Identifying Heterogeneous Bank Responses to U.S. Monetary Policy Shocks*

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Abstract

Using an informationally-robust monetary policy instrument we identify a strong heterogeneity in the monetary policy transmission across commercial banks. We show that the degree of liquidity systematically influences how banks change their lending behavior when faced with an unexpected change in monetary policy. Highly liquid banks (those with excess reserves exceeding 1% of total assets) react by significantly expanding lending, whereas less liquid banks have a largely muted response. Additionally, our instrument allows us to distinguish between conventional and unconventional monetary policy. We find that our results are qualitatively robust, but exhibit quantitative differences across the alternative monetary policies. Finally, we show that neglecting to control for the information effects of monetary policy yield qualitatively different results for cash-liquid banks that are at odds with economic theory.

Keywords: Excess Reserves; External Instruments; Local Projections; Bank-lending Channel; Information Channel

JEL Classification: C13; E42; E44; E52

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1 Introduction

What is the role of bank liquidity in determining commercial banks' responses to monetary policy shocks? And second, what is the role of the information effect of monetary policy announcements in this context? These questions are motivated by the fact that, at the peak of the Great Financial Crisis (GFC henceforth), the Fed implemented (for that time) unconventional policies that relied on increasing transparency and public communication, such as forward guidance. Additionally, the Fed provided liquidity injections via large-scale asset purchases (LSAPs henceforth)[1] that significantly expanded the amount of excess liquidity in the financial system. Commercial banks are at the core of the financial system and play a key role in the transmission of monetary policy to the real economy through several channels.

Among the various transmission mechanisms that have been analysed in the literature the bank-lending channel and the information channel of monetary policy are the most closely related to our research questions. First, the broad interpretation of the bank-lending channel[2] predicts that, in response to a monetary tightening, liquidity constrained banks will contract their credit supply while leaving their securities portfolio unchanged. Arguably, the assumption of banks being at their liquidity constraint was largely valid until the early 1990's. However, making this assumption when looking at more recent data turns into a more difficult task. As shown in figure 1, in the decades preceding the GFC the share of banks with high excess liquidity was always very low, and thus, largely in line with the assumption of the bank-lending channel. This share was below 20% at the beginning of the 1990's and was also decreasing over time. However, the implementation of LSAPs to mitigate the effects of the GFC reversed this trend, and after 2008Q3 the share of cash-liquid banks reached a peak of almost 75% in 2011 and stabilized above 60% by the end of our sample.[3]

Second, the information channel of monetary policy, as proposed by Nakamura & Steinsson (2018), highlights that Fed announcements do not only affect beliefs about (the future path of) monetary policy "but also about other economic fundamentals." That is, economic agents are also updating their beliefs about the economic outlook in reaction to Fed announcements. Disregarding of the information content of Fed announcements leads to biased inference, as has been manifested in long-standing puzzles in the literature on monetary policy shocks. For example, Miranda-Agrippino & Ricco (2021) show that in reaction to a monetary contraction, established instruments (which do not account for the information effect) produce an expansion in industrial production and a decline in the unemployment rate.

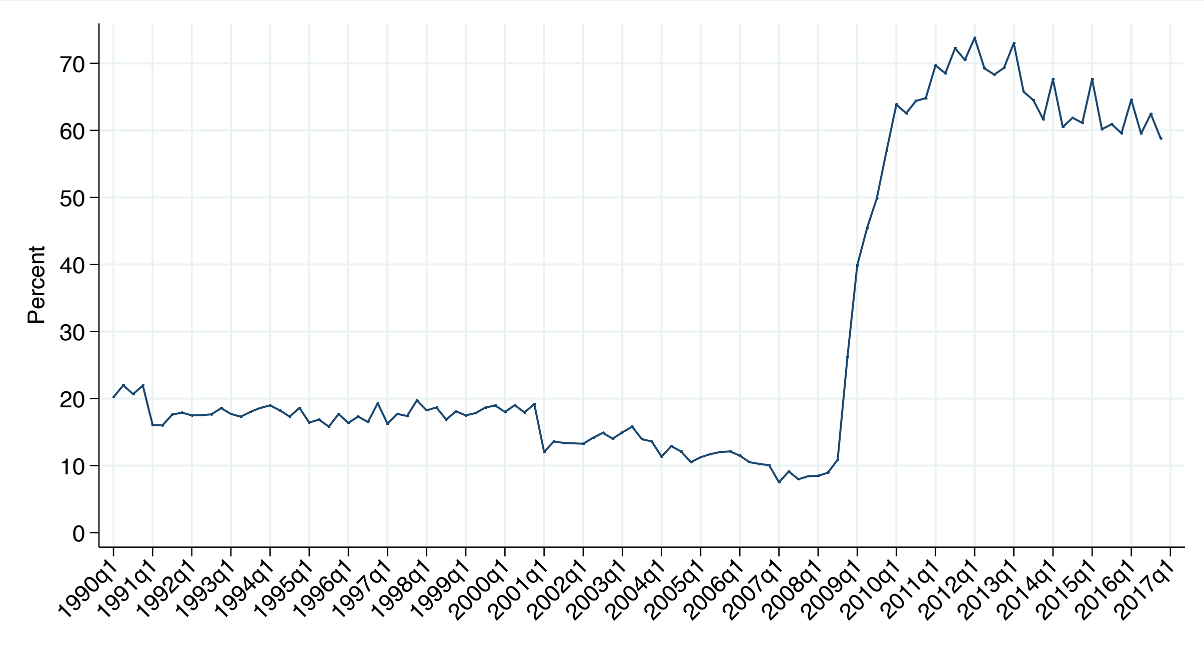
The persistent changes in the financial system's liquidity levels in the aftermath of the GFC, together with an increasing reliance on central bank communication policies, raises the question of whether banks' reactions to monetary shocks are still in line with pre-GFC estimates. Specifically, we first ask whether banks' reactions to monetary policy shocks depend on their cash-liquidity levels and, second, whether they also depend on the information effect from policy announcement.

[1] This is also referred at times simply as quantitative easing (QE). We use both terms interchangeably throughout this paper.

[2] The original formulation of this transmission mechanism is owed to the seminal contributions by Bernanke & Blinder (1988, 1992).

[3] Figure B.1 in Appendix B splits figure 1 by size categories. Although, the share of liquid banks used to be slightly larger among small banks in the early 1990s, the difference between them and large and medium banks was imperceptible right before the financial crisis.

Figure 1: **Share of banks with an excess reserves to total assets ratio exceeding 1%**



In order to answer these questions, we employ a state-dependent, lag-augmented (panel) local projection instrumental variables (LP-IV) setup, which allows us to distinguish between liquid and illiquid banks, and also to control for large sets of bank-level characteristics. We further use an informationally-robust monetary policy instrument (MPI henceforth) following Miranda-Agrippino & Ricco (2021). This instrument has two significant advantages: First, it is orthogonal to both the central bank's projections as well as past market surprises. And, second, we can differentiate between total, conventional and unconventional monetary policy shocks.[4]

Our results provide two key insights. First, monetary policy transmission crucially depends on banks' individual liquidity levels, as well as the aggregate liquidity composition of the banking sector, i.e., our findings depend on the inclusion of post-2007 data. In the pre-GFC sample, we find supporting evidence for an active bank-lending channel independently of a bank's liquidity state, i.e., we identify homogeneous bank responses. In response to a 100bp monetary policy tightening, banks reduce lending by three percent after three years (cumulative). Additionally, we show that expansionary and contractionary shocks affect bank lending in a qualitatively symmetric fashion. However, the magnitude of the responses after a contractionary shock are two to three times larger than those after an equally large expansionary shock.

Our full sample results, however, highlight that banks do react systematically differently to monetary policy shocks depending on their liquidity state. In reaction to a 100bp contractionary monetary policy shock, highly liquid banks show a cumulative increase in their loan supply by 9% after three years. In contrast, illiquid banks show a largely muted response to the same shock. In aggregate, the responses of liquid banks dominate those from illiquid banks, as our analysis suggests that the average bank increases total lending after a contractionary monetary policy

[4]Total monetary policy refers to our instrument where we consider the cumulative effects of conventional and unconventional shocks together.

shock. This implies that the bank-lending channel is no longer active in the U.S. A more detailed look, however, reveals that illiquid banks still behave in line with the broad interpretation of the bank-lending channel and that the counter-intuitive results are driven by contractionary shocks only. In particular, we find that banks now increase their lending both after an expansionary and contractionary shock, i.e., they react asymmetrically to policy shocks.

Second, as emphasized in various recent contributions on the information effect of monetary policy, monetary policy instruments neglecting this effect ultimately deliver biased impulse response functions when used as external instruments in (S)VAR or local projections (LPs) setups. In this regard we show that in our full sample analysis instrumenting the changes in the policy rate with the high-frequency market-based surprises coming from Swanson (2021) (which do not control for the information effect of monetary policy) lead to opposite reactions compared to what we find when employing our own informationally-robust MPI in the spirit of Miranda-Agrippino & Ricco (2021) or the informationally-robust monetary shock series from Bu, Rogers & Wu (2021). This suggests that similar to the previously mentioned long-standing puzzles in the monetary literature, informational robustness of MPIs leads to qualitative differences in the dynamic consequences of monetary policy shocks. Specifically, as we show below, our results are more closely aligned with economic theory than those that are based on instruments not taking into account the information effect of monetary policy.

These results are robust to a number of factors: We show that they are robust to different lag specifications and to alternative liquidity thresholds. In fact, there is a clear positive relationship showing a growing responsiveness with rising liquidity thresholds. The qualitative responses of bank variables do not depend on the specific type of monetary policy regime or tools. That is, when constructing our MPI only with the forward guidance and LSAP factors from Swanson (2021) we still find the same qualitative differences across liquid and illiquid banks. Our results show that the different policy dimensions do not yield different impulse responses other than expected quantitative differences. Finally, our main results are also robust to the use of alternative policy indicators. Namely, replacing the Effective Federal Funds rate with the one-year Treasury rate or the short-term shadow rate from Wu & Xia (2016) leaves our results unchanged.

Let us relate our findings to the literature. First, we contribute to the empirical literature on the bank-lending channel by showing that banks' credit supply decisions crucially depend on their cash-liquidity levels when including post-2007 data in our analysis. This strand of the literature can be traced back to the seminal contribution by Bernanke & Blinder (1992), who developed a simple VAR model to asses the relevance of the bank-lending channel using U.S. data. Other studies have built on Bernanke & Blinder's approach by looking at different categories of bank loans (see, e.g., den Haan, Sumner & Yamashiro (2007, 2009), Dave, Dressler & Zhang (2013) and Greenwald, Krainer & Paul (2020)), or by focusing on the housing market (see Iacoviello & Minetti (2008)). Other related studies analysing bank-level data (see, e.g., Kashyap & Stein (1994, 2000), Cetorelli & Goldberg (2012), Cao & Dinger (2018) and Eggertsson, Juelsrud, Summers & Wold (2019)) or a mix between aggregate and micro-level data (see, e.g., Carpenter & Demiralp (2012) or Dave et al. (2013)) have found mixed evidence on the presence of an active lending channel. To the best of our knowledge, our contribution is the first to shed light on the systematically different responses based on bank level cash-liquidity after both conventional and unconventional monetary shocks.

Second, our paper further contributes to the literature on monetary policy shocks and the relevance of informational effects conveyed around monetary policy announcements. Our contribution lies in contrasting high-frequency market-based surprises with informationally robust shocks. We show the importance of information effects in determining the impact of monetary policy shocks on key bank variables using informationally-robust monetary policy instruments à la Miranda-Agrippino & Ricco (2021).

Related to the high-frequency shock identifying literature, early path-setting contributions are Kuttner (2001) and Gürkaynak, Sack & Swanson (2005). The key element of these methods is to examine changes in a benchmark rate in 30-minute windows around FOMC announcements. For example, in Jarociński & Karadi (2020) this is done for the three-months Federal Funds futures rate, whereas in Barakchian & Crowe (2013) a factor model using different futures contracts is being employed. In Nakamura & Steinsson (2018) as well as Swanson (2021) the market surprises are extracted through principal components analyses using a number of Fed Funds futures with different maturities, allowing the latter to identify separate effects of the Fed Funds rate, forward guidance and LSAPs. High-frequency identified shocks are able to bridge periods of conventional and unconventional monetary policy, a key characteristic that has made them more appealing since the onset of the GFC compared to, e.g., a narrative approach as in Romer & Romer (2004). However, recently, a number of studies have highlighted the relevance of the "information channel" of monetary policy. Among others, this includes Hoesch, Rossi & Sekhposyan (2020), Jarociński & Karadi (2020), Cieslak & Schrimpf (2019) and Nakamura & Steinsson (2018). The major insight of this strand of the literature is that monetary policy instruments need to account for the information effect of monetary policy adjustments to be unbiased. Popular instruments such as the Gürkaynak et al. (2005) or Swanson (2021) high-frequency market surprises do not control for these information effects. Bu et al. (2021) also show that Jarociński & Karadi (2020)'s series still contains an information effect. In contrast, Miranda-Agrippino & Ricco (2021), as well as Bu et al. (2021), develop an approach to control for these information effects allowing them to find a solution for long-standing puzzles in the monetary policy literature, as further documented in Ettmeier & Kriwoluzky (2019). In this spirit, our contribution is to show that failing to control for the information channel of monetary policy leads to significant qualitative differences when employing such policy instruments in a macro-finance setup.

Finally, the econometric specification is closely related to the recent branch of the empirical literature on estimating impulse response functions using local projections (LPs henceforth) following Jordà (2005). This rapidly evolving literature shows that LPs are not only more flexible in estimating dynamic responses than standard SVAR models by imposing fewer restrictions (see, e.g., Ramey (2016)), but also that the impulse responses are the same as the ones from VARs (see, e.g., Plagborg-Møller & Wolf (2021)). Recently, Montiel Olea & Plagborg-Møller (2021) prove that lag-augmented LP models, i.e., models that include sufficient lags of the variables in the regressions as controls, yield robust estimates even at longer horizons or if the data is highly persistent. Additionally, Montiel Olea & Plagborg-Møller (2021) show that by including enough lags as controls, i.e., in a lag-augmented LP model, there is no need to compute Heteroskedasticity and Autocorrelation Robust (HAR) standard errors and that the simple Eicker-Huber-White heteroskedasticity-robust standard errors are sufficient since, under weak assumptions, the regression scores are serially uncorrelated. Our approach to estimate dynamic responses of key banks' balance sheet items is based on the "external instruments" insights obtained by Mertens & Ravn (2013) and Stock & Watson (2012, 2018), given that we instrument the changes in the policy rate with our informationally-robust MPIs when estimating our lag-augmented LP models.

The remainder of the paper is organized as follows: Section 2 briefly describes our data, and section 3 describes the construction of our informationally-robust monetary policy instruments. In section 4 we present the empirical setup using lag-augmented LP-IV models. The results of our quantitative exercise are given in section 5. Section 6 presents a battery of robustness checks and some further extensions. Finally, section 7 concludes.

2 Data

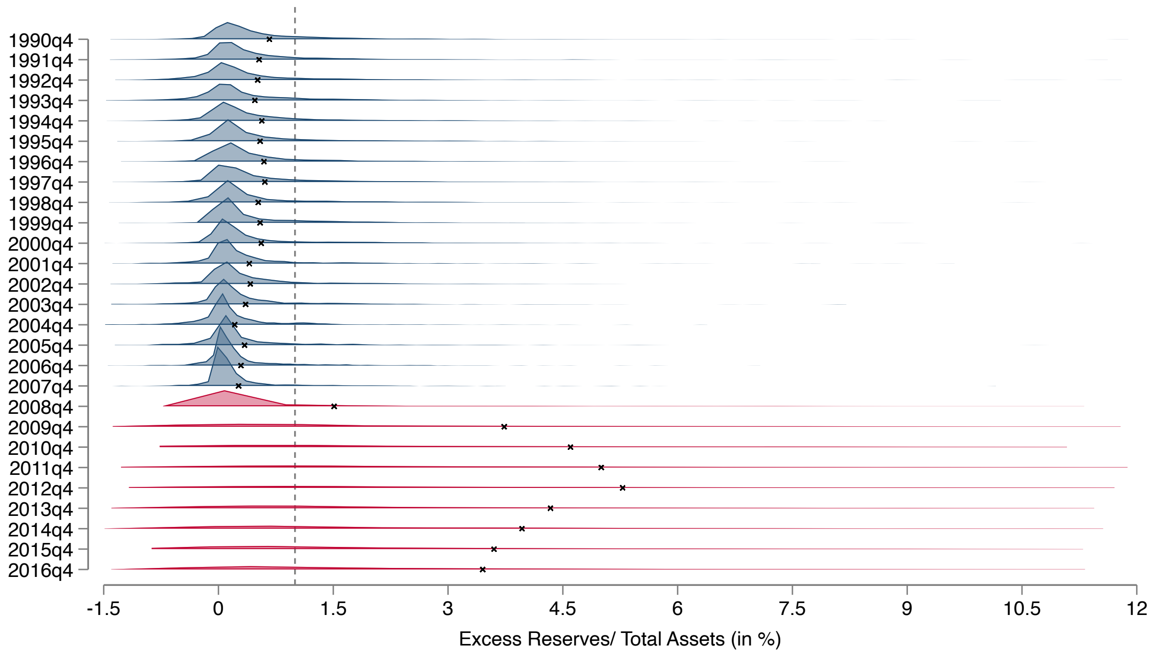
Our analysis draws on several data sources. First, for the construction of our MPIs, we use the high-frequency policy factors from Swanson (2021) and the Philadelphia Fed's Tealbook/Greenbook data set.[5] The high-frequency data from Swanson (2021) covers the period from 1990Q1 to 2019Q3. Because the Fed's Greenbook data is published with a five year lag, our MPI construction ends in 2016m12 (or 2016Q4 at quarterly frequency).

Balance sheet data is taken from the Consolidated Report of Condition and Income (also known as "Call Reports"). These reports include detailed information on a number of key variables, allowing us to obtain our estimates of interest while incorporating a broad set of bank-level controls in our subsequent analysis. We then merge the bank level data with excess reserves information taken from Afonso, Armenter & Lester (2019). Specifically, we use and extend their procedure to obtain bank-level data on excess and required reserves prior to 2007, which is the earliest year in Afonso et al. (2019)'s calculations. The details of the excess reserves construction can be found in the Data Appendix A.1.1. [6] A minor drawback of this approach is that it requires regulatory information that only banks with at least \$300 million in total assets (or with foreign offices) have to report. Nevertheless, we regard this minor drawback as negligible as the majority of reserves are held in these large institutions as shown in Afonso et al. (2019).

While it is well known that the levels of cash-liquid assets increased as a consequence of the Fed's standing facilities and LSAPs (see figure 1), the distributional consequences for these assets within the commercial banking system are usually not. Figure 2 depicts the kernel densities for excess reserves as a fraction of total assets at each year's end in our sample. By 2007Q4, i.e., the last navy-blue curve, the right-end of the distribution is relatively small compared to the beginning of the sample and to the subsequent years. Furthermore, figure 2 shows very clearly that LSAPs distributed liquid funds across the entire banking population as the distributions flatten out and increase a significant mass to the right-end of the distribution (see Ennis & Wolman (2015)). Note also that the dotted vertical line marks the 1% threshold used below to identify our state-dependency regarding cash-liquidity holdings across banks.

[5] Available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/greenbook.
[6] They calculate excess reserves at the bank-level from 2007Q1 until 2016Q4.

Figure 2: **Excess Reserves to Total Assets Densities (1990Q4-2016Q4)**



Note: Navy-blue curves from 1990q4 until 2007q4, and cranberry-red from 2008q4 until 2016q4. The "x" marks denote the mean of each period's distribution. The dotted vertical line marks our baseline threshold for our cash-illiquid state, i.e., 1% of total assets held as excess reserves.

