Thus, investors may not only reduce the supply of funds on the jumbo CD market in general, they may shift the supply towards relatively safe banks and accept lower rates of return. If this effect is large enough, then the average CD rate may decline along with the volume of CDs and we would falsely conclude that the CD market is driven by a decline in the demand for funds, rather than a change in supply. However, as we are not interested in the supply of funds on the jumbo CD market *per se*, but only to the extent that it is associated with the RPC, this is unproblematic for our approach. In particular, such a compositional effect is at odds with the RPC in the aggregate, and therefore, given the imposed restrictions, this effect is adequately captured by the residual channel, despite being supply related.

3 Results

3.1 Impulse Response Analysis

Figure 1 shows the responses of the endogenous variables to the three different types of monetary policy shocks. The solid lines are the point-wise median impulse responses and the dashed lines show the impulse response functions obtained with the closest-to-median model (Fry and Pagan, 2011). The light gray and dark gray areas represent 90% and 68% of the restricted posterior distribution in each period.

The first column shows the responses to a monetary policy shock associated with supply

[12] Ciccarelli et al. (2015) point out that compositional effects generally impair the identification of loan supply dynamics using aggregate data (see also Peersman, 2011).

effects on the market for jumbo CDs. In other words, shocks that induce dynamics on the CD market in line with the RPC. Here we restrict the CD volume to decline and the CD rate to increase along with an increase in the Federal Funds rate. Although we only restrict the responses of the two CD market variables for two periods, both variables revert only slowly back to their steady state values. Turning to the unrestricted variables, we see that the volume of loans declines. Although this finding is consistent with the interpretation that higher funding costs induce banks to reduce their loan supply, as suggested by the RPC, the decline is only small and rather short-lived. We also find a decline in demand deposits, although the response is only transitory.

The second column shows the responses to a policy shock that is associated with funding effects on the market for jumbo CDs. The responses of the CD market variables display even more persistence than in the case of supply effects. We also see that the policy shock gives rise to a pronounced decline in the volume of demand deposits, as documented in e.g. Bernanke and Blinder (1992). So far, these results are consistent with the standard BLC, where banks respond to a contractionary policy shock by switching from demand deposits to non-reservable sources of funding, such as jumbo CDs. Nevertheless, the BLC also holds that banks reduce loan supply since non-insured sources of funding and demand deposits are only imperfect substitutes. We find, however, that the loan volume increases in response to the policy shock. While this outcome is at odds with a dominant BLC, it is consistent with the view that firms exhaust credit lines when monetary policy is tightened (Carpenter and Demiralp, 2012; Peersman, 2011; Sofianos et al., 1990). In other words, banks may use funds obtained on the market for jumbo CDs to accommodate the higher demand for loans arising from borrowers exhausting credit lines.[13]

Finally, the last column of Figure 1 presents the responses to policy shocks that are transmitted through the residual channel. That is, shocks that are neither associated with an increase in banks' demand for funds, nor with a decline in investors' supply of funds. The response of the CD rate, which is restricted to respond negatively for two periods, remains negative only as long as the restriction is binding. Thus, although this restriction is necessary to identify the residual channel, this pattern appears only to a limited extend in the data. The CD volume, which we leave unrestricted in this case, declines slightly and the demand deposits respond marginally

[13] In an additional estimation we included unused loan commitments (series RCON3423 from the Call reports) instead of total loans in the VAR. The results based on the baseline identification scheme confirm that credit lines are increasingly exhausted after a policy contraction, which supports our interpretation (see Figure A.2 in the Appendix).

positive in early periods. The response of total loans does not show a systematic pattern.

Concerning the macroeconomic impact of policy shocks, we find that the output responses to policy shocks are rather limited, regardless of the transmission channel. This result is not unexpected for our sample period (see e.g. Ramey, 2016).

Recall that funding effects are consistent with the standard BLC as well as with changes in the demand for loans. Although the result that shocks that give rise to funding effects are associated with increasing loan volumes suggests that loan demand effects feature more prominently in the data, the imposed restrictions do not allow us to explicitly identify this effect. Therefore, we now impose additional restrictions as discussed in Section 2 (see Table 3). With the additional restrictions on loan volumes, however, we impose a rather rich set of sign restrictions. While we find an admissible transformation for each model drawn from the unrestricted posterior distribution with our baseline identification approach, imposing the additional restrictions, this is the case for roughly 20% of the model draws. Nevertheless, our inference is still based on 1,054 models that satisfy the imposed restrictions when we explicitly disentangle BLC and loan demand effects.

The first column of Figure 2 shows that the responses to shocks that are characterized by supply effects on the market for jumbo CDs are similar to those obtained with the baseline identification scheme. From the second column, we see that policy shocks that give rise to dynamics on the CD market that are consistent with the BLC closely resemble those associated with funding effects shown in Figure 1, except for the response of loan volumes, which essentially shows no response. In contrast, the responses associated with higher loan demand dynamics, displayed in the third column, show an increase in loan volumes. Thus, these results support the interpretation that funding effects in our baseline specification largely reflect variations in the demand for bank loans.

3.2 Variance Decomposition

To quantify the contributions of the individual transmission channels of monetary policy, we compute the forecast error variance decomposition (FEVD) for total loans. Figure 3 shows the contributions of the three monetary policy shocks, identified using the baseline restrictions, to the forecast error variance of total loans for different forecast horizons. The light gray area represents the contribution of shocks associated with supply effects on the CD market. The dark gray area is the contribution of shocks that give rise to funding effects, and the black area is the contribution of the residual policy channel.[14]

We see that although supply effects account for the largest share of the forecast error variance at a horizon of one quarter, funding effects quickly gain importance and dominate at most horizons. The residual channel provides the smallest contributions at short horizons, but accounts for higher shares of the forecast error variance at longer horizons.

To obtain a more detailed picture of the driving forces behind the funding effects, Figure 4 presents the FEVD of total loans for the alternative identification scheme, which allows us to disentangle dynamics consistent with the standard BLC and loan demand effects.[15] Here, loan demand effects account for the largest share of the variation in loan volumes, especially during the first six quarters after a shock. Monetary shocks that give rise to dynamics consistent with the standard BLC, account for a smaller fraction of the variation, especially at shorter horizons. In contrast, the contribution of shocks associated with supply effects is particularly pronounced during the first few quarters. This result is in line with (Kishan and Opiela, 2012) who argue that risk-pricing effects should be particularly relevant in the intermediate aftermath of a policy shock.

How important are the individual channels relative to the overall contribution of the policy shocks? Table 5 shows the shares of the shocks associated with the transmission channels relative to the sum of the contributions of all three types of policy shock, averaged over the forecast horizon of 3 years. Here we interpret the sum of the contributions of all three identified shocks as the total effect of the policy shock. For the baseline identification scheme as well as for the alternative identification scheme with additional restrictions on loan volumes, all three identified shocks account for roughly 7% of the variance of the forecast error.[16]

We see that supply effects account for 25.71% of the total contribution of monetary policy shocks, while funding effects contribute 53.00%, based on the baseline identification scheme (first line). The smallest relative contribution of 21.29% comes from the residual channel. The results obtained with the alternative identification scheme (second line) show that supply effects

[14]The figure only shows the point-wise median contributions of the identified shocks. Table A.1 in the Appendix shows the contributions of all shocks at selected forecast horizons plus the corresponding error bands (16th and 84th percentile) of the FEVD distribution. Calculating the FEVD from the closest-to-median model gives similar results (see Figure A.1 in the Appendix).

[15]Again, Table A.2 in the Appendix presents contributions of all shocks at selected forecast horizons.

[16]In comparison, Hristov et al. (2012) and Peersman (2011) find that monetary policy in the euro area accounts for roughly 20% of the forecast error variance of total loans.

account for 27.20%, which is similar to what we find using the baseline identification scheme, and the contribution of the standard BLC is 15.57%. The contribution of loan demand effects is 57.23%, which is the largest share of the error variance.

