Monetary Policy and Credit Flows: A Tale of Two Effective Lower Bounds

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Abstract

This paper evaluates the quantitative effects of monetary policy on credit flows. Using Compustat data and a factor-augmented vector autoregression where monetary policy shocks are identified via external instruments, we show that monetary policy increases aggregate long-term credit creation and destruction, while it tends to have a negative effect on aggregate short-term credit creation and destruction. Focusing on two effective lower bound periods, we show that monetary policy prompted a reshuffling of credit toward financially constrained firms, notably small, young, and high-default-probability firms, during these unconventional times. Our findings underscore the effectiveness of monetary policy in steering credit toward financially constrained firms and stimulating future economic activity during unconventional times.

Keywords: Monetary Policy, Credit Reallocation, Business Cycles, External Instruments.

JEL Classification: E44, E51, E52, E58.

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We thank participants at several seminars and conference, including the BI Norwegian Business School, the Bureau of Economic Analysis, the International Association of Applied Econometrics Annual Conference, the Midwest Econometrics Group Meeting, the Southern Economics Association Meetings, Universitat de Girona, Universitat Rovira i Virgili, and the IX Time Series Workshop in Zaragoza for useful comments and suggestions. All remaining errors are ours.

1 Introduction

At an unscheduled Federal Open Market Committee (FOMC) meeting on March 15, 2020, the Federal Reserve (Fed) responded to fears of the Covid-19 pandemic crippling the global economy by lowering the federal funds rate to a range of 0 to 1/4 percent. This move brought policymakers to the ostensible effective lower bound (ELB), whereby conventional monetary policy options were exhausted. However, the Fed did not cease their efforts to stimulate the economy and swiftly prepared to implement further aggressive policy measures. Indeed, in the FOMC statement, the Fed declared that it was "prepared to use its full range of tools to support the flow of credit to households and businesses and thereby promote its maximum employment and price stability goals" and that it would "use its tools and act as appropriate to support the economy." The subsequent unconventional policy actions undertaken over the next two years likely helped stave off a full-blown economic collapse.

Of course, March 2020 was not the first occurrence of the federal funds rate reaching the ELB. In the late 2000s, the Fed employed unconventional policy methods to provide monetary accommodation amid a Global Financial Crisis. By November 2014, the Fed had purchased nearly $4 trillion worth of mortgage-backed securities, agency debt, and long-term U.S. Treasuries. Additionally, Fed officials engaged in forward guidance to shape expectations of market participants about the future course of policy actions. These unprecedented measures aimed to stabilize the financial system, which had been impeding economic growth due to tight credit standards. Monetary policy accommodation was achieved, in part, through artificially boosting collateral prices. This, in turn, improved the availability of credit to borrowers pledging assets as collateral for external financing. Furthermore, through the utilization of forward guidance and rounds of quantitative easing, the Fed managed to lower market expectations of long-term yields. This decrease – once the ELB was reached – eased financial conditions for households and firms.[1] Lessons learned from the research on the

[1] See Krishnamurthy and Vissing-Jørgensen (2011), Rodnyansky and Darmouni (2017), Fieldhouse et al. (2018), Chakraborty et al. (2020), and Di Maggio et al. (2020).

effectiveness of unconventional monetary policy appear to have been at the forefront of the Fed's effort to support the economy again during the Covid-19 crisis.

While there is no full consensus regarding the effects of unconventional monetary policy (see Kuttner (2018) and Greenlaw et al. (2018)), a majority of articles suggest that quantitative easing and forward guidance were effective in lowering long-term rates and that such reductions had a significant impact on macroeconomic aggregates. However, an understanding of the role played by unconventional monetary policy in shaping the dynamics of credit reallocation remains limited. Do these policies intensify the process of credit reallocation by fostering the creation of credit or delaying the destruction of credit lines? Can they boost economic activity by upholding and facilitating the flow of credit towards financially constrained firms? Moreover, if such effects exist, is credit reshuffled towards more efficient uses? Nevertheless, an understanding of the similarity of these effects on credit flows during the two ELB periods remains limited.

To address these questions, we first compute quarterly measures of inter-firm credit flows starting from the balance sheets and income statements of all publicly traded U.S. firms reported in the Standard and Poor's Full-Coverage Compustat tapes.[2] Next, we employ a factor-augmented vector autoregressive (FAVAR) model to estimate the impact of monetary policy shocks on these credit flows. To identify the monetary policy shocks, we employ external instruments, specifically the unexpected fluctuations observed in federal funds futures rates within a 30-minute window surrounding the release of the FOMC announcement similar to Gürkaynak et al. (2005) and Kuttner (2001).

Our first empirical finding highlights that expansionary monetary policy easing has a notable impact on aggregate credit creation and destruction, resulting in increased fluidity in the credit market. A researcher would miss this insight had they restricted their attention solely to net credit growth. Specifically, we observe a cumulative increase of 0.81 percentage

[2]We follow the same methodology employed by Herrera et al. (2011) to construct yearly flows. See Herrera et al. (2021), Bianco (2021), and Contessi and Francis (2013) for other studies that utilize similar credit flow measures.

points in credit reallocation 16 quarters after a -25 basis point shock. This increase is driven by a 0.55 percentage point rise in credit creation and a 0.25 percentage point increase in credit destruction over the same time horizon. This finding implies that the reshuffling of credit induced by the shock is nearly three times the overall net credit change.

We then explore the potential heterogeneous impacts of monetary policy on credit flows for groups of firms based on their financial constraints. We show that the short-term credit flows of specific groups, such as small, young, and high-default-probability firms, increase in response to a monetary easing shock. Conversely, we do not find any significant impact on the short-term credit flows of large, old, or low-default-probability firms, thus suggesting that monetary policy may be effective in easing financial constraints. Furthermore, while various groups' long-term credit flows exhibit significant increases following monetary easing, the responses tend to be larger for small firms compared to large firms and marginally larger for young and high-default-probability firms compared to old and low-default-probability firms.

To further investigate the heterogeneous impact of unconventional monetary policy, particularly during the two ELB periods, we construct counterfactual scenarios by simulating alternative situations where the monetary policy instrument is constrained by the ELB. This allows us to examine the potential effects of unconventional policy measures on credit flows when the ELB is reached.

The counterfactual analysis reveals meaningful impacts of unconventional monetary policy on credit flows during two ELB periods. We find that unconventional policies contribute substantially more to the short-term credit creation for small, young, and high-default-probability firms, with these effects being more notable during the ELB of the Financial Crisis than the Covid-19 pandemic. Unconventional monetary policy also caused a substantial reallocation of short-term credit among firms with high probability of default. Regarding long-term credit, the impact of unconventional monetary policy is more uniform across various groups, except for small versus large firms, where the former experience relatively greater increases in credit creation and credit reallocation.

Finally, our results reveal a silver lining to the monetary policy measures implemented during the first ELB period, as these policies facilitated the reshuffling of credit toward firms whose credit is more efficient. Using a measure of credit efficiency inspired by the work of Galindo et al. (2007), we find that the groups of firms experiencing increased credit flows were also those with relatively higher credit efficiency. However, the evidence regarding credit efficiency during the second ELB period is mixed, suggesting that the impact of monetary policy on credit allocation efficiency may vary.

Our paper contributes to two key strands of literature. First, we build upon a large body of empirical research that examines the transmission of monetary policy in relation to firm heterogeneity. Recent theoretical modeling, e.g., Heterogeneous Agent New Keynesian (HANK) models (See Kaplan et al. (2018)), commonly accounts for heterogeneity in agents. However, earlier HANK models tend to highlight heterogeneity in households rather than firms. This paper contributes to a growing literature that examines the crucial role of firm heterogeneity in the transmission of monetary policy.[3] Previous empirical studies, such as those by Kashyap et al. (1994), Gertler and Gilchrist (1994), and Kashyap and Stein (1995), have argued that monetary policy has a more pronounced effect on small and/or young firms, which are more vulnerable to credit constraints. This line of research has been further supported by recent studies such as Anderson and Cesa-Bianchi (2024), Durante et al. (2022), and Cloyne et al. (2023). In our study, we build upon this literature by providing further evidence that supports the relevance of firm heterogeneity, specifically in financial constraints, in the transmission of monetary policy.

Furthermore, our paper complements the research conducted by Kudlyak and Sánchez (2017), who examined the behavior of credit for small firms during the Great Recession and the early stages of the ELB period beginning in the late 2000s. They demonstrate that the tightening of borrowers' collateral constraints did not play a notable role in accounting for the behavior of credit markets during the Great Recession. However, their study does not

[3]See Sims and Wu (2020), Ottonello and Winberry (2020), Koby and Wolf (2020), Jeenas (2023), and González et al. (2024) for theoretical models akin to HANK models, yet focusing on firm heterogeneity.

quantify the impact of unconventional monetary policy on credit flows, nor do they analyze the entirety of the two ELB periods.

The second strand of literature empirically studies the transmission of monetary policy to the aggregate economy. To date, this literature has focused on the impact of monetary policy shocks on macroeconomic aggregates (see, e.g., Bernanke et al. (2005); Gertler and Karadi (2015); Wu and Xia (2016)). Our study complements the work by Contessi and Francis (2013), who explore the behavior of gross credit flows in the period leading to the Great Recession using balance sheet data for insured U.S. commercial bank and by Contessi et al. (2015), who study the response of gross borrowing and lending flows to several macroeconomic shocks. Our paper is more closely related to work by Bianco (2021) that assesses the channels of monetary policy transmission to inter-firm credit flows.

2 Data and Measurement

2.1 Credit Flows

As in Herrera et al. (2011) –hereafter HKM–, we compute measures of inter-firm credit flows starting from the balance sheets of all publicly traded U.S. firms reported in the Standard and Poor's Full-Coverage Compustat tapes. Firms in the finance, insurance, and real estate industry sectors are removed from the sample, given our objective to study the impact of monetary policy on the firms that demand credit, instead of firms that create credit. Using these data to study the effect of monetary policy shocks on credit reallocation presents some advantages and shortcomings. A clear shortcoming is that Compustat only includes publicly traded firms, which tend to be larger and less financially constrained. Therefore, small private firms whose short-term credit and sales were traditionally thought to be more responsive to monetary policy (see, e.g., Gertler and Gilchrist (1994)) are excluded. However, Kudlyak and Sánchez (2017) found that large firms exhibited a greater contraction in sales and short-term credit than small firms in 2008–09. Furthermore, in the last three decades, the share of employment and revenue of large firms has increased significantly (Begenau et al., 2018), thus increasing the contribution of these firms to the aggregate dynamics of employment and production. Understanding how credit is reallocated among large firms is essential in evaluating the impact of unconventional monetary policy during and after the Great Recession.

A key advantage of the Compustat tapes is the lengthy period of time spanned by the data and the availability of quarterly data. This allows us to estimate a FAVAR model to study the dynamic response of credit flows to monetary policy shocks and compute the historical decomposition to evaluate counterfactual scenarios (see, e.g., Wu and Xia (2016)).

We follow HKM's definition and measurement of credit flows in most aspects, but depart from their approach in that we use quarterly, instead of annual, data and expand the sample to include the period of the ELB.[4] While using annual data would permit the inclusion of earlier years – annual data are available since the early 1950s–, the use of higher frequency data is key for our identification strategy. We note that: (i) the unit of observation is the firm, as we do not have data on the firm's individual projects; (ii) we exclude accounts payable by suppliers from the measure of credit; (iii) we exclude firms for which the ratio of end-of-period gross capital to end-of-period net capital exceeds 120% to control for existing firms that enter the dataset;[5] (iv) only exits due to merger or acquisition, liquidation, or bankruptcy are treated as credit subtractions.

We compute the quarter-to-quarter rate of debt growth, g_{it}, for firm i in quarter t as

$$g_{it} = \frac{debt_{it} - debt_{it-1}}{(debt_{it} + debt_{it-1})/2}. \tag{1}$$

This definition follows that used by Davis et al. (1998) for job flows and is akin to quarterly job flow measures used in related studies (see, e.g., Davis and Haltiwanger (2001);

[4]HKM compute annual credit flows using Compustat over the period 1952–2007. Reliable quarterly data are only available from Compustat starting in the early 1970s.

[5]See Ramey and Shapiro (1998) for the use of similar criteria applied to flows of physical capital and HKM for a detailed description.

Davis et al. (2012); Davis and Haltiwanger (2014)). Moreover, as in the cited studies, the rate of growth is symmetric around zero and bounded, thus allowing for a unified treatment of continuing, newborn, and dying firms (see, e.g., Davis and Haltiwanger (1992); HKM). In particular, $g_{it} \in [-2, 2]$, where -2 corresponds to the debt growth of firms that died in the current year and 2 is the debt growth of new firms.

With the rate of growth defined as above, we proceed to calculate aggregate credit creation and destruction for a set of firms s in quarter t. These are the weighted sums of the rates of debt growth for expanding or entering firms and the weighted sum of the rates of debt growth for contracting or exiting firms, respectively. Specifically, aggregate credit creation for group s in t (POS_{st}) is defined as

$$POS_{st} = \sum_{g_{it} > 0, i \in s} g_{it} \left(\frac{debt_{it}}{debt_{st}} \right). \tag{2}$$

Similarly, credit destruction (NEG_{st}) is defined as

$$NEG_{st} = \sum_{g_{it} < 0, i \in s} |g_{it}| \left(\frac{debt_{it}}{debt_{st}} \right). \tag{3}$$

Furthermore, we compute the gross credit reallocation as the sum of credit creation and credit destruction

$$SUM_{st} = POS_{st} + NEG_{st}. \tag{4}$$

We obtain net credit growth by subtracting credit destruction from credit creation

$$NET_{st} = POS_{st} - NEG_{st} \tag{5}$$

and excess credit reallocation as

$$EXC_{st} = SUM_{st} - |NET_{st}|. \tag{6}$$

Table 1 summarizes aggregate credit flows, including POS, NEG, NET, SUM, and EXC for the period Q1:1974 – Q1:2022. On average, credit creation during this period was 5.30 percent, while credit destruction averaged 3.51 percent, resulting in an average net credit change of 1.79 percent. The table confirms the finding by HKM that the intensity of inter-firm credit flows far exceeds the reallocation needed to accommodate net credit changes, as indicated by the average gross and excess credit reallocation of 8.81 percent and 6.77 percent, respectively. During the period under analysis, the volatility of credit creation is substantially greater than that of credit destruction, with a coefficient of variation of 41.29 for credit creation and 27.80 for credit destruction. The table also provides descriptive statistics for short- and long-term credit flows, and we observe that the average credit flows of long-term credit closely mimic those of total credit, while those of short-term credit are larger. However, short-term credit flows tend to be less volatile than long-term credit flows.