Finally, our full sample starts in 1990Q1 and ends in 2016Q4, and contains close to 250,000 bank-quarter observations.

3 An Informationally-Robust Monetary Policy Instrument

The construction of our monetary policy instrument closely follows that in Miranda-Agrippino & Ricco (2021). We combine the high-frequency identification of Swanson (2021) with the narrative approach in Romer & Romer (2004). This combination ensures that the resulting MPI picks up both market surprises and changes in the monetary policy stance not due to current or anticipated economic conditions.[7] Further controlling for informational rigidities (such as the slow absorption of information) allows Miranda-Agrippino & Ricco (2021) to solve long-standing empirical puzzles in the monetary policy literature. Therefore, we are following the same steps in our construction.[8]

[7]The latter would not facilitate a monetary policy shock since the central bank publishes its economic forecasts a week prior to each scheduled FOMC meeting.

[8]Section 6.5 shows the construction of an additional feature of using a moving average of the raw shocks weighted by the number of days in the month after the shock occurs, see Ottonello & Winberry (2020). This 'smooth time-aggregation' further accounts for the fact that shocks occurring at the end of some given month m may unfold their full impact in the month following, $m+1$. This smoothing procedure is motivated by the fact that the underlying variables of, for example, banks cannot always be quickly and fully adjusted to a monetary policy shock. This goes beyond the above considerations regarding the slow absorption of information.

3.1 Removing Information Effects from High-Frequency Surprises

The procedure involves four steps. In the first step, the high-frequency market based surprises in the fourth federal funds futures (FF4) market around FOMC announcements is projected on the Federal Reserve's Greenbook forecasts and forecast revisions for real output growth, inflation (measured as the GDP deflator) and the unemployment rate. This step is similar to the Romer & Romer (2004) method and controls for the central bank's private information. Thus, in the first step we run the following regression at FOMC-meeting frequency

$$FF4_m = \alpha_0 + \sum_{j=-1}^{3} \theta_j F_m^{cb} x_{q+j} + \sum_{j=-1}^{2} \varphi_j \left[F_m^{cb} x_{q+j} - F_{m-1}^{cb} x_{q+j} \right] + MPI_m^D, \tag{1}$$

where $FF4_m$ denotes the high-frequency market-based surprise around meeting m stemming from Swanson (2021)'s series.[9] Furthermore, $F_m^{cb} x_{q+j}$ denotes Greenbook forecasts for the vector of variables x at horizon $q+j$ that are assembled prior to each meeting, and $\left[F_m^{cb} x_{q+j} - F_{m-1}^{cb} x_{q+j}\right]$ denotes revisions to forecasts between consecutive FOMC meetings. The forecast horizon is expressed in quarters, and q denotes the current quarter of the meeting. The residual of the first step, MPI_m^D, delivers an instrument for monetary policy shocks that reflects changes in the monetary policy stance that cannot be accounted for by the central bank's information set (i.e., vector x), nor the information transfer to market participants (i.e., $FF4_m$).

Next, in the second step, we aggregate all intra-monthly daily MPI_m^D from the previous step to a monthly frequency

$$MPI_t^M = \sum_{i=1}^{I} MPI_{i,t}^D, \tag{2}$$

where $MPI_{i,t}^D$ reflects the i'th FOMC announcement-specific MPI_m^D in month t.

In the third step we further account for the slow absorption of information by economic agents by removing the autoregressive component in the monthly surprises MPI_t^M.[10] In order to do so, we run the following autoregressive setup

$$MPI_t^M = \phi_0 + \sum_{j=1}^{12} \phi_j MPI_{t-j}^M + MPI_t^N. \tag{3}$$

Finally, we construct our monetary policy instrument, MPI_t, by aggregating the residuals of equation (3) to the quarterly frequency.[11] The resulting MPI_t is now orthogonal to both past high-frequency market-based surprises, and to the information set of the central bank. Hence, we obtain an informationally-robust monetary policy instrument, MPI_t.

[9] Swanson (2021)'s method is largely identical to Gürkaynak et al. (2005), extending that analysis with the identification of a third, LSAP, factor.

[10] As mentioned by Miranda-Agrippino & Ricco (2021), this is a trademark of models of imperfect information, see e.g. Coibion & Gorodnichenko (2015).

[11] Note that in non-meeting months both MPI_t^M and MPI_t^N are equal to zero.

3.2 Conventional versus Unconventional Monetary Policy

Our monetary policy instrument covers the period 1992m8-2016m12 and therefore a significant time range covering two different monetary policy regimes. Traditional instruments, such as that of Romer & Romer (2004), cannot be used during the zero-lower bound (ZLB) period. The dependent variable (i.e., the Fed's Federal Funds Rate target) for a narrative identification of conventional monetary policy shocks is, of course, not available at the ZLB.

Because our MPI builds on the three factors identified in Swanson (2021), we can not only overcome these problems (due to the high-frequency identification approach), but also embrace the fact that our analysis covers two monetary policy regimes. Hence, we perform the steps described in section 3.1 for three different MPIs. The first version of our MPI denotes the total policy shock, MPI_t^{tot}, in a given period. The next version covers conventional monetary policy only, denoted by MPI_t^{con} and is constructed using the first factor of the Swanson-series. Finally,

Figure 3: **Informationally-robust Monetary Policy Instruments**

Note: $\mathrm{MPI}^{\mathrm{tot}}$ (blue solid line), $\mathrm{MPI}^{\mathrm{con}}$ (red dashed line) and $\mathrm{MPI}^{\mathrm{ump}}$ (green dash-dotted line), the residuals to equation (3) for each of the three specifications, plotted for the period 1992q3-2016q4.

our last instrument is obtained by using the second and third factors from the Swanson-series. We denote this factor by MPI_t^{ump}, covering unconventional monetary policy stemming both from forward guidance and LSAPs factors. Figure (3) shows the three MPIs at quarterly frequency. Figure B.2 in appendix B plots our MPI against the market-based surprises.

3.3 Assessing the Performance of our Informationally-robust Instruments

Next, we conduct three exercises to assess the performance of our instruments. First, we test for the presence of any remaining information effects. Second, we relate our MPIs to the yield curve, as it is well known from the term-structure literature that the effects of monetary policy do not unfold uniformly along the yield curve. Finally, we compare our MPIs with other monetary policy instruments commonly used in the literature.

3.3.1 The Fed's Information Effect

In order to test for the presence of any remaining information effects we follow the procedure presented in Nakamura & Steinsson (2018). The estimations aim at showing the effect that our identified monetary policy shocks have on the Blue Chip economic forecasts.[12] Accordingly, an informationally-robust identified series should yield as little explanatory power over the changes in the Blue Chip forecasts as possible. Table 1 shows that this is indeed the case for our instruments. The point estimates of all versions of our instruments, i.e., MPI^{tot}, MPI^{con} and MPI^{ump}, are close to zero and their p-values are extremely large (implying almost no explanatory power at all). We therefore conclude that our instruments hold no significant informational content.

Table 1: **Fed's Information Effect**

	1 Year Yield		**EFFR**	
	Coeff.	p-Value	Coeff.	p-Value
MPI (Tot)	0.001 (0.011)	0.926	0.000 (0.001)	0.927
MPI (Conv.)	0.001 (0.009)	0.898	0.000 (0.001)	0.900
MPI (UMP)	-0.007 (0.134)	0.957	0.026 (14.850)	0.999
SW (Tot)	0.011 (0.008)	0.157	0.020 (0.378)	0.957
SW (Conv.)	0.011 (0.007)	0.125	-0.011 (0.098)	0.912
SW (UMP)	-0.011 (0.254)	0.966	0.000 (0.001)	0.962
BRW	-0.005 (0.009)	0.539	-0.001 (0.002)	0.627
Observations	51		51	

Note: Coefficient is the point estimate of the regression coefficient on the instrumented independent variable (1Yr yield or EFFR). Standard errors reported in parentheses. The number of observations is constrained by our access to Blue Chip forecasts (2006m1-2013m8).

For comparison, table 1 also shows the results using both the monetary policy shock series from Bu et al. (2021) as well as the raw Swanson series (total, conventional, UMP). We observe that the Bu et al. (BRW, henceforth) series yields similar results, with negligibly larger absolute values for the point estimates and very large p-values. The Swanson factors yield slightly larger coefficients which are still negligibly small. The corresponding p-values are still large (0.157 for the total Swanson series), but significantly smaller than those for the informationally-robust MPIs or BRW series.[13]

[12] In the interest of space we limit the description of the regression to its intuition, while appendix C shows further details.

[13] Note that the standard errors (and thus corresponding p-values) are not robust. In this very specific case this is the least favorable constellation from the researcher's point of view since non-robust standard errors yield better (i.e., smaller) p-values, but we want 'bad p-values'. Using robust standard errors shows that the Swanson series also yield very high p-values.

With these results in mind we conclude that the procedure proposed by Miranda-Agrippino & Ricco (2021) is successful in removing the information content of FOMC announcements.

3.3.2 An Informationally-Robust MPI and the Yield Curve

We next analyze the effect of our MPI on different constant maturity treasury yields. Our goal is to isolate the effect of an identified monetary policy shock across the yield curve. It is well known that monetary policy does not have a constant effect across the yield curve (see for example Altavilla, Brugnolini, Gürkaynak, Motto & Ragusa (2019)), and that alternative monetary policy tools have a differential effect across the term structure (see Lane (2019) for an overview). For example, conventional measures such as the policy target rate have their major impact on very short maturities (6 months or shorter) and can have effects up to a maximum maturity of one to two years.

Moreover, unconventional policies such as forward guidance unfold their major impact in the middle of the yield curve, that is, the main impact can be found on 5 year (up to 10 year) yields, with little effect on shorter durations, and practically zero effect on very short terms (i.e., less than 6 months). Altavilla et al. (2019) report a zero effect of quantitative easing on durations shorter than 5 years.[14] Since we are able to decompose our MPI into conventional and unconventional policies, we investigate if our instruments can reproduce these regularities reported in the literature.

In order to measure the differential effect of our MPI we regress returns at different maturities on the policy indicator instrumented by our MPIs. Specifically, we employ a 2SLS approach, where the daily changes (around FOMC announcement days) in the constant maturity treasury yields across the yield curve are our dependent variables. As independent variables we use two different policy indicators: In our first setup we instrument the one-year constant maturity treasury yield with our MPIs. In our second setup we instrument the Effective Federal Funds rate (EFFR) with our MPIs. Thus, our estimation model takes the following form

$$\Delta y_{t,t-1} = \alpha_0 + \delta^{IV} \Delta r_{t,t-1} + \varepsilon_t, \tag{4}$$

where $\Delta y_{t,t-1}$ are the different daily changes in constant maturity treasury yields, and where $\Delta r_{t,t-1}$ gives the instrumented change in the one-year treasury rate (or, alternatively, in the EFFR).

The results of the separate estimations of equation (4) can be found in table 2. The effect of our MPI on key treasury yields takes an inverse u-shape with the peak impact on 6-month maturities for either setup (that is, when instrumenting the one-year treasury rate (1.127) or the EFFR (1.690)). The coefficients presented in table 2 represent the change (in basis points) across the yield curve after a positive 100 basis points monetary policy shock. For example, the 3-months coefficient in column 2 implies that the 3-months constant maturity treasury yield will rise by 95.9 basis points. From our second setup (instrumenting the EFFR) we can infer that the impact of the identified monetary policy shocks is not much lower for one-year maturities (149 bps). The effect of the identified shocks remains strong for up to 5-year maturities and falls

[14] However, it may be noteworthy that this result is a function of the QE programs analyzed being implemented at the long end of the yield curve.

down to 16.9 bps for 10-year yields.

As for the individual elements of the total MPI (that is, the MPI^{con} and MPI^{ump}) the conventional MPI is behaving very similarly to the total MPI. The unconventional MPI^{ump}, however, generates very imprecise point estimates both when instrumenting the one-year treasury rate or the EFFR.[15]

Table 2: **Responses of Interest Rates to the Monetary Policy Instrument**

	Instrumenting 1 Year Treasury Rate			**Instrumenting EFFR**		
	MPI (Total)	**MPI (Conv.)**	**MPI (UMP)**	**MPI (Total)**	**MPI (Conv.)**	**MPI (UMP)**
EFFR	0.667	0.536	7.807			
	(0.787)	(0.737)	(15.201)			
3M Treasury Yield	0.959	0.922	2.196	1.438	1.720	0.281
	(0.257)	(0.253)	(2.674)	(1.523)	(2.180)	(0.238)
6M Treasury Yield	1.127	1.104	1.888	1.690	2.059	0.242
	(0.146)	(0.137)	(1.858)	(1.817)	(2.647)	(0.229)
1Y Treasury Yield				1.499	1.865	0.128
				(1.641)	(2.431)	(0.214)
2Y Treasury Yield	0.717	0.741	0.152	1.074	1.382	0.019
	(0.174)	(0.164)	(1.680)	(1.201)	(1.820)	(0.270)
3Y Treasury Yield	0.713	0.751	-0.085	1.069	1.402	-0.011
	(0.171)	(0.164)	(2.047)	(1.207)	(1.855)	(0.299)
5Y Treasury Yield	0.506	0.584	-1.248	0.759	1.090	-0.160
	(0.214)	(0.191)	(3.747)	(0.907)	(1.474)	(0.369)
10Y Treasury Yield	0.169	0.233	-1.125	0.254	0.435	-0.160
	(0.216)	(0.191)	(3.460)	(0.487)	(0.730)	(0.333)

Note: Results of separate 2SLS regressions of the dependent variables (left column) on the instrumented independent variable (columns 2-4: 1Y treasury rate, columns 5-6: EFFR), using the MPI. Robust standard errors in parentheses. Number of observations 176 meetings over the whole sample period.

The results presented in table 2 are in line with those reported by the term-structure literature. We find the strongest effect of the MPI on shorter maturities (three months up to one year) and a slow decline in the impact up to three years. This pattern arises because the relative magnitudes within our total MPI are strongly dominated by the conventional MPI (see figure 3). The same argument also explains why the total MPI has very little impact on longer maturities. The noisy results for the MPI^{ump} do not allow us to draw strong conclusions about this policy dimension of our MPI. All in all, our MPI yields differential effects across the yield curve that are in line with the related literature.

3.3.3 Comparing the Informationally-robust MPI with the Literature

Before turning to our empirical framework, in this section, we compare our MPI with commonly-used alternative instruments for monetary policy shocks. Recently, it has become a common practice to compare new monetary policy shock series with previously existing series. These comparisons intend to provide an assessment of how credible a new method for constructing a shock series is. While at its root our MPI is following the framework developed in Miranda-Agrippino & Ricco (2021), there are two significant differences: First, our underlying high-frequency series is coming from Swanson (2021) as opposed to Gürkaynak et al. (2005), and second, our MPI covers a significantly longer period following the GFC. In table 3 we present the correlations

[15] Note that the exact magnitudes presented in table 2 are also a product of the normalizations performed on the unit-free raw factors coming from Swanson (2021). Because we do not have competing economic arguments to those in Swanson (2021) and our focus of this section was to better understand the differential effect of our MPI across different maturities (that is, the term-structure of monetary policy), we do not further normalize our MPI.

between our MPI and several popular shock series currently in use in the macro literature. We present this comparison for both the maximum possible overlap between the MPI and any other series, and for the zero lower bound (ZLB) period.

Table 3: **Correlations of our MPIs with Other Shock Series**

	MPI (Total)		**MPI (Conv.)**		**MPI (UMP)**		
	Full	ZLB	Full	ZLB	Full	ZLB	Common Period
MPI MA-R	0.818	0.674	0.828	0.610	0.037	0.217	1992m8 - 2009m12
Swanson (Total)	0.915	0.695	0.891	0.626	0.209	0.290	1992m8 - 2016m12
FF4GK	0.502	0.356	0.485	0.368	0.154	0.058	1992m8 - 2012m6
MPS GSS	0.786	0.662	0.803	0.704	0.017	-0.047	1992m8 - 2012m6
BRW	0.221	0.171	0.228	0.183	-0.001	-0.004	1994m2 - 2016m12
NS 95	0.688	0.478	0.704	0.497	0.006	-0.003	1995m2 - 2014m3
NS FFR 95	0.839	0.579	0.852	0.586	0.013	-0.007	1995m2 - 2014m3
MPI (Total)	1	1					1992m8 - 2016m12
MPI (Conv.)	0.978	0.934	1	1			1992m8 - 2016m12
MPI (UMP)	0.219	0.339	0.016	-0.007	1	1	1992m8 - 2016m12

Note: **MPI MA-R** (Miranda-Agrippino & Ricco (2021)), **Swanson** (Total) (Swanson (2021)), **FF4GK** (Gertler & Karadi (2015)), **MPS GSS** (Gürkaynak et al. (2005), extended series from the authors), **BRW** (Bu et al. (2021)), **NS 95** (Nakamura & Steinsson (2018)), **NS FFR 95** (first factor of Nakamura & Steinsson (2018)). Common Period refers to the maximum overlapping period (ZLB period starting in 2008m7).

Table 3 shows very high positive correlations of our total MPI with all other shock series. By means of construction, we find the strongest values for the MPI coming from Miranda-Agrippino & Ricco (2021) as well as the high-frequency identified series from Swanson (2021). The lowest correlation is the one associated with the series from Bu et al. (2021), which also deviates the strongest in its construction from most other series presented in table 3.[16] As for the zero lower bound sub-sample, we find that the MPI retains the strong values found for the full sample overlaps.

Throughout this section we showed that our informationally-robust instruments are indeed free of any information effect, have the expected influence on the yield curve, and are similar to alternative shock series over the common time period. In the following section, we describe our empirical framework, where we employ our informationally-robust MPIs to account for exogenous monetary policy shocks and their effects on banks' balance-sheet items.

4 Local Projections Instrumental Variables Models

For our analysis we are mostly interested in the reactions of key balance-sheet variables that are related to the bank-lending channel. Hence, we obtain the dynamic responses by estimating Local Projections Instrumental Variables (LP-IV) models using our panel of U.S. banks described in section 2. Recall that the broad interpretation of the bank-lending channel predicts that a contractionary monetary policy shock leads to a decline in bank lending. Hence, we are interested

[16] All shock series presented in the table are relying (in part or completely) on high-frequency identified market surprises (that is, typically, using a principal components analysis of changes in 30-minute windows around FOMC announcements). The Bu et al. (2021) series, in contrast, uses a Fama-MacBeth two-step procedure which combines cross-sectional and time-series estimates over the whole yield curve at daily frequency.

in the response of total loans and it's three main components, i.e., commercial and industrial loans (C&I loans, henceforth), real estate loans and consumer loans. Additional assets of interest are bank-level liquid securities and total assets. On the liability-side of the balance sheet we are interested in total deposits and total capital. All variables are deflated by the CPI.

4.1 Linear Model

The baseline LP-IV model we estimate is a simple linear model. In particular, the dynamic average cumulative response of the variable of interest z_t at horizon h is computed by estimating the following panel regression

$$z_{i,t+h} - z_{i,t-1} = \alpha_{i,h} + \beta_h^{IV} \Delta r_t + \sum_{\ell=1}^{L} \Gamma_{h,\ell} X_{i,t-\ell} + \mu_{j,h} + \gamma_h t + \varepsilon_{i,t+h}, \tag{5}$$

for $h = 0, 1, ..., H$ and where Δr_t denotes the change in the monetary policy indicator, which is instrumented by our MPIs.[17] In our baseline specification our policy indicator is the Effective Federal Funds Rate (EFFR, henceforth).[18] The coefficients $\{\beta_h^{IV}\}_{h=0}^{H}$ trace out the response of the dependent variable z_t to a +100 bp monetary policy shock.