Thus, once we take loan demand developments explicitly into account, the contribution of supply effects on the market for jumbo CDs, which are consistent with the operation of the RPC, is substantially larger than the contribution of the standard BLC, relative to the total effect of policy shocks. Through either of these channels policy shocks are transmitted to loan volumes through variations in banks' supply of loans. In addition, our results also suggest that policy shocks give rise to fluctuations in the demand for loans that account for roughly half of the variation in total loans induced by monetary policy shocks.

4 Robustness Analysis

We examine the robustness of our results with respect to the imposed restrictions, the sample selection, and the lag length. Since we are mainly interested in the contributions of the different channels, we concentrate on the FEVD in this section.[17]

In our baseline identification scheme we order total loans below the policy rate in the vector of endogenous variables (see Christiano et al., 1999; Den Haan et al., 2007; Eickmeier and Hofmann, 2013). Ciccarelli et al. (2015) emphasize that monetary authorities monitor credit markets closely and may therefore respond contemporaneously to developments in the banking sector (see also Buch et al., 2014). To address this point we now order total loans above the Federal Funds rate. The identification scheme is summarized in Table 4, and Panel (A) of Figure 5 shows the corresponding FEVD. Due to the contemporaneous zero restriction, the contributions start to increase only slowly over time. Overall, however, we again see a similar pattern as in our main analysis (see Figure 3) in the sense that the funding effects dominate the forecast error variance of total loans, followed by the contribution of supply effects. Panel (B) shows that increasing the horizon over which we impose the sign restrictions also results in a similar pattern. In Panel (C) we present the FEVD obtained with the longer estimation sample ranging up to 2015Q1. So far, we have excluded the period during and after the Great Recession of 2007 from our analysis, mainly due to concerns about the constraint on monetary policy imposed by the Federal Funds rate remaining at historically low levels since December

[17] The impulse response functions are provided in Appendix A.

2008.[18] Interestingly, while we still find that funding effects play an important role, we also see that the contribution of policy shocks associated with supply effects becomes larger in the longer sample.

Next, we reestimate the VAR using interpolated data for the jumbo CD rate. Since interest expenses of jumbo CDs are not reported for the first two quarters of 1997, we have dropped these missing quarters in the main analysis. The FEVD in Panel (D) shows that re-estimating the model with interpolated data for the missing values using the X-13 ARIMA method leaves our results unchanged. As a final robustness check we increase the number of included lags to $p = 4$. Panel (E) shows again that the overall pattern does not change.

Turning to the contributions of the individual effects relative to the overall contribution of monetary policy shocks, Table 6 shows a rather uniform picture across the different robustness checks. The relative contribution of supply effects range from 24% to 44% of the total contribution of monetary policy shocks to the forecast error variance of total loans. Funding effects account for 37% to 52%, and the residual channel accounts for approximately 18% to 26%. Overall the contributions are of a similar order of magnitude as those obtained with our baseline identification scheme reported in Table 5.

5 Conclusion

A large empirical literature shows that the supply of bank loans responds to changes in monetary policy (see Kashyap and Stein, 1995, 2000; Kishan and Opiela, 2000; Gambacorta, 2005, 2008). However, it remains unclear through which channels policy shocks are transmitted to loan volumes, as the evidence is essentially consistent with different transmission mechanisms. In this paper, we provide a novel approach to disentangle and quantify the contributions of these different channels.

When we explicitly disentangle the standard BLC and the RPC, we find that the two channels account on average for 16% and 27% of the overall effect of monetary policy shocks on total loans over a forecast horizon of three years. Thus, while both channels matter, the transmission

[18] See Gambacorta et al. (2014) for a discussion of the implications of unconventional monetary policy on the identification. One approach, that works with our identification restrictions, is to replace the Federal Funds rate with the *Shadow Short Rate* (SSR) in the estimation. The SSR is an estimated short-term rate that captures the effects of unconventional monetary policy on longer-maturity interest rates (see Krippner, 2015, for details). Hence, it can turn negative although the actual nominal interest rates are bounded by zero. We also estimate the longer sample with the SSR but the main findings remain robust (results are available upon request).

effects of the RPC are substantially larger than those associated with the standard BLC. This finding supports recent contributions that put a stronger focus on banks' external financing (Disyatat, 2011; Kishan and Opiela, 2012). Given banks' tendency to expand their wholesale funding liabilities (Gambacorta and Marques-Ibanez, 2011) and the increasing share of non-bank institutions (Disyatat, 2011), the importance of the RPC is likely to become even stronger over time.

We also find that policy shocks give rise to fluctuations in the demand for loans as discussed in Carpenter and Demiralp (2012). According to our results, loan demand effects account for slightly more than half of the forecast error variance in loan volumes that is generated by policy shocks. Thus, although monetary policy influences loan supply through the BLC and the RPC, banks also accommodate loan demand which counteracts the supply effects, reducing, or even compensating, the overall influence of monetary policy on loan volumes.

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A Additional Tables and Figures

INSERT TABLES A.1 and A.2 HERE.

INSERT FIGURES A.1, A.2, A.3, A.4, A.5, A.6 and A.7 HERE.

Table 1: Variable description

Variables	Name	Source	Code	Period
$RGDP_t$	Real gross domestic product (quarterly, seasonally adjusted, chained 2009)	FRED	GDPC1	1984Q1-2007Q3
CPI_t	Consumer price index: Total all items for the United States (quarterly, end of period, seasonally adjusted)	FRED	CPALTT01USQ661S	1984Q1-2007Q3
FFR_t	Effective federal funds rate (quarterly, end of period, not seasonally adjusted)	FRED	FEDFUNDS	1984Q1-2007Q3
$DDVOL_t$	Demand Deposits at Commercial Banks (quarterly, end of period, seasonally adjusted)	FRED	DEMDEPSL	1984Q1-2007Q3
$TOLN_t$	Loans and leases in bank credit (monthly, domestically chartered commercial banks, seasonally adjusted)	H8	B1020NDMAM	1984Q1-2007Q3
$CDVOL_{it}$	Quarterly average of time certificates of deposit in denominations of $100,000 or more in domestic offices	CALL	RCON3345	1984Q1-1996Q4
	Quarterly averages of time deposits of $100,000 or more	CALL	RCONA514	1997Q1-2007Q3
$CDVOL_t$	Quarterly sum of $CDVOL_{it}$ across banks			1984Q1-2007Q3
$INTEX_{it}$	Interest on time certificates of deposit of $100,000 or more issued by domestic offices	CALL	RIAD4174	1984Q1-1996Q4
	Interest on time deposits of $100,000 or more	CALL	RIADA517	1997Q3-2007Q3[1]
$INTEX_t$	Quarterly sum of $INTEX_{it}$ across banks			1984Q1-2007Q3
$CDRATE_t$	$(INTEX_t/CDVOL_t) \cdot 4$			1984Q1-2007Q3

Notes: Federal Reserve Economic Data (FRED); Reports of Condition and Income (CALL reports); H.8 Assets and Liabilities of Commercial Banks in the United State (H8). [1]Officially, this series starts in 1997Q1 but no data is reported in the first two quarters. The interest expenses on jumbo CDs (RIAD4174 and RIADA517) cumulate yearly and therefore we take first differences within each year to obtain quarterly interest expenses. The CD rate is multiplied by four to annualize the CD rate.

Table 2: Imposed restrictions

Perturbations	RGDP	CPI	FFR	CDVOL	CDRATE	TOLN	DDVOL
Innovation (RGDP)							
Innovation (CPI)	0						
MP Supply Effects	0	0	↑	↓	↑		
MP Funding Effects	0	0	↑	↑	↑		
MP Residual Effects	0	0	↑		↓		
Innovation (TOLN)	0	0	0	0	0		
Innovation (DDVOL)	0	0	0	0	0	0	

Notes: Zero and sign restrictions identify contractionary monetary policy shocks (MP) associated with either supply, funding, or residual effects on the jumbo CD market. Sign restrictions are imposed on impact and the next period. Zero restrictions hold contemporaneously.

