

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 an external instrument, we show that monetary policy promotes long-term credit creation while delaying or preventing long-term credit destruction. In parallel, it reduces short-term credit creation and destruction, effectively reallocating credit toward longer maturities. 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. Our findings underscore the effectiveness of monetary policy in steering credit toward financially constrained firms and stimulating future economic activity near the effective lower bound.

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

JEL Classification: E44, E51, E52, E58.

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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 were aimed to stabilize the financial system, which some believed had been impeding economic growth due to tight credit standards. Now, whether the credit expansion that ensued led to financial deepening and economic growth, or whether it was the forerunner of a slower recovery and possible future recession is a question of heated debate. On the one hand, some studies argue that 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 On the other hand, work by Brunnermeier et al. (2021) and Jordà et al. (2013),

¹See Krishnamurthy and Vissing-Jørgensen (2011), Rodnyansky and Darmouni (2017), Fieldhouse et al.

among others, finds evidence of a long-run negative response of GDP to credit growth.

While there is no full consensus regarding the effects of unconventional monetary policy (see Kuttner (2018), Greenlaw et al. (2018), Bhattarai and Neely (2022)), 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 (UMP hereafter) 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? 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?

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 use 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 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

(2018), Chakraborty et al. (2020), and Di Maggio et al. (2020).

²We follow the same methodology employed by Herrera et al. (2011) to construct yearly flows. See Herrera et al. (2024), Bianco (2021), and Contessi and Francis (2013) for other studies that use similar credit flow measures.

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 monetary easing. 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 relaxing financial constraints. Furthermore, while various groups' long-term credit flows exhibit significant increases following monetary easing, the responses tend to be larger for small publicly listed (hereafter smaller) 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 UMP during the two ELB periods, we construct counterfactual scenarios where the shadow federal funds rate is constrained to 0.25%. This allows us to examine the potential effects of UMP on credit flows when the ELB is reached. Counterfactual analysis reveals meaningful impacts of UMP on credit flows during two ELB periods. We find that unconventional policies contribute substantially more to 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. UMP also caused a substantial reallocation of short-term credit among firms with high probability of default. Regarding long-term credit, the impact of UMP is more uniform across various groups, except for smaller 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 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 of Kashyap et al. (1994), Gertler and Gilchrist (1994), and Kashyap and Stein (1995), have argued that monetary policy has a more pronounced effect on smaller 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), Cloyne et al. (2023), and Ottonello and Winberry (2020). However, using restricted data from the Quarterly Financial Report, Crouzet and Mehrotra (2020) find that, while small firms are more cyclically sensitive than large firms, these differences in cyclicity are not systematically correlated with proxies for financial strength. Their results cast doubts on the importance of the financial accelerator mechanism. Kudlyak and Sánchez (2017) find that short-term credit of small firms contracted less than that of large firms during the Great Recession. Relative to these studies, we focus on aggregate measures of credit flows to investigate the impact of monetary policy shocks on the inter-firm credit reallocation process and then inquire whether groups of firms with similar characteristics (e.g., smaller or large, low or high leverage) exhibit differences in the dynamic response to these shocks.

The second strand of literature empirically studies the transmission of monetary policy, and especially UMP, to macroeconomic aggregates such as inflation and GDP growth. Re-

³See Sims and Wu (2020), Ottonello and Winberry (2020), Koby and Wolf (2020), Jeena (2023), and González et al. (2024) for theoretical models focusing on firm heterogeneity.

garding methodological aspects, our work is more closely related to investigations that use shadow interest rates as an UMP instrument (Wu and Xia, 2016) and to studies that employ high-frequency identification in structural vector autoregressions (SVARs) models (see e.g., Gertler and Karadi (2015), Lakdawala (2019), Eberly et al. (2020)). As for aggregate outcomes of interest, 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 banks 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 Bianco (2021), who 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 excluded 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. Thus, when we group firms by size, we refer to smaller and large firms. Regarding the importance of large firms, it is worth noting that Kudlyak and Sánchez (2017) found that they exhibited a greater contraction in sales and short-term credit than small firms in 2008–2009. 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 UMP 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 ELB periods.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

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

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);

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

⁵See 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 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 is defined as

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

Similarly, credit destruction is defined as

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

Furthermore, we compute the gross credit reallocation as

$$SUM_{st} = POS_{st} + NEG_{st}. \quad (4)$$

We obtain net credit growth by subtracting NEG_{st} from POS_{st}

$$NET_{st} = POS_{st} - NEG_{st} \quad (5)$$

and excess credit reallocation as

$$EXC_{st} = SUM_{st} - |NET_{st}|. \quad (6)$$

Table 1 summarizes the aggregate credit flows from Q1:1974 to Q1:2022. During this period, *POS* averaged 5.30 percent, *NEG* 3.51 percent, and *NET* 1.79 percent. The table supports HKM’s finding 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. Furthermore, *POS* is more volatile than *NEG*, with coefficients of variation of 41.29 and 27.80. Short- and long-term credit flow statistics indicate that long-term flows align with total credit averages, whereas short-term flows are higher but less volatile.

Figure 1 shows the evolution of credit flows over time. Regarding *SUM*, three characteristics emerge. First, it intensified during the 1980s compared to the 1970s, as noted by HKM. Second, it declined in the late 1980s and early 1990s, but ramped up in the late 1990s. Yet, further declines in *SUM* occurred in the early 2000s and at the onset of the Great Recession in 2007. Credit reallocation rates decreased from more than 12 percent before the recession to approximately 6 percent before 2010. This decline and the reduced fluidity of the credit market were primarily driven by decreased activity in long-term credit.

During the Covid-19 pandemic, *SUM* was close to its historical average while *NET* reached its nadir of -2.59 percent at the start of 2021. This was due to notable declines in *POS* and increases in *NEG* during the pandemic. For instance, in 2021, *POS* fell to 2.17 percent, its lowest point experienced throughout the sample. Further, *NEG* 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 *NEG* is attributed to exiting firms, particularly in the late 1990s. The gap between intensive and aggregate

NEG narrowed and was more stable in the 2000s, suggesting that recent increases in *NEG* were the result of a shrinking of exiting credit rather than of exiting firms.

The disparities between *NET*, *SUM* and *EXC* for all firms and continuing firms, shown in Figure 3, arise mainly from differences in *NEG*. The extent to which *SUM* was driven by debt refinancing (i.e., obtaining financing to pay off existing debt, resulting in increases in both *POS* and *NEG*) is unclear due to the limited information in Compustat. However, we observe that aggregate *EXC* was high in the late 1990s and early 2000s, indicating simultaneously elevated levels of *POS* and *NEG*. 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, from December 2008 to December 2015 and March 2020 to March 2022, the rate remained at the ELB, thus limiting its use to stimulate the economy and its validity as the monetary policy variable in SVARs.