Moreover, coefficient $\alpha_{i,h}$ stands for bank fixed effects (hence, i for the cross-section), $\mu_{j,h}$ are fixed effects for any region j, and t is a time trend. The vector $X_{i,t}$ contains additional bank-level and macroeconomic controls. The bank-level controls include four lags of banks' capitalization ratio, securities to total assets ratio, and four lags of the dependent variable. The macroeconomic controls are four lags of our MPI, GDP growth, industrial production log-differences and the unemployment rate.

The inclusion of $L = 4$ lags in equation (5) increases the number of covariates significantly, and raises the computational costs of estimating our models. However, the advantage of including sufficient lags is that it simplifies the standard errors calculation, as shown in Montiel Olea & Plagborg-Møller (2021). This so-called lag-augmented LP setting simplifies the computation of standard errors (clustered at the bank level throughout this paper) since we only have to consider the usual Eicker-Huber-White heteroskedasticity-robust standard errors instead of using Driscoll-Kraay standard errors which account both for cross-sectional and autocorrelation dependance in a panel setting (see Montiel Olea & Plagborg-Møller (2021)).

4.2 State-Dependent Model

The linear model presented in equation (5) allows us to identify the average effect of a monetary policy shock on our variables of interest. In order to assess whether bank liquidity plays a role in the transmission of monetary policy, we now develop a state-dependent model.

Banks' individual level of excess reserves determines our two states for cash-liquid and cash-illiquid banks. Let $\mathbb{1}_t = 1$ if a bank holds excess reserves at or below 1% of their total assets in period t, and $\mathbb{1}_t = 0$ otherwise. In other words, $\mathbb{1}_t$ is our illiquid state indicator. Similar to the linear model, we estimate the dynamic average cumulative responses in the following

[17] For more details on our IV (2SLS) estimation approach see section 4.3 below.

[18] As a robustness we have used the 1 year treasury rate, see section 6.

state-dependent model[19]

$$z_{i,t+h}-z_{i,t-1} = \alpha^R_{i,h} + \beta^{R,IV}_h \Delta r_t + \sum_{\ell=1}^{L} \Gamma^R_{h,\ell} X_{i,t-\ell} + \mu^R_{j,h} + \gamma^R_h t + \dots$$
$$\dots + \mathbb{1}_{t-1}\left[\alpha^B_{i,h} + \beta^{B,IV}_h \Delta r_t + \sum_{\ell=1}^{L} \Gamma^B_{h,\ell} X_{i,t-\ell} + \mu^B_{j,h} + \gamma^B_h t\right] + \varepsilon_{i,t+h}, \qquad (6)$$

for $h = 0, 1, ..., H$, and where coefficients $\{\beta^{R,IV}_h\}^H_{h=0}$ and $\{\beta^{R,IV}_h + \beta^{B,IV}_h\}^H_{h=0}$ trace out the response of the dependent variable, z_t, to a +100 bp monetary policy shock in the liquid and illiquid states, respectively. All other covariates are identical to the ones described in our linear model (see the description around equation (5) above).

4.2.1 Expansionary vs. Contractionary Shocks

In addition to our baseline state-dependent model presented above we specify a model with an additional source of non-linearities. Specifically, we will use the following state-dependent model to distinguish the effects of expansionary and contractionary shocks

$$z_{i,t+h}-z_{i,t-1} = \alpha^R_{i,h} + \beta^{R,IV}_h \Delta r_t + \lambda^{R,IV}_h \Delta r_t \cdot hike_t + \sum_{\ell=1}^{L} \Gamma^R_{h,\ell} X_{i,t-\ell} + \mu^R_{j,h} + \gamma^R_h t + \dots$$
$$\dots + \mathbb{1}_{t-1}\left[\alpha^B_{i,h} + \beta^{B,IV}_h \Delta r_t + \lambda^{B,IV}_h \Delta r_t \cdot hike_t + \sum_{\ell=1}^{L} \Gamma^B_{h,\ell} X_{i,t-\ell} + \mu^B_{j,h} + \gamma^B_h t\right] + \varepsilon_{i,t+h}, \qquad (7)$$

for $h = 0, 1, ..., H$ and where, as before, Δr_t denotes the change in the policy indicator, which is instrumented by MPI_t, and where $hike_t$ is a dummy that takes the value 1 for policy rate hikes, i.e., contractionary monetary policy shocks, and 0 otherwise.[20]

Thus, to estimate our cumulative impulse response functions in this setting there are four relevant cases to keep track of depending on the combination of the liquidity state and the nature of the policy shock:

- Expansionary Shock & Liquid State: $\{\beta^{R,IV}_h\}^H_{h=0}$
- Contractionary Shock & Liquid State: $\{\beta^{R,IV}_h + \lambda^{R,IV}_h\}^H_{h=0}$
- Expansionary Shock & Illiquid State: $\{\beta^{R,IV}_h + \beta^{B,IV}_h\}^H_{h=0}$
- Contractionary Shock & Illiquid State: $\{\beta^{R,IV}_h + \beta^{B,IV}_h + \lambda^{R,IV}_h + \lambda^{B,IV}_h\}^H_{h=0}$

Finally, note that we can also extend our linear model presented in equation (5) to analyze whether banks responses are symmetrical to policy hikes and cuts by setting our illiquidity indicator $\mathbb{1}_t = 0$ for all observations in equation (7). In other words, we can investigate whether

[19] Note that we use the superscript "R" for the covariates associated with the responses of cash-liquid banks which are plotted with Red (solid) lines in the figures below. Similarly, the superscript "B" is chosen since the responses from the illiquid state are depicted using Blue (dashed) lines in the figures below.

[20] For a similar setting see, among others, Schularick, ter Steege & Ward (2021).

banks' responses are symmetrical by estimating the following sequence of LPs

$$z_{i,t+h} - z_{i,t-1} = \alpha_{i,h}^{R} + \beta_h^{R,IV} \Delta r_t + \lambda_h^{R,IV} \Delta r_t \cdot hike_t + \sum_{\ell=1}^{L} \Gamma_{h,\ell}^{R} X_{i,t-\ell} + \mu_{j,h}^{R} + \gamma_h^{R} t + \varepsilon_{i,t+h}, \quad (8)$$

for $h = 0, 1, ..., H$, and where all the variables are identical to the ones defined above.

In this setting there are only two relevant cases to keep track of to calculate cumulative impulse responses. First, the reaction after an expansionary shock is given by $\{\beta_h^{R,IV}\}_{h=0}^{H}$, and second, the response after a contractionary shock is obtained by $\{\beta_h^{R,IV} + \lambda_h^{R,IV}\}_{h=0}^{H}$.

4.3 First-Stage Regressions

In order to estimate models (5)-(8) we employ an IV (2SLS) estimation approach. These four equations present the second-stage of this two-step estimation procedure, which rely on the first-stage regressing the change in our policy indicator, Δr_t, on our informationally-robust policy instrument, MPI_t, developed in section 3.1 above. Thus, the first-stage regression necessary to

Table 4: **All Variables First-Stage Estimation Results, Pre-GFC Sample**

	Total Loans	Cons. Loans	RE Loans	C&I Loans	Liquid Securities	Deposits	Total Capital	Total Assets
MPI (Total)	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.MPI (Total)	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.log(Dependent Variable/CPI)	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Δ log(GDP/CPI)	-0.016***	-0.017***	-0.017***	-0.016***	-0.017***	-0.016***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Δ Unemployment	-0.622***	-0.622***	-0.622***	-0.621***	-0.622***	-0.622***	-0.621***	-0.622***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.Δ log(Industrial Production)	0.098***	0.099***	0.098***	0.099***	0.098***	0.098***	0.098***	0.098***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Δ log(Total Capital/Total Assets)	-0.286***	-0.206**	-0.381***	-0.368***	-0.266***	-0.422***	0.366***	-0.398***
	(0.072)	(0.083)	(0.072)	(0.082)	(0.066)	(0.079)	(0.097)	(0.075)
L.Δ log(Securities/Total Assets)	-0.263***	-0.221***	-0.241***	-0.230***	-0.024	-0.162***	-0.161***	-0.140***
	(0.022)	(0.021)	(0.021)	(0.022)	(0.029)	(0.020)	(0.019)	(0.020)
Time Trend	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Regional Dummies (b)	0.057	0.054	0.062	0.051	0.056	0.059	0.060	0.059
	(0.046)	(0.047)	(0.049)	(0.045)	(0.045)	(0.046)	(0.047)	(0.047)
Regional Dummies (c)	0.095**	0.091**	0.095**	0.092**	0.092**	0.098**	0.097**	0.096**
	(0.043)	(0.042)	(0.046)	(0.042)	(0.042)	(0.043)	(0.045)	(0.044)
Regional Dummies (d)	0.097*	0.096*	0.100*	0.092	0.095*	0.099*	0.098*	0.097*
	(0.057)	(0.057)	(0.059)	(0.057)	(0.057)	(0.057)	(0.058)	(0.058)
Observations	112772	111684	111776	109499	112707	112772	112772	112772
Number of Firms	4756	4724	4724	4663	4754	4756	4756	4756

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Selected first-stage estimates at horizon $h = 0$ using our linear model given in equation (5). Note that the dependent variable is always the change in the EFFR, i.e., our policy indicator Δr_t. Each column title gives the short-hand name of our dependent variable from the second-stage regression. For example, the first column title "Total Loans" stands for the log of (real) total loans.

instrument the policy indicator with our monetary policy instrument is given by

$$\Delta r_t = \alpha_i + \eta MPI_t + \sum_{\ell=1}^{L} \Gamma_\ell X_{i,t-\ell} + \mu_j + \gamma t + \epsilon_{i,t}, \quad (9)$$

where the vector $X_{i,t}$ contains the same additional bank-level and macroeconomic controls as before, and where coefficient α_i stands for bank fixed effects, μ_j are fixed effects for any region j, and t is a time trend. Since we include the lag values from our second-stage dependent variable, $z_{t-\ell}$, in the vector of controls, $X_{i,t}$, the results from the first-stage regression are slightly different across our variables of interest.

Table 4 provides some selected estimates from the first-stage regression in our pre-GFC sample at horizon $h = 0$.[21] Similarly, table 5 shows our full sample, first-stage estimates at horizon $h = 0$ for the case where total loans is the dependent variable in the second-stage, z_t, across our four models presented in equations (5)-(8).

Table 5: **Total Loans' First-Stage Estimation Results, Full Sample**

	Linear Model	Linear HvC Model	State-Dep. Model	State-Dep. HvC Model
MPI (Total)	0.017***	0.025***	0.015***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
L.MPI (Total)	0.006***	0.006***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Δ log(Total Loans/CPI)	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Δ log(GDP/CPI)	-0.032***	-0.023***	-0.008***	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
L.Δ Unemployment	-0.243***	-0.240***	-0.141***	-0.147***
	(0.003)	(0.002)	(0.005)	(0.005)
L.Δ log(Industrial Production)	0.143***	0.137***	0.133***	0.130***
	(0.000)	(0.000)	(0.001)	(0.001)
L.Δ log(Total Capital/Total Assets)	-0.289***	-0.263***	-0.074	-0.067
	(0.074)	(0.074)	(0.100)	(0.103)
L.Δ log(Securities/Total Assets)	-0.196***	-0.217***	0.039	0.030
	(0.023)	(0.023)	(0.039)	(0.038)
Time Trend	-0.001***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Regional Dummies (b)	0.052	0.051	0.053	0.052
	(0.038)	(0.036)	(0.037)	(0.035)
Regional Dummies (c)	0.083***	0.078***	0.082***	0.078***
	(0.027)	(0.026)	(0.027)	(0.027)
Regional Dummies (d)	0.096**	0.089**	0.079*	0.075*
	(0.040)	(0.038)	(0.041)	(0.040)
Observations	177931	177931	177931	177931
Number of Firms	5721	5721	5721	5721

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Note: Selected first-stage estimates at horizon $h = 0$ for z_t = log of (real) total loans. Note that the dependent variable is always the change in the EFFR, i.e., our policy indicator Δr_t. Each column represent one of the four models presented in section 4, where "HvC" stands for hikes vs. cuts, i.e., the models describe in section 4.2.1.

Across all first-stage regressions depicted in tables 4 and 5 our instrument, i.e., the first-row coefficients, has a positive and statistically significant value. Thus, our instrument fulfills the standard IV relevance condition.

Moreover, an appropriate instrument in a LP-IV setting needs to fulfill two additional requirements besides the relevance condition (see Stock & Watson (2018)). First, our instrument should

[21] Note that this table omits the estimates for the majority of control lags for brevity. Table D.1 in the appendix provide the full set of results for the pre-GFC sample, and table D.2 does the same for our full sample results.

be orthogonal to all other concurrent structural shocks, i.e., it must fulfil the contemporaneous exogeneity condition. In our setting this condition holds because of several reasons. First, our instruments are based on the high-frequency market surprises and on the identification procedure from Swanson (2021). The narrow time-window around FOMC announcements used in Swanson (2021) implies that these high-frequency surprises are uncorrelated to any further structural shocks, and therefore avoids the endogeneity problem of monetary policy. Second, by removing information effects (see section 3.1), and by controlling for macroeconomic and bank-level conditions in our first-stage regressions, we can be confident that the contemporaneous exogeneity condition is also fulfilled.

Finally, an appropriate instrument should also adhere to the lead-lag exogeneity condition. This is an additional condition to the standard exogeneity and relevance conditions in an IV estimation common in many microeconometric applications that arises from the dynamics of the LP-IV models introduced above. Concretely, the lead-lag exogeneity condition states that an appropriate instrument must be uncorrelated with all shocks at all leads and lags (see Stock & Watson (2018)). Following Stock & Watson (2018) and Montiel Olea & Plagborg-Møller (2021) we include a large set of macroeconomic and bank-level controls that not only improve estimator efficiency by reducing the variance of the regression error, but also maximizes the probability that the lead-lag exogeneity condition is fulfilled in our application. In fact, this is our motivation to include lags of our instrument in our vector of controls $X_{i,t}$.

5 Results

In this section we present dynamic responses to an unexpected contractionary monetary policy shock estimated using the linear and non-linear models presented in the previous section. Recall that the broad interpretation of the bank-lending channel suggests that such a shock is equivalent to a negative funding shock from the perspectives of the commercial banks, and thus, that banks will reduce their lending after such a unexpected monetary tightening. We therefore focus on total lending and the three main lending categories, i.e., consumer, real estate and C&I loans.

As a starting point we first present the results for the pre-GFC sample, which allows us to compare our estimates with previous studies using exclusively data up to the crisis. Next, we describe our full sample estimates, and conclude this section by looking into the effect of the information channel on banks' responses to monetary policy shocks.[22]

5.1 Pre-GFC Estimates

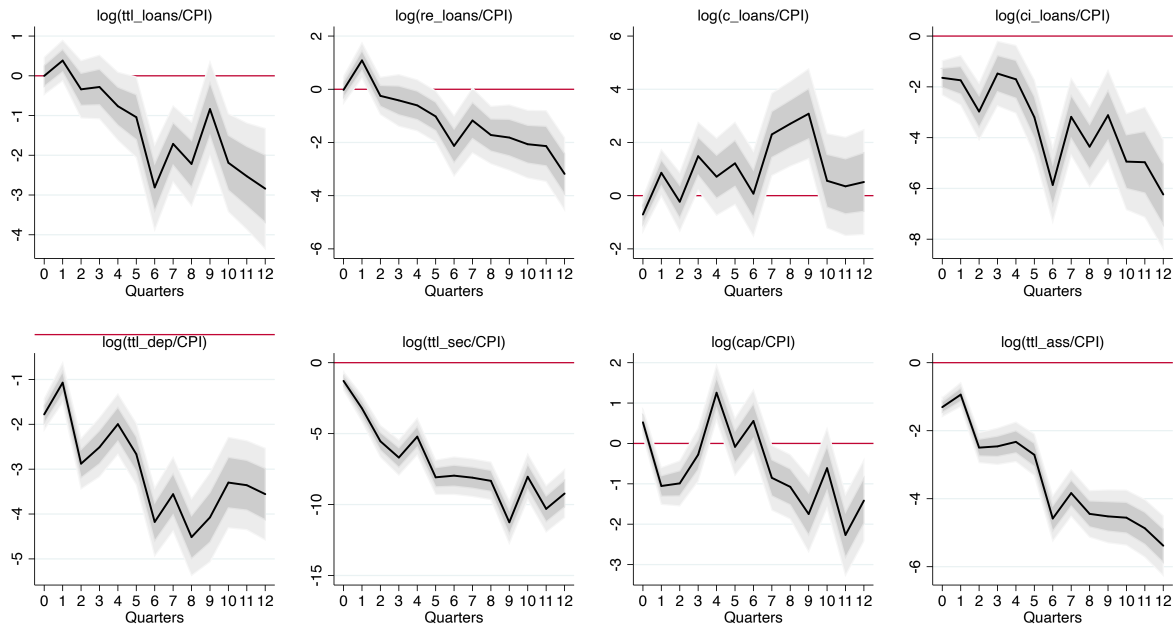
For the pre-GFC sub-sample (1990Q1-2007Q4) the linear model provides supporting evidence for an active bank-lending channel, as can be seen in figure 4. The top row depicts the cumulative responses of total, consumer, real estate and C&I loans after a 100bp contractionary shock (in percent), while the second row shows the responses (also in percent) of total assets, securities, deposits and capital.

[22]Due to data limitations on excess reserves, as well as the Greenbook data, we are unable to estimate our baseline state-dependent models using only post-GFC data. However, section 6.7 shows the results of our linear model using the shock series from Bu et al. (2021).

As the bank-lending channel predicts, after a contractionary shock, total loans show a cumulative fall of 3% after 12 quarters, while total deposits have a slightly larger fall. The response of consumer loans remains insignificant for most of the impulse horizon, which indicates that C&I and real estate loans are the main drivers of the reduction in total loans. The lower panels also show that total capital oscillates initially around zero before falling significantly after two years from the initial shock. On the other hand, securities and total assets fall rapidly and in a persistent way.

The fact that our results support an active bank-lending channel prior to the GFC contrasts with the findings by Carpenter & Demiralp (2012). However, in Carpenter & Demiralp (2012) monetary policy shocks are identified via Choleski ordering. Hence, we consider that our informationally-robust MPIs allows us to disentangle any information effects behind the results in Carpenter & Demiralp (2012) and to overcome the strong implications such an ordering imposes on the results.[23]

Figure 4: **Active Bank-lending Channel, Pre-GFC Sample**



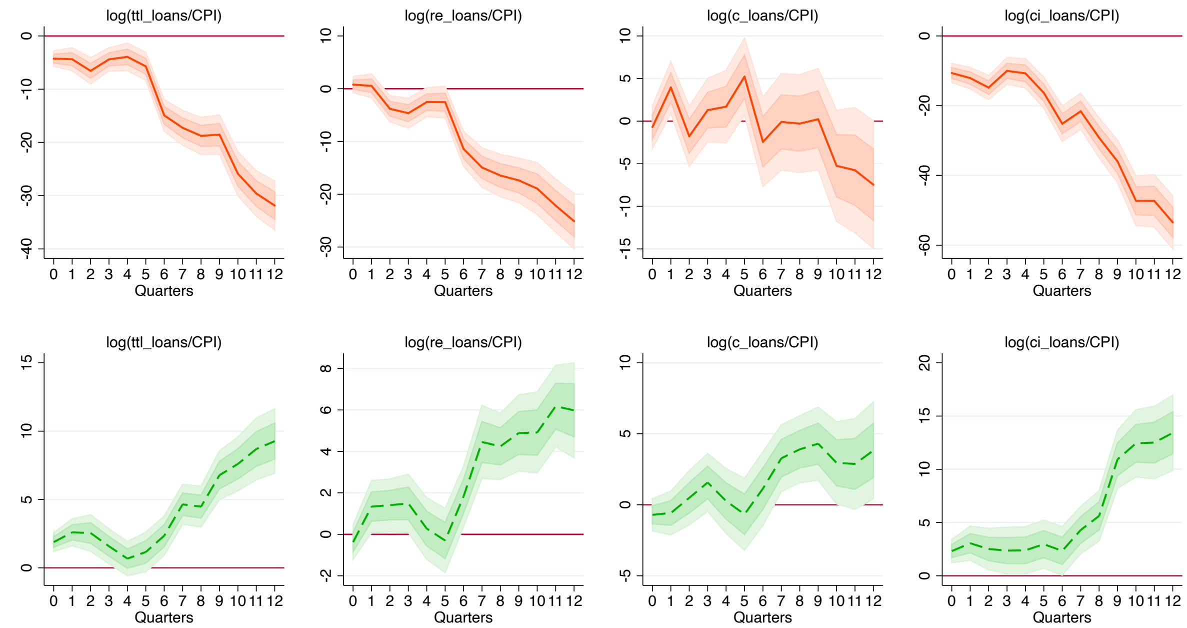
Note: Cumulative responses (in %) to a +100bp monetary shock in the pre-GFC sample (1990Q1-2007Q4). Dark-gray and light-gray shaded areas are 65% and 90% confidence bands, respectively.