Figure 1 shows the evolution of credit flows over time. Regarding credit reallocation, three notable characteristics emerge. First, credit reallocation intensified during the 1980s compared to the 1970s, as noted by HKM. Second, credit reallocation declined in the late 1980s ad early 1990s, but ramped up in the late 1990s. At this time, the U.S. experienced a secular decline in the pace of job reallocation since 1990 (Davis and Haltiwanger, 1992). Yet, further declines in credit reallocation occurred in the early 2000s and at the onset of the Great Recession in 2007. Credit reallocation rates decreased from over 12 percent before the recession to roughly 6 percent before 2010. This decline in credit reallocation and the reduced fluidity of the credit market were primarily driven by decreased activity in long-term credit.

During the Covid-19 pandemic, credit reallocation was near its historical average while the net credit change reached its nadir of -2.59 percent at the start of 2021. This was due to notable declines in credit creation and increases in credit destruction during the pandemic. For instance, in 2021, credit creation fell to 2.17 percent, its lowest point experienced across the entire sample. Further, credit destruction reached as high as 4.85 percent in 2021, its highest point since the second quarter of 2006.

Figure 2 compares aggregate credit flows to those when entering and exiting firms are excluded (i.e., credit flows at the intensive margin). Credit creation for both aggregate and continuing firms aligns closely, indicating minimal contribution from entering firms, except in Q1:1977 and Q1:1984, where spikes at the aggregate level are likely due to new firms entering the database, primarily from the utilities and telecommunications sectors.

The second panel of Figure 2 highlights that a significant proportion of credit destruction is attributed to exiting firms, particularly in the late 1990s. The gap between intensive and aggregate credit destruction narrowed and was more stable in the 2000s, suggesting that any more recent increases in credit destruction was chiefly the result of shrinking credit rather than exiting firms.

The disparities between NET, SUM and EXC for all firms and continuing firms, shown in Figure 3, arise mainly from differences in credit destruction. The extent to which credit reallocation was driven by debt refinancing (i.e., obtaining financing to pay off existing debt, resulting in increases in both credit creation and destruction) is unclear due to limited information in Compustat. However, we observe that aggregate excess credit reallocation was high in the late 1990s and early 2000s, indicating simultaneously elevated levels of credit creation and destruction. Yet, for continuing firms, it was more stable, peaking in 2006 before falling to a low of 1.74 before the Great Shutdown. Nonetheless, the decline in the intensity of reallocation among continuing firms suggests that the loss of fluidity during the Great Recession and the Covid-19 pandemic was not driven solely by entering and exiting firms, but by reshuffling of credit among existing firms.

2.2 Monetary Policy

Earlier empirical investigations into the effect of monetary policy shocks on economic activity often rely on the federal funds rate as a monetary policy instrument. However, during two periods, namely from December 2008 to December 2015 and again from March 2020 to March

2022, the federal funds rate was stuck at the ELB, thus limiting the use of the instrument to stimulate the economy and invalidating its use as the monetary policy variable in SVARs.

To address this issue, we follow two approaches. First, to identify monetary policy shocks over time, including the ELB, we employ the high-frequency instruments proposed by Gürkaynak et al. (2005) and extended throughout and beyond the two ELBs. Following their work, we first compute changes in various rates around the 30-minute window surrounding planned and unplanned FOMC announcements, and extract the first principal component of the rate changes. We consider three sets of rates: (i) current month through six-month ahead federal funds futures, (ii) current quarter through eight-quarter-ahead Eurodollar future, and (iii) 3-month through 30-year Treasury yields. We sum these within each quarter to fit the frequency of the Compustat data. We then proceed in two ways. First, akin to the method employed by Miranda-Agrippino and Ricco (2021), we regress this measure on four-quarter lags to account for serial correlation and use the residual as the potential external instrument.[6] Alternatively, similar to Bauer and Swanson (2023), we regress the first principal component at the quarterly frequency on six macroeconomic variables and use the residual as a potential external instrument. We evaluate the validity of the instruments and report the results of several tests in Section 3.2.

Second, in our counterfactual analysis, we utilize an alternative measure of the monetary policy stance at the ELB as proposed by Wu and Xia (2016) –hereafter WX–, who develop an approximation to the forward rate in the multifactor shadow rate term structure model.[7] As WX shows, their proposed shadow rate contains relevant information regarding monetary policy when the effective federal funds rate is bounded by zero. We replace the effective federal funds rate with the shadow rate in structural vector autoregressions (SVARs) during

[6]Miranda-Agrippino and Ricco (2021) transform their measure from the FOMC to monthly frequency by regressing the the first principal component on 12 monthly lags, yet we transform to the quarterly frequency by regressing the first principal component on four quarterly lags.

[7]Data for the federal funds rate is obtained from the Fed's H.15 releases, while WX's shadow rate –which corresponds to their benchmark shadow rate term structure model – is provided by the Federal Reserve Bank of Atlanta. See the appendix for a figure depicting the effective federal funds rate and the Wu-Xia shadow rate over time.

the ELB period.[8]

As in Bernanke et al. (2005) –hereafter BBE– and Wu and Xia (2016) we incorporate a large set of economic variables to capture the information available to Fed policymakers when determining the course of monetary policy. These variables include various industry-level measures of labor, consumption, housing, exchange rates, among others. In our study, we used 94 of the original 120 series used by BBE.[9] Additionally, we rotate the measures of aggregate credit creation and destruction of interest (e.g. total creation and destruction or creation and destruction for a group of firms). In the cases where the variables are not reported as rates or indices, we transform them into logged differences to induce stationarity.

3 Empirical Methodology

3.1 Econometric Model

To study the effect of monetary policy shocks on credit flows, we utilize a factor-augmented VAR (FAVAR) model similar to BEE and WX. The transition equation that describes the joint dynamics of the latent factors, F_t, and the monetary policy variable r_t is given by a $VAR(p)$:

$$\begin{bmatrix} \boldsymbol{F_t} \\ r_t \end{bmatrix} = \boldsymbol{c} + \boldsymbol{\Phi(L)} \begin{bmatrix} \boldsymbol{F_{t-1}} \\ r_{t-1} \end{bmatrix} + \boldsymbol{u_t} \tag{7}$$

[8]The reader might wonder: what are the theoretical underpinnings for using the shadow rate to replace the effective federal funds rate during the ELB? Wu and Zhang (2019) build a New Keynesian model where the central bank follows a Taylor rule in normal times but targets a negative shadow rate when unconventional monetary policy is conducted at the ELB. They show that, contrary to what happens at the ELB when a typical Taylor rule is used in a New Keynesian model, in the modified model, negative aggregate supply shocks are contractionary and the magnitude of the government-spending multiplier is reasonable. A similar framework used by Sims and Wu (2020) indicates the effect of unconventional monetary policy on economic activity was equivalent to a two-percentage point decrease in the federal funds rate.

[9]It is worth noting that WX incorporates 97 out of the 120 original series employed by BBE. Of these 97 series, data for (1) new orders (NET) - consumer goods and materials, (2) M2 - money supply - M1 + savings deposits, small time deposits, & MMMFs, and (3) NAPM commodity price index (percent) is not available over the extended sample period. Hence, we include 94 of the 97 variables included in WX in our analysis.

where $\boldsymbol{F_t}$ is a 3×1 vector of latent factors,[10] $\boldsymbol{\Phi(L)}$ is a lag polynomial of order $p = 4$, as chosen by the Akaike information criterion, and $\boldsymbol{u_t}$ is an i.i.d. normal $(m+1) \times 1$ vector of zero mean disturbances such that $\mathrm{E}(\boldsymbol{u_t u_t}') = \boldsymbol{\Omega}$.

The observation equation, which describes the mapping from the latent and observable factors into the informational time series, is given by:

$$\boldsymbol{X_t} = \boldsymbol{k} + \boldsymbol{\Lambda F_t} + \lambda r_t + \boldsymbol{e_t} \tag{8}$$

where $\boldsymbol{X_t}$ is $N \times 1$ vector that comprises large set of macroeconomic variables used by BEE and WX (see Appendix for details) as well as the credit creation and destruction rates, $\boldsymbol{e_t}$ is a $N \times 1$ vector of i.i.d. normal errors with variance $Var(\boldsymbol{e_t} = \boldsymbol{\Sigma})$. The factor loadings on the unobserved factors and the the monetary policy variable are given by $\boldsymbol{\Lambda}$ and λ, respectively. As in Stock and Watson (2018), we impose the assumption that $\boldsymbol{\Lambda}'\boldsymbol{\Lambda} = \boldsymbol{I}$. Equation (8) reflects the notion that both the monetary policy variable and the unobserved factors drive the behavior of the credit flows and the macroeconomic variables.

We estimate the FAVAR model in equations (7)-(8) using a procedure similar to BEE and WX. That is, we first estimate the latent factors and their loading from the observed data $\boldsymbol{X_t}$ using an iterative procedure that purges the factors from the monetary policy variable, r_t. This ensures that the latent factors are orthogonal to the monetary variable of interest. The extracted factors are then used in conjunction with r_t to estimate the reduced-form $VAR(p)$ in equation (7).

To estimate the dynamic causal effect of the monetary policy shock, we follow an approach similar to Alessi and Kerssenfischer (2019), Gertler and Karadi (2015), Mertens and Ravn (2013) and Stock and Watson (2012), among others, and impose additional structure on the contemporaneous effect of the structural shocks by assuming that the reduced-form errors, $\boldsymbol{u_t}$, map into the structural errors, $\boldsymbol{\varepsilon_t}$, so that

[10] To simplify the comparison with WX, we opt for a parsimonious model with three factors. Estimation results not reported here, but available from the authors upon request– indicate that the results are robust to using an alternative number of factors.

$$\boldsymbol{u_t} = \boldsymbol{S}\boldsymbol{\varepsilon_t} \tag{9}$$

where $\boldsymbol{S}$ is a 4×4 nonsingular matrix. Therefore, the variance-covariance matrix of the reduced-form shocks is given by

$$\boldsymbol{\Sigma} = E[\boldsymbol{u_t}\boldsymbol{u_t}'] = E[\boldsymbol{S}\boldsymbol{S}'] \tag{10}$$

Then, to identify the effect of monetary policy, we use external instruments.[11] That is, assume that ε_{4t} is the structural shock of interest (i.e., the monetary policy shock) and let $\boldsymbol{\varepsilon_{4t}}$ collect the remaining three structural shocks. Then, letting $\boldsymbol{s_4}$ denote the fourth column of $\boldsymbol{S}$, it is easy to see that since we are only interested in identifying the effect of the monetary policy shock and not the effect of shocks to the latent factors, we only need to identify the elements of the vector $\boldsymbol{s_4}$. To do so, consider the relationship between the structural shock ε_{4t} and an instrument to be given by

$$z_t = \beta\varepsilon_{4t} + \nu_t \tag{11}$$

where ν_t is i.i.d. normal with mean zero and variance σ_ν.

Now, for the instrument to be valid it needs to be contemporaneously correlated with the monetary policy shock (i.e., $E(z_t, \varepsilon_{4t} \neq 0)$) and uncorrelated with all other shocks $\boldsymbol{\varepsilon_{qt}}$ (i.e., $E(z_t, \boldsymbol{\varepsilon_{qt}} = 0)\ \forall t$). These are the usual exogeneity and relevance assumptions. Hence, in the following section we consider several possible instruments used in the literature and discuss their validity.

[11] The application of external instruments for SVAR identification has become increasingly popular in recent years to analyze the impact of monetary policy on financial and economic outcomes. See Gertler and Karadi (2015), Lakdawala (2019), Miranda-Agrippino and Ricco (2021), Alessi and Kerssenfischer (2019), Jarociński and Karadi (2020), Jarociński (2024), and Cieslak and Schrimpf (2019).

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3.2 Possible instruments for monetary policy shocks

As we discussed in Section 2.2, several instruments have been used in the empirical literature to identify monetary policy shocks. In this section, we assess their validity by performing several tests, which we report in Table 2. We start by testing for serial correlation in the external instruments derived from the Federal funds futures, Eurodollar futures, and Treasuries. Recall that the potential instruments are the residuals of the first principal components derived from the rate changes on (1) four quarterly lags, similar to Miranda-Agrippino and Ricco (2021) or (2) six macroeconomic variables, as in Bauer and Swanson (2023). We find no evidence of serial correlation in any external instruments using Miranda-Agrippino and Ricco (2021)'s method. However, we do find evidence of serial correlation in the external instruments derived from Eurodollars and Treasuries when using Bauer and Swanson (2023)'s method, thus invalidating these two as useful external instruments without additional transformation.

Next, we test whether the potential external instruments Granger-cause the estimated factors in the FAVAR, as this would also cast doubt on their validity. Of the remaining potential external instruments, we find that only the instruments derived from the Federal funds future and Eurodollar futures, both using Miranda-Agrippino and Ricco (2021)'s method, do not Granger-cause the estimated factors, providing further validation for their use as external instruments in our analysis.

Finally, the F-statistic for the strength of the instrument exceeds the typical threshold of 10 when the principal component is extracted from federal funds futures and Eurodollar futures. For our baseline, we use the instrument derived from the federal funds futures and following Miranda-Agrippino and Ricco (2021)'s transformation method as its F-statistic (25.518) exceeds that of the Eurodollar futures (12.578).[12]

[12] Estimation results, available from the authors upon request, using Eurodollar futures are almost identical despite the instrument being somewhat weaker. See the Appendix for the instrument that we utilize plotted across time.

4 The Effect of Monetary Policy and the Flow of Credit

4.1 The Impulse Responses of Credit Flows

This section first compares the responses of aggregate credit flows to a monetary policy shock identified using a baseline recursive scheme –as in WX and BBE– and identified using the external instrument. Building on work such as Lakdawala (2019) and Swanson (2021), we expect the responses of credit flows to a monetary easing shock obtained using external instruments to also capture the effect of unconventional monetary policy on credit flows.

Figure 4 plots the responses of POS and NEG to a −25 basis point monetary policy shock. Confidence bands are obtained using a wild bootstrap (Gonçalves and Kilian, 2004).[13] Given the recursive identification scheme of the baseline model, the response of the credit flow measures are zero on impact. However, when the monetary policy shock is identified using the external instrument, the initial impact of the shock on aggregate credit creation and destruction is 0.078 and 0.012 percentage points, respectively, and statistically significant.