We address this issue by utilizing an alternative measure of the monetary policy stance at the ELB, following Wu and Xia (2016) –hereafter WX–, who develop an approximation to the forward rate in the multifactor shadow rate term structure model.⁶ 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

⁶The federal funds rate data are sourced from the Fed’s H.15 releases, and WX’s shadow rate, based on their benchmark shadow rate term model, comes from the Federal Reserve Bank of Atlanta. Refer to the Online Appendix (hereafter Appendix) for a figure comparing the effective federal funds rate and the WX shadow rate over time.

with the shadow rate in structural vector autoregressions (SVARs) during the ELB periods.⁷

Then, to identify the monetary policy shock, 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 futures, 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.⁸ 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.

As in Bernanke et al. (2005) –hereafter BBE– and WX, 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, and exchange rates, among others. In our study, we used 94 of the original 120 series used by BBE.⁹ Additionally, we rotate the aggregate measures of *POS* and *NEG* 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.

⁷For the theoretical underpinnings for using the shadow rate to replace the effective federal funds rate during the ELB, see Wu and Xia (2016) and Sims and Wu (2020).

⁸Miranda-Agrippino and Ricco (2021) transform their measure from the FOMC to monthly frequency by regressing 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.

⁹WX incorporates 97 out of the 120 series employed by BBE. Of these, data for new orders -consumer goods and materials, M2 - money supply - M1 + savings deposits, small time deposits, & MMMFs, and the NAPM commodity price index (percent) are not available during the extended sample period.

3 Empirical Methodology

3.1 Econometric Model

To study the effect of monetary policy shocks on credit flows, we employ 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 $VAR(p)$:

$$\begin{bmatrix} F_t \\ r_t \end{bmatrix} = \mathbf{c} + \Phi(L) \begin{bmatrix} F_{t-1} \\ r_{t-1} \end{bmatrix} + \mathbf{u}_t \quad (7)$$

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

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

$$\mathbf{X}_t = \mathbf{k} + \Lambda F_t + \lambda r_t + \mathbf{e}_t \quad (8)$$

where $\mathbf{X}_t$ is a $N \times 1$ vector comprising a large set of macroeconomic variables (see Appendix A for details) as well as *POS* and *NEG*, $\mathbf{e}_t$ is a $N \times 1$ vector of i.i.d. normal errors with variance $Var(\mathbf{e}_t) = \Sigma$. The factor loadings on the unobserved factors and the monetary policy variable are given by Λ and λ , respectively. As in Stock and Watson (2018), we impose the assumption that $\Lambda' \Lambda = \mathbf{I}$. 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

¹⁰To 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.

WX. That is, we first estimate the latent factors and their loading from the observed data $\mathbf{X}_t$ 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).

Several identification schemes have been used in the literature to estimate the dynamic causal effect of monetary policy shocks. BEE and WX employ zero restrictions in a FAVAR setup. Following the work of Uhlig (2005), numerous studies use sign restrictions or a combination of sign and zero restrictions in SVARs. In recent years, the use of instrumental variables (IV) to identify the monetary policy shock has become common (see, e.g., Miranda-Agrippino and Ricco (2021)). We opt to estimate a proxy-FAVAR where we use an external instrument to identify the monetary policy shock, as such an identification scheme is less restrictive than the identification employed by BEE and WX.¹¹

The motivation to estimate a proxy-FAVAR instead of a FAVAR identified by sign and short-term restrictions is three-fold. First, using an external IV to identify the monetary policy shock allows us to take a more agnostic approach to identification, where we do not have to worry about imposing restrictions on the factors or the large set of variables in the FAVAR. Second, while existing Bayesian algorithms employed for inference in SVARs identified via sign and zero restrictions work well in small-dimensional SVARs, their performance can falter in large-dimensional SVARs models (see Korobilis (2022)) and –to the best of our knowledge– has not been well studied in FAVARs. Last but not least, recent work by Wolf (2022) underscores the limitations of sign-restricted SVARs and suggests the use of robust methods to overcome these limitations. Thus, we provide impulse responses for total *POS* and *NEG* estimated with a robust Bayesian SVAR (Giacomini and Kitagawa, 2021) in Appendix B, but use a Proxy-FAVAR as the baseline.¹²

¹¹For comparison, Figure 4 reports total credit response estimated using a SVAR with WX recursive identification scheme.

¹²The 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

As in Alessi and Kerssenfischer (2019), Gertler and Karadi (2015), Mertens and Ravn (2013) and Stock and Watson (2012), we assume that the reduced-form errors, $\mathbf{u}_t$, map into the structural errors, $\boldsymbol{\varepsilon}_t$, so that $\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t$ where $\mathbf{S}$ is a 4×4 nonsingular matrix and the variance-covariance matrix is given by $\boldsymbol{\Sigma} = E[\mathbf{u}_t\mathbf{u}_t'] = E[\mathbf{S}\mathbf{S}']$.

To identify the monetary policy shock (ε_{4t}), we let $\boldsymbol{\varepsilon}_{1:3,t}$ collect the remaining three structural shocks. Since we only aim to identify the monetary policy shock's effect, we only need to identify the elements of vector $\mathbf{s}_4$, which is the fourth column of $\mathbf{S}$. To do so, consider the relationship between the structural shock ε_{4t} and an instrument to be given by $z_t = \beta\varepsilon_{4t} + \nu_t$ where $\nu_t \sim \mathcal{N}(0, \sigma_\nu)$. 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 assumptions of exogeneity and relevance.

3.2 Possible instruments for monetary policy shocks

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 first test for serial correlation in the external instruments derived from the Federal funds futures, Eurodollar futures, and Treasuries. 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 instrument using Miranda-Agrippino and Ricco (2021)'s method. However, the instruments derived from Eurodollar futures and Treasuries when using Bauer and Swanson (2023)'s method are serially correlated, thus invalidating their use 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

Karadi (2015), Lakdawala (2019), Miranda-Agrippino and Ricco (2021), Alessi and Kerssenfischer (2019), Jarociński and Karadi (2020), Jarociński (2024), and Cieslak and Schrimpf (2019).

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.

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. 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).¹³

We conclude this section by noting that the constant parameter proxy-VAR estimates correspond to average responses over the estimation period. While we recognize the importance of studying time-variation stemming from differences in the monetary policy target or the stances of heterogeneous UMP, we leave this question for future research.