Estimating banks' lending reaction to expansionary and contractionary shocks suggest that until the end of 2007, monetary policy shocks had a symmetric effect. Figure 5 depicts the responses of our four lending indicators to both a 100 bp contractionary shock (first row, with red solid point estimate lines) and a 100 bp expansionary shock (second row, with green dashed point estimate lines).

Comparing the two rows in figure 5 implies that banks respond less strongly to expansionary shocks than to contractionary shocks of the same magnitude. For example, the bottom-left panel suggest that three years after the monetary shock, banks total loans increase by approximatley 9%, while at the same horizon after a monetary contraction of 100 bp bank lending falls by 30%.

[23]Note that the drop in banks' securities is in line with the results in Miranda-Agrippino & Ricco (2021).

Figure 5: **Symmetric Bank Responses, Pre-GFC Sample**



Note: Cumulative responses (in %) to a contractionary (1st row) & an expansionary (2nd row) 100bp monetary shock, in the pre-GFC sample (1990Q1-2007Q4). Dark and light shaded areas are 65% and 90% confidence bands, respectively.

The individual components of total loans behave in a similar fashion.

Figure 6 plots the estimates of the model that takes into account both the cash-liquidity and the direction of the shock state dependencies presented in equation (7) for the pre-GFC period. Looking at the results, we are able to identify homogeneous and symmetric bank responses. In other words, before the financial crisis and the current monetary regime of ample liquidity, banks with excess reserves (i.e., those with ample liquidity) reduced (increased) their credit supply in similar fashion to illiquid banks after a contractionary (expansionary) shock.[24]

All in all, the pre-crisis results from the linear and state-dependent models show not only that banks' reactions to monetary policy shocks are, in general, independent of their liquidity levels, but also that the (broad) bank-lending channel was active until the eve of the financial crisis.

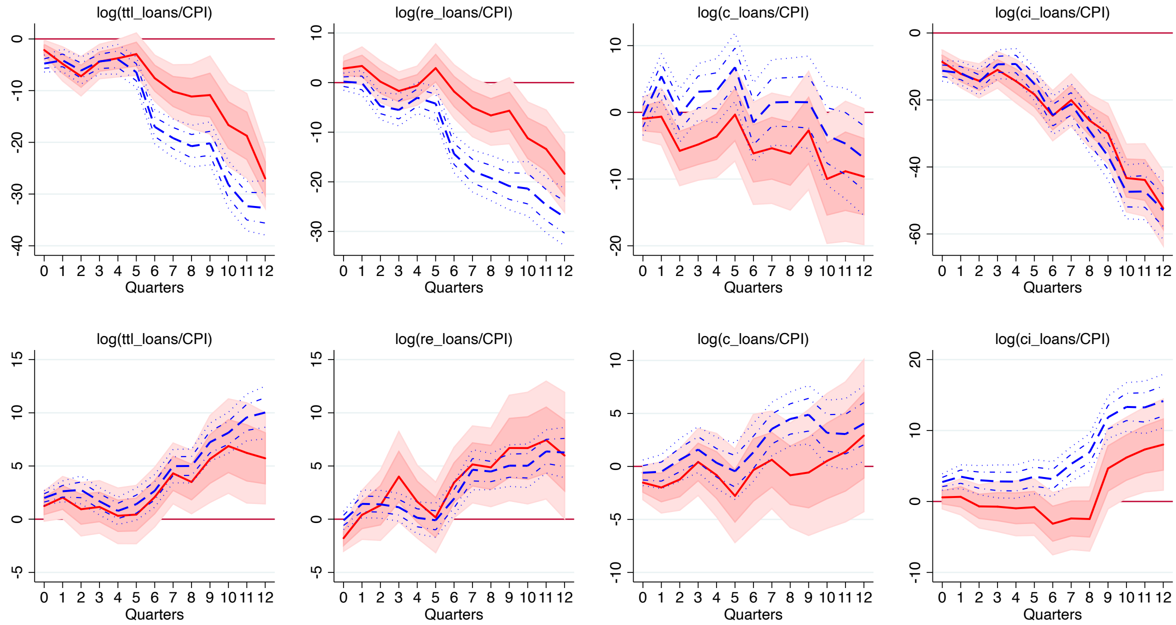
5.2 Full Sample Estimates

The results in this section are based on our full sample, which starts in 1990Q1, includes the GFC and the period until 2016Q4. In contrast to the pre-GFC results, the full sample estimates indicate that the bank-lending channel in the U.S. is inactive.

Figure 7 is the full sample analog of figure 4, i.e., it presents the same eight panels for the linear model. The figure shows that the bank-lending channel is clearly inactive. Including periods of significant excess liquidity in the banking system causes total loans to exhibit a steady cumulative *increase* in reaction to a contractionary monetary policy shock, peaking at around 4% after 9 quarters.

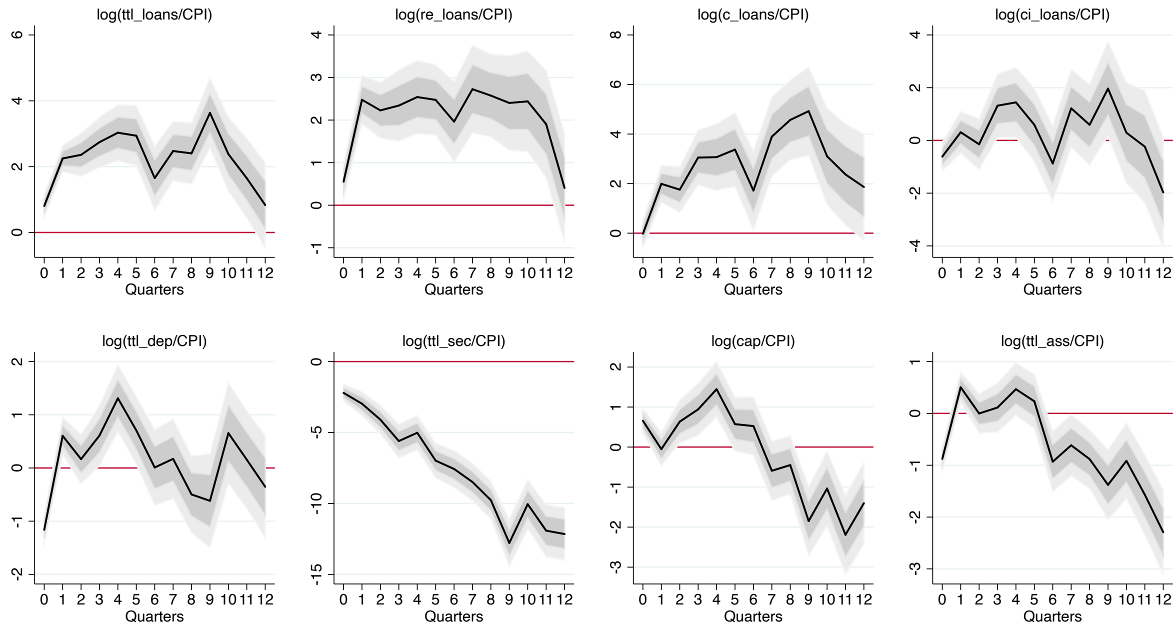
[24]Figure D.3 in the appendix depicts the results from the state-dependent model introduced in equation (6), focusing only on the liquidity state dependency. These results also suggest that before the GFC banks' responses were homogeneous.

Figure 6: **Homogeneous and Symmetric Bank Responses, Pre-GFC Sample**



Note: Cumulative responses (in %) to a contractionary (1st row) & an expansionary (2nd row) 100bp monetary shock, in the pre-GFC sample (1990Q1-2007Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure 7: **Inactive Bank-lending Channel, Full Sample**



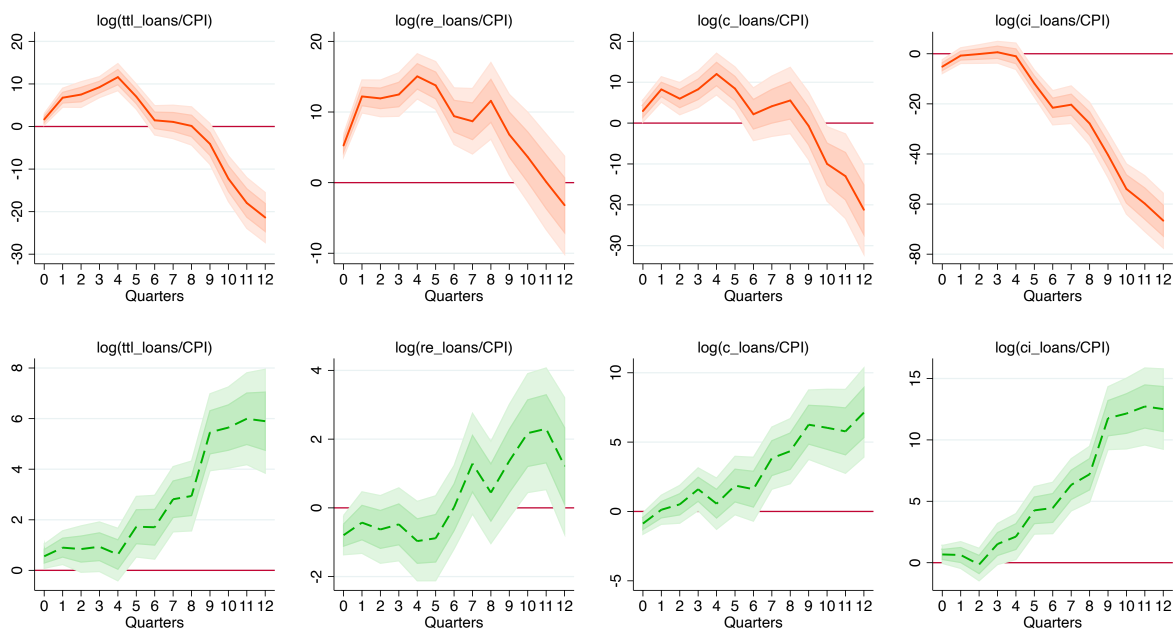
Note: Cumulative responses (in %) to a +100bp monetary shock in the full sample (1990Q1-2016Q4). Dark-gray and light-gray shaded areas are 65% and 90% confidence bands, respectively.

Moreover, total deposits do not fall after a contractionary shock anymore, but rather move around zero, while total capital increases by one percent after one year and then declines to -2% after eleven quarters. Banks' total securities show a clear and relatively strong decline. This is in line with what Miranda-Agrippino & Ricco (2021) find in reaction to a monetary contraction.

What is driving this counter-intuitive response of total loans? From the top panels it is evident that real estate and consumer loans are behind the total loans increase. Meanwhile, C&I loans remain unchanged for the first three years after the policy shock and decline to -2% after 12 quarters. A similar but smaller delayed decrease is also present in real estate loans, and thus, total loans decline, to a lesser extend, at the end of the projected horizon.

Figure 8 suggest that, in contrast to our pre-GFC analysis, in our full sample U.S. commercial banks respond asymmetrically to monetary policy shocks. Specifically, consumer and real estate loans, and consequently total loans, increase in the first six quarters after a tightening shock. On the other hand, C&I loans still behave as in the pre-GFC sample and as the bank-lending channel would predict, since it remains close to zero for the first year and then declines rapidly towards the end of the projected horizon.

Figure 8: **Asymmetric Bank Responses, Full Sample**

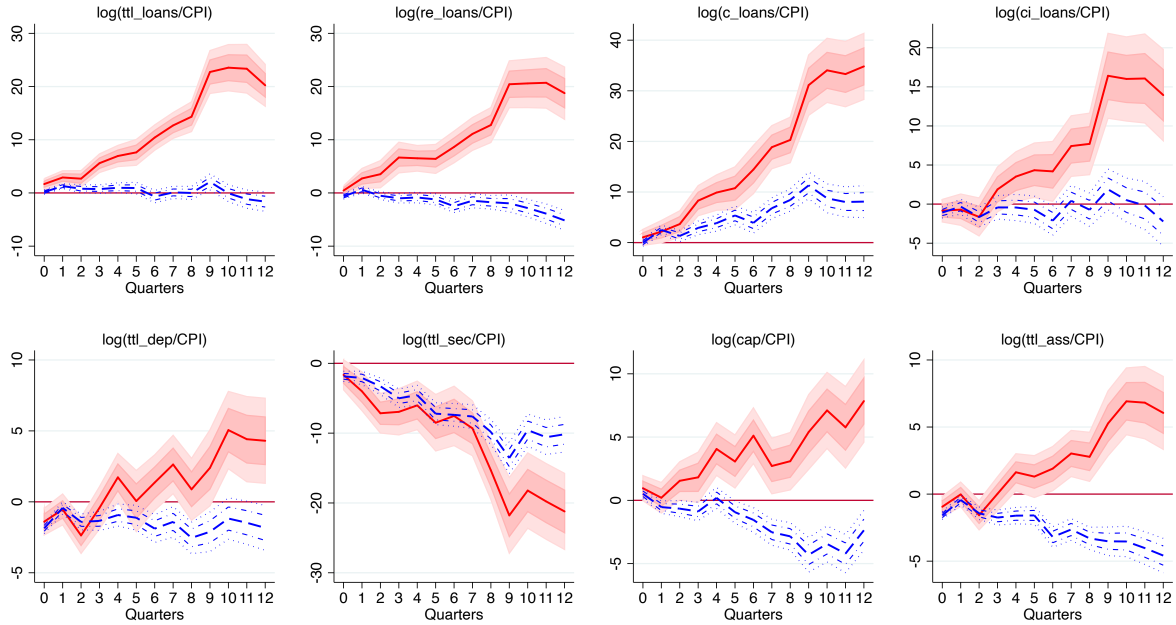


Note: Cumulative responses (in %) to a contractionary (1st row) & an expansionary (2nd row) 100bp monetary shock, in the full sample (1990Q1-2016Q4). Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Expansionary shocks, in contrast, are followed by an increase in total lending, driven by increases in consumer and C&I loans. Moreover, real estate loans fall on impact, and the point estimates for the first five quarters are negative but statistically insignificant. Hence, and in contrast to the pre-GFC estimates in figure 5, real estate loans' responses to both types of shocks seems to be at odds with the prediction of the bank-lending channel.

Turning to figure 9, we identify heterogeneous bank responses using the results from the state-dependent model for the full sample. The top-left panel shows that after a contractionary shock, liquid banks react with a cumulative 20 percent increase in their credit supply after three years, while illiquid banks show a largely muted response.

Figure 9: **Heterogeneous Bank Responses, Full Sample**



Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Moreover, total deposits and total capital decrease now only for the illiquid banks. In contrast, liquid banks see an increase in both types of liabilities. Note also that while in both states banks significantly reduce their securities portfolio, liquid banks are able to increase their total assets, i.e., they are not just substituting liquid securities for loans. On the other hand, illiquid banks reduce their securities in favor of an increase in consumer loans.

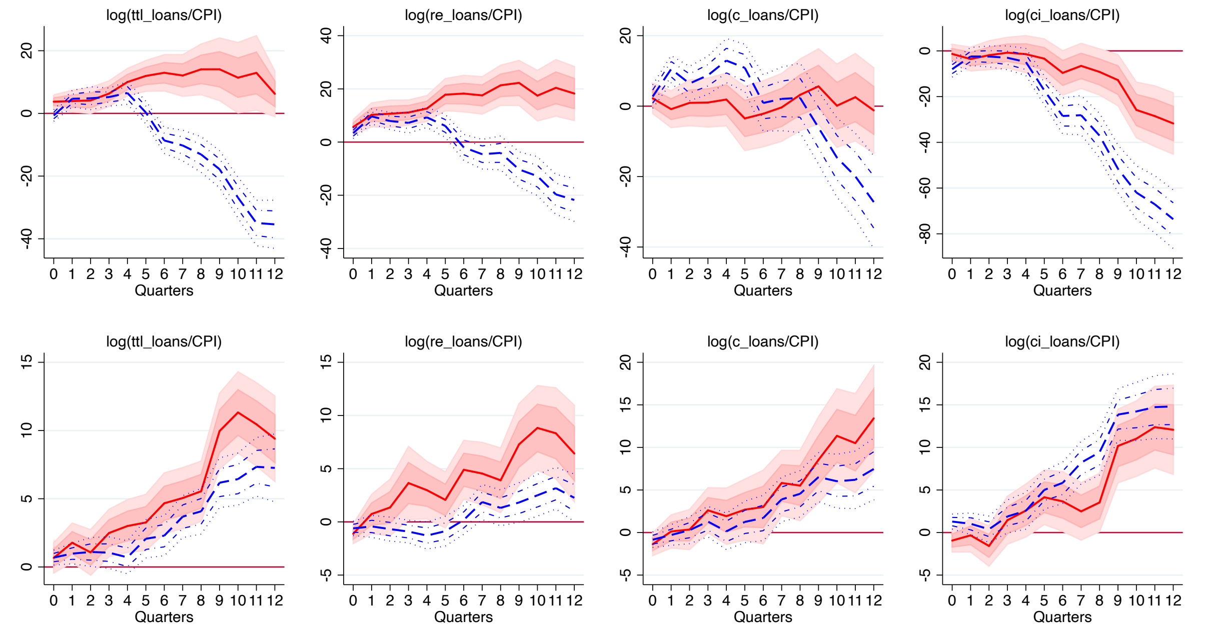
Finally, figure 10 depicts the results from our model given by equation (7) that takes both state dependencies into account. The symmetry of responses to contractionary and expansionary monetary policy shocks suggests that at least for the illiquid banks the bank-lending channel is still active. For example, total lending from illiquid banks increases slightly for the first four quarters after a tightening shock before falling rapidly to an almost 40% cumulative reduction after 12 quarters. Nevertheless, liquid banks responses in figure 10 still suggests that over the full sample the bank-lending channel is inactive as both real estate and total loans increase after a policy contraction.

Our full sample results are in stark contrast with the estimates prior to the financial crisis. Not only do we now identify a systematic difference between the responses of illiquid and liquid banks, but we also show that the bank-lending channel is inactive for liquid banks since the on-set of the GFC.