Figure 5 plots the responses of POS, NEG, SUM, NET, and EXC to a −25 basis point monetary policy shock. We show that monetary policy easing leads to a prolonged increase in aggregate credit creation at longer horizons (three through 16 quarters) in addition to the initial increase. By the 16$^{\text{th}}$ quarter, the cumulative increase in credit creation reaches 0.55 percentage points. Credit destruction responds significantly to the shock at similar horizons, but with a smaller magnitude compared to credit creation. By the 16$^{\text{th}}$ quarter, aggregate credit destruction increases by 0.25 percentage points. These effects are nontrivial considering that the average credit creation and destruction are 5.30 and 3.51 percent, respectively. 16 quarters after the shock, net credit increases 0.30 cumulative percentage points, and there is an intense and significant response of credit reallocation (0.81 percentage points). Although Compustat does not record the specific reasons for firms' credit changes from one period to the next, our findings suggest that monetary policy easing not only leads to an

[13] We re-sample ε_t using wild bootstrapping and generate the artificial factors, $\widehat{F}_t^*$, using Kilian (1998)'s bias correction method.

increase in credit creation – through lines of credit, bank loans, or bond issuance, for instance – but also induces firms to deleverage (i.e., repay debt or allow debt to mature), such as to reduce the overhang of debt (e.g. Eggertsson and Krugman (2012)), among other possible motivations.

Next, we analyze the impact of monetary policy shocks on short- and long-term credit flows, considering their typical roles in financing current business operations and long-term investment plans, respectively. The responses of short-term credit flows to monetary easing are shown in Figure 6. We observe significant declines in short-term credit creation in response to the shock, which are more immediate than the declines in short-term credit destruction. Although the responses are small, they are statistically significant and lead to small and short-lived changes in net credit. However, both gross and excess short-term credit reallocation show consistently negative and significant responses at short- and medium-term horizons. Although we do not explore the specific mechanism by which monetary policy easing leads to a decrease in credit reallocation, we conjecture that factors such as increased asset prices and reduced loan defaults associated with expansionary monetary policy, as well as lower interest expenses reduce the need for borrowing (Bianco, 2021).

Figure 7 highlights the impact of monetary easing on long-term credit flows, which closely resembles the overall response of total credit flows. When the short-term component is excluded, the effects of these shocks become more pronounced. For example, after 16 quarters, long-term credit creation experiences a cumulative increase of 0.81 percentage points in response to the monetary policy shock as opposed to 0.55 percentage points in total credit. Similarly, long-term credit destruction increases by 0.35 cumulative percentage points in response to the shock.

4.2 Credit Flows at the Effective Lower Bounds

To shed further light on the effect of unconventional monetary policy on credit flows during the ELB, we first follow Kilian and Lütkepohl (2017) and Sims and Zha (2006) by expressing the paths of the variables of interest as a function of all past shocks and initial conditions. We then calculate the contribution of the monetary policy shocks[14] to the path of these variables over time. Second, we construct a policy counterfactual to describe the path that the economy would have taken had a certain scenario occurred. We analyze the contribution of monetary policy shocks to credit flows during periods where the shadow rate was negative ("Financial Crisis ELB": Q3:2009 – Q3:2015 and "Covid-19 ELB": Q4:2020 – Q4:2021). In the counterfactual analysis, we replace the series of monetary policy shocks with one that forces the shadow federal funds rate to the ELB during the counterfactual periods. This is achieved by adding the difference between the observed shadow rate and the ELB rate, 0.25%, to the monetary shock series and using the parameter estimates to simulate the counterfactual. Doing so allows us to quantify how credit flows would have responded had monetary policy been constrained by the ELB. We compute wedges between the actual and counterfactual values of the variables of interest at time τ such that

$$wedge^i_\tau = Y^i_\tau - \sum_{s=t_1}^{\tau} \Psi^{r,i}_s \upsilon^{cf}_s \tag{12}$$

where t_1 refers to the beginning of each ELB period. In the counterfactual, we let $\upsilon^{cf}_s = \upsilon_s + 0.25 r_s$, which corresponds to the case where the federal funds rate is set to 0.25%, and compute the counterfactual path for credit creation and destruction. Then, using the definitions for credit reallocation, net credit change, and excess credit reallocation in (4) through (6), we compute the counterfactual for the remaining credit flow measures. In effect, the counterfactual evaluates the impact of unconventional monetary policy by assuming that the shadow rate remains at 0.25 percent, which is equivalent to the Fed funds rate during the two ELB periods.

The first column of Figure 8 presents the counterfactual wedges for short- and long-term credit flows during the two ELB periods. Unconventional monetary policy led to slight declines in short-term credit creation during both ELB periods, with an exception at the end

[14]See the Appendix for a plot of the monetary policy shock series throughout the ELB periods.

of the Financial Crisis ELB. In contrast, long-term credit creation increased throughout both ELB periods and by substantially larger magnitudes. The figure also shows that the effect of unconventional monetary policy in the third quarter of the Covid-19 ELB was in line with the highest peaks during the previous ELB. The effects of unconventional monetary policy on short- and long-term credit destruction were small in both ELB periods. Although, unconventional monetary policy appears to have staved off the destruction of short-term credit during both ELB periods (the wedges are negative), it does not appear to have had the same effect on long-term credit destruction. Overall, unconventional monetary policy also resulted in increased long-term gross and excess credit reallocation during both ELB periods, with a largest peaks observed during the Financial Crisis ELB.

The impact of unconventional monetary policy on short- and long-term credit creation is similar for continuing firms (Figure 8, second column) and all firms. However, the response of long-term (short-term) credit destruction is slightly smaller (larger) for continuing firms than for all firms. Nevertheless, the magnitudes are comparable, suggesting that the responses are qualitatively similar for continuing and entering/exiting firms. Yet, long-term excess credit reallocation is notably smaller for continuing firms, indicating that unconventional monetary policy brings about a less fluid reallocation of long-term credit for exiting and entering firms in comparison to that of all firms.

5 The Role of Financial Frictions in Monetary Policy's Effect on Credit Flows

To investigate the potential heterogeneity in the impact of monetary policy on credit flows among firms with different levels of financial friction, we draw insights from the works of Bianco (2021) and Cloyne et al. (2023). We first categorize firms into different subgroups based on various proxies commonly used in the corporate finance literature to capture financial constraints. We then compute the credit flows for each subgroup. The proxies we employ include:

(i) The value of the total assets at the beginning of the quarter, as suggested by Gertler and Gilchrist (1994) and Kudlyak and Sánchez (2017).

(ii) Firm age, measured as the number of years since the firm was first listed in the Compustat database.

(iii) Default probability as suggested by Farre-Mensa and Ljungqvist (2016).

(iv) Leverage, calculated as the ratio of short-term debt to total assets following Kudlyak and Sánchez (2017).

Next, in each quarter, we sort the firms by these financial constraint measures and refer to firms that fall in the top tercile by leverage ratio, bottom tercile by value of assets, and age. Following Farre-Mensa and Ljungqvist (2016), firms with a default probability greater than 25% are classified as financially constrained.[15]

5.1 Heterogeneous Effects of Monetary Policy Shocks

The analysis in the previous section sheds light on the evolution of credit flows during the ELB periods. In this section, we investigate the interaction between monetary policy and several firm characteristics that may proxy for financial frictions.

5.1.1 Size of Firms

The first panel of Table 4 reports the impulse responses of short- and long-term credit flows for both large and small firms to a monetary easing shock. Although we estimate that *aggregate* short-term credit flows generally respond negatively to a negative 25 basis points

[15] The average percentage of firms that switch from being classified as not financially constrained to financially constrained in a quarter is a mere 0.38 percent by the leverage ratio (3,603 instances), 0.00 percent by the value of assets (32 instances), 0.00 percent by age (0 instances), and 2.64 percent by default probability (25,188 instances).

monetary shock, the table highlights that short-term credit creation of small firms exhibits a positive and significant response to the shock. This is to be expected, as small firms are commonly regarded to be more financially restricted (Gertler and Gilchrist, 1994; Kudlyak and Sánchez, 2017). Specifically, in response to the monetary policy shock, small firms experience an immediate increase of 0.16 percentage points in short-term credit creation, which reaches 0.90 percentage points after eight quarters. On the contrary, no significant change in short-term credit creation is observed for large firms at these horizons. The table also shows that the impact of the shock on short-term credit destruction is small on impact. However, there are significant increases in short-term net credit and credit reallocation for small firms, mainly driven by the response of credit creation. Consequently, the responses of short-term excess credit reallocation for small firms are significant only on impact.

In response to the shock, we find a significant response of long-term credit creation of both groups of firms, yet the response is larger in magnitude for small firms at each horizon. While we find that long-term credit destruction increases slightly for large firms, we find no significant changes in long-term credit destruction for small firms in response to the shock. The resulting increases in small firms' long-term net credit change and credit reallocation are primarily due to the responses of credit creation.

5.1.2 Age of Firms

Expansionary monetary policy can have a dual impact on young firms. These firms often face financial constraints due to limited collateral and perceived riskiness, making them more susceptible to such constraints compared to more established borrowers (Carreira and Silva, 2010). If expansionary monetary policy alleviates these constraints, it is expected to result in a relatively greater increase in credit creation for young firms. However, as highlighted in Dinlersoz et al. (2018), young firms typically incur more costly debt, which they repay as they mature and switch to cheaper external financing options. In this context, expansionary monetary policy, by reducing borrowing costs, is likely to induce a larger proportional increase in credit creation for young firms. However, it may also lead to credit destruction as young firms engage in deleveraging by replacing expensive debt with cheaper financing options.

According to the second panel of Table 4, the response of short-term credit creation for old firms to a monetary policy shock is not significant. However, there are significant increases in short-term credit creation for young firms. By the eighth quarter after the shock, short-term credit creation for young firms increases by 0.52 percentage points. The responses of short-term credit destruction for both groups of firms are not statistically significant.

Both young and old firms experience significant increases in long-term credit creation following the shock. By the eighth quarter after the shock, long-term credit creation increases by 0.58 percentage points for young firms and 0.52 percentage points for old firms. The response of long-term credit destruction for young firms is not significant. However, both groups of firms show a significant increase in long-term credit reallocation of similar magnitudes in response to the shock. These findings indicate that monetary policy has an impact on the credit flows of financially constrained firms, particularly for short-term credit.

5.1.3 Default Probability of Firms

The next panel of Table 4 shows that high-default-probability firms experience a significant increase in short-term credit creation in response to the monetary policy shock. However, unlike small and young firms, these responses are accompanied by significant increases in credit destruction at several horizons, resulting in a fluid reallocation of short-term credit for this group of firms. The cumulative increase in credit reallocation, eight quarters after the shock, is 0.79 percentage points. Short-term credit creation and destruction responses are similar in magnitude, indicating that monetary policy increases the fluidity of credit markets for high-default-probability firms. No significant responses are found for any short-term credit flows of low-default-probability firms, suggesting that monetary policy has a more pronounced effect on the short-term credit dynamics of financially constrained firms, as measured by default probabilities.

High-default-probability firms and low-default-probability firms experience significant increases in long-term credit creation of similar magnitudes, rising a cumulative 0.53 and 0.51 percentage points, eight quarters after the shock, respectively. We find no evidence that monetary policy influences the long-term credit destruction of high-default-probability firms, and the effect of the shock is small, yet statistically significant, on the long-term credit destruction of low-default-probability firms.

Similar to the results by age, we find that monetary policy leads to a more robust reallocation of short-term credit for financially constrained firms, measured by default probabilities. The magnitude of the effect on long-term credit flows across these groups of firms is comparable.

5.1.4 Leverage of Firms

The final proxy for financial constraints that we consider is leverage. Thus, we group firms into high- and low-leverage groups. Impulse responses, presented in the last panel of Table 4, indicate that monetary policy does not significantly affect short-term credit creation for financially-constrained firms when categorized by their leverage ratio. However, the shock has an immediate and persistent effect on long-term credit flows. In particular, the shock leads to significant increases in the long-term credit creation of both high- and low-leverage firms. Furthermore, the impact of the shock on credit destruction tends to be greater for low-leverage firms.

In general, we find that monetary policy influences short-term credit flows of financially constrained firms when firms are grouped by size, age, and default probabilities. Yet, it also increases credit flows of low-leverage firms, which are less likely to be financially constrained. The responses of long-term credit flows among financially constrained and non-financially constrained firms are similar when using age and default probabilities as proxies for financial constraints. However, the response of long-term credit creation is greater for large firms and low-leverage firms compared to their counterparts.

5.2 Heterogeneity in Monetary Policy's Influence on Credit Flows during ELB Periods

5.2.1 Two Effective Lower Bound Periods

During the Financial Crisis ELB, the Federal Reserve implemented unconventional monetary policy in several rounds of quantitative easing (QE1, QE2, Operation Twist, QE3). QE1 involved the creation of the Term Asset-Backed Securities Loan Facility (TALF), which ultimately lent up to $1 trillion to holders of AAA-rated asset-backed securities. The Fed also committed to purchasing large quantities of agency debt, mortgage-backed securities, and Treasury securities. QE2, from November 2010 to June 2011, consisted of monthly $75 billion purchases of Treasury securities, totaling up to $600 billion. Operation Twist, initiated in September 2011, involved purchasing $400 billion of long-term Treasuries and selling $400 billion of short-term Treasuries to reduce long-term yields and stimulate credit markets. The Fed also agreed to purchase additional agency mortgage-backed securities. Although the simultaneous purchase and sale of Treasuries ended in December 2012, the purchase of mortgage-backed securities continued beyond this time. QE3, starting September 2012, involved monthly purchases of $40 billion of agency mortgage-backed securities and $45 billion of long-term Treasuries. At this time, they also announced that these purchases would continue until economic conditions improved. At the beginning of 2014, the Fed reduced purchases by $5 and $10 billion each month, eventually concluding QE3 by October 2014.

During the Covid-19 ELB, the Fed took similar actions, but with faster implementation. The Fed extended credit to financial institutions, provided liquidity to credit markets, and affected long-term interest rates through the purchase of long-term securities. The Fed reintroduced TALF and continued to engage in forward guidance. New programs were created, such as the Main Street Lending Program (MSLP), which facilitated up to $600 billion in loans to small and medium sized businesses and non-profit organizations. The Fed took on portions of the five-year loans made to firms with less than 15,000 employees or $5 billion in revenue. Primary and secondary corporate credit facilities were created, where the Fed purchased new and secondary corporate bonds, respectively. Unlike MSLP, this was to provide credit to larger, investment-grade firms. Other programs included the Paycheck Protection Program Liquidity Facility and the Municipal Liquidity Facility of up to $500 billion. Both aimed at providing more extensive support to the economy, with the former facilitating Paycheck Protection Program loans for small businesses and the latter supporting state and local governments.