Table 3: Imposed Restrictions: Additional restrictions on total loans

Perturbations	RGDP	CPI	FFR	CDVOL	CDRATE	TOLN	DDVOL
Innovation (RGDP)							
Innovation (CPI)	0						
MP Supply Effects	0	0	↑	↓	↑	↓	
MP Standard BLC	0	0	↑	↑	↑	↓	
MP Loan Demand	0	0	↑	↑	↑	↑	
Innovation (TOLN)	0	0	0	0	0		
Innovation (DDVOL)	0	0	0	0	0	0	

Notes: Zero and sign restrictions identify contractionary monetary policy shocks (MP) associated with either supply, standard BLC, or loan demand effects. Sign restrictions are imposed on impact and the next period. Zero restrictions hold contemporaneously.

Table 4: Imposed restrictions: Alternative ordering

Pertubations	RGDP	CPI	TOLN	FFR	CDVOL	CDRATE	DDVOL
Innovation (RGDP)							
Innovation (CPI)	0						
Innovation (TOLN)	0	0					
MP Supply Effects	0	0	0	↑	↓	↑	
MP Funding Effects	0	0	0	↑	↑	↑	
MP Residual Effects	0	0	0	↑		↓	
Innovation (DDVOL)	0	0	0	0	0	0	

Notes: Please refer to notes of Table 2.

Table 5: Relative contributions to the forecast error variance of total loans

Identification Scheme	Relative Contributions to Monetary Policy		
	Supply Effects	Funding Effects	Residual Effects
Baseline	25.71	53.00	21.29
	Supply Effects	Standard BLC	Loan Demand
Restriction on Loans	27.20	15.57	57.23

Notes: Relative contributions correspond to the shares of individual monetary policy shocks (associated in the first line with supply, funding, or residual effects on the jumbo CD market; or in the second line with supply, standard BLC, or loan demand effects) to the total contribution of monetary policy shocks in the FEVD of total loans, i.e. the sum of the effects of the three different monetary policy shocks. All values are in percent and averaged over a three year forecast horizon.

Table 6: Robustness Analysis: Relative contributions to the forecast error variance of total loans

Models	Relative Contributions to Monetary Policy		
	Supply Effects	Funding Effects	Residual Effects
1. Alternative ordering	32.76	48.53	18.71
2. SR for four quarters	24.45	51.81	23.74
3. Extended sample	43.81	37.69	18.49
4. No missings	27.04	49.48	23.48
5. Four lags	23.93	50.35	25.72

Notes: The robustness checks are described in Section 4. Please also refer to notes of Table 5.

Table A.1: FEVD of Total Loans (baseline)

Horizon	RGDP	CPI	MP Supply Effects	MP Funding Effects	MP Residual Effects	TOLN	DDVOL
0	8.97	22.57	2.51	1.18	0.61	60.93	0.00
	(3.99, 15.45)	(15.66, 30.02)	(0.58, 5.88)	(0.13, 4.13)	(0.05, 2.56)	(53.28, 68.42)	(0.00, 0.00)
4	21.35	13.19	1.58	4.47	1.31	47.22	4.73
	(11.48, 32.75)	(6.53, 21.80)	(0.65, 4.10)	(1.32, 11.11)	(0.32, 4.49)	(36.83, 57.94)	(1.69, 9.02)
8	23.53	20.37	1.34	3.09	1.56	38.68	4.93
	(12.04, 36.98)	(11.07, 31.59)	(0.46, 3.80)	(1.55, 6.26)	(0.39, 5.25)	(26.51, 51.49)	(1.26, 10.84)
12	23.21	24.91	1.51	3.90	2.10	31.24	4.71
	(10.61, 37.71)	(13.66, 37.34)	(0.42, 4.86)	(1.62, 8.57)	(0.49, 6.78)	(17.53, 46.70)	(1.12, 12.34)

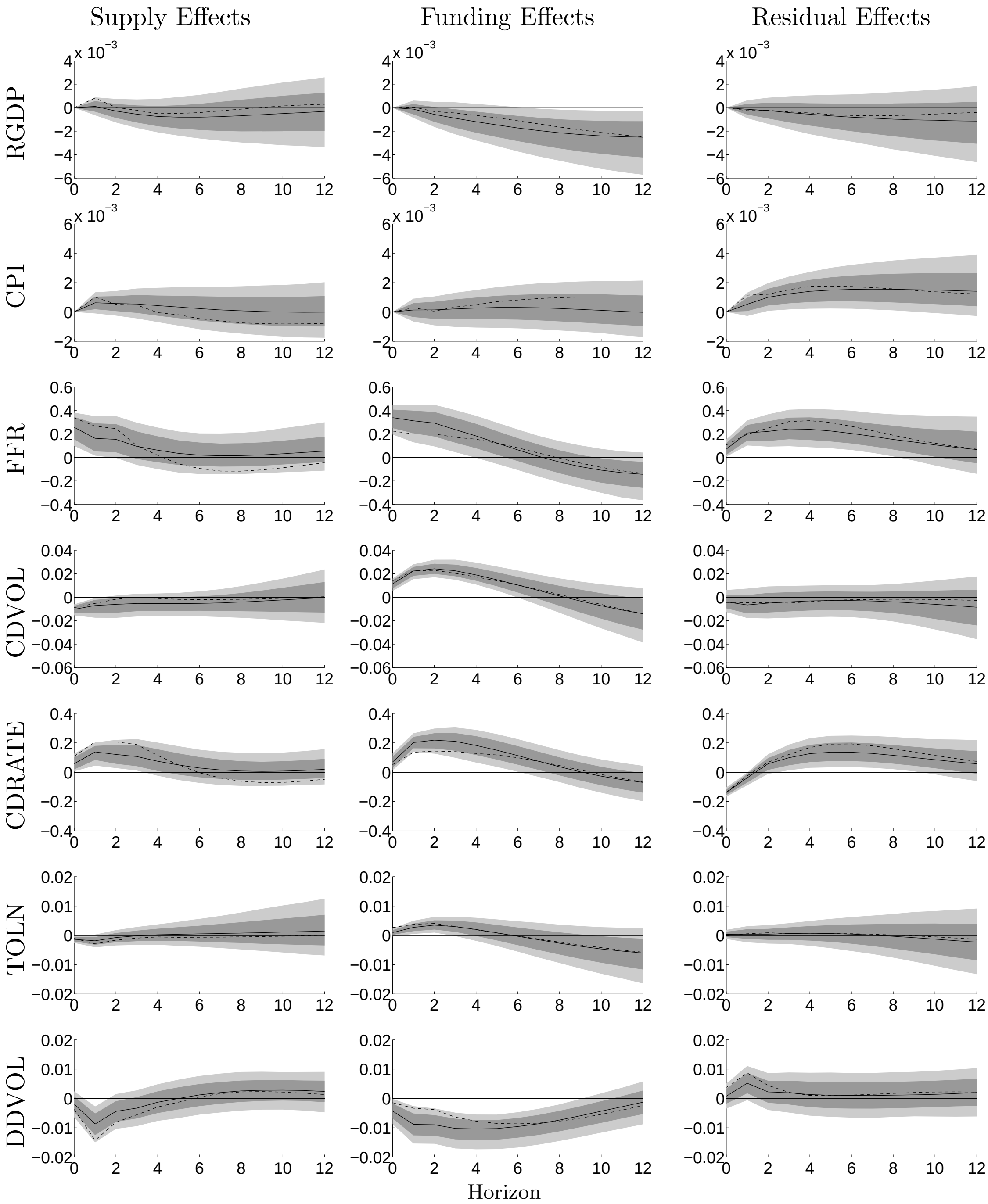
Notes: Columns 4 to 6 report the contributions of monetary policy shocks (MP) associated with either supply, funding, or residual effects on the jumbo CD market. Values correspond to the point-wise median values of the FEVD distribution at each forecast horizon (values in parentheses correspond to the 16^{th} and 84^{th} percentiles).