5.3 The Information Effect of Monetary Policy on U.S. Banks

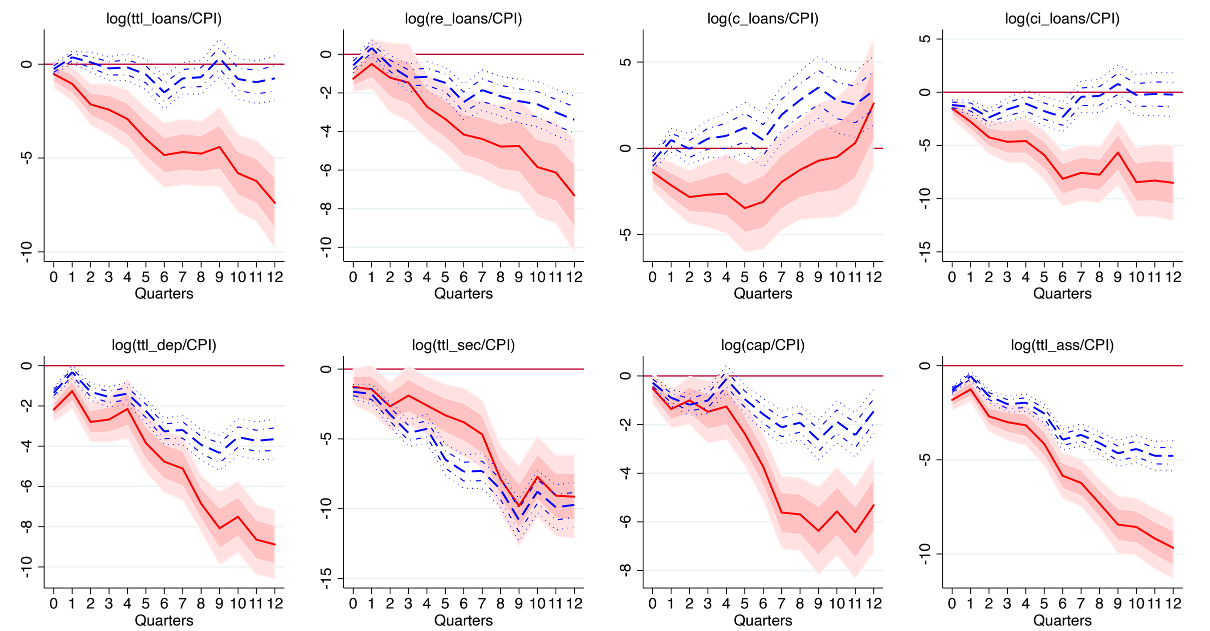
In order to highlight the importance of accounting for the informational effect contained in high-frequency identified shock series we now reproduce our full sample estimates of the state-dependent model using the sum of the three factors identified by Swanson (2021).

Figure 10: **Heterogeneous and Asymmetric Bank Responses, Full Sample**



Note: Cumulative responses (in %) to a contractionary (1st row) & an expansionary (2nd row) 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure 11: **Information Effect (Raw High-frequency Surprises), Full Sample**



Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure 11 provides impulse responses for the full sample using the raw shock series from Swanson (2021) rather than the informationally-robust instruments developed in section 3.[25] In contrast to the results of our baseline state-dependent model, depicted in figure 9, figure 11 suggests that not taking into account the information effect of monetary policy generates qualitatively different responses, primarily for liquid banks. Concretely, liquid banks' total loans, deposits and capital now decline after a monetary contraction, i.e., they all show the opposite sign of what we obtain using our informationally-robust instruments.[26]

Focusing on the main components of total loans we see that real estate and C&I loans fall by around 5% after two years. However, once we control for the informational effects we see that C&I loans do not react significantly and that real state loans actually increase for liquid banks driving the total loans expansion in the liquid state (see figure 9).

Moreover, the responses of total lending using the raw high-frequency surprises from both liquidity states is still at odds with the broad interpretation of the bank-lending channel. The reason is that if this channel were active we should expect illiquid banks to reduce their lending more strongly than liquid banks since the latter could potentially use their excess liquidity to dampen the negative funding shock implied by the monetary contraction. On the other hand, our baseline results are in line with the predictions of this transmission mechanism of monetary policy as illiquid banks reduce their lending after a tightening shock (see figure 8).

Hence, if we do not take into account the information effect of monetary policy on banks' lending variables, especially real estate loans, one might consider that the bank-lending channel was not affected by the GFC and the resulting changes in liquidity levels in the commercial banking system. However, taking this effect into consideration, i.e., using our informationally-robust MPIs, demonstrates that monetary shocks affect bank lending for illiquid banks just as the bank-lending channel predicts, and in a counter-intuitive way for cash-liquid banks.

In what follows we document a battery of robustness tests to our baseline estimation results presented so far.

6 Robustness and Extensions

In this section we check the sensitivity of our baseline results (see section 5) in multiple dimensions, and in addition, we present two extensions. First, we show that our baseline estimates are robust when analyzing conventional and unconventional shocks separately, and to different liquidity thresholds, lag specifications and policy indicators. Additionally, our results are robust to the time aggregation approach when constructing our quarterly monetary policy instrument series from daily, high-frequency market surprises.

Second, we analyze how conventional monetary shocks interact with unconventional ones using a Kitagawa-Blinder-Oaxaca Decomposition (see Cloyne, Jorda & Taylor (2020)), and finally, we focus on the post-GFC sample estimates based on the shock series from Bu et al. (2021) which are available beyond 2016Q4. As we will show below, our results remain qualitatively stable and

[25] Figure B.2 in appendix B plots our MPI against Swanson's raw high-frequency market-based surprises.

[26] Comparing our baseline pre-GFC estimates (see figure D.3) with the results using the raw high-frequency surprises from Swanson (2021) depicted in figure D.4 yield similar results, which suggest that before the crisis the information channel had no significant effect on balance sheet variables.

exhibit only expected quantitative differences.

6.1 Conventional vs. Unconventional Monetary Policy

In order to control for alternative dimensions of monetary policy we re-estimate our state-dependent models for the two sub-samples using our policy-specific MPIs (i.e., our conventional policy instrument, MPI_t^{con} and our unconventional policy instrument, MPI_t^{ump}) instead of the total MPI depicting the full impact of both types of monetary policy instruments.

Figures D.5 and D.6 in Appendix D show the impulse responses of our variables of interest to our two alternative instruments, i.e., MPI^{con} and MPI^{ump}, respectively. Similar to Swanson (2021) we find that both conventional and unconventional measures of monetary policy exhibit an equivalent impact on the economy. This is also in line with the broad interpretation of the bank-lending channel since it considers monetary policy shocks to be, from the individual commercial bank's perspective, equivalent to funding shocks. Hence, regardless of the specific monetary policy shock, the (broad) bank-lending channel predicts that after any type of contractionary monetary policy shock, illiquid banks will reduce their lending.

In line with these reasoning, we also find that the heterogeneity between liquidity constrained and unconstrained banks remains stable across all three of our instruments (total, conventional, unconventional) and for almost all variables of interest.

The biggest differences we can observe occur in banks' securities, total capital and deposits when comparing an unconventional monetary policy (UMP) shock with the two alternatives. After a contractionary UMP shock, illiquid banks now increase their securities and total capital, although this increase is smaller than the one for liquid banks. Despite the fact that deposits from illiquid banks do not fall in this case, their reaction is significantly lower than for liquid banks. Nevertheless, the main finding of our previous analyses still holds: there is a clear heterogeneity in the loan supply of liquid (rising supply) and illiquid banks (muted reaction).[27]

6.2 Alternative Liquidity Thresholds

Figures D.7 and D.8 in Appendix D show the impulse responses of our variables of interest to two alternative liquidity thresholds. In our baseline setup we selected a liquidity threshold that classifies banks with excess reserves above 1% of total assets as cash-liquid. This choice is driven by the following trade-off: An economically sensible choice requires us not to set the threshold too low, while data limitations also dictate us not to set this bar too high.

We consider the 1% threshold to be a reasonable baseline calibration for two reasons: First, it largely splits the observations evenly around the mid 2000's while also not having a too extreme split at the very beginning and end of our observation period. Second, it is reasonable to assume that any banks beyond that threshold are holding reserves, not only for liquidity buffer concerns arising from regular transaction needs, but simply out of an abundance of liquidity on their balance sheets.

[27]Note that in contrast to the conventional factors, a one-standard deviation shock to the LSAP factor in Swanson (2021) exhibits its major impact on the longer end of the yield curve. In order to achieve a 100bp effect on the federal funds rate, we have to send an unusually large shock into the system, explaining the magnitudes found in figure D.6.

In light of these considerations it is therefore not surprising that there is a less pronounced heterogeneity across the two groups when performing our analysis for a lower threshold of 0.5%, as shown in figure D.7. However, we can still observe qualitatively similar results to our baseline threshold: The loan supply of liquid banks is unambiguously positive, whereas illiquid banks' loan supply remains at around zero over the impulse horizon.

As expected, choosing a higher threshold of 2% further strengthens the heterogeneity in impulse responses (see figure D.8 in the appendix). These experiments show that the heterogeneous reactions across banks can indeed be traced back to our dimension of heterogeneity: Bank liquidity crucially matters in the determination of the effects of monetary policy.

6.3 Alternative Lag Specifications

Next, we employ two alternative lag specifications to control for the sensitivity of our baseline specification (i.e., $L = 4$). In particular, we re-estimate our state-dependent model with fewer lags, $L = 1$, and also with more lags, $L = 6$, and present these impulse responses in figures D.9 and D.10, respectively.

The main findings can be observed in both alternative lag specifications: Our qualitative results are completely robust to different lag specifications and the heterogeneity between our two liquidity groups remains unchanged. However, some variables' reactions show different magnitudes. For example, while using six lags yields slightly smaller results to our baseline model, using only one lag leads to a larger peak increase in liquid bank's total loans of 20% (see figure D.9).

Regardless of the lag specification, our baseline specification's result remains qualitatively unchanged, i.e., liquid banks increase their total loans and illiquid banks show a muted response after a contractionary monetary policy shock.

6.4 Alternative Policy Indicators

One could argue that using the changes in the Effective Federal Funds rate (EFFR) as policy indicator in our full sample estimation might drive our results due to the lack of variation during the ZLB period. Hence, we re-estimate our state-dependent model using the changes in the one-year Treasury rate as our policy indicator instead. Among others, Miranda-Agrippino & Ricco (2021) use this rate as a policy indicator during the ZLB episode.

Nevertheless, as the results in figure D.11 show, using this alternative indicator yield almost identical responses to our baseline results. The reason for this is the fact that even during the ZLB episode both the EFFR and the one-year treasury rate are highly correlated and thus, when we instrument either of them with our MPIs the results are almost identical.[28]

One further concern with our baseline specification is that while the EFFR is usually taken to be an appropriate indicator for conventional, but not unconventional monetary policy, we are instrumenting it with our total MPI which considers both conventional and unconventional types of shocks. To address this, figure D.12 depicts the results from our state-dependent model using the short-term shadow rate from Wu & Xia (2016).

The shadow rate developed in Wu & Xia (2016) is meant to capture the overall impact of monetary policy, i.e., including conventional and unconventional policies during the ZLB.

[28] Jeenas (2019) also finds that using the EFFR or the one-year rate yield similar results.

Therefore, we can assess whether our baseline specification yields different results using an overall policy indicator instead of conventional indicators such as the EFFR and the one-year Treasury rate. Once again, our baseline results are robust to this alternative policy indicator, as illustrated in figure D.12.[29]

6.5 Smooth Time Aggregation

We further test for the sensitivity of our results by aggregating the high-frequency surprises using a so-called smooth time aggregation strategy developed in Ottonello & Winberry (2020).

The underlying motivation is to account for frictions faced by banks (and other economic agents) in the adjustment of balance sheet variables in reaction to a monetary policy shock. For this, a shock is being split into two parts: Its effect on the current end-of-month reported variables and its effect on the end-of-month variable of the next month. For example, suppose that a shock occurred on the 25th of January. Then, as shown in equation (10), its weight for the current month is about 0.19 and, therefore, about 81% of the shock will be counted towards the following month (February), accounting for frictions in how fast banks can adjust their balance sheets to an unexpected change in monetary policy.

Formally, the smoothing will be implemented into the second step of our original MPI construction described in section 3.1. That is, into equation (2) of section 3. The new aggregation from announcement-frequency to monthly frequency takes the following form:

$$MPI_t^M = \sum_{i \in J(t)} \omega_t^a MPI_{i,t}^D + \sum_{i \in J(t-1)} \omega_t^b MPI_{i,t}^D \tag{10}$$

where $\omega_t^a \equiv \frac{d_t - d_{i,t}}{d_t}$, $\omega_t^b \equiv \frac{d_{i,t}}{d_t}$, and $d_{i,t}$ denotes the day of $\text{MPI}_{i,t}^D$ in month t and d_t the total number of days in month t. $J(t)$ refers to the set of MPIs in any given month t. Hence, in the above example $\omega^a = 0.19$ and $\omega^b = 0.81$.

Figure D.13 depicts the full sample results from our state-dependent model using this alternative constructions of our MPI. These estimates suggest that the strategy to time-aggregate high-frequency surprises to the quarterly frequency plays only a minor role and that our main result, i.e., the identification of heterogeneous responses to U.S. monetary shocks depending on banks' liquidity state, remains valid.

6.6 Kitagawa-Blinder-Oaxaca Decomposition

In this section we further analyze the interaction between conventional and unconventional monetary policy employing a Kitagawa-Blinder-Oaxaca (KBO, henceforth) decomposition as proposed by Cloyne et al. (2020). These authors introduce a novel framework for decomposing impulse responses that allows one to go beyond estimating average effects by revealing the heterogeneity behind them using a popular approach in the applied microeconomics literature, i.e., the KBO decomposition (see Cloyne et al. (2020)).

[29] Furthermore, we conducted the same robustness exercise using the alternative shadow rates developed in Krippner (2016) and Lombardi & Zhu (2018). The results from this analyses are very similar to the ones presented in figure D.12 using Wu & Xia's shadow rate, and are available upon request.

In the interest of space, we focus on the responses of total loans to a conventional monetary policy shock in our full sample. Concretely, we extend our linear model (5) to analyze whether the response of total lending to conventional shocks depend on the behavior of unconventional monetary policy. Following Cloyne et al. (2020) we estimate the following sequence of LPs,

$$z_{i,t+h} - z_{i,t-1} = \alpha_{i,h} + \beta_h^{IV} \Delta r_t + \sum_{\ell=1}^{L} \Gamma_{h,\ell} X_{i,t-\ell} + \mu_{j,h} + \gamma_h t \dots$$

$$\dots + \sum_{\ell=1}^{L} \Xi_{h,\ell} \left(X_{i,t-\ell} \cdot \Delta r_t \right) + \theta_h \left(\Delta r_t \cdot MPI_t^{ump} \right) + \varepsilon_{i,t+h}, \tag{11}$$

for $h = 0, 1, ..., H$ and where z_t is our variable of interest, total loans. Moreover, the first row of equation (11) is identical to our linear model introduced in section 4.1, where Δr_t gives the change in the EFFR which is instrumented with our conventional instrument, MPI_t^{con}. The second row in equation (11) introduce the Kitagawa-Blinder-Oaxaca extension by interacting our conventional policy indicator (Δr_t, which we still instrument with MPI_t^{con}) with our vector of controls ($X_{i,t-\ell}$) as well as our unconventional monetary instrument, MPI_t^{ump}.

The advantage of this decomposition is that it provides the direct effect from conventional shocks on total bank lending by tracing the coefficient $\{\beta_h^{IV}\}_{h=0}^{H}$, and the indirect effects from the interaction with UMP which are given by $\theta_h \cdot MPI_t^{ump}$.

Figure 12 shows the results from the KBO decomposition for the total lending responses. Panel 12a shows the response of total loans varies with the degree of UMP accommodation. The black line reports the direct effect, which should be roughly similar to the average effect in figure 7.[30] The gray lines consider experiments which vary the degree of UMP accommodation. A larger marker indicates a tighter unconventional monetary policy scenario.

Panel 12b plots the indirect effect on total loans for the effect at h = 4. The figure illustrates the effect of the interaction between conventional and unconventional monetary policy relative to the average response in the full sample (the black line in panel 12a). As unconventional policy becomes more contractionary, the expansion in total lending becomes even larger.

All in all, extending our linear model to use the KBO decomposition shows that even though the response of bank lending is counter-intuitive, as it increases after a contractionary shock in our full sample estimates, at least both dimensions of monetary policy work in the same direction and thus, reinforce each other's effects.

6.7 Post-GFC Estimates

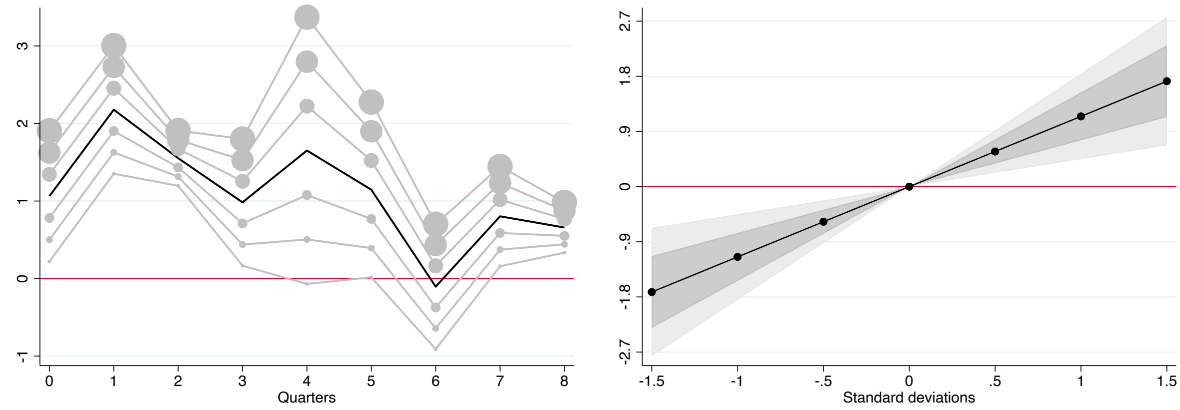
One limitation of the state-dependent model is that due to data availability we cannot estimate it using only post-crisis data. The data set necessary to calculate bank-level excess reserve holdings is only available until the end of 2016 (see appendix A.1.1 for more details). Additionally, the Greenbook forecasts are also only available until 2016 preventing us to extend our informationally-robust MPIs beyond that date (see section 3).

Thus, in this extension, and in order to estimate dynamic responses for the post-crisis period

[30] Note that in figure 7 we use our baseline MPI and not the conventional one. However, the responses are very similar. Thus, in the interest of space we don't include them here but are available upon request.