To gain some insight into the evolution of inter-firm credit flows during the ELB periods, Table 3 reports the changes in short- and long-term credit flows for these financially-constrained and non-financially-constrained firms during two ELB periods. Two key findings emerge from our analysis;

During the Financial Crisis ELB, all groups, except high-leverage firms, experienced increases in short-term credit creation; short-term credit destruction only increased for small, young, and low-leverage firms. This led to heightened short-term net credit changes for all groups of firms, other than young firms. While groups of firms, such as those with high default probabilities, young firms, small firms, and low-leverage firms, experienced increases in short-term credit reallocation, others, such as low-default-probability firms and large firms, saw decreases. While high-default-probability firms experienced the largest increase in credit reallocation, young firms experienced the largest increase in excess credit reallocation.

During the Covid-19 ELB period, the high-default-probability firms experienced a notable increase in short-term credit creation (12.77 percentage points), while short-term credit destruction was largely unchanged (0.37 percentage points). As during the first ELB, the gross credit reallocation of short-term credit increased substantially during the second ELB for this group, yet excess credit reallocation was low. The largest increase in excess credit reallocation for short-term credit was experienced by small firms, rising 12.73 percentage points; however, this increased credit reshuffling was mainly due to a substantial increase in credit destruction.

Regarding long-term credit flows, credit creation tended to increase during the Financial Crisis ELB, particularly for small firms, rising 8.47 percentage points. Changes in long-term credit destruction are mixed as some groups experienced increases and some decreases, but the changes were often smaller than that of credit creation. During the Covid-19 ELB, long-term credit creation decreased for most groups of firms, whereas long-term credit destruction increased for all firms. Low-leverage firms experienced the largest increase in gross and excess long-term credit reallocation as the increases in credit creation and destruction were large in magnitude and of similar size.

5.2.2 Monetary Policy Counterfactuals, Financial Constraints, and the Effective Lower Bound

Although there is evidence of heterogeneity in the effects of monetary policy on credit flows, particularly on short-term credit, the magnitudes of the policy impacts during the two ELB periods are still uncertain. To assess the impact of this policy, Figures 9 and 10 present the counterfactual wedges of POS and NEG, respectively, for financially-constrained and non-financially-constrained firms using (12). This allows for a clearer understanding of the potential effects and implications of unconventional monetary policy and how they differ across the two ELBs.

Across the ELBs, the counterfactual wedges for short-term credit creation tend to be, on average, positive and large for small firms, young firms, and high-default-probability firms, all of which are more likely to be financially constrained. The difference is particularly striking when we group firms by size, despite Compustat firms being large relative to the universe of US firms. In fact, the wedges tend to be negative for large firms, old firms, and low-default-probability firm throughout much of the ELB periods. This suggests that unconventional monetary policy brought about more short-term credit creation for financially constrained firms, yet the opposite holds for non-financially constrained firms. In contrast, we find that the wedges are more often larger for low-leverage than high-leverage firms. This finding is consistent with empirical evidence put forward by Farre-Mensa and Ljungqvist (2016), who show that constrained firms in Compustat tend to have less leverage than unconstrained firms.

For long-term POS, the wedges for all groups of firms is positive across both ELBs. The wedges are notably larger in magnitude for small firms compared to large firms, indicating that unconventional monetary policy led to more long-term credit creation of financially constrained smaller firms. However, the counterfactual wedges of the other pairs show little difference to one another.

Compared to credit creation, the counterfactual wedges for NEG are small in magnitude during the ELBs. The wedges for short-term credit destruction also tend to be negative with some exceptions, indicating that unconventional monetary policy reduced the destruction of credit. The two most notable exceptions are for high-default-probability firms and low-leverage firms. Further, there are no discernible patterns to suggest that unconventional monetary policy consistently impacts the short-term credit destruction of financially constrained firms more strongly than non-financially constrained firms.

To complete our analysis, we present the counterfactual wedges of NET, SUM, and EXC in Figures 11 - 13. Since the counterfactual wedges for credit creation tend to be large and those for credit destruction tend to be small, by construction, the counterfactual wedges for NET and SUM are also large, while those for EXC are small. When comparing financially constrained to non-financially constrained firms, we show that unconventional monetary policy tends to lead to notably larger increases in short-term credit reallocation for certain groups of financially constrained firms (small, young, and high-default-probability firms). For long-term credit reallocation, the impact of unconventional monetary policy is similar for young and old firms, as well as for high- and low-default-probability firms, but the effects are larger for small firms compared to large firms and for low-leverage firms compared to high-leverage firms.

Interestingly, the counterfactual wedges for long-term excess credit reallocation tend to be larger for non-financially constrained firms because the increases in credit destruction are more aligned with the increases in credit creation for these firms. Additionally, the counterfactual wedges for short-term excess credit reallocation tend to be negative for small and young firms, but positive for high-default-probability firms. This occurs because both the credit creation and credit destruction wedges for high-default-probability firms are large, suggesting that unconventional monetary policy brought about more fluid reallocation for financially constrained high-default-probability firms.

These figures also show that the contributions of unconventional monetary policy to credit flows were generally larger during the Financial Crisis ELB compared to the Covid-19 ELB. However, the impact of unconventional monetary policy was more immediate during the Covid-19 ELB, typically peaking three quarters into the ELB. In contrast, the contributions were small at the start of the Financial Crisis ELB and peaked toward the end of 2014, several years after the introduction of unconventional policies.

6 Monetary Policy and Credit Efficiency

A question that arises when studying the link between the inter-firm allocation of credit, investment, and monetary policy is whether the effect of the latter varies across firms with differing degrees of credit efficiency. Answering this question is key, as credit extended to firms of high credit efficiency should lead to higher economic growth. Although we do not perform a causal analysis of the impact of monetary policy on credit efficiency, this section seeks to illustrate the evolution of credit efficiency during the ELB periods.

Because data required to calculate firm-level factor productivity are not available from Compustat, we ask whether credit was allocated to more productive firms by computing a proxy of efficiency in the allocation of credit. Our proxy is an index similar to that proposed by Galindo et al. (2007) constructed as

$$CE_{jt} = \frac{\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt}}{debt_{jt}}}{\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt-1}}{debt_{jt-1}}} \tag{13}$$

This index measures the efficiency of the allocation of credit (debt) for group j in quarter t relative to the total return obtained if credit had been allocated to firms in proportion to its share in the group's credit, $debt_{ij-1}$.[16] Note that, as in Galindo et al. (2007), the marginal return of credit is proxied by the ratio of sales to capital at the end of quarter t, and we use the fraction of firm i in group j's debt stock at the end of quarter $t-1$ relative to the debt for all firms in the same group in the same quarter to measure the fraction of credit the firm would have received if credit was allocated in the same proportion as in the past.

The average short- and long-term credit efficiency of each group of firms previously analyzed is shown in Table 5. Throughout the period, the highest average credit efficiency belongs to high-default-probability firms (1.1476 for short-term credit and 1.0818 for long-term credit), while the lowest are high-leverage and large firms, respectively.

In previous sections, we showed that unconventional monetary policy resulted in increased short-term credit creation for small, young, high-default-probability, and low-leverage firms relative to their counterparts. During the Financial Crisis ELB, the average short-term credit efficiency of these groups of firms notably exceeds that of their counterparts, as well. During the Covid-19 ELB, the average short-term credit efficiency is notably higher for low-leverage and high-default-probability firms. Yet, the average credit efficiency of large firms and old firms exceeds that of small and young firms. These differences suggests that unconventional monetary policy may have led to a more efficient allocation of short-term credit, particularly during the Financial Crisis ELB.

Similar relationships are observed for long-term credit efficiency. During the Financial

[16]See Galindo et al. (2007) for a discussion on why a sales-based index is preferable to a profit-based index.

Crisis ELB, the efficiency of long-term credit was higher for small, young, high-default-probability, and low-leverage firms. In turn, in previous sections, we showed that these firms experienced relatively large increases in long-term credit creation due to monetary policy easing. However, during the Covid-19 ELB, larger, younger, high-default-probability, and low-leverage firms had higher long-term credit efficiency. Hence, it is not clear whether monetary policy easing aids in channeling funds to more credit-efficient firms during the Covid-19 ELB. In all, our calculations suggest that during a ”normal” financial crisis (i.e. the Financial Crisis ELB), monetary policy easing may have a positive effect on credit efficiency.

7 Conclusion

In this paper, we illustrate the significant and persistent impact of unconventional monetary policy on credit allocation of firms. A monetary policy shock of −25 basis points results in a significant increase of 81 basis points in aggregate long-term credit creation and a 35 basis point increase in aggregate long-term credit destruction after 16 quarters. We also observe that unconventional monetary policy leads to declines in aggregate short-term credit creation and destruction.

However, focusing on heterogeneity in financial constraints, we found that groups of small, young, and high-default-probability firms experienced substantial increases in short-term credit creation after a monetary policy shock. These responses tended to be more pronounced than those of their less financially constrained counterparts (i.e., large, old, and low-default-probability firms). While we find that the responses of long-term credit flows to the monetary policy shock are generally more uniform across different groups, we do find notably larger responses of small firm's long-term credit creation compared to those of large firms.

Analysis of two effective lower bound (ELB) periods, the Financial Crisis and Covid-19, showed that unconventional monetary policy contributed most to short-term credit creation of small firms compared to large firms, young firms compared to old firms, high-default-probability firms compared to low-default-probability firms, and low-leverage firms compared to high-leverage firms. Unconventional monetary policy's heterogeneous effect is less apparent for long-term credit, yet we found that it contributed relatively more to the long-term credit creation of small firms compared to large firms.

Despite evidence of larger credit destruction effects on certain groups, positive effects on credit creation dominated, signifying the policy's effectiveness in easing financial constraints during ELB periods.

Lastly, the study found mixed evidence on the efficiency of credit allocation that monetary policy influenced during the ELB periods. Short- and long-term credit efficiency tends to be higher for groups of firms for which unconventional monetary policy leads to increases in credit creation, particularly during the Financial Crisis ELB. Yet, during the Covid-19 ELB, the long-term credit creation that unconventional monetary promoted tended to flow to firms with lower credit efficiency.

Our findings offer important insights into how unconventional monetary policy impacts credit flows and the broader economy. They underscore the potency of the Federal Reserve's measures, particularly when the federal funds rate hits the ELB, in reallocating credit towards financially constrained firms. Additionally, unconventional monetary policy has potentially directed credit towards firms better positioned for investment and growth. In general, the implementation of unconventional monetary policy in the ELB is an effective tool to stimulate economic activity by intensifying credit reallocation and improving the fluidity of the credit market.

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Tables

Table 1: Descriptive Statistics of Aggregate Credit Flows

		POS	NEG	NET	SUM	EXC
Average	Total credit	5.30	3.51	1.79	8.81	6.77
	Long-term credit	5.79	3.59	2.20	9.37	7.01
	Short-term credit	15.11	7.15	7.96	22.26	14.26
Coefficient of variation	Total credit	41.29	27.80	119.67	29.81	27.39
	Long-term credit	41.61	31.30	99.60	32.57	31.54
	Short-term credit	28.78	23.43	55.50	21.97	22.86

Note: POS refers to credit creation, NEG is credit destruction, NET is net credit change ($NET = POS - NEG$), SUM is credit reallocation ($SUM = POS + NEG$), and EXC is excess credit reallocation ($EXC = SUM - |NET|$). Values are based on data from Q1:1974 to Q1:2022.

Table 2: Validity of External Instruments

	Transformation	Serial correlation	Granger causality	Instrument strength
Federal funds futures	(1)	0.419	1.295	25.518
		(0.795)	(0.234)	(0.000)
	(2)	0.627	2.163	3.565
		(0.6440)	(0.019)	(0.062)
Eurodollar futures	(1)	0.015	1.596	12.578
		(0.999)	(0.109)	(0.001)
	(2)	2.779	1.115	0.154
		(0.031)	(0.359)	(0.695)
Treasury yields	(1)	0.018	2.539	6.317
		(0.999)	(0.006)	(0.013)
	(2)	2.080	1.667	0.772
		(0.089)	(0.087)	(0.382)

Note: This table provides F-statistics and p-value in parentheses to test for serial correlation of the external instrument, Granger causality from the factors in the FAVAR to the external instrument and the strength of the external instrument. The external instruments consist of the first principal components extracted from the rates described in the first column and transformed using various approaches. Transformation (1) denotes the residual of the quarterly sum of the first principal component regressed on four lags. Transformation (2) represents the residual of the first principal component when regressed on six macroeconomic variables at the FOMC frequency, which is then summed to a quarterly frequency.

Table 3: Change in Credit Flows during the Effective Lower Bound Periods

	Financial Crisis (Q3:2009 – Q3:2015)									
	Short-term credit					Long-term credit				
	POS	*NEG*	*NET*	*SUM*	*EXC*	*POS*	*NEG*	*NET*	*SUM*	*EXC*
Small firms	6.18	1.92	4.26	8.09	3.83	8.47	−2.92	11.40	5.55	−5.84
Large firms	0.58	−2.66	3.24	−2.07	−5.32	0.02	0.72	−0.70	0.74	1.45
High-leverage firms	−0.82	−1.02	0.20	−1.85	−2.05	−0.47	1.13	−1.60	0.67	2.27
Low-leverage firms	3.86	1.76	2.10	5.62	4.03	1.93	−0.54	2.47	1.39	0.23
Young firms	2.83	3.96	−1.13	6.78	7.92	2.76	0.42	2.35	3.18	0.83
Old firms	4.60	−5.59	10.19	−0.99	−8.89	0.90	−0.14	1.04	0.76	−0.28
High-default-probability firms	12.94	−0.43	13.37	12.51	−0.86	4.35	−0.31	4.66	4.03	2.11
Low-default-probability firms	0.59	−3.04	3.62	−2.45	−6.07	−0.35	0.71	−1.06	0.36	1.42

	Covid-19 (Q4:2020 – Q4:2021)									
	Short-term credit					Long-term credit				
	POS	*NEG*	*NET*	*SUM*	*EXC*	*POS*	*NEG*	*NET*	*SUM*	*EXC*
Small firms	0.11	6.37	−6.26	6.47	12.73	−4.89	3.86	−8.75	−1.03	7.72
Large firms	1.82	0.36	1.46	2.18	0.73	−0.53	1.58	−2.11	1.05	1.30
High-leverage firms	1.29	−0.01	1.29	1.28	−0.02	−0.65	1.22	−1.86	0.57	1.71
Low-leverage firms	−0.18	9.48	−9.66	9.30	8.92	10.01	10.10	−0.09	20.11	20.20
Young firms	6.94	2.65	4.29	9.59	5.30	1.35	0.25	1.10	1.60	0.50
Old firms	1.60	−1.00	2.60	0.60	−2.00	−0.58	1.20	−1.78	0.61	1.71
High-default-probability firms	12.77	0.37	12.40	13.14	0.74	0.72	2.26	−1.53	2.98	4.51
Low-default-probability firms	−0.62	−0.78	0.16	−1.40	−1.56	−0.99	1.39	−2.38	0.39	−0.87

Note: This table presents the percentage point changes in the credit flow measures during two distinct periods: Q3:2009 to Q3:2015 and Q4:2020 to Q4:2021. The classification of firms is based on certain criteria within each quarter. Firms whose total assets fall within the bottom tercile among all firms in a given quarter are considered small, and those in the top tercile are large. Firms whose number of years listed in Compustat falls within the bottom tercile among all firms in a given quarter are considered young and those in the top tercile are old. Following Farre-Mensa and Ljungqvist (2016), firms whose default probability exceeds 25 percent in a given quarter are considered high-default-probability firms and all others are low-default-probability firms. Firms whose leverage ratio falls within the top tercile among all firms in a given quarter are considered high-leverage firms, those in the bottom tercile are low-leverage firms.