Table A.2: FEVD of Total Loans (with sign restrictions on total loans)

Horizon	RGDP	CPI	MP Supply Effects	MP Standard BLC	MP Loan Demand	TOLN	DDVOL
0	8.52	22.46	2.47	0.54	1.64	61.12	0.00
	(3.75, 15.15)	(15.72, 29.44)	(0.56, 5.76)	(0.05, 1.98)	(0.25, 5.05)	(53.65, 68.53)	(0.00, 0.00)
4	21.04	13.30	1.62	0.65	4.99	47.80	4.72
	(10.91, 32.70)	(6.66, 22.38)	(0.63, 3.94)	(0.20, 2.14)	(1.70, 11.57)	(37.23, 58.69)	(1.67, 8.87)
8	22.90	20.85	1.47	1.28	3.07	39.00	4.81
	(11.33, 37.70)	(11.31, 32.13)	(0.46, 3.93)	(0.28, 5.01)	(1.53, 6.03)	(26.65, 51.47)	(1.31, 10.46)
12	22.24	25.44	1.67	1.64	4.00	31.06	4.49
	(10.16, 37.55)	(14.11, 38.51)	(0.44, 5.14)	(0.34, 7.08)	(1.69, 8.30)	(17.34, 46.63)	(1.14, 12.03)

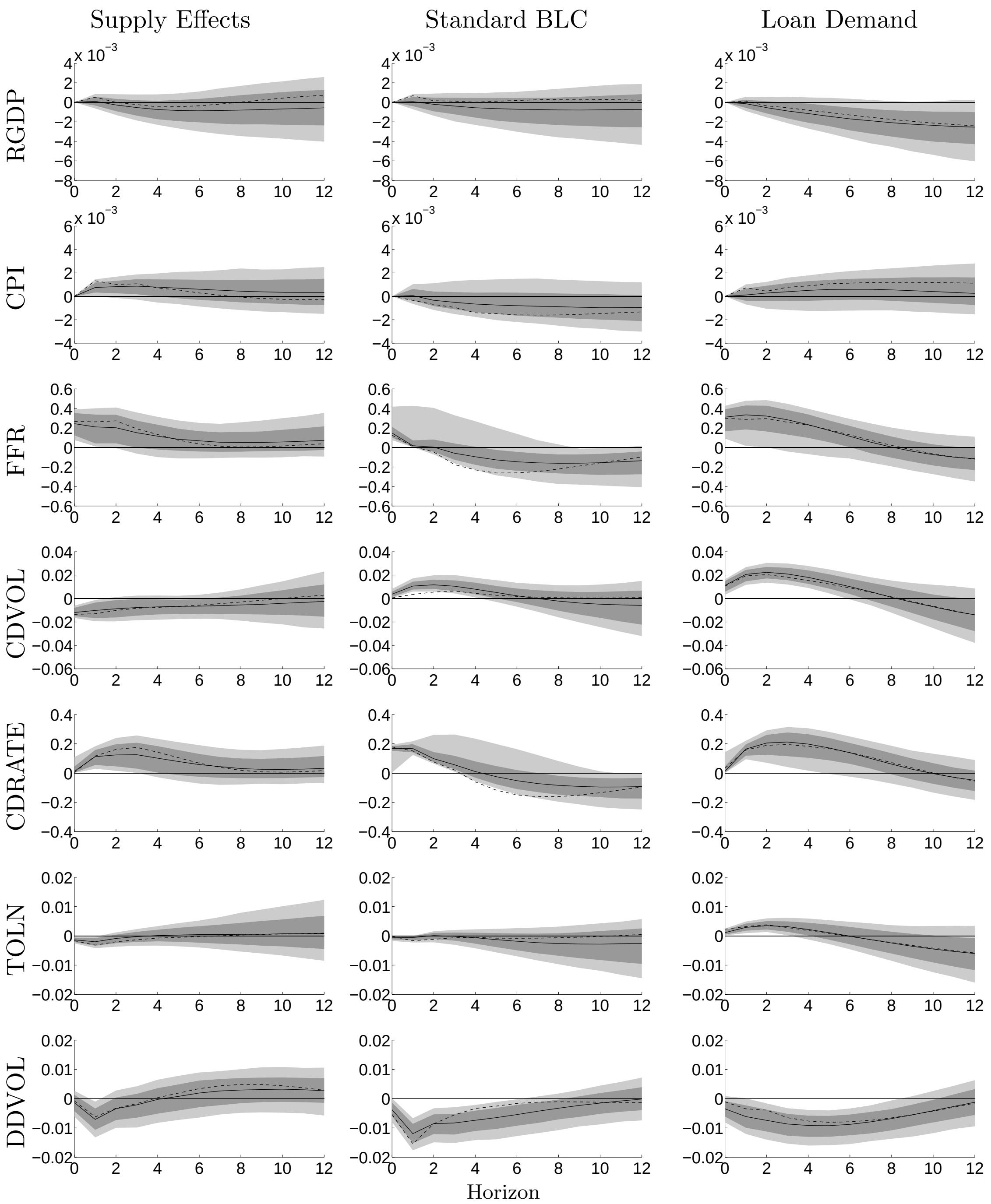
Notes: Columns 4 to 6 report the contributions of monetary policy shocks (MP) associated with either supply, standard BLC, or loan demand effects. Values correspond to the point-wise median values of the FEVD distribution at each forecast horizon (values in parentheses correspond to the 16^{th} and 84^{th} percentiles).

Figure 1: Responses to monetary policy shocks (baseline)



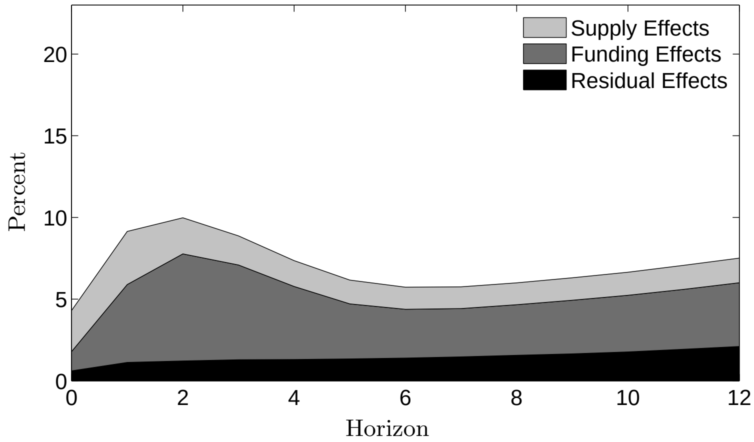
Notes: The columns correspond to monetary policy socks associated with either supply, funding, or residual effects on the jumbo CD market. Responses are either measured in log-deviations or percentage-points. The light gray and dark gray areas represent 90% and 68% of the restricted posterior distribution. The solid line represents the point-wise median response and the dashed line shows the responses of the closest-to-median model (Fry and Pagan, 2011).

Figure 2: Responses to monetary policy shocks (with sign restrictions on total loans)



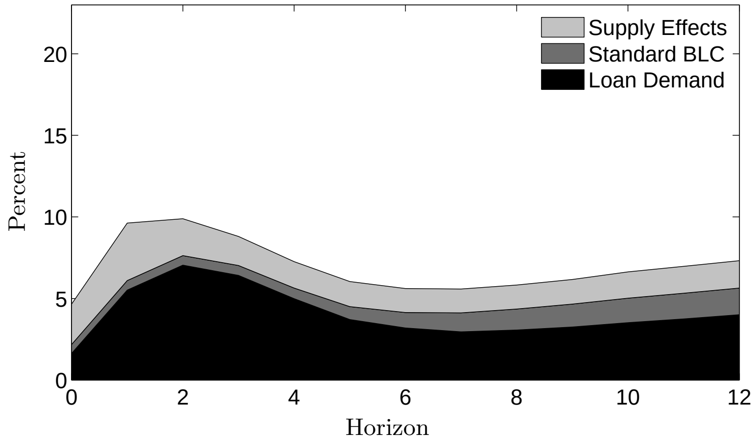
Notes: The columns correspond to monetary policy socks associated with either supply, standard BLC, or loan demand effects. Responses are either measured in log-deviations or percentage-points. The light gray and dark gray areas represent 90% and 68% of the restricted posterior distribution. The solid line represents the point-wise median response and the dashed line shows the responses of the closest-to-median model (Fry and Pagan, 2011).