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 the recursive scheme in WX and BBE and our preferred method when the shock is 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 the external instrument to also capture the effect of UMP 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).¹⁴

¹³Estimation results, available from the authors upon request, using Eurodollar futures are almost identical despite the instrument being somewhat weaker. See Appendix A for the instrument that we utilize plotted across time.

¹⁴We re-sample ε_t using wild bootstrapping and generate the artificial factors, $\widehat{F}_t^*$, using Kilian (1998)’s bias correction method.

For the recursive identification scheme, 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 *POS* and *NEG* is 0.078 and 0.012 percentage points, respectively, and statistically significant. The shape and magnitudes of the responses at longer horizons are similar.

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 significant increase in aggregate *POS* at longer horizons (three through 16 quarters) in addition to the initial increase. By the 16th quarter, the cumulative increase in *POS* reaches 0.55 percentage points. Credit destruction responds significantly to the shock at similar horizons, but with a smaller magnitude compared to *POS*. By the 16th quarter, aggregate *NEG* increases by 0.25 percentage points. These effects are non-trivial considering that the average *POS* and *NEG* are 5.30 and 3.51 percent, respectively. Sixteen quarters after the shock, *NET* increases 0.30 cumulative percentage points, and there is an intense and significant response of *SUM* (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 increase in *POS* – 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 *POS* in response to the shock, which are more immediate than those of short-term *NEG*. Although the responses are small, they are statistically significant and lead to small and short-lived changes in *NET*. However, both gross and excess short-term credit reallocation show consistently negative and

significant responses at short- and medium-term horizons.

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 *POS* 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 *NEG* increases 0.35 cumulative percentage points in response to the shock.

Although we do not explore the specific mechanism behind the differential responses of short- and long-term credit flows, the theoretical and empirical macro-finance literature suggests possible explanations for these patterns. On the one hand, expansionary policy is likely to boost asset prices, modify lenders' risk preferences, decrease loan defaults, and to lower agency costs in lending and banks' external finance premiums.¹⁵ Yet, the effect of monetary policy can differ by debt maturities. In particular, Black and Rosen (2018) find that during periods of loose credit, banks increase the maturity of the loan supply, which is consistent with the bank lending channel of monetary policy and our finding of a decline (increase) in short-term (long-term) credit flows. Similarly, Jungherr et al. (2024) find that unconventional monetary policies that lower long-term interest rates while leaving short-term interest rates unchanged have a greater effect on firms that have a higher share of maturing debt when monetary policy shocks hit. In addition, short-term debt has a shorter repayment period, and hence usually involves smaller loan amounts than long-term debt. In turn, since banks recover only between 50% and 80% of the loans that are terminated (see Keuschnigg and Kogler (2020), incentives to liquidate nonperforming loans when interest rates are low could differ between debt maturities leading to a reduction (increase) in short-term (long-term) *NEG*. We note that Figures 6 and 7 depict the results for all firms; Section 5 further investigates heterogeneity in the response between different groups of firms and assesses what type of firms account for the differential response of short- and long-term credit flows.

¹⁵See Bianco (2021) for a detailed discussion of the theoretical underpinnings associated with credit flows' expected response to monetary easing.

4.2 Credit Flows at the Effective Lower Bounds

To shed further light on the effect of UMP 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 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) by replacing the series of monetary policy shocks with one that forces the shadow federal funds rate to 0.25%.¹⁶ Doing so allows us to quantify how credit flows would have responded had monetary policy been constrained by the ELB. The wedge between the actual and counterfactual value of the variable Y_τ^i at time τ is given by

$$wedge_\tau^i = Y_\tau^i - \sum_{s=t_1}^{\tau} \Psi_s^{r,i} v_s^{cf} \quad (9)$$

where t_1 refers to the beginning of each ELB period. In the counterfactual, we let $v_s^{cf} = v_s + 0.25r_s$ (i.e., the federal funds rate equals 0.25%) and compute the path for *POS* and *NEG*. Then, using equations (4) - (6) we compute the counterfactual paths for *SUM*, *NET*, and *EXC*.

The first column of Figure 8 presents the counterfactual wedges for short- and long-term credit flows during the two ELB periods. UMP led to slight declines in short-term *POS* during both ELB periods, with an exception at the end of the Financial Crisis ELB. In contrast, long-term *POS* increased throughout both ELB periods and by substantially larger magnitudes. The figure also shows that the effect of UMP in the third quarter of the Covid-19 ELB was in line with the highest peaks during the previous ELB. The effects

¹⁶Results for an alternative scenario where we fix the rate at 0.1% are reported in Appendix C.

of UMP on short- and long-term *NEG* were small in both ELB periods. Although, UMP 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 *NEG*. Overall, UMP 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 UMP on short- and long-term *POS* is similar for continuing firms (Figure 8, second column) and all firms. However, the response of long-term (short-term) *NEG* is slightly smaller (larger) for continuing firms than for all firms. Yet, long-term *EXC* is notably smaller for continuing firms, indicating that UMP 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

This section explores whether individual differences within broad groups of firms influence the response of aggregate credit flows to monetary policy shocks. The motivation for this investigation is two-fold. First, as mentioned above, a large body of empirical literature uses panels of firms to investigate the role of financial frictions in the transmission of aggregate shocks. This literature employs micro-level data to estimate the sensitivity of different groups of firms to aggregate shocks and does not focus on the dynamic response of credit flows to monetary policy shocks. Time series data on credit flows shed new light on the connection between monetary policy and the reallocation of credit among firms. Second, the credit flow data point to considerable heterogeneity in the growth of firm-level credit during the ELBs (see Table 3).¹⁷ The pervasiveness and magnitude of these flows indicate that aggregate credit dynamics are closely entwined with the cross-sectional distribution of firm-

¹⁷Summary statistics reported in Appendix A document the presence of heterogeneity in the average credit flows for the entire sample.

level credit. In turn, as underscored by several central bank officers since the Financial Crisis (Kaplan and Violante, 2018), understanding the role of firm heterogeneity in the response to aggregate shocks is key for understanding business cycles.

Thus, we examine how monetary policy affects credit flows by groups of firms with characteristics that may proxy for financial constraints (i.e., asset size, age, default probability, and leverage).¹⁸ In each quarter, we classify firms in the top tercile by leverage ratio, bottom tercile by value of assets, and bottom tercile by age as financially constrained. Following Farre-Mensa and Ljungqvist (2016), firms with a default probability over 25% are deemed financially constrained.¹⁹

5.1 Heterogeneous Effects of Monetary Policy Shocks

Before we delve into the response of credit flows during the ELB periods, we briefly examine whether the average response to an expansionary monetary policy shock differs across groups of firms with heterogeneous characteristics.