Figure 12: **Conventional Monetary Policy experiments varying the response of UMP**

(a) **Total Loans Response** (b) **Indirect Effect for Total Loans $h = 4$**

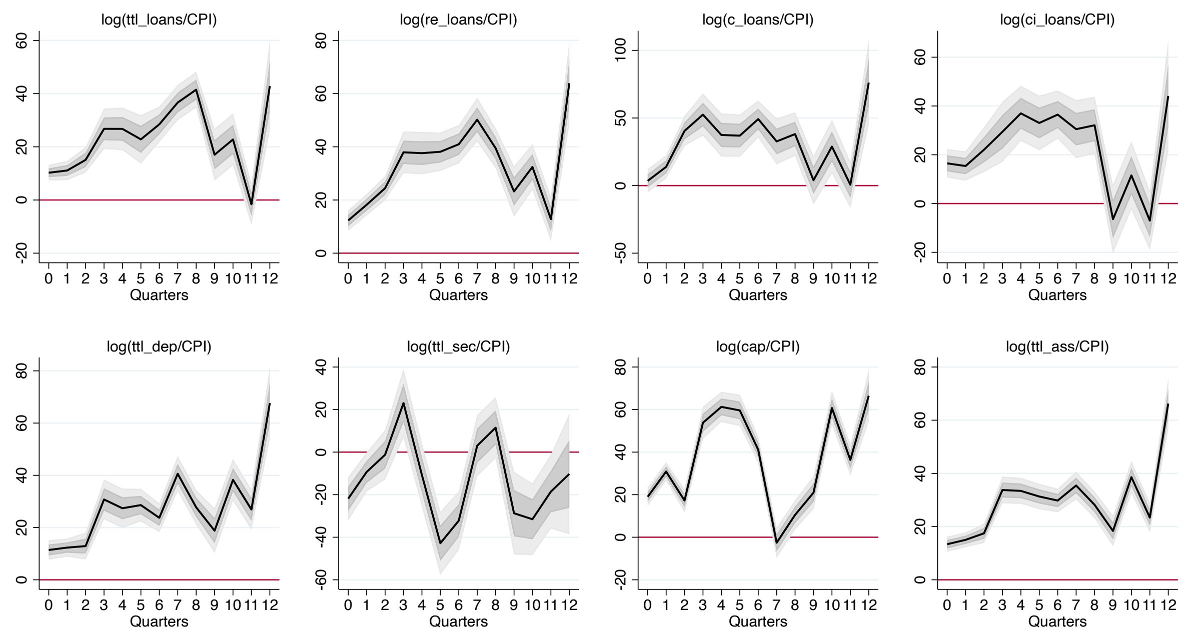


Note: Panel 12a shows the response of Total Loans varies with the degree of UMP accommodation. The black lines report the direct effect, which should be compared to the average effect in figure 7. The gray lines consider experiments which vary the degree of UMP accommodation. A larger marker indicates a tighter unconventional monetary policy scenario. Panel 12b plots the indirect effect on Total Loans for the effect at h = 4. The figure illustrates the effect of the interaction between conventional and unconventional relative to the average response in the full sample. This also allows us to formally test whether the indirect effect is statistically significant. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

we rely exclusively on the linear model presented in section 4.1. Additionally, we employ the monetary policy shock series identified by Bu et al. (2021) which is, similar to our MPI, robust to information effects and has the additional advantage of being available until 2019Q3.

Figure 13 depicts cumulative responses to a 100bp tightening shock using Bu et al.'s shock series as a policy instrument. Bank loans increase by 40% after 8 quarters, while deposits increase

Figure 13: **Linear Model, Post-GFC Sample (2009Q1-2019Q3)**



Note: Cumulative responses (in %) to a +100bp monetary shock in the post-GFC sample (2009Q1-2019Q3). Dark-gray and light-gray shaded areas are 65% and 90% confidence bands, respectively.

on impact and fluctuate between 20 and 40 percent after the first year. Zooming in into the main components of total loans, figure 13 shows a very similar reaction across C&I, real estate and consumer loans. All three lending variables increase after a contractionary shock. Two years after the shock C&I loans do so by 30%, real estate loans rise by 40%, and consumer loans by close to 35%. The magnitude of these responses are much larger than the full sample estimates using our own informationally-robust MPIs above (see figure 7).[31]

All in all, the post-GFC sample estimates suggest that our full sample estimates presented previously are a conservative lower bound on the rise of banks' loans and deposits after a tightening shock since our results in this subsection are significantly larger.

7 Conclusion

In this paper we ask whether banks' reactions to monetary policy shocks depend on their liquidity levels and whether their responses are sensitive to informational effects of Fed announcements. To answer these questions we first construct informationally-robust MPIs, following the approach of Miranda-Agrippino & Ricco (2021). These instruments allow us to avoid long-standing empirical puzzles following monetary policy shocks. We use these MPIs as proxies for monetary policy shocks when estimating dynamic responses of key balance-sheet variables via Local Projections.

Our findings suggest that prior to the GFC, banks had homogeneous responses, i.e., their reaction to monetary shocks did not differ when conditioning on their liquidity levels, and that the information channel does not systematically affects banks' reactions. This provides supporting evidence for an active bank-lending channel in the U.S. for the period preceding the GFC.

In contrast to the pre-crisis period, estimates including the GFC and the years following show a clear heterogeneity in impulse responses of key bank balance sheet variables in reaction to contractionary monetary policy shocks. Most prominently, total deposits and total loans of cash-liquid banks exhibit an expansionary reaction to contractionary monetary policy shocks. Furthermore, cash illiquid banks show a largely muted reaction to contractionary monetary policy shocks. These results do not support the bank lending channel and suggest that the bank lending channel is inactive in U.S. data. Our analysis shows that real estate and consumer loans are the driving factors of the increase in total lending shown for liquid banks. Additionally, we show that in our full sample estimates, the information channel significantly affects the reactions of cash-liquid banks to monetary policy shocks.

Finally, we have performed a number of robustness checks, supporting the notion that cash-liquidity is the driving force behind heterogeneous bank responses to monetary policy. Our results are not sensitive to the type of monetary policy (conventional or unconventional), they show a clear positive relationship between the degree of liquidity and the heterogeneity between banks, and we show that alternative lag specifications of our LP-IV model do not impact our results.

[31] Nevertheless, the dynamic responses using the Bu et al. (2021) series during the pre-crisis sample (see figure D.14 in the appendix) depict similar magnitudes as figure 4 above which is based on our own MPI. For example, total loans and deposits decline by approximately 2% after three years in the pre-GFC sample under both informationally-robust instruments.

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Appendix

A Data

A.1 Balance Sheet Variables

The sample between 1990Q1 and 2000Q4 was taken from the Chicago Fed web page,[I] and between 2001Q1 and 2019Q3 from the Federal Financial Institutions Examination Council web site.[II]

For the individual variables we constructed the key time series following Kashyap & Stein (2000). Total loans is taken from rcfd2122 ("Total Loans and Leases, Net of Unearned Income") between 1990Q1 and 2000Q4, and from rcfdb529 ("Loans and Leases, Net of Unearned Income and Allowance") thereafter.[III] C&I loans are taken between 1990Q1 and 2000Q4 from rcfd1600 and rcon1766 for the remaining of the sample (if rcfd1600 or rcon1766 was missing, we used the sum of rcfd1763 and cfd1764). Real estate loans can be found using item rcfd1410 ("Loans secured by real estate"), and if a bank is missing this item then real estate loans are given by the sum of rcon1415 (replaced by the sum of rconf158 and rconf159 after 2008), rcon1420, rcon1797, rcon5367, rcon5368, rcon1460 and rcon1480 (replaced by the sum of rconf160 and rconf161 after 2008). Consumer loans can be obtained from item rcon1975 ("Loans to individuals for household, family, and other personal expenditures (i.e., consumer loans)"), and if missing from the sum of items rconb538, rconb539 and rcon2011 (replaced by the sum of rconk137 and rconk207 after 2010). Total assets is taken from rcfd2170, and "total bank equity capital" from rcfd3210.

The more challenging variable is the securities one, since over the past 30 years there have been considerable changes in the reporting format of securities across different institutions. Between 1990Q1 and 1993Q4 we added "Available-for-sale securities" (rcfd0390) with "Held-to-maturity securities" (rcfd2146) and "Federal funds sold and securities purchased under agreements to resell" (rcfd1350). From 1994Q1 until 2001Q4 we use the same variables, which are now identified by rcfd1773, rcfd1754, rcfd1350, respectively. Later, starting in 2002Q1 the variable rcfd1350 ("Federal funds sold and securities purchased under agreements to resell") was split in two separates variables which we add up to keep consistency, i.e., rconb987 ("Federal funds sold") and rcfdb989 ("securities purchased under agreements to resell").

A.1.1 Excess Reserves

We follow the approach from Afonso et al. (2019) to calculate bank-level excess reserves simply defined as the difference between total reserve balances and required reserve balances, i.e., $ER_t = TR_t - RR_t$. Total Reserve balances, TR_t, can be obtain directly from item RCFD0090[IV].

Required reserve balances, RR_t, on the other hand, cannot be find in a particular Call Report

[I] https://www.chicagofed.org/banking/financial-institution-reports/commercial-bank-data-complete-1976-2000

[II] https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx

[III] In recent years, regulators have introduced different reporting formats for different bank's total assets. Thus, in many cases, where an individual bank has no foreign activities, the variable used is rcon. For example, for total loans, starting in 2001, for small banks the variable reporting total loans is called rconb529.

[IV] Afonso et al. (2019) limit their sample to banks that report this item, which considerably reduces the amount of observations in the Call Reports, since only banks with at least $300 million in assets or with foreign offices, need to report this item. In our sample the median bank has $397 million in total assets, whereas in the entire Call Reports covering the same sample, the median bank has $97 million in total assets.

item, but is rather defined as the difference between required reserves and vault cash.

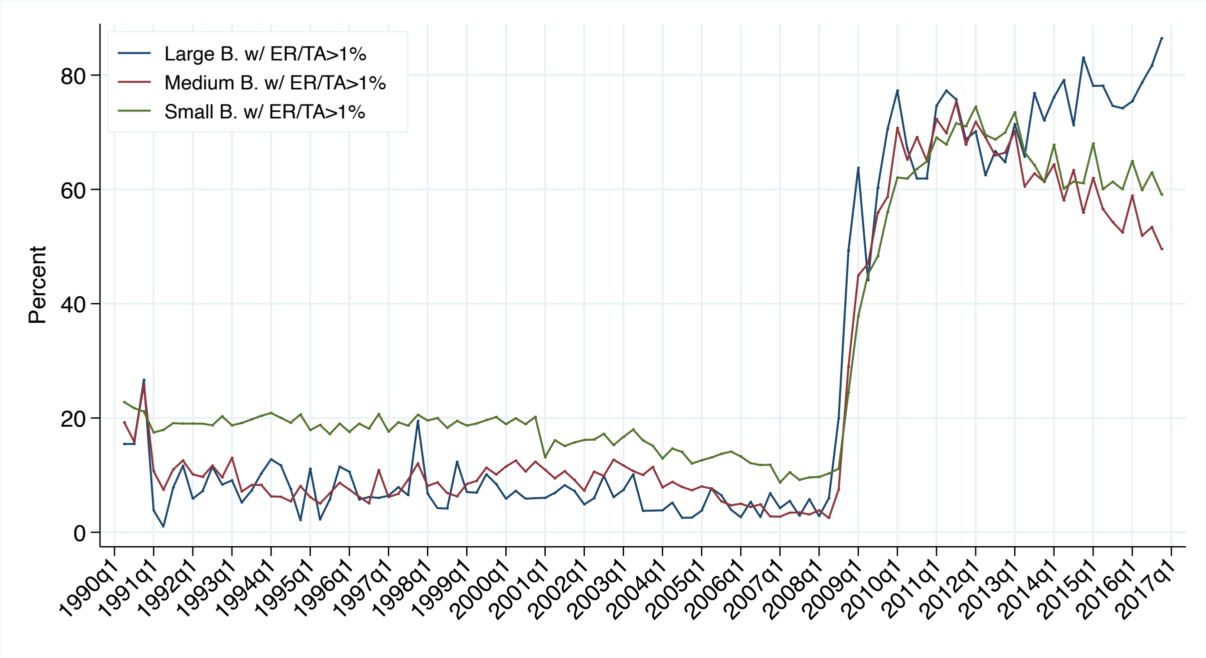
Required reserves are obtained as an increasing function of a bank's net transaction accounts minus amounts due from other depository institutions and cash items in the process of collection. "To calculate net transactions, we take from the Call item RCON2215 (the bank's "Total Transaction Accounts" (including "Total Demand Deposit" in domestic offices, which also includes ATS and NOW accounts)) to estimate total transaction accounts, and subtract from it our estimate of amounts due from other depository institutions (the sum of item RCFD0083 ("Balances due from depository institutions in the U.S.: U.S. branches and agencies of foreign banks (including their IBFs)") and RCFD0085 ("Balances due from depository institutions in the U.S.: Other depository institutions in the U.S. (including their IBFs)") and cash in the process of collection, item RCON0020 ("Cash items in process of collection and unposted debit")" Afonso et al. (2019).

Finally, required reserves are obtained using reserve requirement information from the Federal Reserve Board.[V]

[V] The reserve requirement information can be found under https://www.federalreserve.gov/monetarypolicy/reservereq.htm.

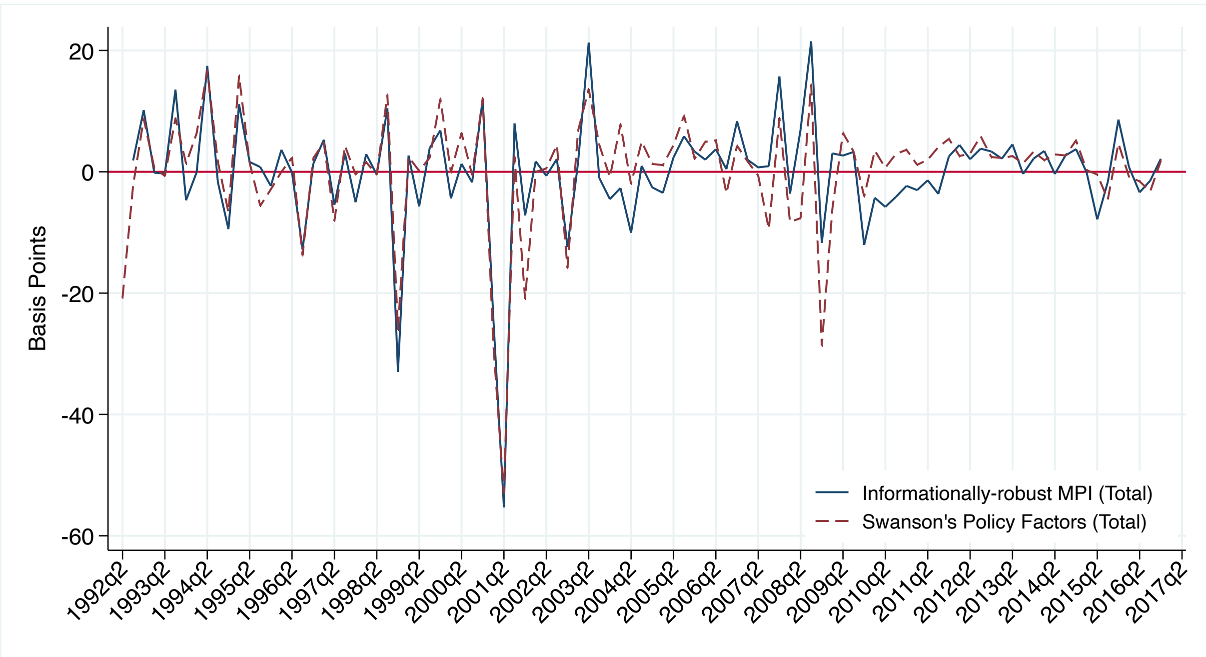
B Additional Time Series

Figure B.1: **Share of banks by size category with ER/TA$>1\%$**



Note: Large banks are defined as those banks above the 99th percentile of the total assets distribution, medium banks are those between the 95th and 99th percentiles, and small banks are all intermediaries below the 95th percentile.

Figure B.2: **Total MPI and the market-based surprises coming from Swanson (2021)**



C Fed Information Effect Regressions

The regressions underlying table 1 take the following form:

$$\Delta y_{t,t-1} = \alpha + \Delta r_{t,t-1} + \varepsilon_t \tag{A-1}$$

As before, $\Delta r_{t,t-1}$ is the instrumented change in either the 1-year treasury yield (setup 1) or the EFFR (setup 2), using either our MPI or the BRW series.
Following Nakamura & Steinsson (2018), the dependent variable $\Delta y_{t,t-1}$ is defined as:

$$\Delta y_{t,t-1} = \frac{gy_{t,q(t)+1} + gy_{t,q(t)+2} + gy_{t,q(t)+3}}{3} - \frac{gy_{t-1,q(t)+1} + gy_{t-1,q(t)+2} + gy_{t-1,q(t)+3}}{3} \tag{A-2}$$

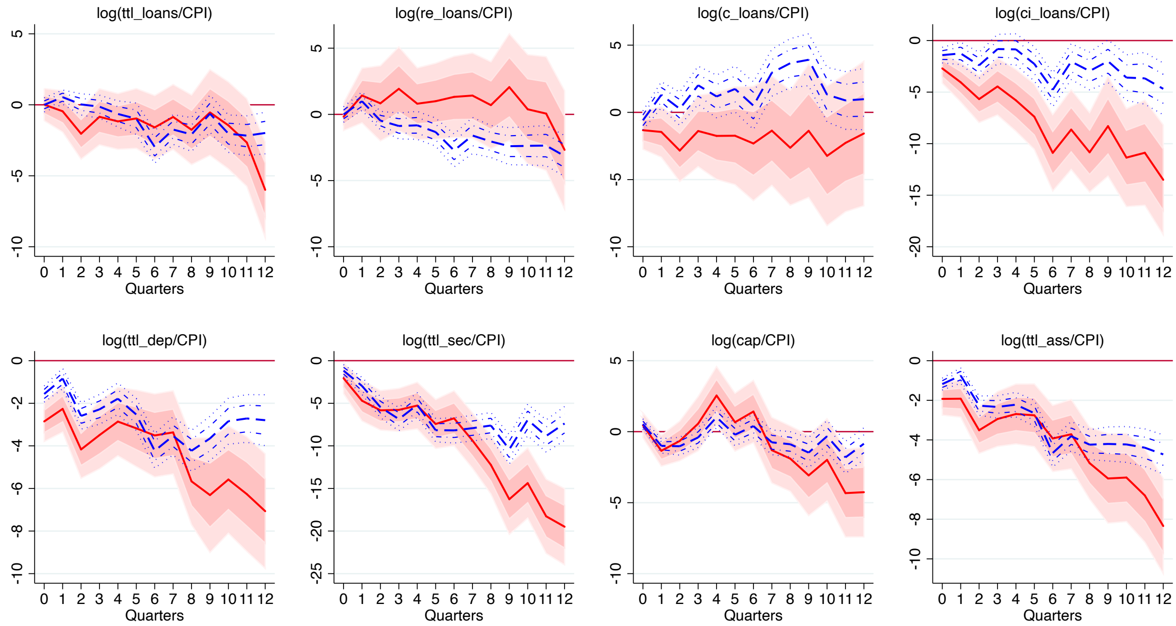
Where $gy_{t,q(t)+1}$ denotes the average Blue Chip forecast made in month t about output growth for quarter $q(t)+j$. $q(t)$ refers to the quarter that month t belongs to. Accordingly, if t is March 2001, $q(t)$ is the first quarter of 2001, and the forecast for $q(t)+1$ refers to the forecast for the second quarter of 2001.
In compact notation:

$$\Delta y_{t,t-1} = \bar{y}_{t,\bar{q}} - \bar{y}_{t-1,\bar{q}} \tag{A-3}$$

Hence, $\Delta y_{t,t-1}$ is defined as the change in the average forecasts between the current month, t, and the previous month, $t-1$, for the averaged upcoming three quarters.