Figure 3: Contributions of monetary policy shocks in the FEVD of total loans (baseline)



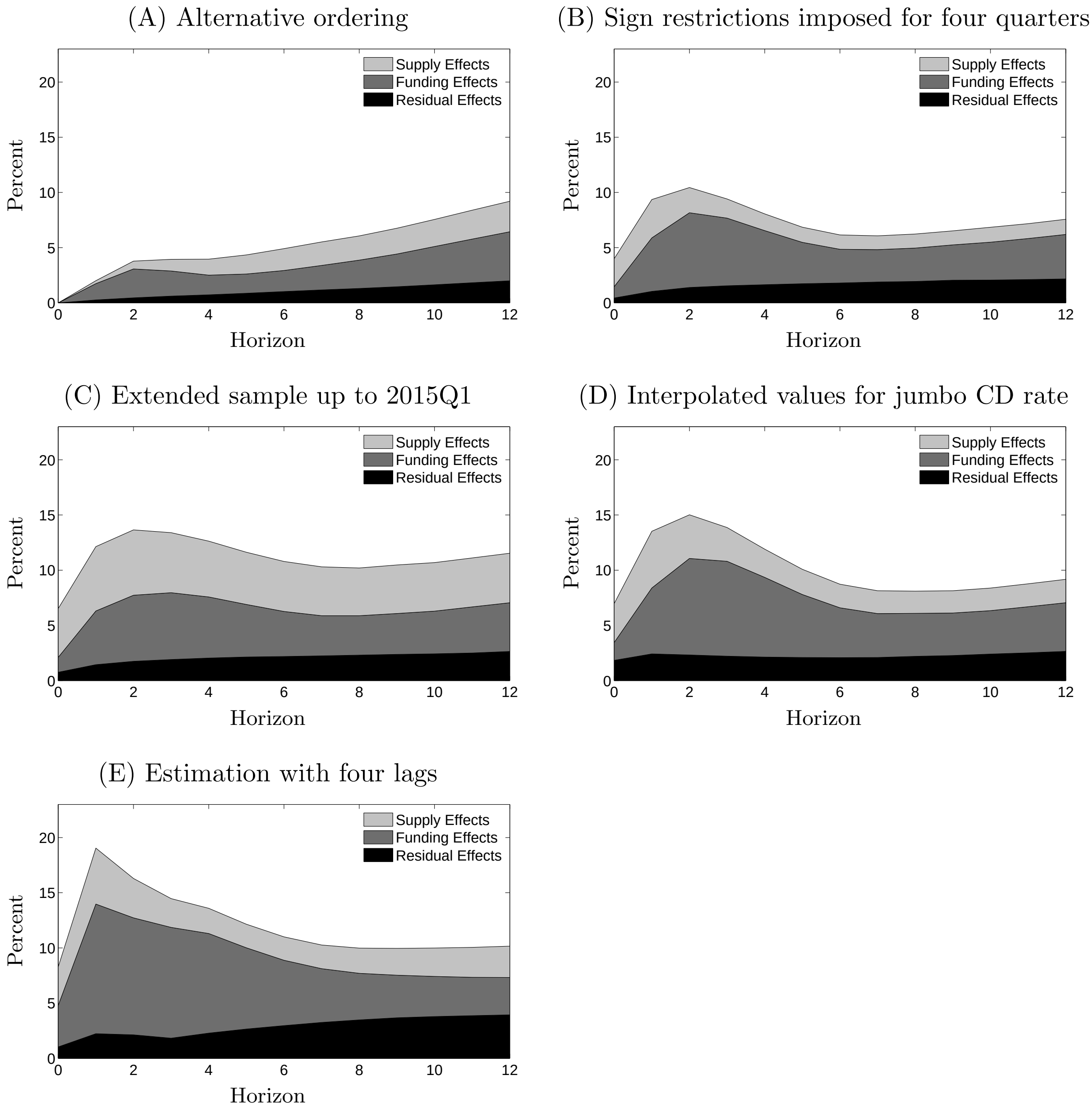
Notes: The areas report the contribution of monetary policy shocks (associated with either supply, funding, or residual effects on the jumbo CD market) to the forecast error variance of total loans. Values correspond to the point-wise median values of the FEVD distribution at each forecast horizon.

Figure 4: Contributions of monetary policy shocks in the FEVD of total loans (with sign restrictions on total loans)



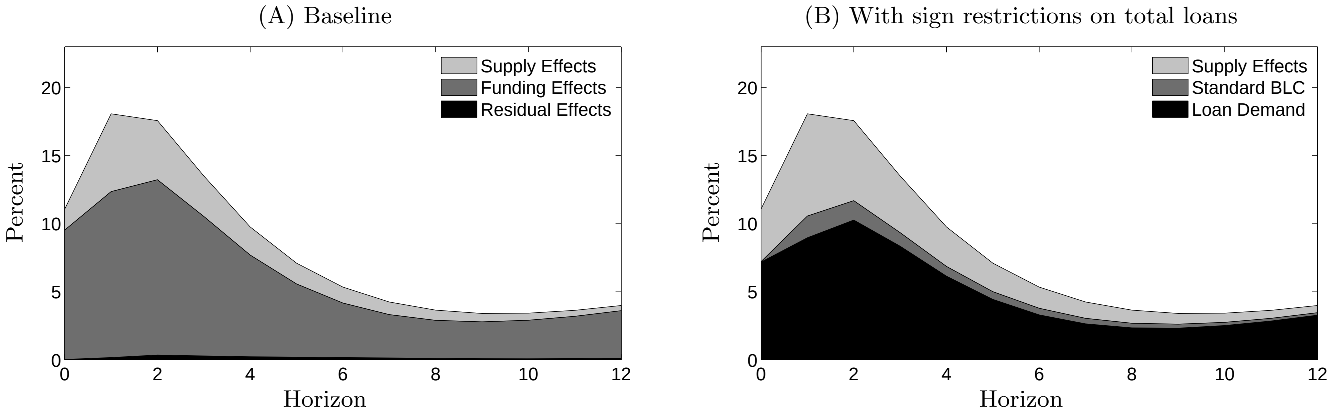
Notes: The areas report the contribution of monetary policy shocks (associated with either supply, standard BLC, or loan demand effects) to the forecast error variance of total loans. Values correspond to the point-wise median values of the FEVD distribution at each forecast horizon.

Figure 5: Robustness Analysis: Contributions of monetary policy shocks in the FEVD of total loans