Size of Firms. Table 4 reports cumulative impulse responses of credit flows to a monetary easing shock on impact, four, and eight quarters after the shock. Short-term *POS* for smaller (publicly listed) firms²⁰ increases by 0.16 percentage points on impact and by 0.90 percentage points after eight quarters, while large firms do not show significant change. The response of short-term *NEG* is minimal on impact, but smaller firms experience significant increases in *NET* and *SUM*, mainly driven by *POS*. In response to the shock, long-term *POS* increases significantly for both groups of firms, with a larger impact on smaller firms. While

¹⁸The size of the firm is the value of total assets at the beginning of the quarter, as suggested by Gertler and Gilchrist (1994) and Kudlyak and Sánchez (2017); age is the number of years since the firm was first listed in the Compustat database; leverage is the ratio of short-term debt to total assets following Kudlyak and Sánchez (2017).

¹⁹The 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).

²⁰We label firms in Compustat’s lowest quartile as “smaller” rather than “small” to avoid potential misinterpretation. Although these firms are small publicly traded firms, they tend to be larger than private firms, which are not in Compustat (see Crouzet and Mehrotra (2020) for a size comparison between Compustat and the Quarterly Financial Report which includes both public and private firms).

we find that long-term *NEG* increases slightly for large firms, we find no significant changes in long-term *NEG* for smaller firms following the shock. The resulting increases in smaller firms' long-term *NET* and *SUM* are primarily due to the responses of *POS*. Whether the greater sensitivity of smaller firms to monetary policy easing –relative to large firms– provides evidence of a financial accelerator (Gertler and Gilchrist, 1994) or reflects differences in industry scope (Crouzet and Mehrotra, 2020) is a question left for future research.

Age of Firms. Expansionary monetary policy may affect young firms by mitigating financial constraints, as these firms often lack collateral and carry higher risk (Carreira and Silva, 2010). If this is the case, we would expect a relatively larger increase in *POS* for young firms. However, as highlighted by Dinlersoz et al. (2018), young firms tend to incur more costly debt, which they repay as they mature and switch to cheaper external financing options. Thus, expansionary monetary policy, by lowering borrowing costs of young firms, may lead to greater *POS* and reduce costly debt by transitioning to cheaper financing.

As shown in the second panel of Table 4, a negative monetary policy shock does not significantly affect short-term *POS* for old firms, but it does for young firms (0.52 percentage points by the eighth quarter). The responses of short-term *NEG* for both groups of firms are not statistically significant. Following the shock, both young and old firms experience significant increases in long-term *POS*. By the eighth quarter, this increase reaches 0.58 percentage points for young firms and 0.52 for old firms. The response of long-term *NEG* for young firms is not significant. However, both groups exhibit significant increases in long-term credit growth and reallocation of similar magnitudes. These results point to a heterogeneous response –by age– of short-term credit with monetary policy easing fostering reallocation among young firms.

Default Probability of Firms. The next panel of Table 4 shows that high-default-probability firms experience a significant increase in short-term *POS* in response to the monetary policy shock. Unlike smaller and young firms, they also experience significant increases in *NEG* at several horizons, leading to fluid short-term credit reallocation. Eight

quarters post-shock, gross (excess) credit reallocation cumulatively increases by 0.79 (0.73) percentage points. The increase in *EXC* indicates a rise in the fluidity of short-term credit among these firms. In contrast, low-default-probability firms show no significant short-term credit flow responses. Both high- and low-default-probability firms experience significant increases in long-term *POS*, rising by 0.53 and 0.51 cumulative percentage points, respectively, by eight quarters after the shock. There is no indication that monetary policy influences long-term *NEG* of high-default-probability firms, and the effect on low-default-probability firms is small, yet statistically significant. Expansionary monetary policy leads to a more dynamic reallocation of short-term credit for financially constrained firms, as indicated by default probabilities, mirroring the findings based on firm age. The magnitude of the effect on long-term credit flows across these groups of firms is also comparable.

Leverage of Firms. We use leverage as the final proxy for financial constraints, categorizing firms into high- and low-leverage groups. Cumulative impulse responses, presented in the last panel of Table 4, indicate that monetary policy does not significantly affect short-term *POS* for firms with high leverage. Yet, the shock has an immediate and persistent effect on their long-term credit flows. In particular, expansionary monetary policy significantly increases the long-term *POS* of both high- and low-leverage firms, with a greater impact on the *NEG* of low-leverage firms.

In general, we find that monetary policy influences short-term credit flows of financially constrained firms when grouped by size, age, and default probabilities, and also increases credit flows of low-leverage firms, which may be less financially constrained. Long-term credit flow responses are similar among financially constrained and non-financially constrained firms based on age and default probabilities, yet with larger impacts for large and low-leverage firms.

5.2 Monetary Policy and Credit Flows during Two ELBs

The Fed, like many central banks worldwide, responded to the Financial Crisis with a variety of UMP tools, such as large-scale asset purchases, “forward guidance”, and conditional bank lending programs. Initially, these policies were aimed at stabilizing the financial market, but were later used to stimulate the economy.²¹ Although central banks tried to revert to more conventional policies, the Covid-19 ELB proved that such policies now form an essential set of instruments when interest rates are close to zero.

How did inter-firm credit flows evolve during the ELBs? As Table 3 shows, during the Financial Crisis ELB, all firms, but high-leveraged, experienced increases in short-term *POS*. The largest gain was observed for high-default-probability firms. In contrast, short-term *NEG* increased only for smaller, young, and low-leverage firms, resulting in heightened short-term credit growth for most groups. Increases in the fluidity of short-term credit, as measured by *EXC*, were observed for smaller, low-leveraged, and young firms. During the Covid-19 ELB period, high-default-probability firms saw the largest gain in short-term *POS* (12.77 percentage points), but minimal in *NEG* (0.37 percentage points). As during the first ELB, these firms experienced a marked increase in *NET* and *SUM* for short-term credit. Smaller firms saw the largest increase in short-term *EXC* (12.73 percentage point). This increased credit reshuffling was mainly due to a substantial increase in *NEG*.

Regarding long-term credit flows, smaller and high-default probability firms exhibited higher *POS* during the Financial Crisis ELB, particularly smaller firms (8.47 percentage points). Changes in long-term *NEG* were moderate, with certain groups experiencing gains and others losses. As a result, most firms saw a rise in long-term credit growth. In contrast, the Covid-19 ELB saw long-term *POS* decreases for most firms, while long-term *NEG* increased for all groups leading to decreases in long-term credit growth. Low-leverage firms experienced the largest rise in gross and excess long-term credit reallocation.