Table 4: Cumulative Impulse Responses to a Monetary Policy Shock

		Small firms				Large firms		
		horizon = 0	*horizon* = 4	*horizon* = 8		*horizon* = 0	*horizon* = 4	*horizon* = 8
Short-term	*POS*	0.16**	0.50**	0.90**	*POS*	−0.01	−0.09	−0.12
	NEG	0.03**	−0.00	−0.04	*NEG*	0.01†	−0.05	−0.15
	NET	0.13**	0.51**	0.93**	*NET*	−0.02	−0.04	0.03
	SUM	0.19**	0.50**	0.86**	*SUM*	0.00	−0.14	−0.27
	EXC	0.06**	−0.01	−0.07	*EXC*	−0.02	−0.21	−0.41
Long-term	*POS*	0.18**	0.82**	1.48**	*POS*	0.10**	0.28**	0.49**
	NEG	−0.02	−0.00	0.03	*NEG*	0.01†	0.10†	0.21*
	NET	0.19**	0.82**	1.45**	*NET*	0.09**	0.18**	0.28**
	SUM	0.16**	0.82**	1.51**	*SUM*	0.12**	0.39**	0.70**
	EXC	−0.03	−0.01	0.06	*EXC*	0.03†	0.20†	0.43*
		Young firms				Old firms		
		horizon = 0	*horizon* = 4	*horizon* = 8		*horizon* = 0	*horizon* = 4	*horizon* = 8
Short-term	*POS*	0.05**	0.27**	0.52**	*POS*	−0.04	−0.17	−0.22
	NEG	−0.04	−0.10	−0.18	*NEG*	0.00	−0.09	−0.25
	NET	0.09**	0.38**	0.69**	*NET*	−0.05	−0.08	0.02
	SUM	0.01	0.17**	0.34**	*SUM*	−0.04	−0.27	−0.47
	EXC	−0.08	−0.21	−0.35	*EXC*	−0.09	−0.39	−0.69
Long-term	*POS*	0.08**	0.32**	0.58**	*POS*	0.12**	0.31**	0.52**
	NEG	−0.02	−0.03	−0.05	*NEG*	0.00	0.06†	0.12*
	NET	0.09**	0.35**	0.63**	*NET*	0.11**	0.25**	0.39**
	SUM	0.06**	0.28**	0.54**	*SUM*	0.12**	0.37**	0.64**
	EXC	−0.03	−0.07	−0.10	*EXC*	0.01	0.11†	0.24†
		High-default-probability firms				Low-default-probability firms		
		horizon = 0	*horizon* = 4	*horizon* = 8		*horizon* = 0	*horizon* = 4	*horizon* = 8
Short-term	*POS*	0.08**	0.23**	0.37**	*POS*	−0.03	−0.16	−0.21
	NEG	0.10**	0.27**	0.42**	*NEG*	−0.01	−0.10	−0.24
	NET	−0.02	−0.04	−0.06	*NET*	−0.02	−0.06	0.03
	SUM	0.19**	0.50**	0.79**	*SUM*	−0.03	−0.26	−0.44
	EXC	0.17**	0.46**	0.73**	*EXC*	−0.05	−0.34	−0.61
Long-term	*POS*	0.15**	0.33**	0.53**	*POS*	0.11**	0.31**	0.51**
	NEG	−0.03	0.03	0.14	*NEG*	0.02*	0.12*	0.24**
	NET	0.17**	0.30**	0.40**	*NET*	0.09**	0.19**	0.27**
	SUM	0.12**	0.35*	0.67*	*SUM*	0.13**	0.43**	0.75**
	EXC	−0.06	0.06	0.27	*EXC*	0.04*	0.24*	0.47*
		High-leverage firms				Low-leverage firms		
		horizon = 0	*horizon* = 4	*horizon* = 8		*horizon* = 0	*horizon* = 4	*horizon* = 8
Short-term	*POS*	−0.07	−0.33	−0.51	*POS*	0.28**	0.82**	1.24**
	NEG	−0.02	−0.15	−0.32	*NEG*	−0.03	0.21**	0.46**
	NET	−0.05	−0.18	−0.19	*NET*	0.31**	0.61**	0.78**
	SUM	−0.09	−0.48	−0.82	*SUM*	0.24**	1.02**	1.69**
	EXC	−0.13	−0.66	−1.03	*EXC*	−0.07	0.41**	0.91**
Long-term	*POS*	0.10**	0.29**	0.53*	*POS*	0.11**	0.49**	0.83**
	NEG	0.03**	0.13**	0.25**	*NEG*	0.01	0.31**	0.64**
	NET	0.07**	0.16**	0.28*	*NET*	0.10**	0.18**	0.19†
	SUM	0.13**	0.42**	0.77**	*SUM*	0.12**	0.80**	1.47**
	EXC	0.05**	0.26†	0.49†	*EXC*	0.02	0.61**	1.28**

Note: This table provides the cumulative impulse responses of credit flows to a −25 basis point monetary policy shock using the sample, Q1:1974:Q1 – Q1:2022, in a proxy SVAR setting using external instruments. †, *, and ** indicate statistical significance at 68, 90, and 95 percent significance from bands generated using the wild bootstrap method.

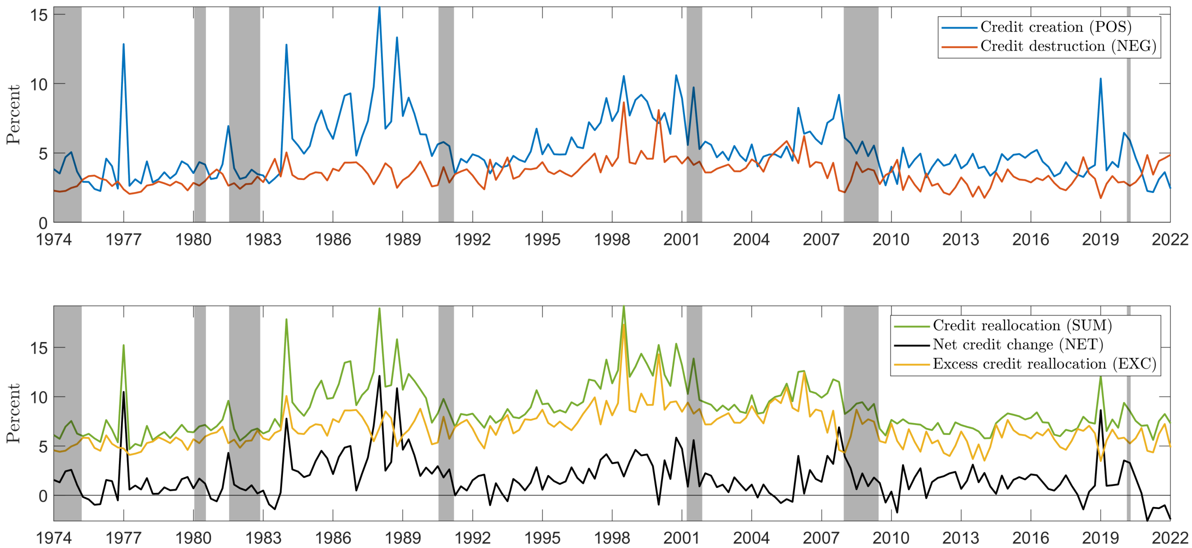
Table 5: Average Ratios of Credit Efficiency of Groups of Firms by Maturity

		(Q2:1974 – Q1:2022)	(Q3:2009 – Q3:2015)	(Q4:2020 – Q4:2021)
Short-term	Small firms	1.0245	1.0224	0.9598
	Large firms	0.9934	1.0033	1.0014
	Young firms	1.0080	1.0674	0.9874
	Old firms	0.9984	1.0020	0.9973
	High-default-probability firms	1.1476	1.1147	1.0999
	Low-default-probability firms	0.9970	1.0023	0.9846
	High-leverage firms	0.9931	1.0102	0.9748
	Low-leverage firms	1.0415	1.0442	1.2373
Long-term	Small firms	1.0202	1.0402	1.0150
	Large firms	0.9985	1.0006	1.0372
	Young firms	1.0064	1.0346	1.0445
	Old firms	1.0015	0.9993	1.0299
	High-default-probability firms	1.0818	1.0417	1.0995
	Low-default-probability firms	1.0015	0.9997	1.0164
	High-leverage firms	0.9989	1.0038	1.0166
	Low-leverage firms	1.0488	1.1226	1.3170

Note: Each group of firm's credit efficiency is measured $CE_{jt} = (\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt}}{debt_{jt}}) / (\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt-1}}{debt_{jt-1}})$ for group j in quarter t at each debt maturity.

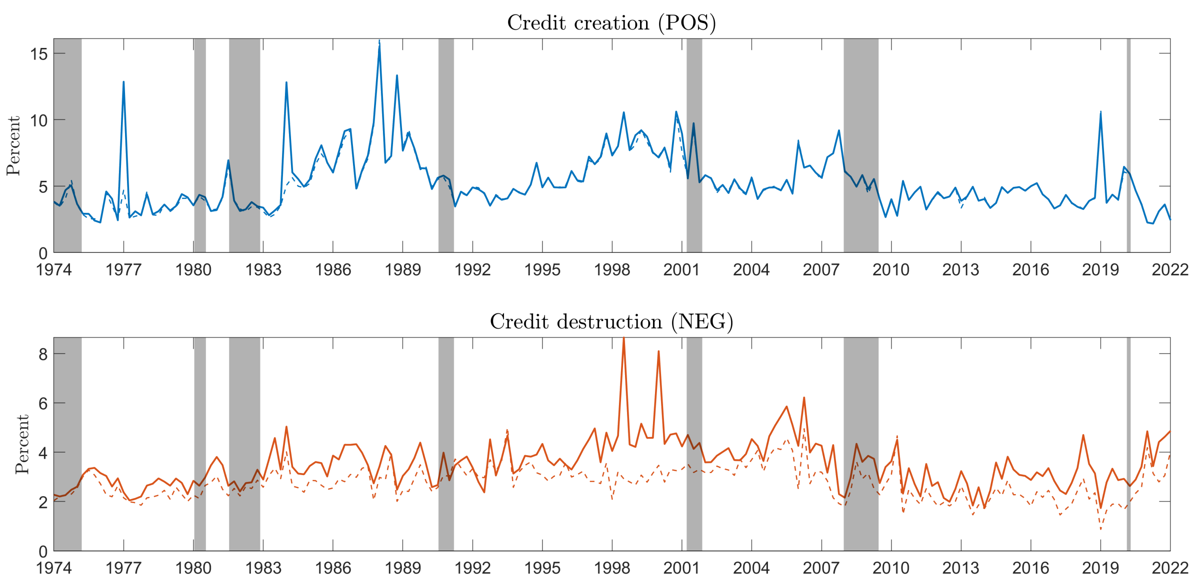
Figures

Figure 1: Aggregate Credit Flows



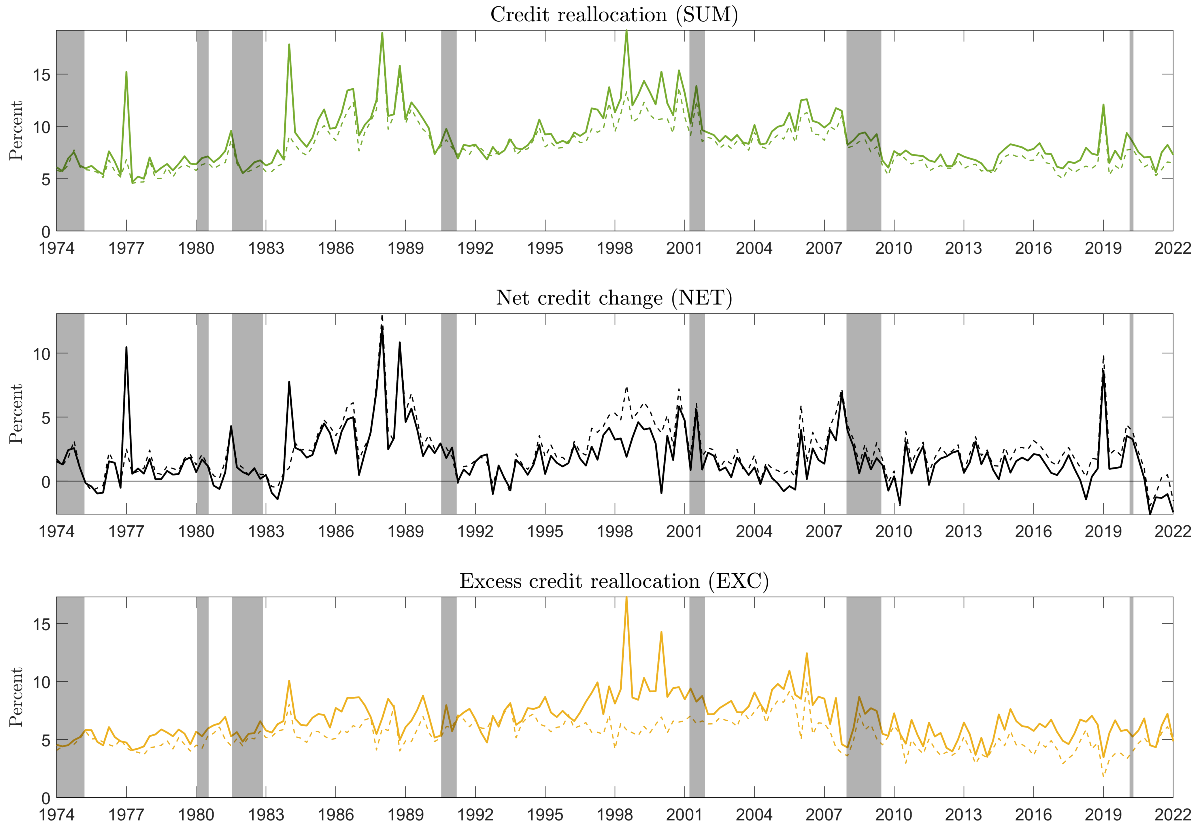
Note: POS refers to credit creation, NEG is credit destruction, NET is net credit change ($NET = POS - NEG$), SUM is credit reallocation ($SUM = POS + NEG$), and EXC is excess credit reallocation ($EXC = SUM - |NET|$). Shaded bars indicate NBER recessions.