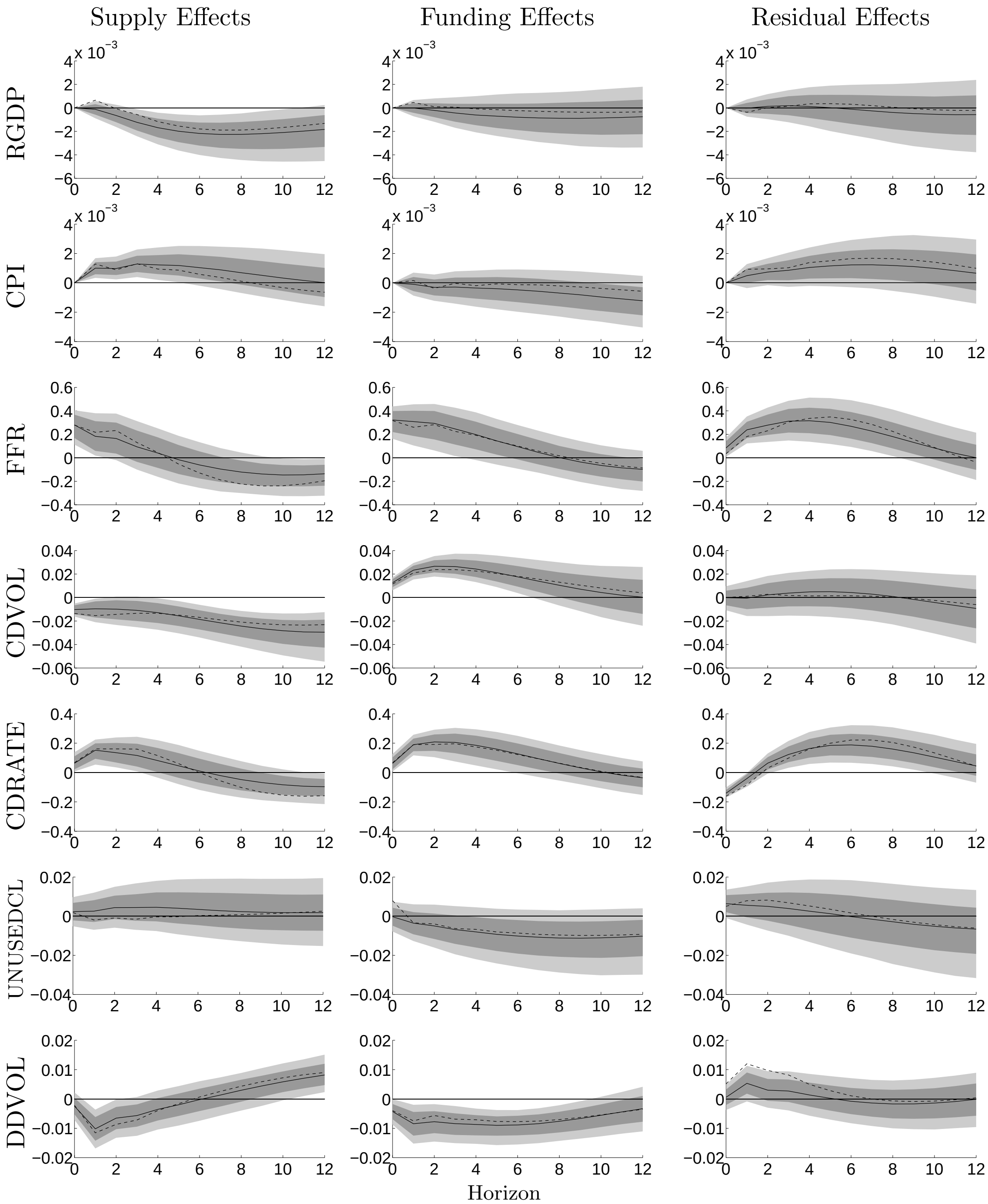
Notes: Please refer to notes of Figure 3.

Figure A.1: Contributions of monetary policy shocks in the FEVD of total loans (closest-to-median model)



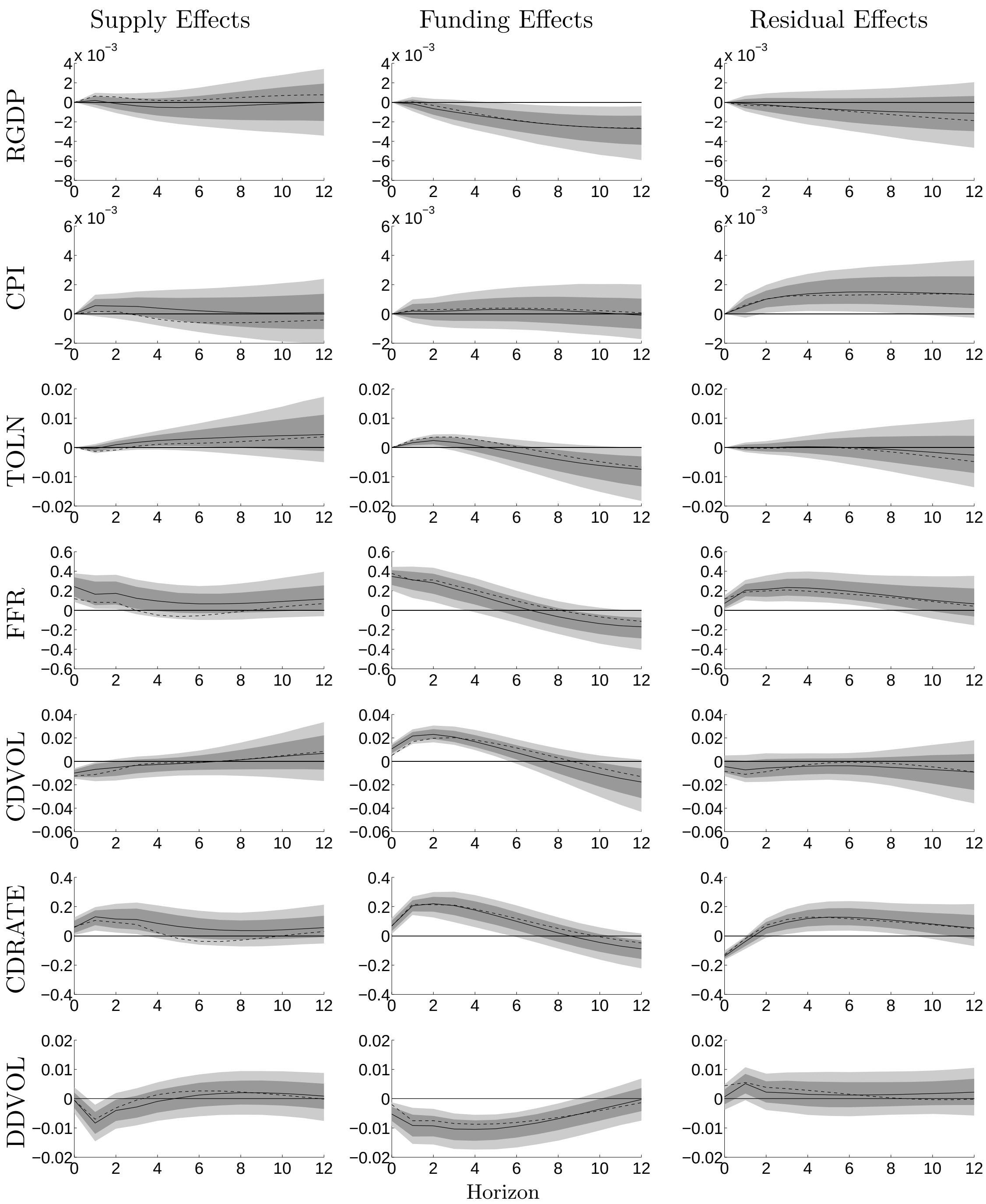
Notes: The areas correspond to the FEVD values of the closest-to-median model (Fry and Pagan, 2011). Please also refer to notes of Figure 3 and 4.