What was the contribution of UMP to the evolution of credit flows during the two ELBs?

²¹See Bhattacharai and Neely (2022) for an excellent summary of the literature on UMP.

To answer this question, we compute a policy counterfactual in which we replace the series of monetary policy shocks in our Proxy-FAVAR with one that forces the shadow federal funds rate to 0.25% during the ELBs.²² The resulting wedges between the actual and counterfactual values for *POS* and *NEG* are reported in Figures 9 and 10.

Throughout the ELBs, smaller, young, and high-default-probability firms generally experienced positive counterfactual wedges in short-term *POS*. The difference is particularly striking when grouped by size, even though Compustat firms are large relative to the universe of US firms. In fact, negative wedges are estimated for large, old, and low-default-probability firms throughout much of the ELB periods. This suggests that UMP brought about more short-term *POS* for financially constrained firms, whereas the opposite holds for non-financially constrained firms. In contrast, we find that these wedges are typically larger for low-leverage firms compared to high-leverage firms. This is consistent with Farre-Mensa and Ljungqvist (2016), who show that constrained firms in Compustat generally have lower leverage than their unconstrained counterparts.

For long-term *POS*, all groups show positive wedges in both ELBs, with smaller firms experiencing notably larger wedges than large firms. This suggests that UMP led to more long-term *POS* for financially constrained smaller firms. For other pairs, long-term counterfactual wedges are similar in magnitude. The wedges for *NEG* are small compared to those for *POS*. Most wedges for short-term *NEG* are negative, indicating that UMP reduced *NEG*, except notably for high-default-probability and low-leverage firms.

To complete our analysis, Figures 11 - 13 present counterfactual wedges for *NET*, *SUM*, and *EXC*. Because counterfactual wedges for *POS* generally exceed those for *NEG*, the resulting wedge for *NET* tends to be positive both for long-term and short-term credit. To be noted are the larger wedges of long-term credit growth for younger, and especially smaller firms, as well as short-term credit growth for smaller, young, and high-default-probability firms. This suggests that UMP led to an increase in *NET* by promoting *POS* among

²²See Figure A.3 in Appendix A for a plot of the monetary policy shock series throughout the ELB periods.

financially constrained firms.

Moreover, differences in short-term *SUM* wedges between financially constrained (smaller, young and high-default probability) firms and their counterparts, as well as the larger wedge of long-term *SUM* for smaller (relative to large) firms, suggest that UMP had a non-trivial reallocative effect among financially constrained firms during the ELBs. Interestingly, for non-financially constrained firms, the counterfactual wedges for long-term *EXC* are typically larger indicating unconventional policies induced credit reshuffling beyond what was needed to accommodate the net short-term credit change at the ELBs.

In summary, we find that UMP promoted *NET* during the ELBs through two channels. First, it fostered long-term *POS* among all firms, especially the smaller tercile, and short-term *POS* among smaller, young, high-default-probability, and high-leverage firms. Second, to a lesser degree, it prevented short-term *NEG* among most firms, but especially for high-default and low-leverage firms. The counterfactual analysis points to the ability of UMP to foster *SUM* among financially constrained firms.²³

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 differs for firms with varying credit efficiency. Answering this question is key, as credit extended to highly credit-efficient firms should boost economic growth. Moreover, our finding that UMP staved off the destruction of short-term credit but accelerated that of long-term credit prompts the question whether such policies played a Schumpeterian role in the allocation of credit by fostering *NEG*.

Although we do not perform a causal analysis of the impact of monetary policy on credit efficiency, we inquire whether credit was allocated to more productive firms by computing a

²³Estimation results reported in Figures C.1-C.4 of Appendix C demonstrate that these findings are robust, albeit slightly smaller in magnitude, to an alternative counterfactual scenario where the shadow federal funds rate is set to 0.10%.

proxy of efficiency in the allocation of credit. Our proxy is an index similar to that proposed by Galindo et al. (2007) constructed as

$$CE_{jt} = \frac{\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt}}{debt_{jt}}}{\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt-1}}{debt_{jt-1}}}. \quad (10)$$

This index measures how efficiently credit (debt) is allocated for group j in quarter t relative to the total return if credit had been allocated according to each firm's share in the group's credit, $debt_{ijt-1}$.²⁴ 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 is shown in Table 5. Throughout the sample, 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 UMP led to a rise in short-term *POS* for small, young, high-default-probability, and low-leverage firms relative to their counterparts. During the Financial Crisis ELB, these groups also showed notably greater credit efficiency. The Covid-19 ELB saw increased credit efficiency mainly for low-leverage and high-default-probability firms, while large and old firms' credit efficiency exceeded that of small and young firms. These differences imply that UMP may have led to a more efficient allocation of short-term credit, particularly during the Financial Crisis ELB.

Long-term credit efficiency also reflects similar patterns. During the Financial 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

²⁴See Galindo et al. (2007) for a discussion on why a sales-based index is preferable to a profit-based index.

relatively large increases in long-term *POS* due to monetary policy easing. However, during the Covid-19 ELB, large, young, high-default-probability, and low-leverage firms had higher long-term credit efficiency. Hence, the impact of monetary policy on directing funds to more efficient firms during the Covid-19 ELB remains uncertain. In all, our findings 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 UMP 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 *POS* and a 35 basis point increase in aggregate long-term *NEG* after 16 quarters. We also observe that UMP leads to declines in aggregate short-term *POS* and *NEG*.

However, focusing on heterogeneity in financial constraints, we found that groups of smaller, young, and high-default-probability firms experienced substantial increases in short-term *POS* 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 smaller firm's long-term *POS* compared to those of large firms.

Analysis of ELB periods (Financial Crisis and Covid-19), showed that UMP contributed most to short-term *POS* of smaller 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. UMP's heterogeneous effect is less apparent for long-term credit, yet we found that it contributed relatively more to the long-term *POS* of smaller firms compared to large firms. Despite evidence of larger *NEG* effects on certain

groups, positive effects on *POS* dominated, signifying the policy’s effectiveness in fostering *NET* during ELB periods.

Lastly, we 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 UMP leads to increases in *POS*, particularly during the Financial Crisis ELB. Yet, during the Covid-19 ELB, the long-term *POS* that UMP promoted tended to flow to firms with lower credit efficiency.