Figure 2: Credit Creation and Credit Destruction at the Intensive Margin



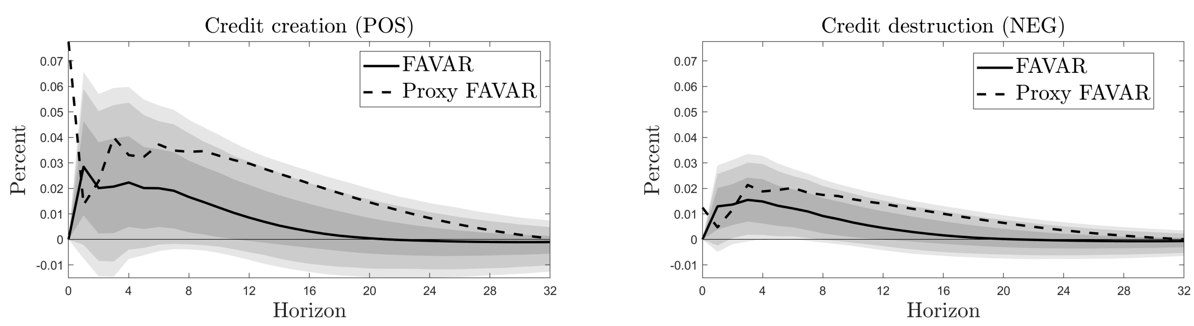
Note: The solid lines represent credit flow measures for all firms, including those entering and exiting the database. The dashed lines represent credit flows of firms that are neither entering nor exiting the database in the current quarter. Shaded bars indicate NBER recessions.

Figure 3: Credit Flows at the Intensive Margin



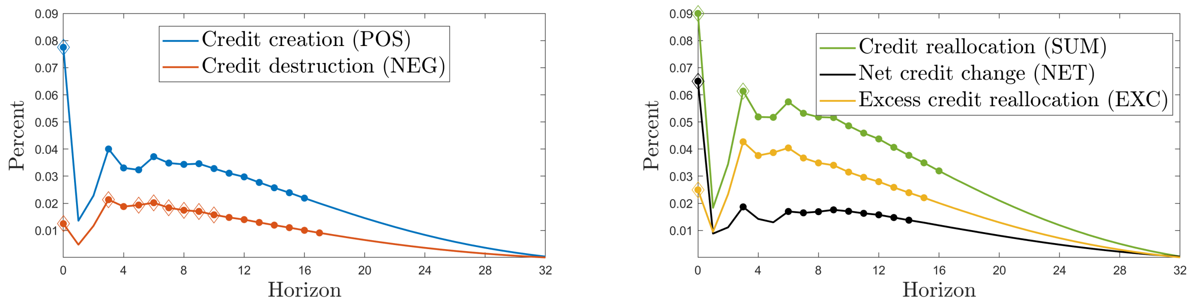
Note: The solid lines represent credit flow measures for all firms, including those entering and exiting the database. The dashed lines represent credit flows of firms that are neither entering nor exiting the database in the current quarter. Shaded bars indicate NBER recessions.

Figure 4: Impulse Responses of Credit Flows



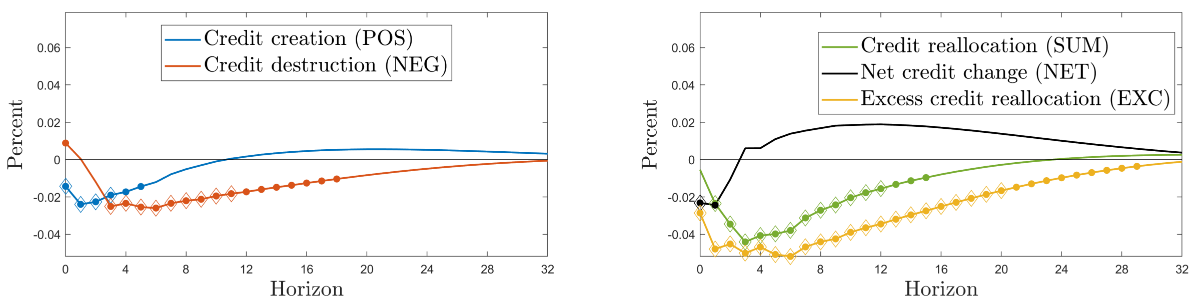
Note: The plots display the impulse responses of aggregate credit flows to a −25 basis point monetary policy shock. These responses are estimated using a FAVAR with no external instruments, along with the 68, 90, and 95 percent confidence intervals using the wild bootstrap method, and a proxy FAVAR framework utilizing external instruments.

Figure 5: Impulse Responses of Credit Flows using External Instruments



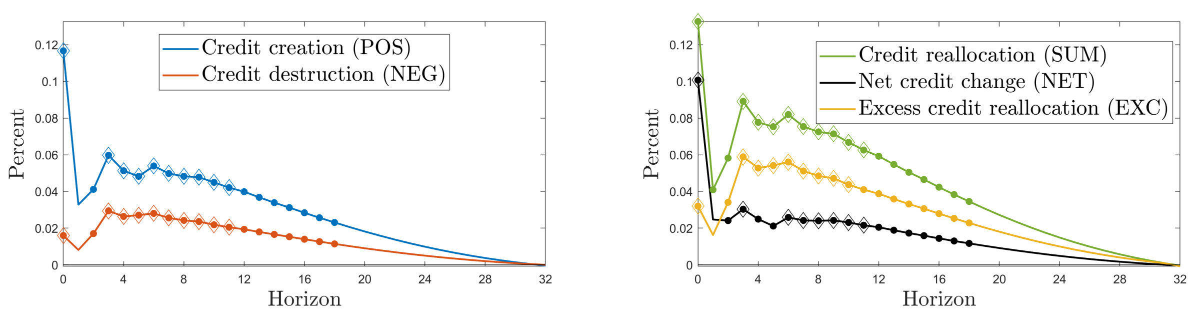
Note: The plots display the impulse responses of aggregate credit flows to a −25 basis point monetary policy shock. These responses are estimated using a proxy SVAR framework utilizing federal funds futures as external instruments. Dots indicate the significance at a 68 percent level and diamonds indicate significance at at 90 percent level, determined using the wild bootstrap method.

Figure 6: Impulse Responses of Short-term Credit Flows using External Instruments



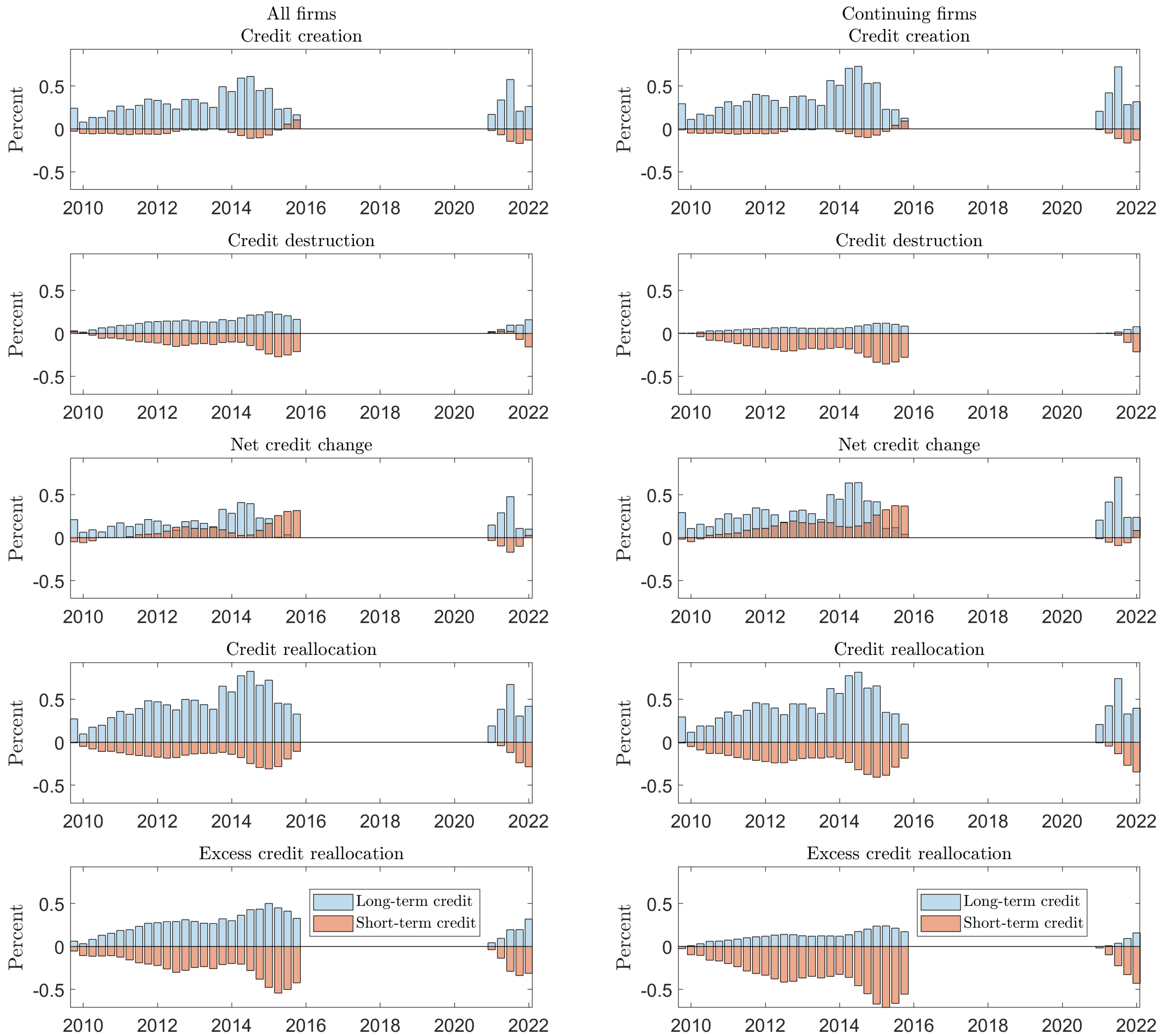
Note: The plots display the impulse responses of aggregate short-term credit flows to a −25 basis point monetary policy shock. These responses are estimated using a proxy SVAR framework utilizing federal funds futures as external instruments. Dots indicate the significance at a 68 percent level and diamonds indicate significance at at 90 percent level, determined using the wild bootstrap method.

Figure 7: Impulse Responses of Long-term Credit Flows using External Instruments



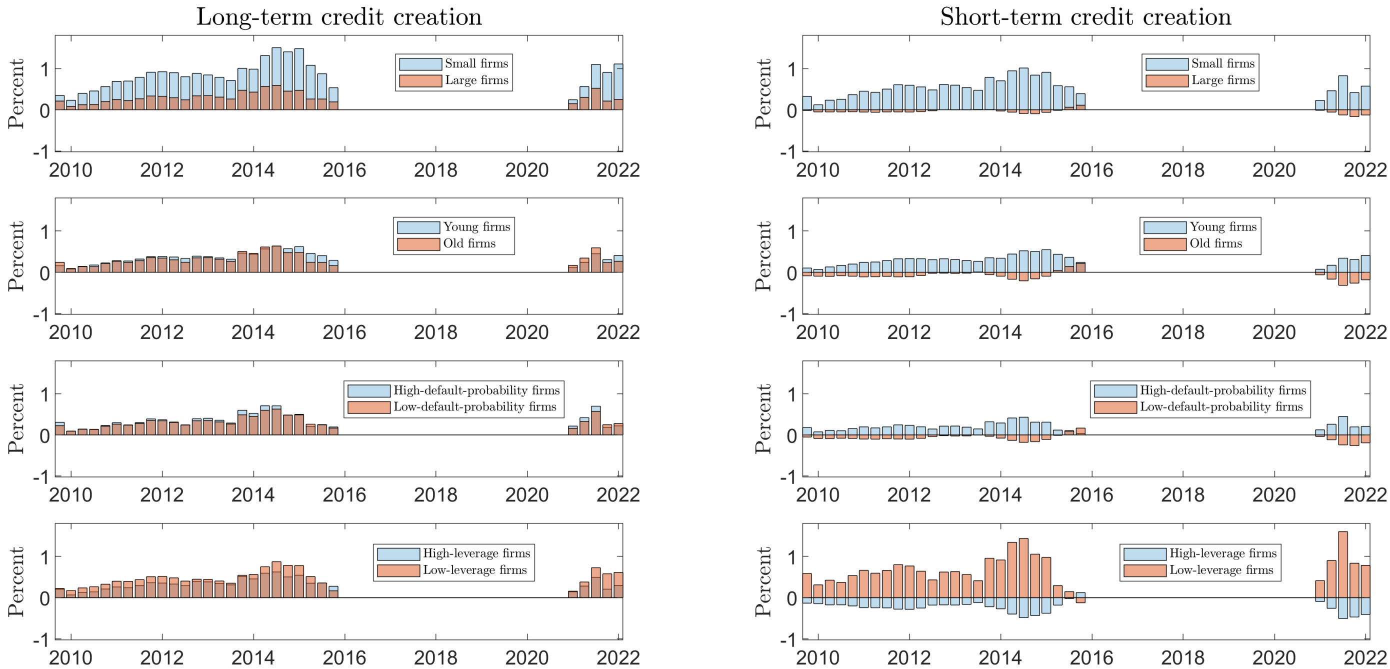
Note: The plots display the impulse responses of aggregate long-term credit flows to a −25 basis point monetary policy shock. These responses are estimated using a proxy SVAR framework utilizing federal funds futures as external instruments. Dots indicate the significance at a 68 percent level and diamonds indicate significance at at 90 percent level, determined using the wild bootstrap method.