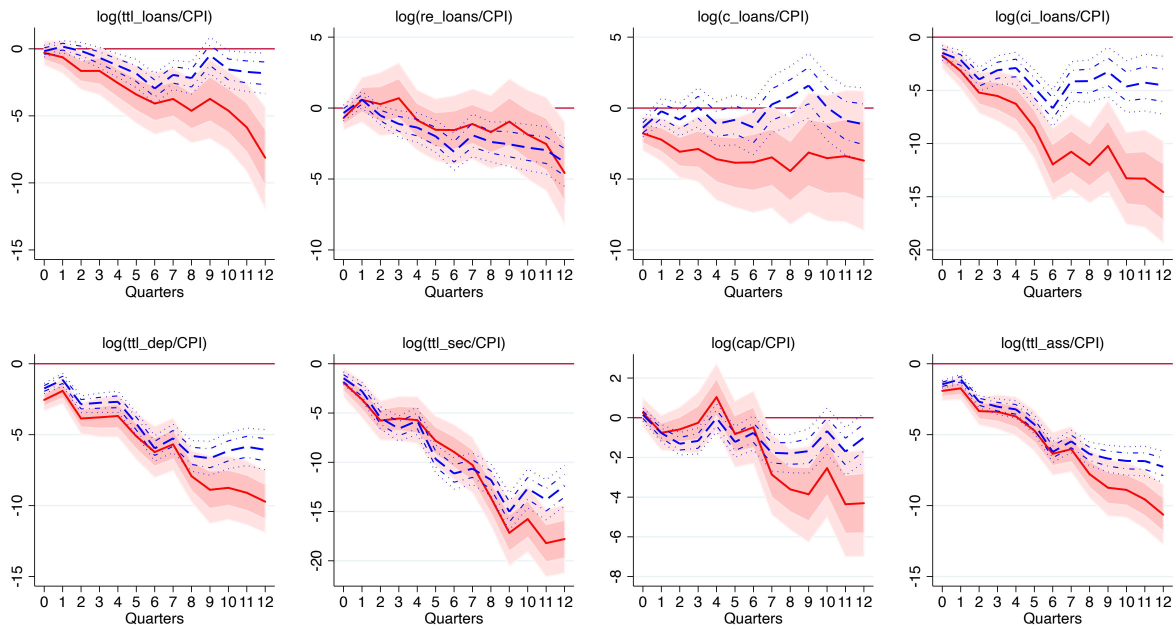
D Robustness Figures and Tables

Figure D.3: **Homogeneous Bank Responses, Pre-GFC**



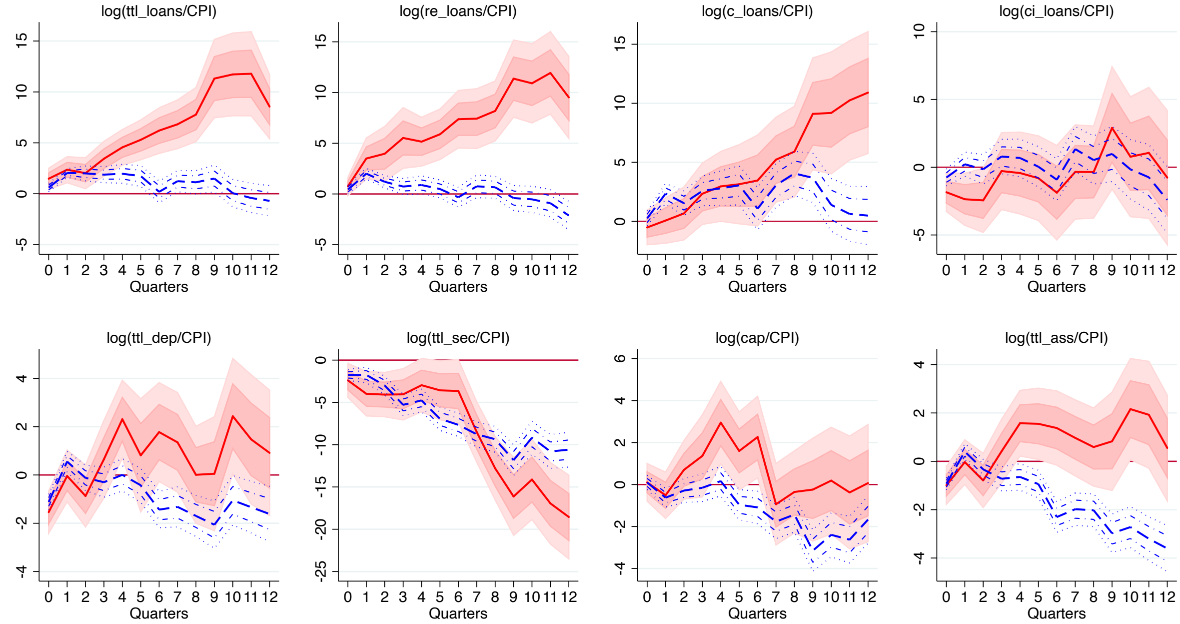
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the pre-GFC sample (1990Q1-2007Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.4: **Swanson's High-Frequency Surprises, Pre-GFC**



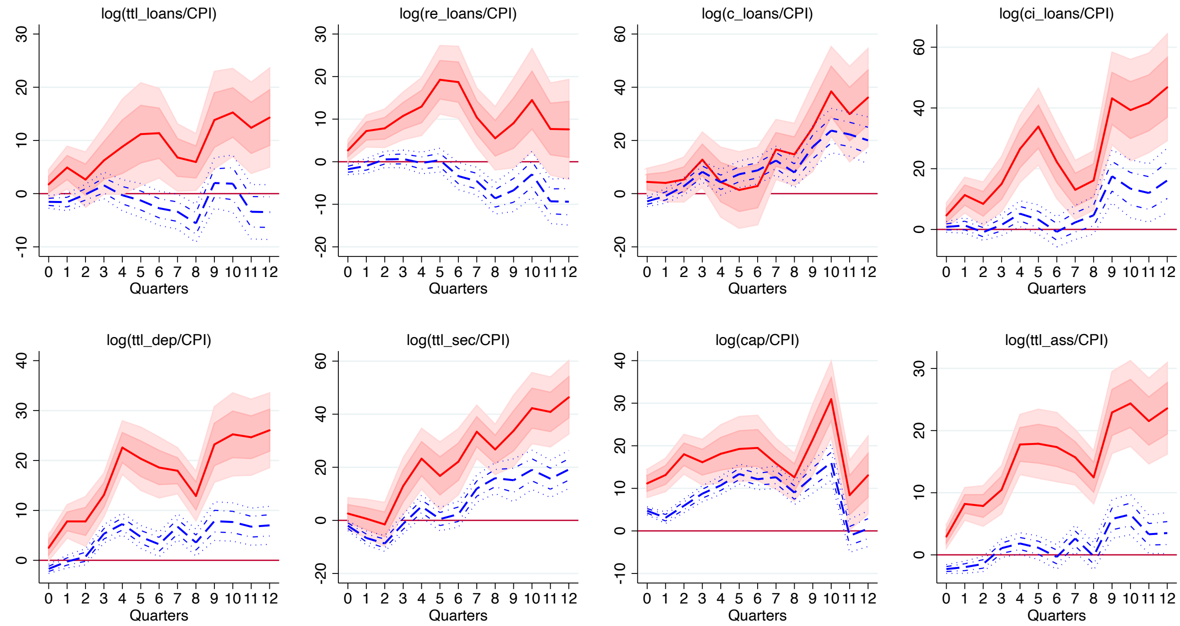
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the pre-GFC sample (1990Q1-2007Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.5: **Conventional MPI only, Full Sample**



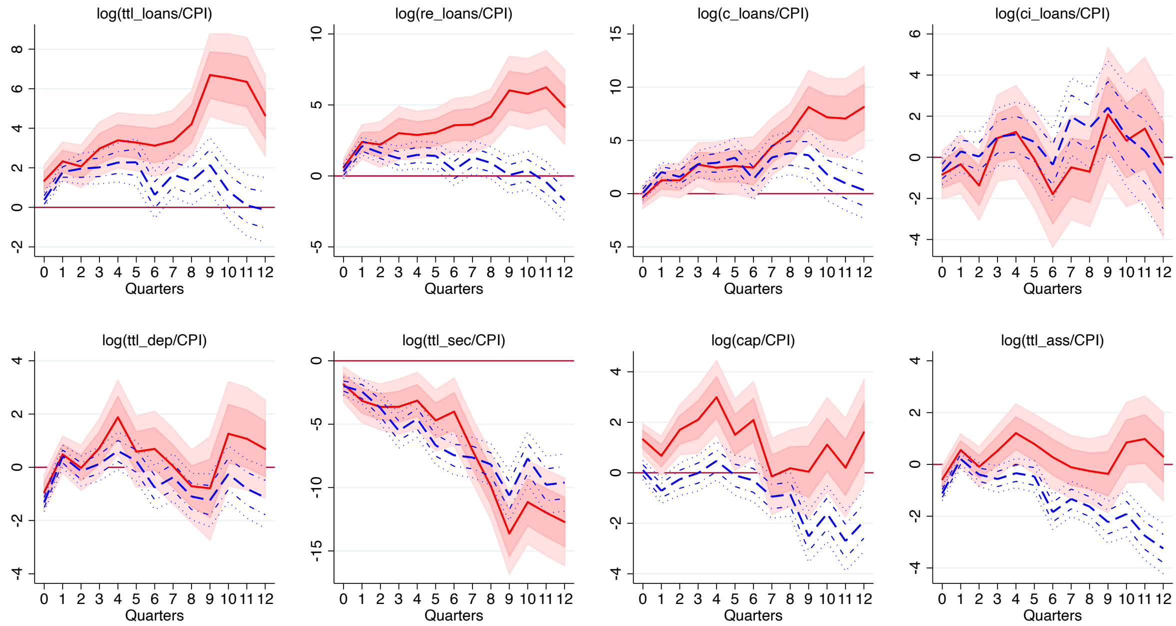
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.6: **Unconventional MPI only, Full Sample**



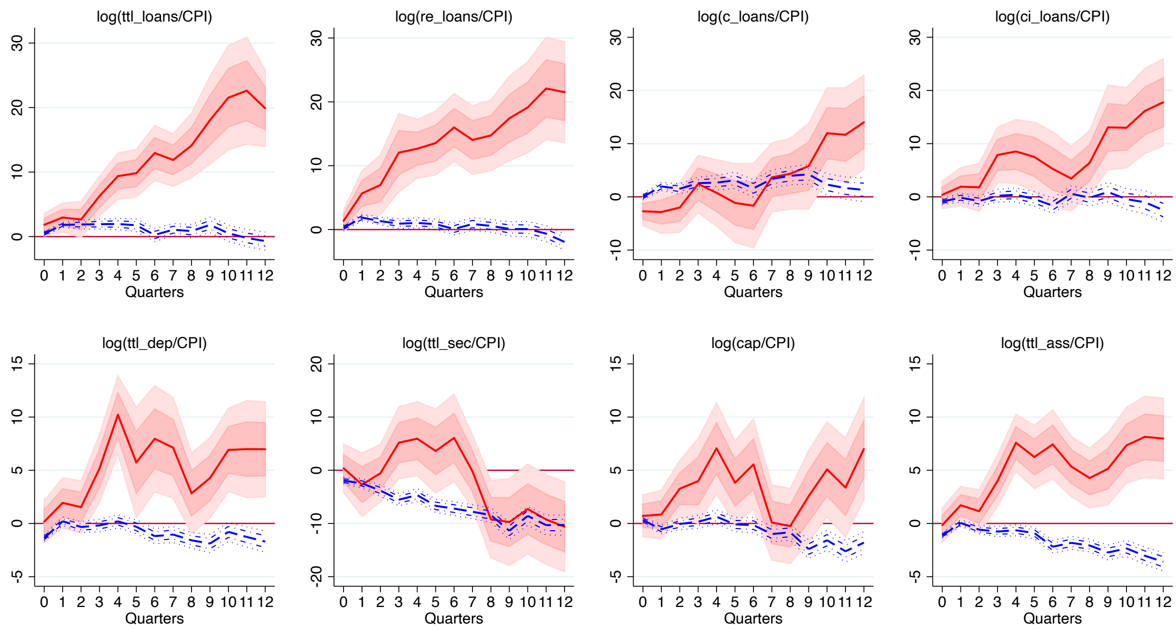
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.7: **Lower Liquidity Threshold (0.5%), Full Sample**



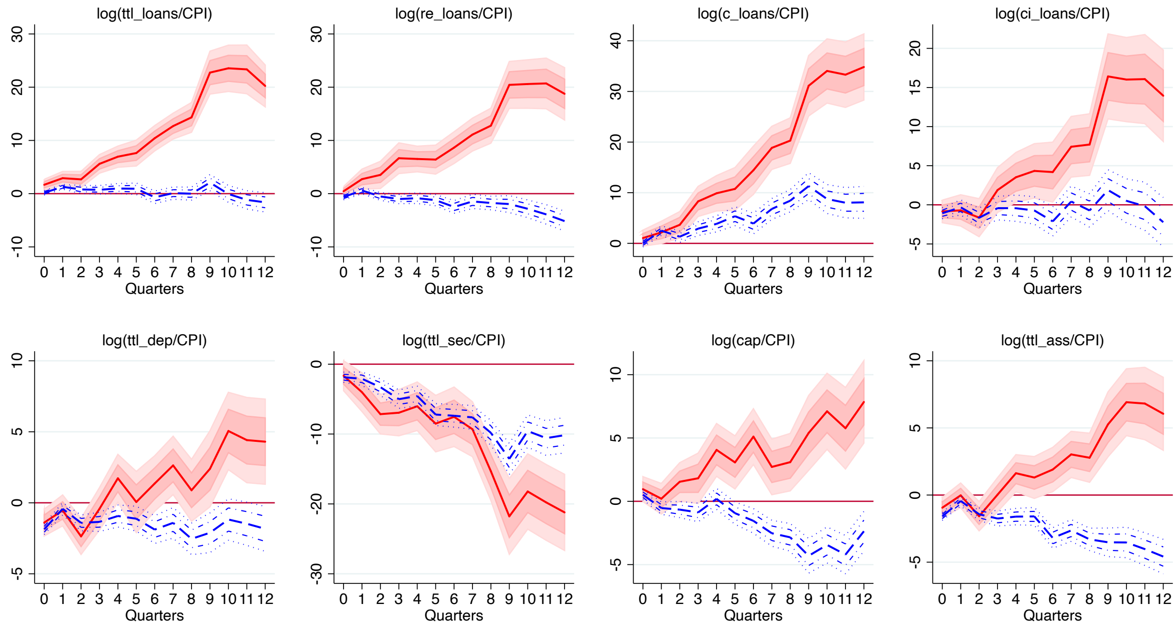
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.8: **Higher Liquidity Threshold (2%), Full Sample**



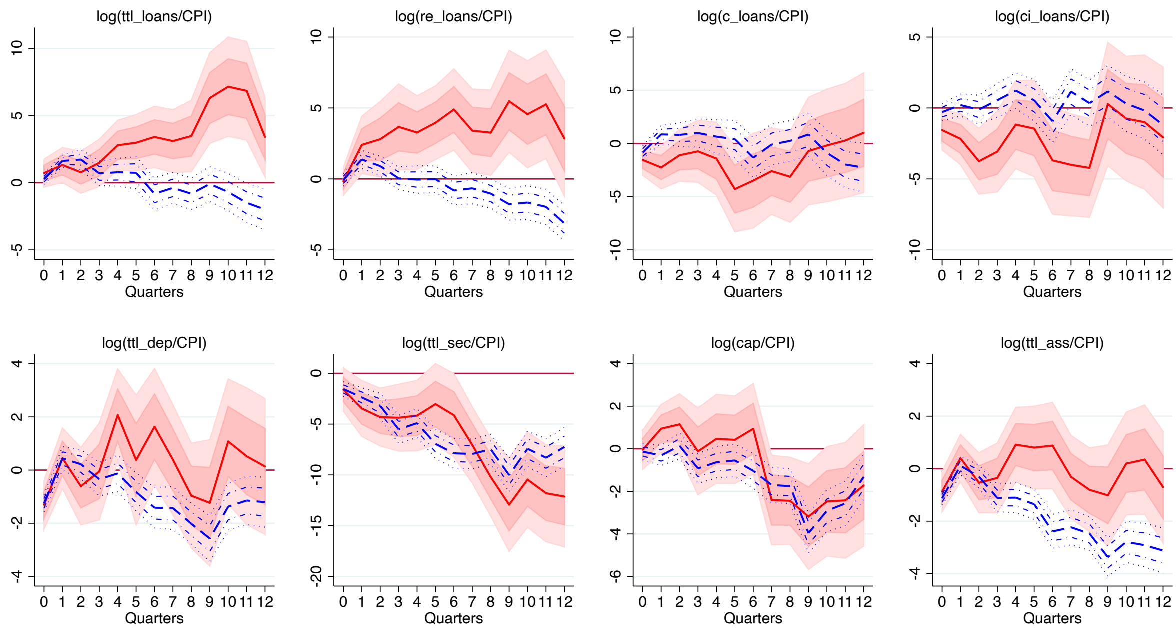
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.9: **Fewer lags ($L = 1$), Full Sample**



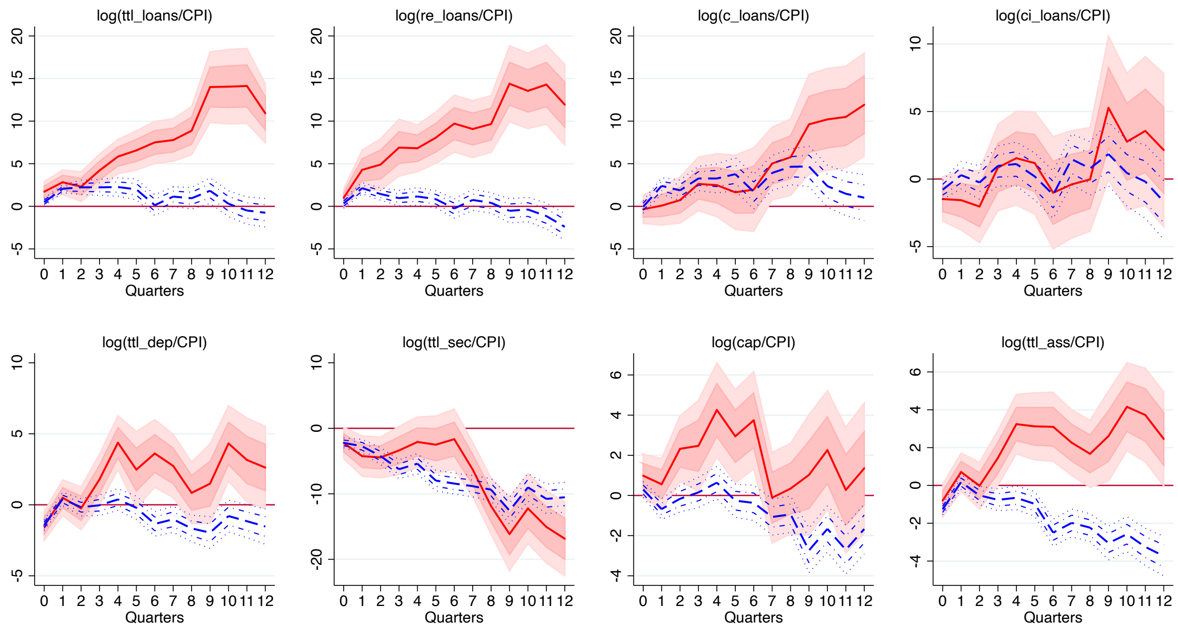
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.10: **More lags ($L = 6$), Full Sample**