Our findings offer important insights into how UMP impacts credit flows and the broader economy. They underscore the potency of the Fed’s measures, particularly when the federal funds rate hits the ELB, in reallocating credit towards financially constrained firms. Additionally, UMP has potentially directed credit towards firms better positioned for investment and growth. In general, the implementation of UMP 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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Table 1: Descriptive Statistics of Aggregate Credit Flows

		<i>POS</i>	<i>NEG</i>	<i>NET</i>	<i>SUM</i>	<i>EXC</i>
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 (0.795)	1.295 (0.234)	25.518 (0.000)
	(2)	0.627 (0.6440)	2.163 (0.019)	3.565 (0.062)
Eurodollar futures	(1)	0.015 (0.999)	1.596 (0.109)	12.578 (0.001)
	(2)	2.779 (0.031)	1.115 (0.359)	0.154 (0.695)
Treasury yields	(1)	0.018 (0.999)	2.539 (0.006)	6.317 (0.013)
	(2)	2.080 (0.089)	1.667 (0.087)	0.772 (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				
	<i>POS</i>	<i>NEG</i>	<i>NET</i>	<i>SUM</i>	<i>EXC</i>	<i>POS</i>	<i>NEG</i>	<i>NET</i>	<i>SUM</i>	<i>EXC</i>
Smaller 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				
	<i>POS</i>	<i>NEG</i>	<i>NET</i>	<i>SUM</i>	<i>EXC</i>	<i>POS</i>	<i>NEG</i>	<i>NET</i>	<i>SUM</i>	<i>EXC</i>
Smaller 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 smaller, 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

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

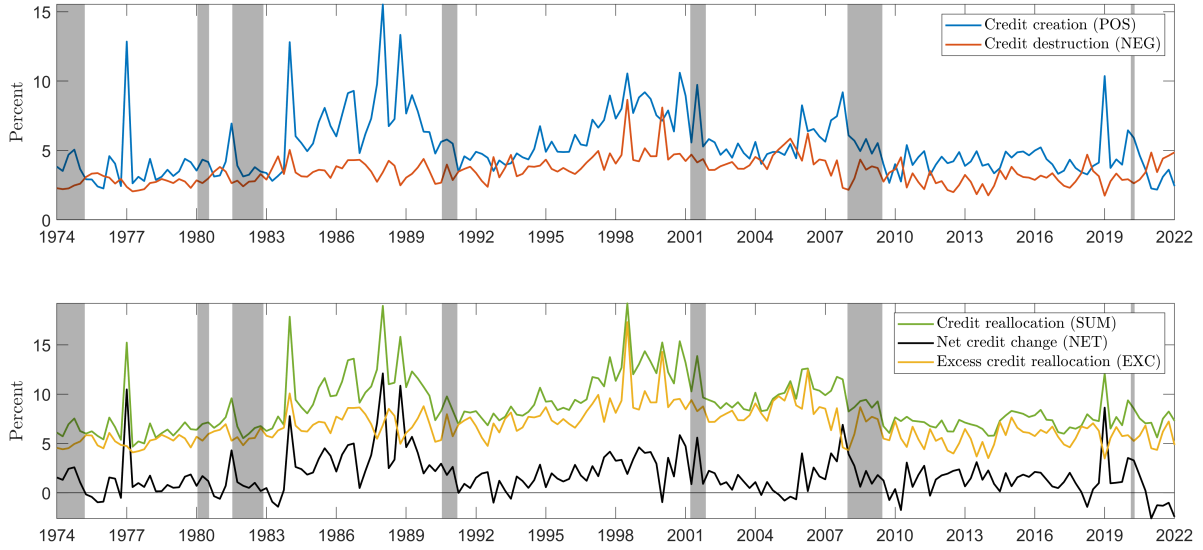
Note: This table provides the cumulative impulse responses of credit flows to a -25 basis point monetary policy shock using the sample, Q1:1974:Q1 – Q1:2022, in a proxy SVAR setting using external instruments. †, *, and ** indicate statistical significance at 68, 90, and 95 percent significance from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

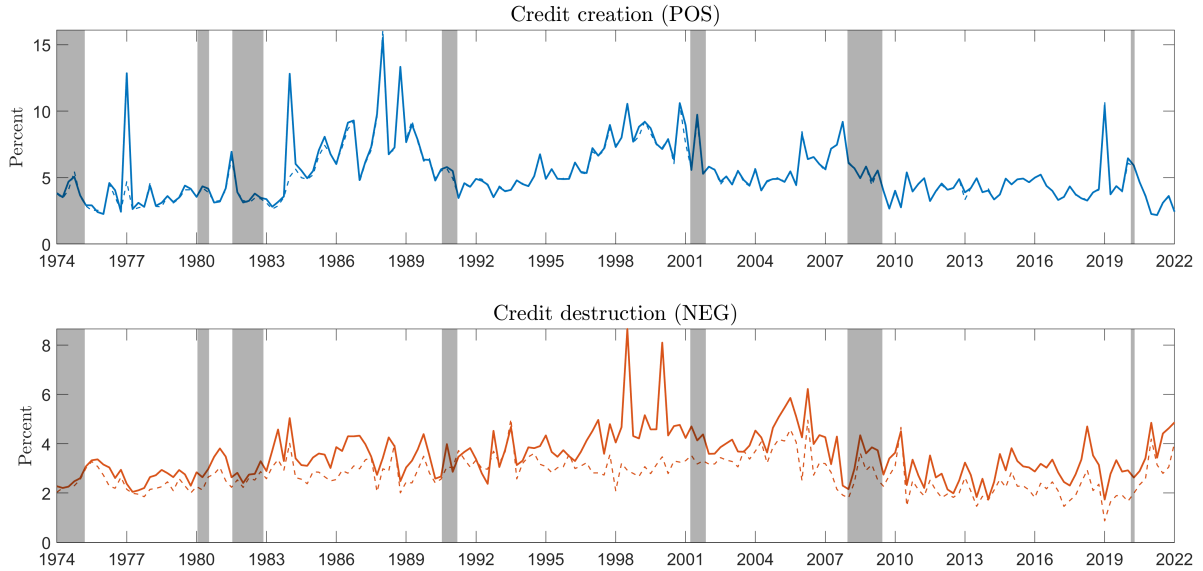
Note: Each group of firm's credit efficiency is measured $CE_{jt} = (\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt}}{debt_{jt}}) / (\sum_{i \in j} \frac{sales_{ijt}}{capital_{ijt}} \frac{debt_{ijt-1}}{debt_{jt-1}})$ for group j in quarter t at each debt maturity.