Figure 8: Counterfactual Wedges



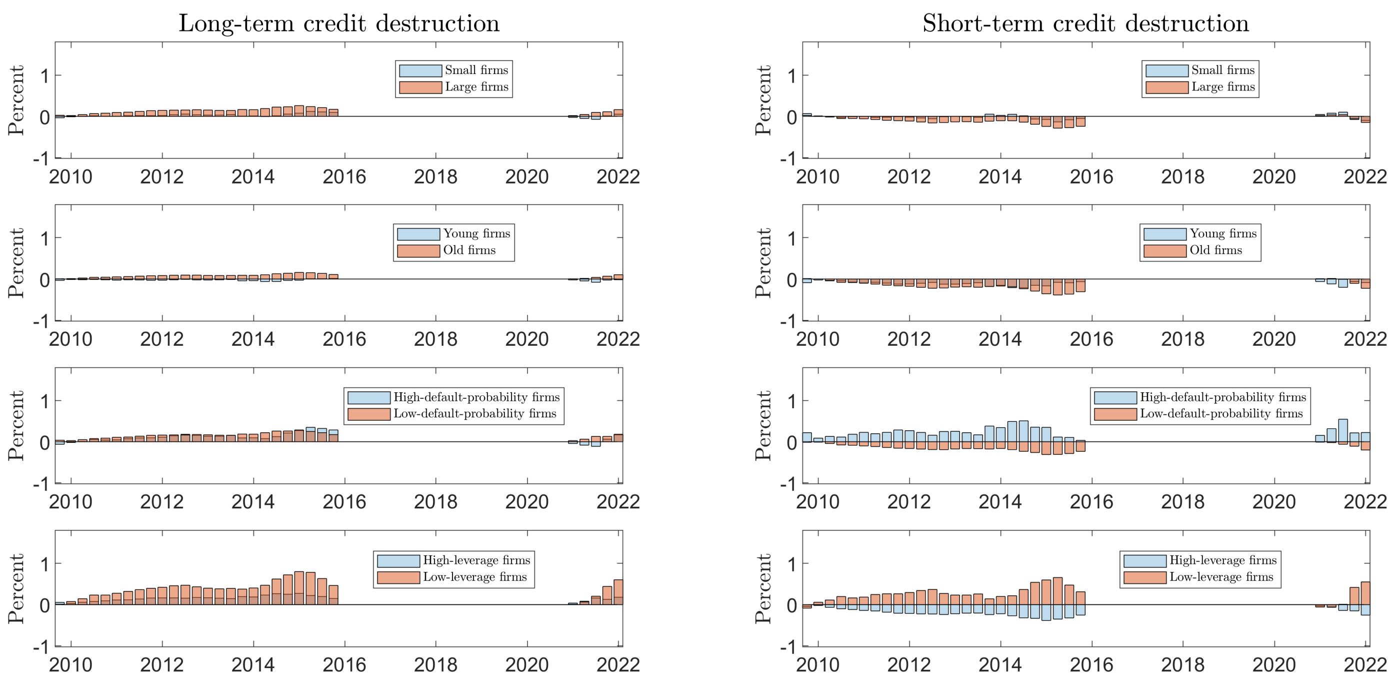
Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 9: Counterfactual Wedges of Credit Creation of Groups of Firms



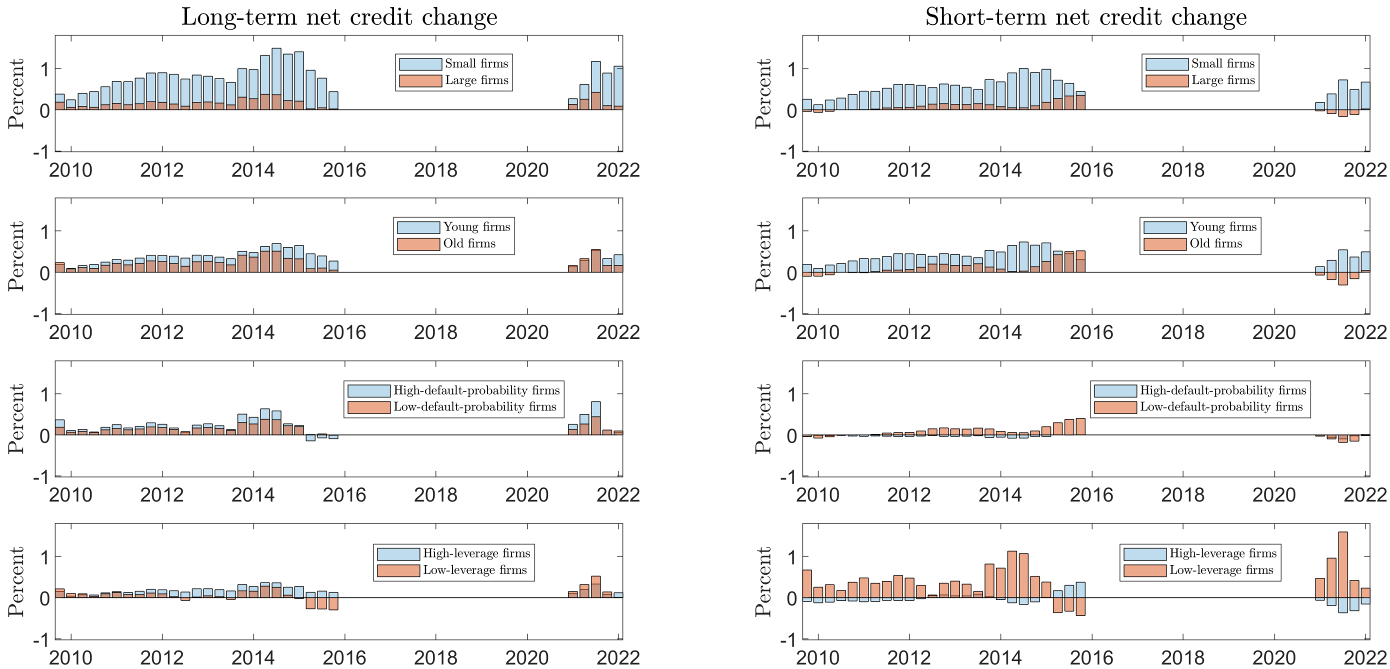
Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 10: Counterfactual Wedges of Credit Destruction of Groups of Firms



Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 11: Counterfactual Wedges of Net Credit Change of Groups of Firms

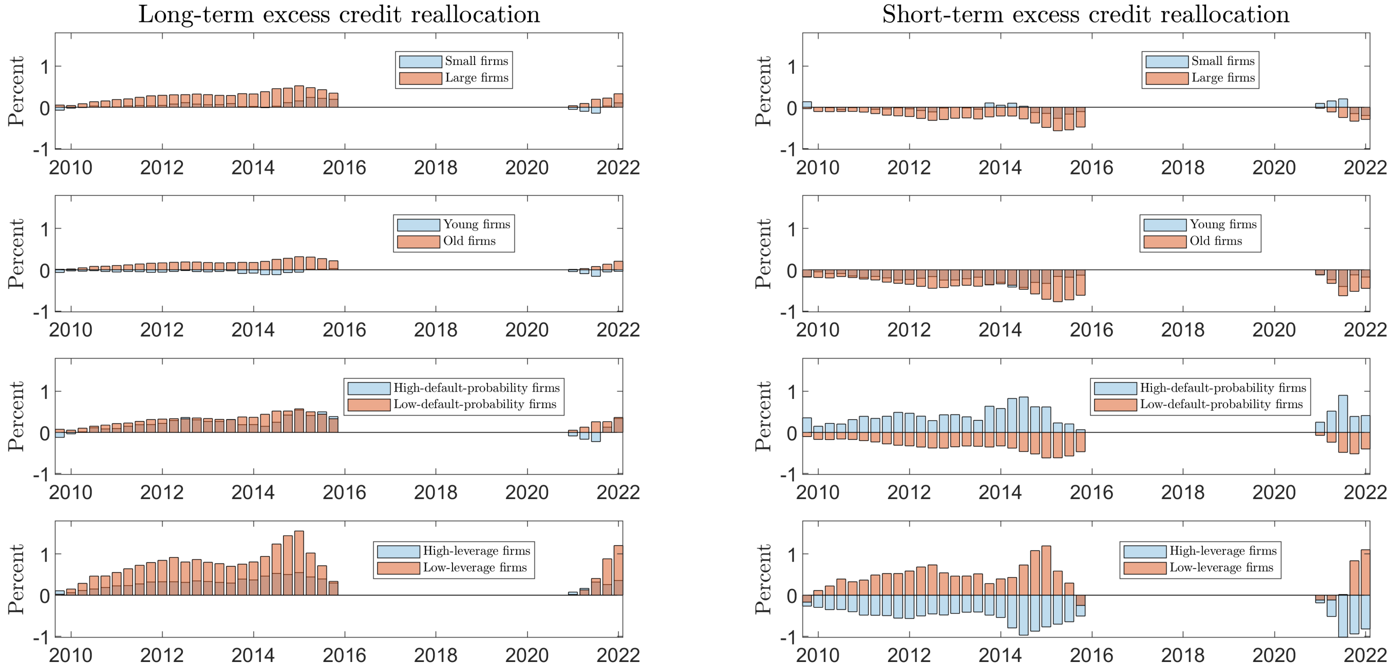


Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 12: Counterfactual Wedges of Credit Reallocation of Groups of Firms

Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

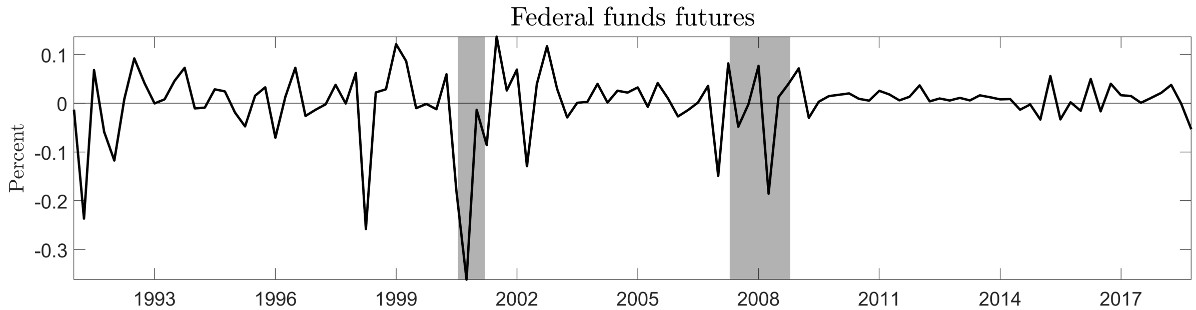
Figure 13: Counterfactual Wedges of Excess Credit Reallocation of Groups of Firms



Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

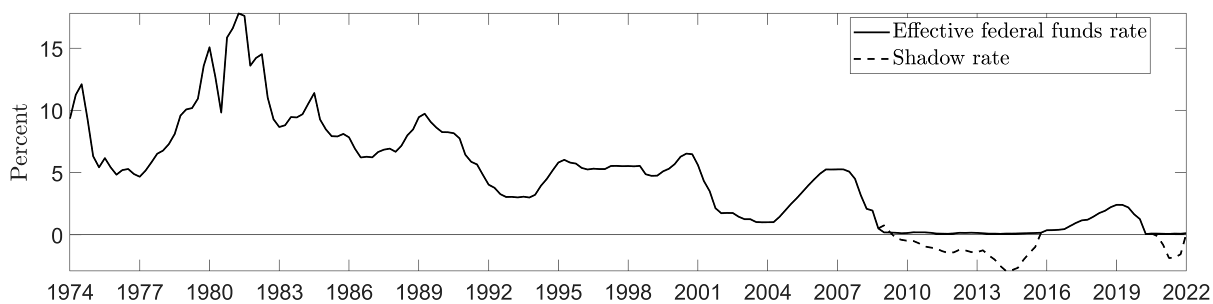
Appendix

Figure A.1: External Instrument: Federal Funds Futures



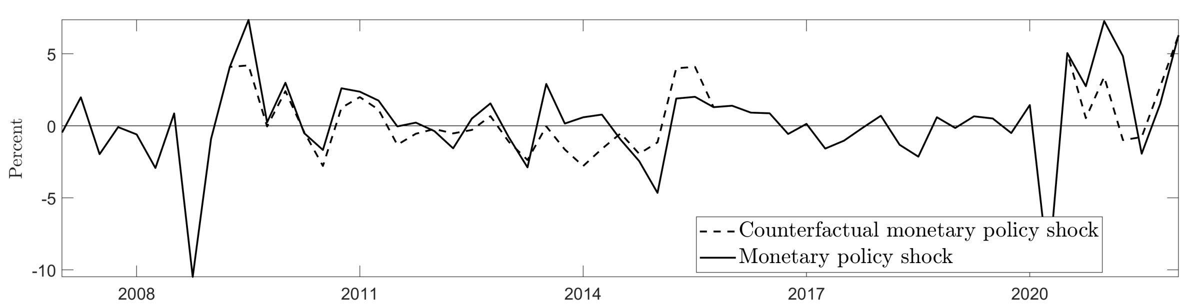
Note: The external instrument is the residuals of the first principal component of federal funds future rates within 30-minute windows around FOMC announcements when regressed on lags four quarterly lags.