Figure A.2: Responses to monetary policy shocks (specification with unused credit lines instead of total loans)



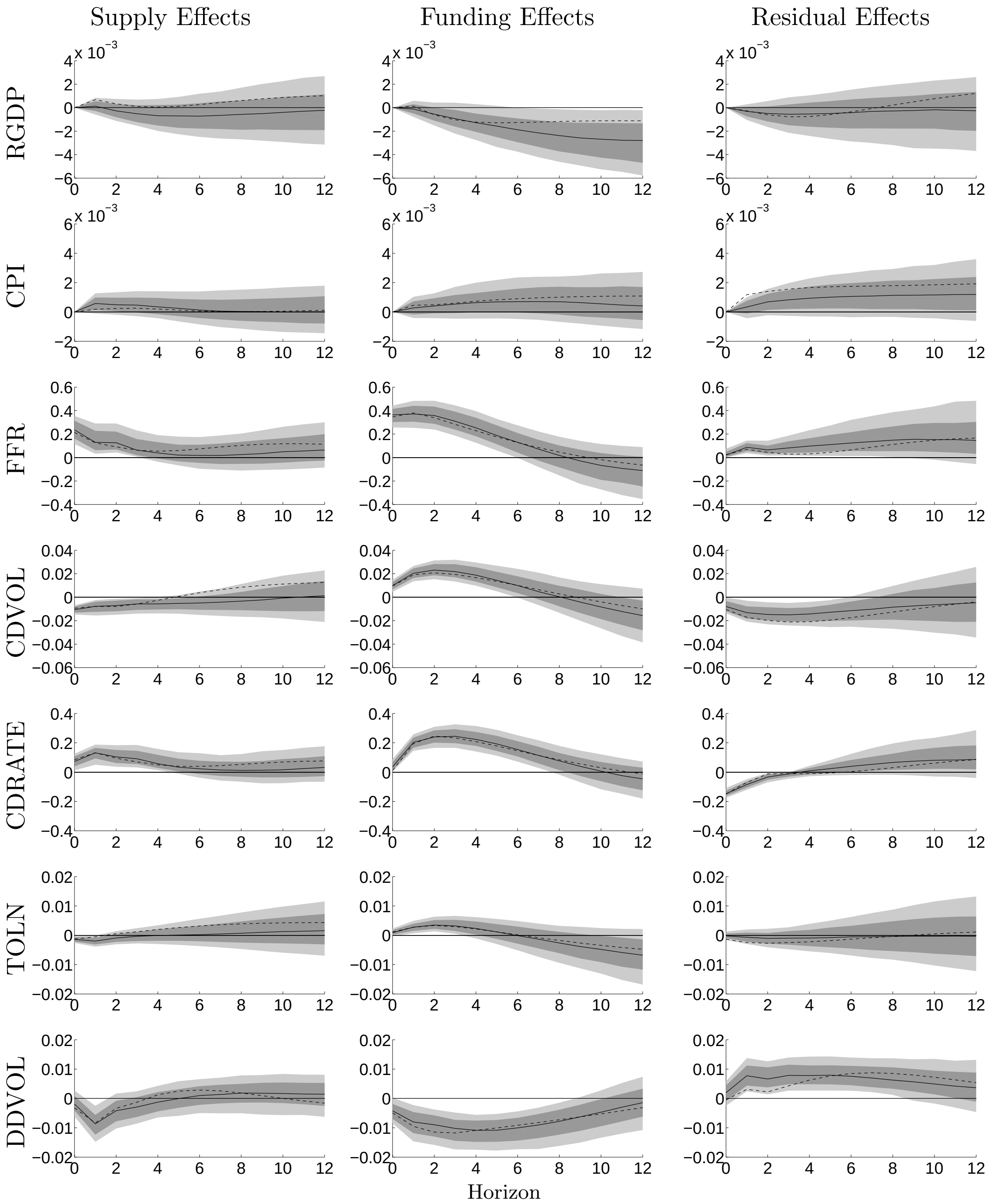
Notes: Unused credit lines (UNUSEDCL); please also refer to notes of Figure 1.

Figure A.3: Responses to monetary policy shocks (alternative ordering)



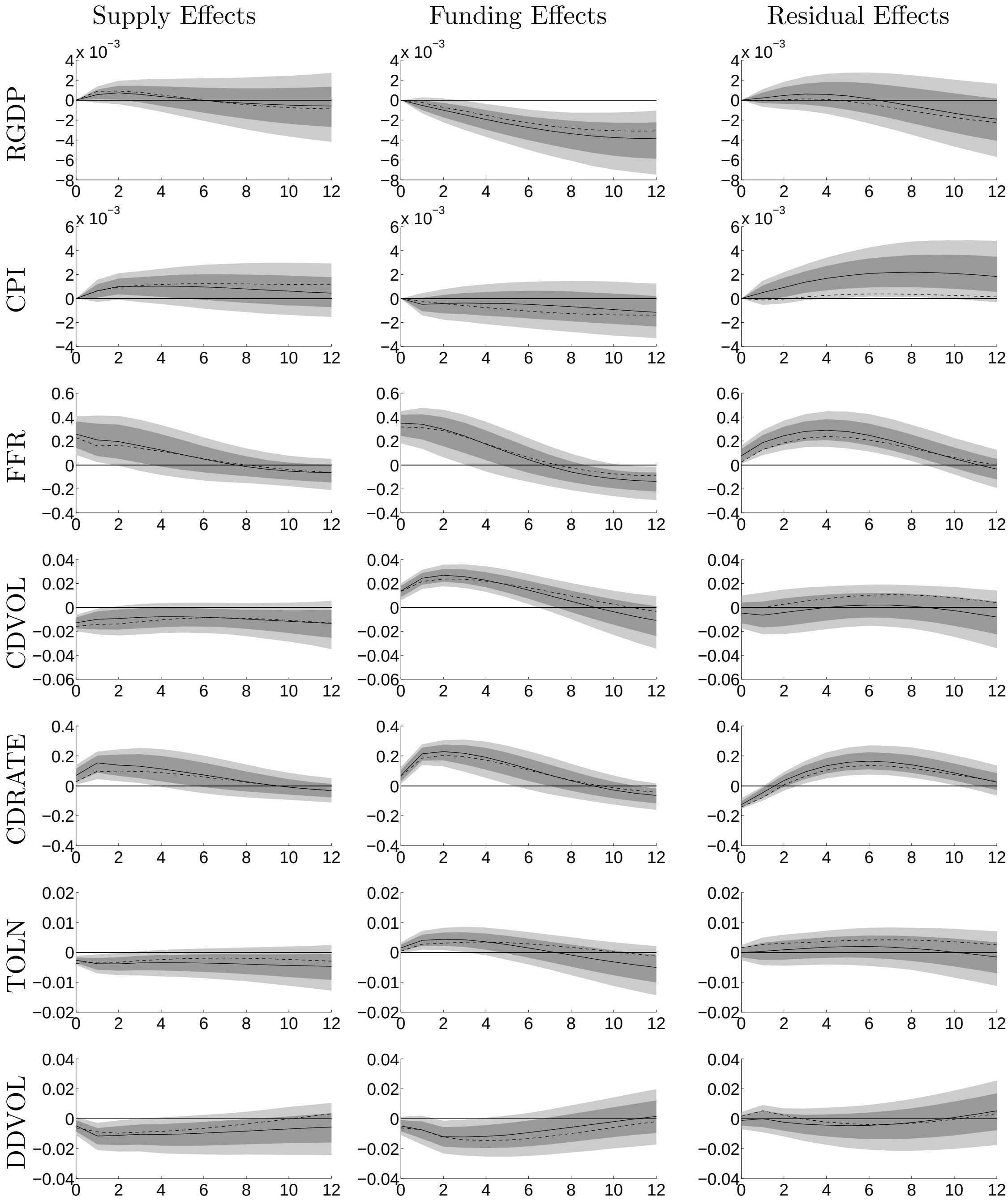
Notes: Please refer to notes of Figure 1.