Figure 1: Aggregate Credit Flows



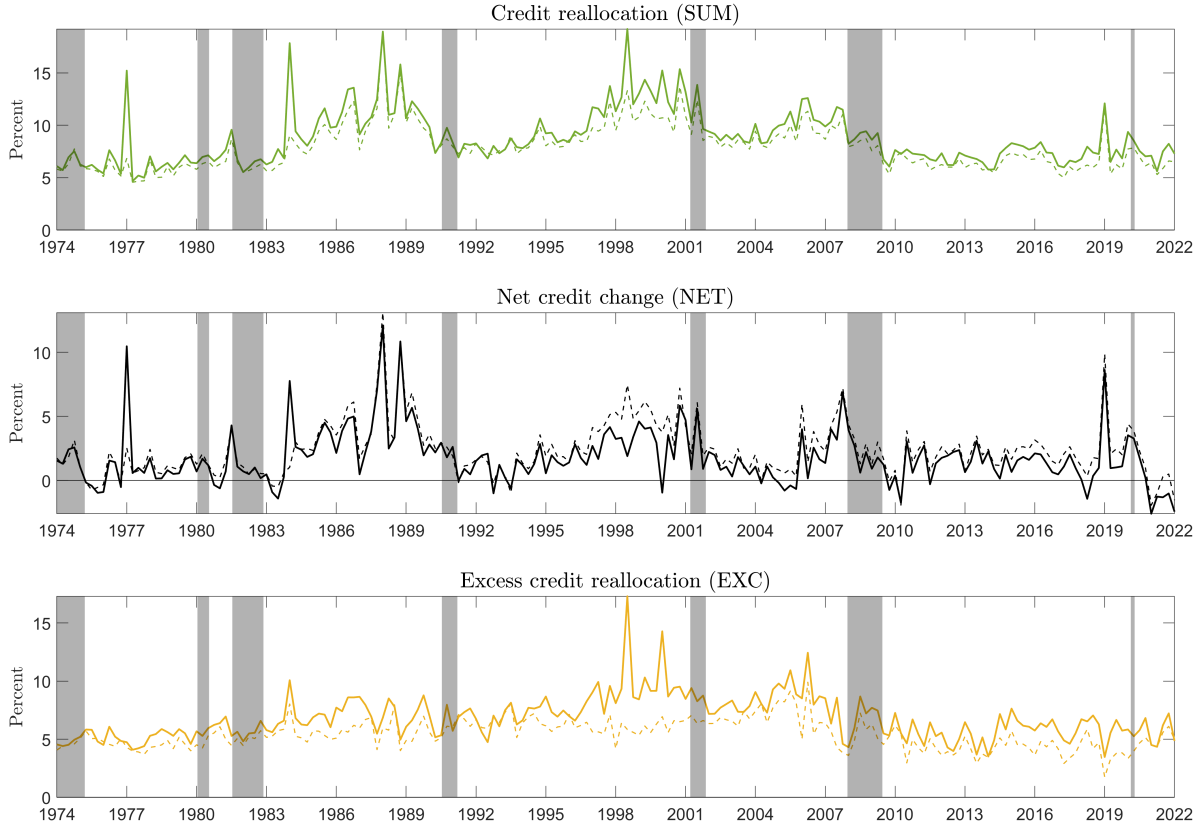
Note: *POS* refers to credit creation, *NEG* is credit destruction, *NET* is net credit change ($NET = POS - NEG$), *SUM* is credit reallocation ($SUM = POS + NEG$), and *EXC* is excess credit reallocation ($EXC = SUM - |NET|$). Shaded bars indicate NBER recessions.

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



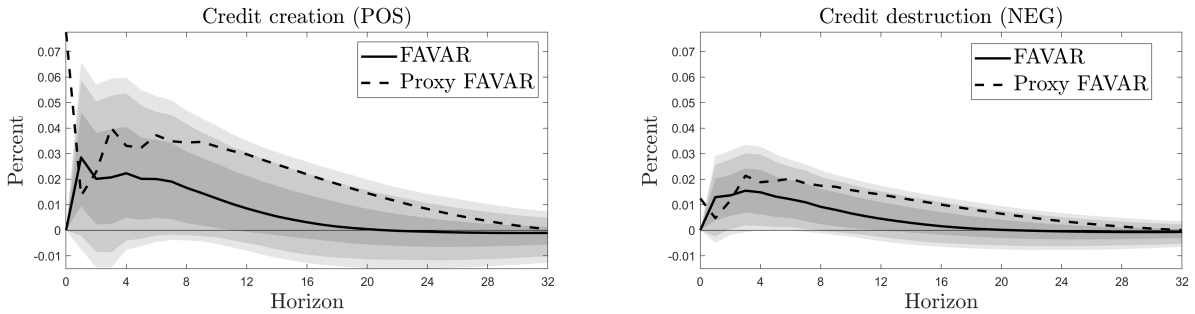
Note: The solid lines represent credit flow measures for all firms, including those entering and exiting the database. The dashed lines represent credit flows of firms that are neither entering nor exiting the database in the current quarter. Shaded bars indicate NBER recessions.

Figure 3: Credit Flows at the Intensive Margin



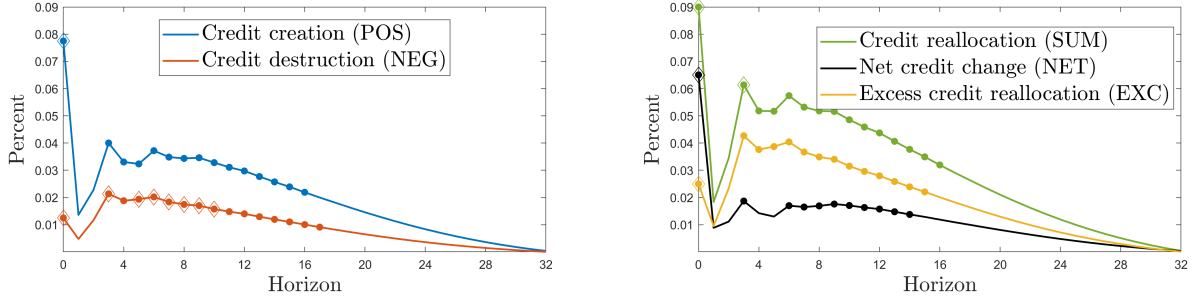
Note: The solid lines represent credit flow measures for all firms, including those entering and exiting the database. The dashed lines represent credit flows of firms that are neither entering nor exiting the database in the current quarter. Shaded bars indicate NBER recessions.