Figure A.2: Effective Federal Funds Rate and Shadow Rate



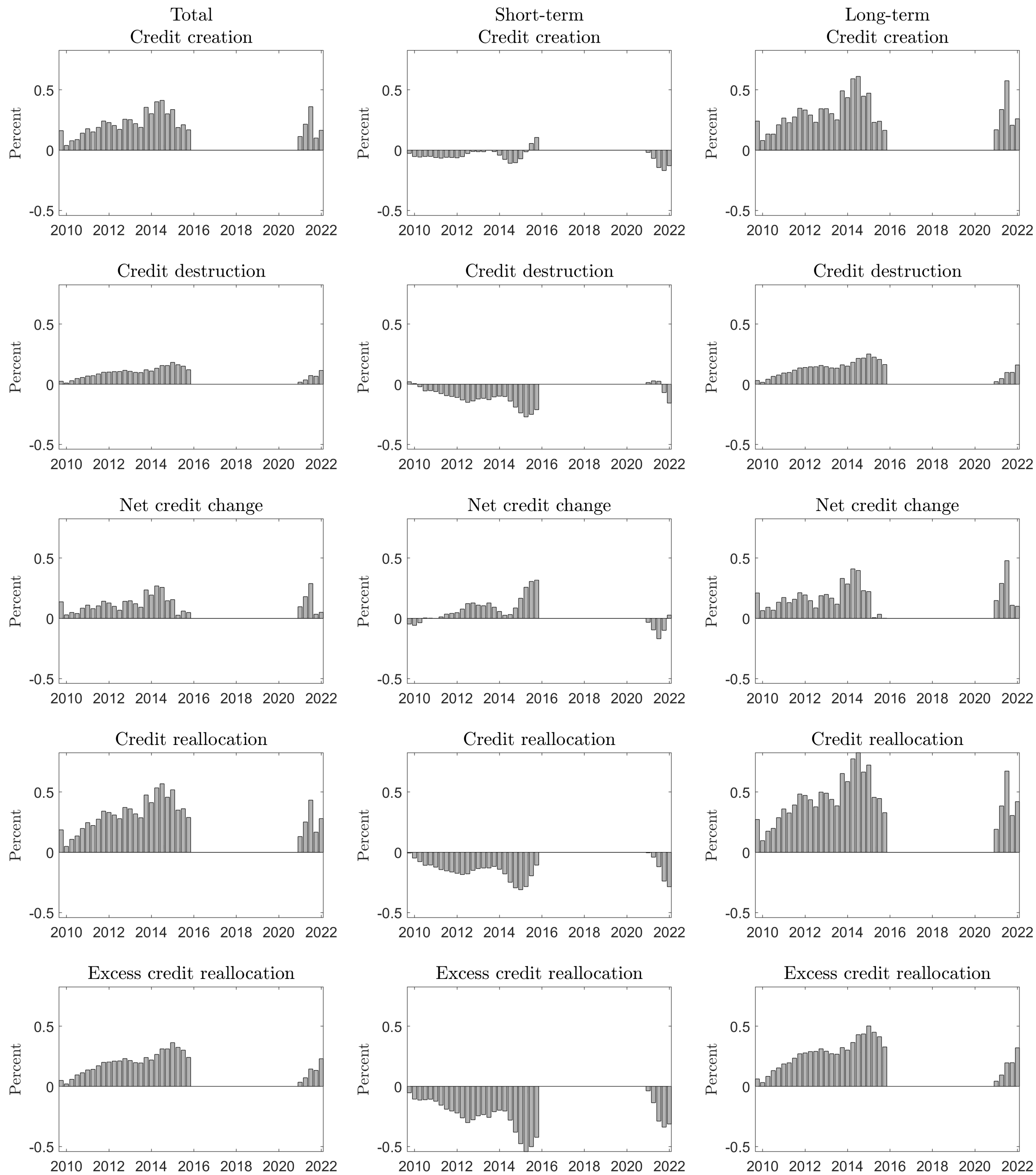
Source: Federal Reserve Board; Federal Reserve Bank of Atlanta.

Figure A.3: Monetary Policy Shocks



Note: The unrestricted monetary policy shocks come from a FAVAR(4) that includes three purged factors and the monetary policy rate. The counterfactual shock is the series that forces the monetary policy to the effective lower bound.

Figure A.4: Aggregate Counterfactual Wedges



Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Table A.1a: Macroeconomic Data and Loadings on Factors

	Source	Transformation	Factor 1 loading	Factor 2 loading	Factor 3 loading
Real output and income					
1. Industrial production: total index	Federal Reserve Board (G.17)	log difference	1.68	−0.54	−0.19
2. Industrial production: final products	Federal Reserve Board (G.17)	log difference	1.65	−0.32	−0.29
3. Industrial production: final products: consumer goods	Federal Reserve Board (G.17)	log difference	1.38	−0.46	−0.25
4. Industrial production: final products: consumer goods: durable	Federal Reserve Board (G.17)	log difference	1.35	−0.58	−0.59
5. Industrial production: final products: consumer goods: nondurable	Federal Reserve Board (G.17)	log difference	1.04	−0.06	0.13
6. Industrial production: final products: equipment, total: business equipment	Federal Reserve Board (G.17)	log difference	1.64	−0.25	−0.26
7. Industrial production: materials	Federal Reserve Board (G.17)	log difference	1.60	−0.67	−0.18
8. Industrial production: materials: non-energy: durable	Federal Reserve Board (G.17)	log difference	1.54	−0.65	0.05
9. Industrial production: materials: non-energy: nondurable	Federal Reserve Board (G.17)	log difference	1.23	−0.43	−0.13
10. Industrial production: manufacturing	Federal Reserve Board (G.17)	log difference	1.65	−0.53	−0.10
11. Industrial production: final products: equipment, total: oil and gas well drilling and manufactures homes	Federal Reserve Board (G.17)	log difference	0.92	−0.08	−0.51
12. Industrial production: final products: consumer goods: nondurable: energy: residential utilities	Federal Reserve Board (G.17)	log difference	−0.29	0.10	0.28
13. Industrial production: total index	Federal Reserve Board (G.17)	log difference	1.68	−0.54	−0.19
14. Capacity utilization: manufacturing, percent of total industry	Federal Reserve Board (G.17)	-	0.99	0.85	1.43
15. Purchasing managers' index	ISM	-	1.07	−0.90	0.53
16. NAPM index	ISM	-	0.99	−0.93	0.40
17. Personal income	Bureau of Economic Analysis	log difference	0.01	0.75	0.58
18. Personal income less transfer payments	Bureau of Economic Analysis	log difference	1.23	−0.47	0.44
Hours and employment					
19. Employment level	Bureau of Labor Statistics	log difference	1.62	−0.20	−0.50
20. Employment level, nonagricultural industries	Bureau of Labor Statistics	log difference	1.63	−0.18	−0.48
21. Civilian unemployment rate	Bureau of Labor Statistics	-	−0.56	0.05	−1.96
22. Average duration of unemployment, in weeks	Bureau of Labor Statistics	-	−0.08	−1.82	−1.45
23. Number of unemployed: Less than 5 weeks	Bureau of Labor Statistics	-	−0.96	0.94	0.01
24. Number of unemployed: 5 to 14 weeks	Bureau of Labor Statistics	-	−1.34	−0.33	−0.55
25. Number of unemployed: 15 weeks and over	Bureau of Labor Statistics	-	−0.21	−1.50	−2.21
26. Number of unemployed: 15 to 26 weeks	Bureau of Labor Statistics	-	−0.16	−1.08	−2.09
27. All employees, thousands: total nonfarm	Bureau of Labor Statistics	log difference	1.70	−0.20	−0.33
28. All employees, thousands: total private	Bureau of Labor Statistics	log difference	1.71	−0.26	−0.34
29. All employees, thousands: goods-manufacturing	Bureau of Labor Statistics	log difference	1.66	−0.54	0.34
30. All employees, thousands: mining and logging: mining	Bureau of Labor Statistics	log difference	0.63	0.29	−0.63
31. All employees, thousands: construction	Bureau of Labor Statistics	log difference	1.44	−0.55	1.04
32. All employees, thousands: manufacturing	Bureau of Labor Statistics	log difference	1.64	−0.54	0.05
33. All employees, thousands: durable goods	Bureau of Labor Statistics	log difference	1.62	−0.54	0.20
34. All employees, thousands: nondurable goods	Bureau of Labor Statistics	log difference	1.53	−0.48	−0.36
35. All employees, thousands: service-providing	Bureau of Labor Statistics	log difference	1.60	−0.01	−0.52
36. All employees, thousands: trade, transportation, and utilities	Bureau of Labor Statistics	log difference	1.71	−0.11	−0.34
37. All employees, thousands: wholesale trade	Bureau of Labor Statistics	log difference	1.63	0.16	0.12
38. All employees, thousands: retail trade	Bureau of Labor Statistics	log difference	1.62	−0.04	−0.56
39. All employees, thousands: government	Bureau of Labor Statistics	log difference	1.00	0.43	0.01
40. Average weekly hours of production and nonsupervisory employees: manufacturing	Bureau of Labor Statistics	-	0.56	−1.60	0.86
41. Average weekly overtime hours of production and nonsupervisory employees: manufacturing	Bureau of Labor Statistics	-	0.44	−1.36	1.56
42. NAPM employment index	ISM	-	1.01	−0.92	0.11
Consumption					
43. Personal consumption expenditures	Bureau of Economic Analysis	log difference	1.49	0.59	−0.90
44. Personal consumption expenditures: durable goods	Bureau of Economic Analysis	log difference	0.75	−0.12	−0.20
45. Personal consumption expenditures: nondurable goods	Bureau of Economic Analysis	log difference	1.22	0.69	−0.98
46. Personal consumption expenditures: services	Bureau of Economic Analysis	log difference	1.40	0.71	−0.90
Housing starts and sales					
47. New privately-owned housing units started, thousands: United States: total	Census Bureau	log	0.86	0.75	2.32
48. New privately-owned housing units started, thousands: Northeast: total	Census Bureau	log	0.78	1.00	1.82
49. New privately-owned housing units started, thousands: Midwest: total	Census Bureau	log	0.79	0.88	1.95
50. New privately-owned housing units started, thousands: South: total	Census Bureau	log	0.77	0.48	2.20
51. New privately-owned housing units started, thousands: West: total	Census Bureau	log	0.85	0.67	2.36
52. New privately-owned housing units authorized in permit-issuing places, thousands: total	Census Bureau	log	0.81	0.35	2.46
53. Shipments of new manufactured homes	Census Bureau	log	0.61	1.48	1.50

Table A.1b: Macroeconomic Data and Loadings on Factors

	Source	Transformation	Factor 1 loading	Factor 2 loading	Factor 3 loading
Orders					
54. NAPM inventories index	ISM	-	0.69	−0.48	0.50
55. NAPM new orders index	ISM	-	0.97	−0.98	0.47
56. NAPM supplier deliveries index	ISM	-	0.69	−0.63	0.53
57. New orders: nondefense capital goods	Census Bureau	log difference	0.87	−0.56	−0.17
Stock prices					
58. S&P common stock price index: composite	S&P Dow Jones Indices	log difference	−0.04	−0.21	−0.15
59. S&P common stock price index: industrials	S&P Dow Jones Indices	log difference	−0.26	−0.23	−0.04
Exchange rates					
60. Foreign exchange rate: United Kingdom	Federal Reserve Board (H.10)	log difference	0.30	−0.03	0.06
61. Foreign exchange rate: Canada	Federal Reserve Board (H.10)	log difference	−0.34	−0.01	0.51
Interest rates					
62. 3-month Treasury yield	Federal Reserve Board (H.10)	-	0.33	1.99	0.30
63. 6-month Treasury yield	Federal Reserve Board (H.10)	-	0.33	1.97	0.32
64. 1-year Treasury yield	Federal Reserve Board (H.10)	-	0.35	1.98	0.27
65. 5-year Treasury yield	Federal Reserve Board (H.10)	-	0.33	1.85	0.19
66. 10-year Treasury yield	Federal Reserve Board (H.10)	-	0.31	1.78	0.05
67. 3-month Treasury yield less effective federal funds rate	Federal Reserve Board (H.10)	-	−0.03	−1.97	−0.47
68. 6-month Treasury yield less effective federal funds rate	Federal Reserve Board (H.10)	-	−0.00	−1.90	−0.40
69. 1-year Treasury yield less effective federal funds rate	Federal Reserve Board (H.10)	-	0.11	−1.69	−0.57
70. 5-year Treasury yield less effective federal funds rate	Federal Reserve Board (H.10)	log difference	−0.03	−1.66	−0.57
71. 10-year Treasury yield less effective federal funds rate	Federal Reserve Board (H.10)	-	−0.10	−1.74	−0.75
Money and credit quantity aggregates					
72. Commercial bank assets: bank credit: loans and leases in bank credit: commercial and industrial loans	Federal Reserve Board (H.8)	log difference	−0.47	0.65	1.21
73. Consumer credit outstanding: nonrevolving: total	Federal Reserve Board (G.19)	log difference	0.59	−0.07	0.81
74. Money stock measure: M1	Federal Reserve Board (H.6)	log difference	−1.07	−0.10	0.37
75. Money stock measure: M2	Federal Reserve Board (H.6)	log difference	−0.78	0.29	0.16
76. Monetary base: total	Federal Reserve Board (H.3)	log difference	−1.04	−0.18	0.01
Price indexes					
77. Producer price index: all commodities	Bureau of Labor Statistics	log difference	0.86	0.75	−1.19
78. Producer price index: finished consumer goods	Bureau of Labor Statistics	-	0.24	0.52	−0.52
79. Producer price index: intermediate material supplies and components	Bureau of Labor Statistics	log difference	−0.06	0.94	−0.72
80. Producer price index: crude materials	Bureau of Labor Statistics	log difference	0.88	0.17	−0.92
81. Consumer price index: all items	Bureau of Labor Statistics	log difference	0.66	1.77	−1.17
82. Consumer price index: apparel and upkeep	Bureau of Labor Statistics	log difference	0.85	0.96	−1.45
83. Consumer price index: transportation	Bureau of Labor Statistics	log difference	0.95	0.76	−1.47
84. Consumer price index: medical care	Bureau of Labor Statistics	log difference	0.01	1.92	−0.61
85. Consumer price index: commodities	Bureau of Labor Statistics	log difference	0.78	1.24	−1.40
86. Consumer price index: durables	Bureau of Labor Statistics	log difference	0.49	1.24	−1.42
87. Consumer price index: services	Bureau of Labor Statistics	log difference	0.38	1.94	−0.66
88. Consumer price index: all items less food	Bureau of Labor Statistics	log difference	0.70	1.73	−1.23
89. Consumer price index: all items less shelter	Bureau of Labor Statistics	log difference	0.74	1.54	−1.38
90. Consumer price index: all items less medical care	Bureau of Labor Statistics	log difference	0.69	1.71	−1.18
91. Avg. hourly earnings of all employees on private nonfarm payrolls: total private: goods-producing: construction	Bureau of Labor Statistics	log difference	0.06	1.51	−0.56
Average hourly earnings					
92. Avg. hourly earnings of all employees on private nonfarm payrolls: total private: goods-producing: manufacturing	Bureau of Labor Statistics	log difference	−0.08	1.65	−0.34
Miscellaneous					
93. Business cycle indicator, consumer expectations	University of Michigan	-	0.59	−0.67	2.53
Credit flows					
94. Credit destruction		-	0.22	−0.22	1.46
95. Credit creation		-	0.00	0.12	1.66