Figure A.4: Responses to monetary policy shocks (sign restrictions are imposed for four periods)



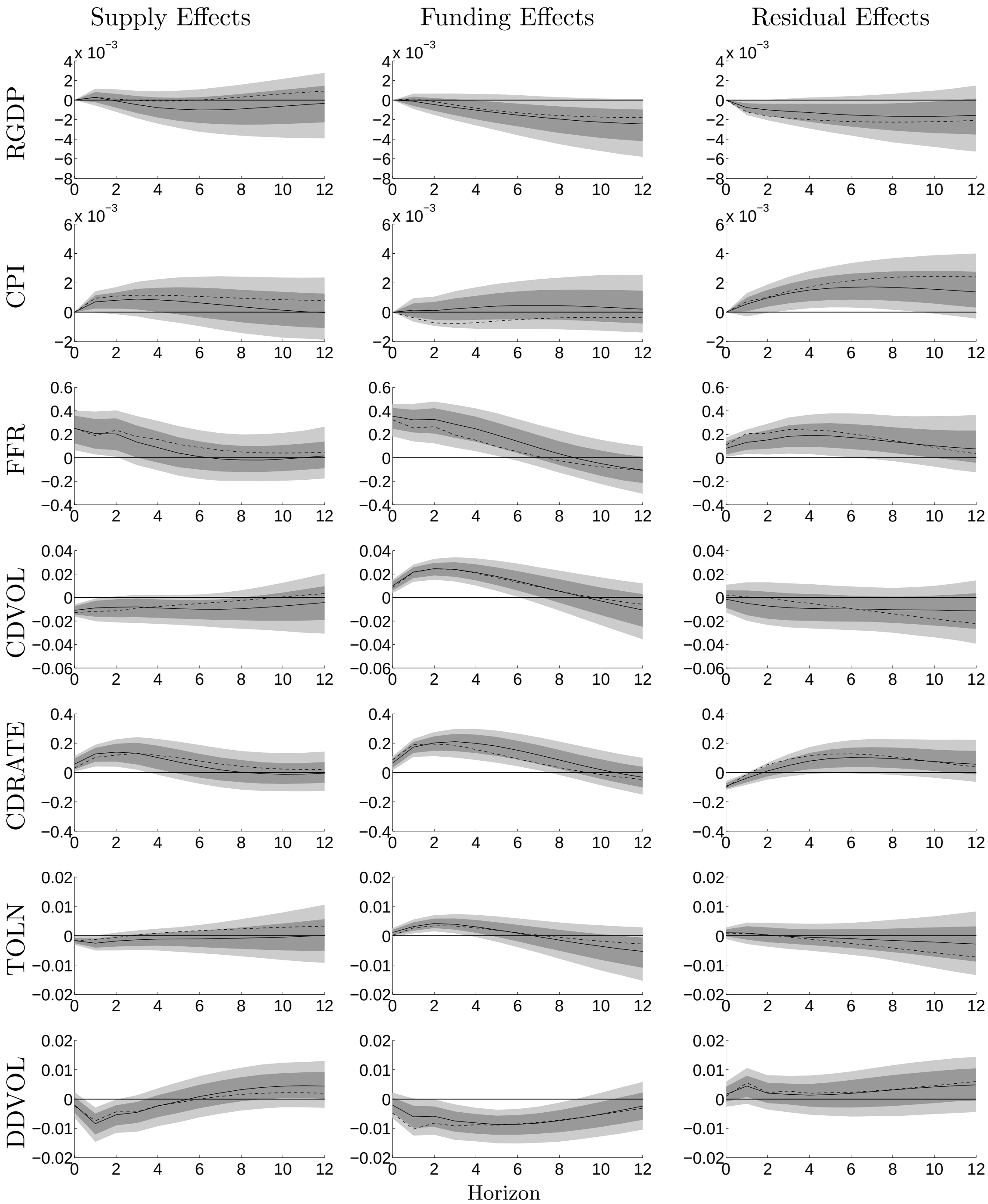
Notes: Please refer to notes of Figure 1.

Figure A.5: Responses to monetary policy shocks (extended sample up to 2015Q1)



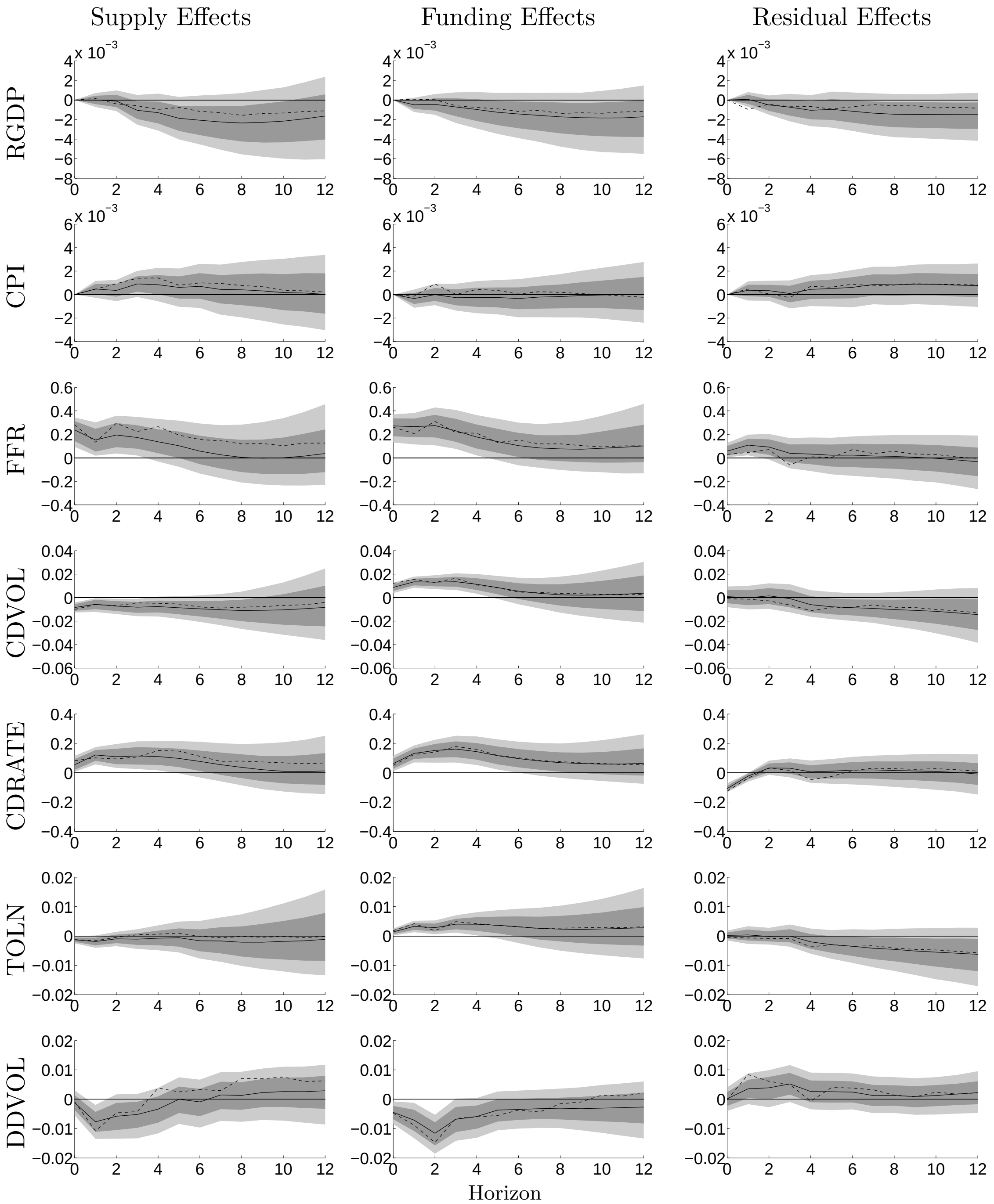
Notes: Please refer to notes of Figure 1.

Figure A.6: Responses to monetary policy shocks (missing values of the CD rate are interpolated)



Notes: Interest expenses of jumbo CDs are not reported for the first two quarters of 1997 and therefore the CD rate is missing in these two and the consecutive quarter; the missing values are interpolated using the X13-ARIMA method. Please also refer to notes of Figure 1.

Figure A.7: Responses to monetary policy shocks (estimation with four lags)



Notes: Please refer to notes of Figure 1.

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Max Breitenlechner, Johann Scharler

How does monetary policy influence bank lending? Evidence from the market for banks' wholesale funding

Abstract

We study the transmission of monetary policy shocks to loan volumes using a structural VAR. To disentangle different transmission channels, we use aggregated data from the market for large certificates of deposits and apply a sign restrictions approach. We find that although the standard bank lending channel as well as the recently formulated risk-pricing channel (Disyatat, 2011; Kishan and Opiela, 2012) contribute to the transmission of policy shocks, the effects associated with the risk-pricing channel are quantitatively stronger. Our results also show that policy shocks give rise to non-negligible effects on loan demand.

ISSN 1993-4378 (Print)
ISSN 1993-6885 (Online)