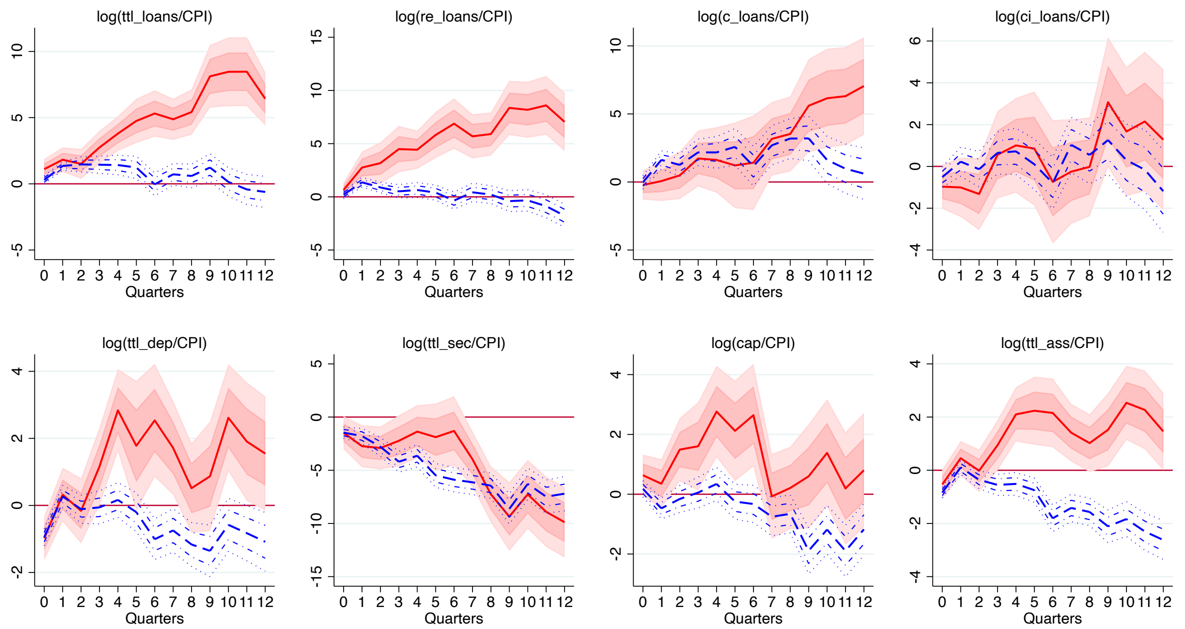
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.11: **One-Year Treasury Rate as Policy Indicator, Full Sample**



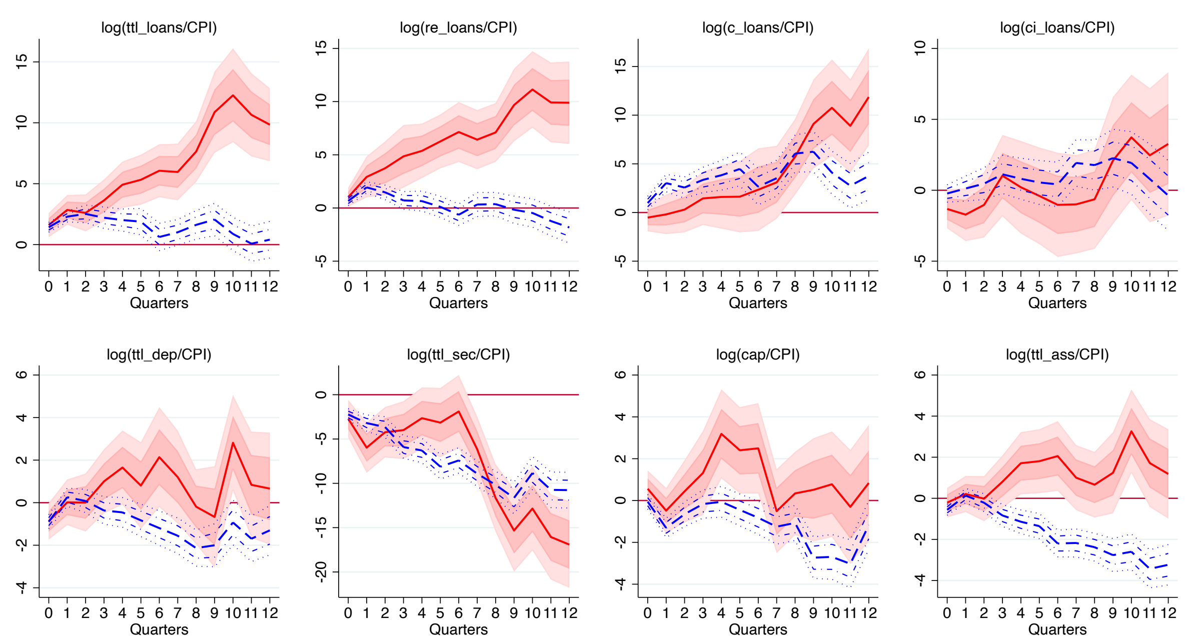
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.12: **Wu & Xia's Shadow Rate as Policy Indicator, Full Sample**



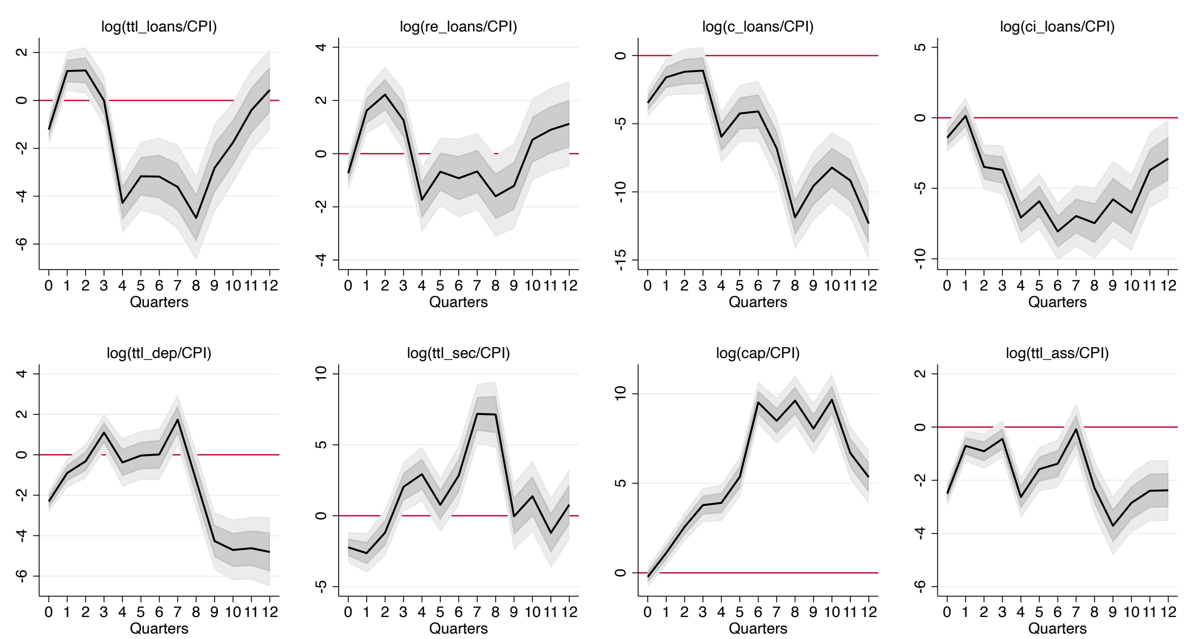
Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.13: **MPI with Smooth-Time Aggregation, Full Sample**



Note: Cumulative responses (in %) to a contractionary 100bp monetary shock, in the full sample (1990Q1-2016Q4), for liquid (red solid lines) and illiquid (blue dash lines) banks. Dark and light shaded areas are 65% and 90% confidence bands, respectively.

Figure D.14: **Linear Model using Bu et al.'s Shock Series, Pre-GFC**



Note: Cumulative responses (in %) to a +100bp monetary shock in the pre-GFC sample (1994Q1-2007Q4). Dark-gray and light-gray shaded areas are 65% and 90% confidence bands, respectively.

Table D.1: **First Stage Estimation Results, Pre-GFC Sample (1990-2007)**

	Total Loans	Cons. Loans	RE Loans	C&I Loans	Liquid Securities	Deposits	Total Capital	Total Assets
MPI (Total)	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.MPI (Total)	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L2.MPI (Total)	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L3.MPI (Total)	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L4.MPI (Total)	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.log(Dependent Variable/CPI)	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L2.log(Dependent Variable/CPI)	-0.000***	-0.000***	-0.000**	-0.000	-0.000	-0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L3.log(Dependent Variable/CPI)	-0.000	0.000	-0.000	-0.000***	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L4.log(Dependent Variable/CPI)	-0.000***	0.000	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Δ log(GDP/CPI)	-0.016***	-0.017***	-0.017***	-0.016***	-0.017***	-0.016***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L2.Δ log(GDP/CPI)	0.098***	0.098***	0.098***	0.098***	0.098***	0.098***	0.097***	0.098***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L3.Δ log(GDP/CPI)	0.197***	0.197***	0.197***	0.197***	0.197***	0.196***	0.196***	0.197***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L4.Δ log(GDP/CPI)	0.208***	0.208***	0.208***	0.207***	0.208***	0.208***	0.207***	0.208***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L.Δ Unemployment	-0.622***	-0.622***	-0.622***	-0.621***	-0.622***	-0.622***	-0.621***	-0.622***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L2.Δ Unemployment	-0.562***	-0.561***	-0.562***	-0.562***	-0.562***	-0.562***	-0.563***	-0.562***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
L3.Δ Unemployment	-0.347***	-0.348***	-0.347***	-0.347***	-0.347***	-0.346***	-0.345***	-0.346***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L4.Δ Unemployment	-0.056***	-0.055***	-0.055***	-0.055***	-0.056***	-0.055***	-0.055***	-0.055***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Δ log(Industrial Production)	0.098***	0.099***	0.098***	0.099***	0.098***	0.098***	0.098***	0.098***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L2.Δ log(Industrial Production)	0.001**	0.001*	0.001*	0.001*	0.001*	0.001**	0.001***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L3.Δ log(Industrial Production)	-0.102***	-0.102***	-0.102***	-0.101***	-0.102***	-0.101***	-0.101***	-0.101***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L4.Δ log(Industrial Production)	-0.123***	-0.123***	-0.123***	-0.122***	-0.123***	-0.122***	-0.122***	-0.123***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Δ log(Total Capital/Total Assets)	-0.286***	-0.206**	-0.381***	-0.368***	-0.266***	-0.422***	0.366***	-0.398***
	(0.072)	(0.083)	(0.072)	(0.082)	(0.066)	(0.079)	(0.097)	(0.075)
L2.Δ log(Total Capital/Total Assets)	-0.593***	-0.814***	-0.793***	-0.883***	-0.546***	-0.543***	-0.284***	-0.520***
	(0.091)	(0.101)	(0.106)	(0.104)	(0.083)	(0.086)	(0.090)	(0.086)
L3.Δ log(Total Capital/Total Assets)	-0.125	-0.199**	-0.095	-0.219**	-0.152*	-0.146	-0.052	-0.096
	(0.092)	(0.087)	(0.101)	(0.088)	(0.092)	(0.092)	(0.101)	(0.092)
L4.Δ log(Total Capital/Total Assets)	0.014	0.052	0.081	0.047	0.034	-0.150*	0.303***	-0.074
	(0.067)	(0.086)	(0.073)	(0.075)	(0.066)	(0.079)	(0.081)	(0.071)
L.Δ log(Securities/Total Assets)	-0.263***	-0.221***	-0.241***	-0.230***	-0.024	-0.162***	-0.161***	-0.140***
	(0.022)	(0.021)	(0.021)	(0.022)	(0.029)	(0.020)	(0.019)	(0.020)
L2.Δ log(Securities/Total Assets)	-0.126***	-0.098***	-0.108***	-0.105***	-0.075***	-0.089***	-0.078***	-0.094***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.028)	(0.021)	(0.021)	(0.021)
L3.Δ log(Securities/Total Assets)	-0.124***	-0.136***	-0.134***	-0.152***	-0.103***	-0.117***	-0.118***	-0.118***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.030)	(0.022)	(0.022)	(0.022)
L4.Δ log(Securities/Total Assets)	-0.296***	-0.294***	-0.301***	-0.310***	-0.215***	-0.249***	-0.260***	-0.246***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.028)	(0.021)	(0.020)	(0.021)
Time Trend	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Regional Dummies (a)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Regional Dummies (b)	0.057	0.054	0.062	0.051	0.056	0.059	0.060	0.059
	(0.046)	(0.047)	(0.049)	(0.045)	(0.045)	(0.046)	(0.047)	(0.047)
Regional Dummies (c)	0.095**	0.091**	0.095**	0.092**	0.092**	0.098**	0.097**	0.096**
	(0.043)	(0.042)	(0.046)	(0.042)	(0.042)	(0.043)	(0.045)	(0.044)
Regional Dummies (d)	0.097*	0.096*	0.100*	0.092	0.095*	0.099*	0.098*	0.097*
	(0.057)	(0.057)	(0.059)	(0.057)	(0.057)	(0.057)	(0.058)	(0.058)
Regional Dummies (e)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Observations	112772	111684	111776	109499	112707	112772	112772	112772
Number of Firms	4756	4724	4724	4663	4754	4756	4756	4756

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: First-stage estimates at horizon $h = 0$ using our linear model given in equation (5). Note that the dependent variable is always the change in the EFFR, i.e., our policy indicator Δr_t. Each column title gives the short-hand name of our dependent variable from the second-stage regression. For example, the first column title "Total Loans" stands for the log of (real) total loans.

Table D.2: **First Stage Estimation Results, Full Sample (1990-2016)**

	Total Loans	Cons. Loans	RE Loans	C&I Loans	Liquid Securities	Deposits	Total Capital	Total Assets
MPI (Total)	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.MPI (Total)	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L2.MPI (Total)	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L3.MPI (Total)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L4.MPI (Total)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.log(Dependent Variable/CPI)	-0.001***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L2.log(Dependent Variable/CPI)	-0.000***	-0.000***	-0.000***	-0.000***	0.000**	0.000***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L3.log(Dependent Variable/CPI)	-0.000***	-0.000***	-0.000***	-0.000***	0.000	0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L4.log(Dependent Variable/CPI)	-0.000***	-0.000**	-0.000***	-0.000***	-0.000	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Δ log(GDP/CPI)	-0.032***	-0.033***	-0.032***	-0.032***	-0.033***	-0.033***	-0.032***	-0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L2.Δ log(GDP/CPI)	0.019***	0.019***	0.019***	0.018***	0.018***	0.019***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L3.Δ log(GDP/CPI)	0.208***	0.207***	0.208***	0.207***	0.207***	0.207***	0.208***	0.209***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L4.Δ log(GDP/CPI)	0.303***	0.302***	0.302***	0.301***	0.302***	0.302***	0.302***	0.303***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Δ Unemployment	-0.243***	-0.245***	-0.244***	-0.242***	-0.245***	-0.245***	-0.243***	-0.243***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L2.Δ Unemployment	-0.281***	-0.281***	-0.281***	-0.281***	-0.281***	-0.282***	-0.282***	-0.281***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L3.Δ Unemployment	-0.091***	-0.092***	-0.091***	-0.091***	-0.091***	-0.090***	-0.090***	-0.089***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L4.Δ Unemployment	0.113***	0.113***	0.114***	0.113***	0.114***	0.115***	0.113***	0.114***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Δ log(Industrial Production)	0.143***	0.143***	0.143***	0.143***	0.143***	0.143***	0.143***	0.143***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L2.Δ log(Industrial Production)	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.025***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
L3.Δ log(Industrial Production)	-0.122***	-0.122***	-0.122***	-0.122***	-0.122***	-0.122***	-0.122***	-0.122***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L4.Δ log(Industrial Production)	-0.138***	-0.138***	-0.138***	-0.137***	-0.138***	-0.137***	-0.137***	-0.138***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Δ log(Total Capital/Total Assets)	-0.289***	-0.227***	-0.322***	-0.337***	-0.245***	-0.386***	0.439***	-0.450***
	(0.074)	(0.084)	(0.083)	(0.084)	(0.073)	(0.079)	(0.097)	(0.077)
L2.Δ log(Total Capital/Total Assets)	-0.846***	-1.040***	-1.002***	-1.083***	-0.775***	-0.655***	-0.450***	-0.719***
	(0.100)	(0.119)	(0.118)	(0.121)	(0.099)	(0.099)	(0.095)	(0.098)
L3.Δ log(Total Capital/Total Assets)	-0.547***	-0.696***	-0.592***	-0.738***	-0.549***	-0.475***	-0.222**	-0.503***
	(0.104)	(0.101)	(0.114)	(0.102)	(0.099)	(0.102)	(0.102)	(0.101)
L4.Δ log(Total Capital/Total Assets)	-0.423***	-0.550***	-0.398***	-0.567***	-0.381***	-0.550***	0.076	-0.489***
	(0.088)	(0.088)	(0.097)	(0.085)	(0.084)	(0.098)	(0.084)	(0.093)
L.Δ log(Securities/Total Assets)	-0.196***	-0.143***	-0.170***	-0.164***	-0.067**	-0.116***	-0.107***	-0.089***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.029)	(0.021)	(0.021)	(0.021)
L2.Δ log(Securities/Total Assets)	-0.134***	-0.098***	-0.107***	-0.107***	-0.146***	-0.095***	-0.077***	-0.095***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.033)	(0.024)	(0.024)	(0.024)
L3.Δ log(Securities/Total Assets)	-0.084***	-0.062**	-0.069***	-0.084***	-0.061*	-0.049**	-0.042*	-0.045*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.032)	(0.024)	(0.024)	(0.024)
L4.Δ log(Securities/Total Assets)	-0.231***	-0.213***	-0.218***	-0.235***	-0.165***	-0.166***	-0.173***	-0.164***
	(0.022)	(0.022)	(0.023)	(0.022)	(0.028)	(0.021)	(0.021)	(0.021)
Time Trend	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Regional Dummies (a)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Regional Dummies (b)	0.052	0.043	0.060	0.050	0.049	0.051	0.051	0.052
	(0.038)	(0.039)	(0.045)	(0.037)	(0.035)	(0.036)	(0.039)	(0.038)
Regional Dummies (c)	0.083***	0.080***	0.090**	0.092***	0.081***	0.082***	0.080***	0.081***
	(0.027)	(0.027)	(0.036)	(0.030)	(0.025)	(0.026)	(0.029)	(0.028)
Regional Dummies (d)	0.096**	0.096**	0.103**	0.106***	0.094**	0.095**	0.094**	0.095**
	(0.040)	(0.040)	(0.047)	(0.040)	(0.038)	(0.039)	(0.042)	(0.041)
Regional Dummies (e)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Observations	177931	175660	176432	173305	177550	177931	177931	177931
Number of Firms	5721	5669	5685	5604	5713	5721	5721	5721

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: First-stage estimates at horizon $h = 0$ using our linear model given in equation (5). Note that the dependent variable is always the change in the EFFR, i.e., our policy indicator Δr_t. Each column title gives the short-hand name of our dependent variable from the second-stage regression. For example, the first column title "Total Loans" stands for the log of (real) total loans.

Table D.3: **Balance Sheets by Liquidity Category**

	Cash Illiquid Banks	Cash Lliquid Banks
Assets		
Total Loans	61.15	59.20
Real Estate Loans	33.42	31.39
Consumer Loans	11.73	10.68
C&I Loans	12.93	13.83
Total Reserves	0.47	2.55
Excess Reserves	0.23	2.22
Required Reserves	0.24	0.34
Securities	29.08	29.27
Total Assets	1033.77	1320.68
Liabilities		
Total Deposits	86.11	86.87
Equity (Net Worth)	7.51	7.51
Nr of Banks in 1990q4:	2209	621
Assets		
Total Loans	68.58	66.25
Real Estate Loans	52.86	50.81
Consumer Loans	3.94	3.71
C&I Loans	10.30	9.00
Total Reserves	0.21	2.18
Excess Reserves	0.10	2.04
Required Reserves	0.11	0.14
Securities	21.07	22.54
Total Assets	5655.93	1530.96
Liabilities		
Total Deposits	77.47	78.89
Equity (Net Worth)	10.53	11.16
Nr of Banks in 2007q4:	1587	146
Assets		
Total Loans	68.69	65.71
Real Estate Loans	53.65	50.89
Consumer Loans	2.97	3.70
C&I Loans	9.34	9.27
Total Reserves	0.59	6.23
Excess Reserves	0.17	5.75
Required Reserves	0.42	0.47
Securities	21.22	18.69
Total Assets	2960.54	10777.53
Liabilities		
Total Deposits	81.48	83.14
Equity (Net Worth)	10.91	11.23
Nr of Banks in 2016q4:	882	1260