Figure 4: Impulse Responses of Credit Flows



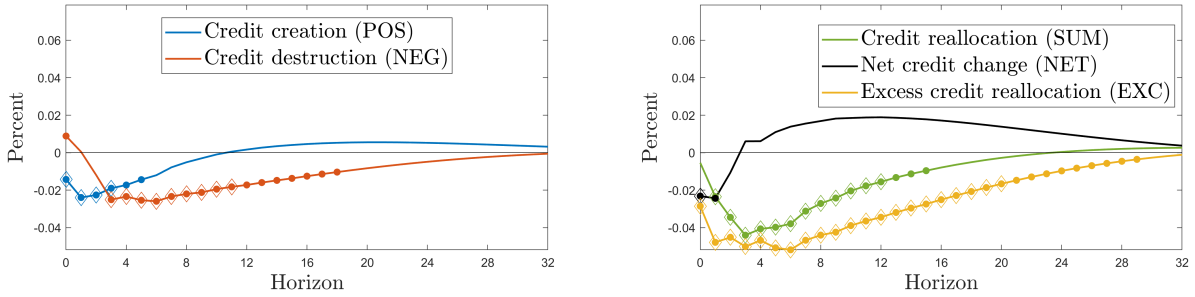
Note: The plots display the impulse responses of aggregate credit flows to a -25 basis point monetary policy shock. These responses are estimated using a FAVAR with no external instruments, along with the 68, 90, and 95 percent confidence intervals using the wild bootstrap method, and a proxy FAVAR framework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

Figure 5: Impulse Responses of Credit Flows using External Instruments



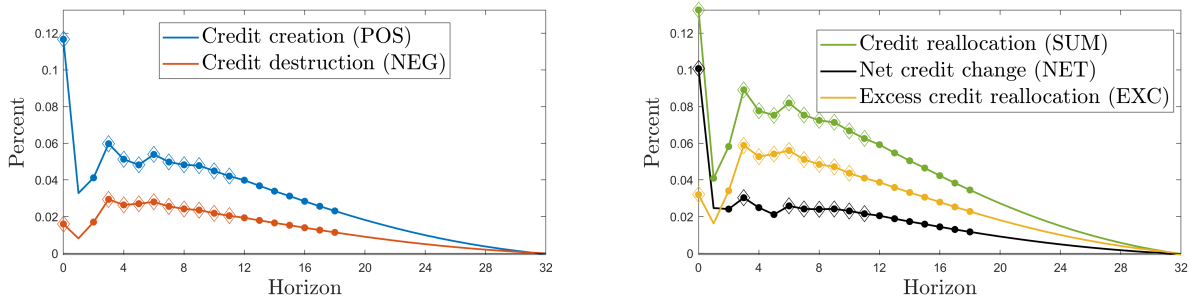
Note: The plots display the impulse responses of aggregate credit flows to a -25 basis point monetary policy shock. These responses are estimated using a proxy SVAR framework utilizing federal funds futures as external instruments. Dots indicate the significance at a 68 percent level and diamonds indicate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

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



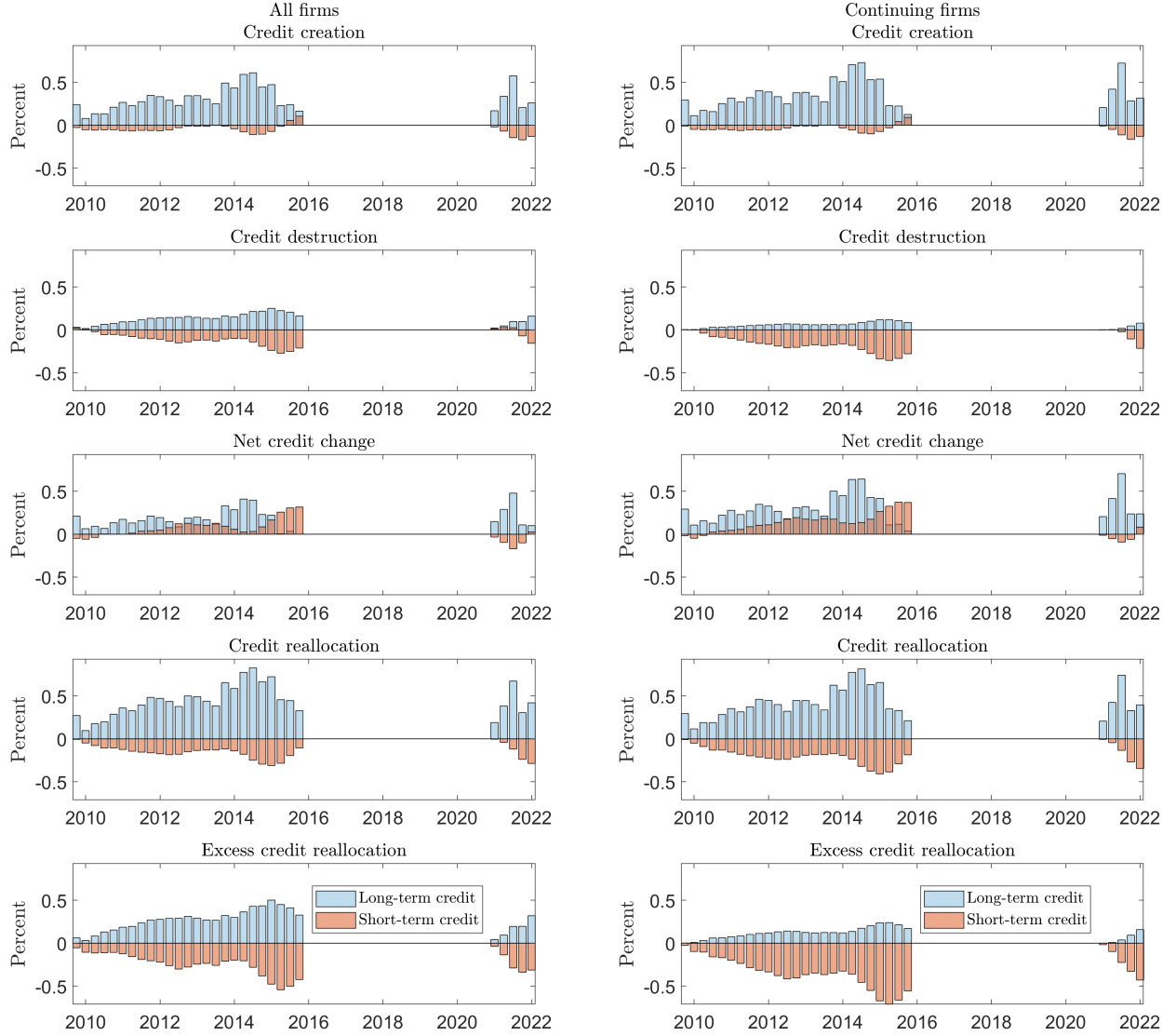
Note: The plots display the impulse responses of aggregate short-term credit flows to a -25 basis point monetary policy shock. These responses are estimated using a proxy SVAR framework utilizing federal funds futures as external instruments. Dots indicate the significance at a 68 percent level and diamonds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



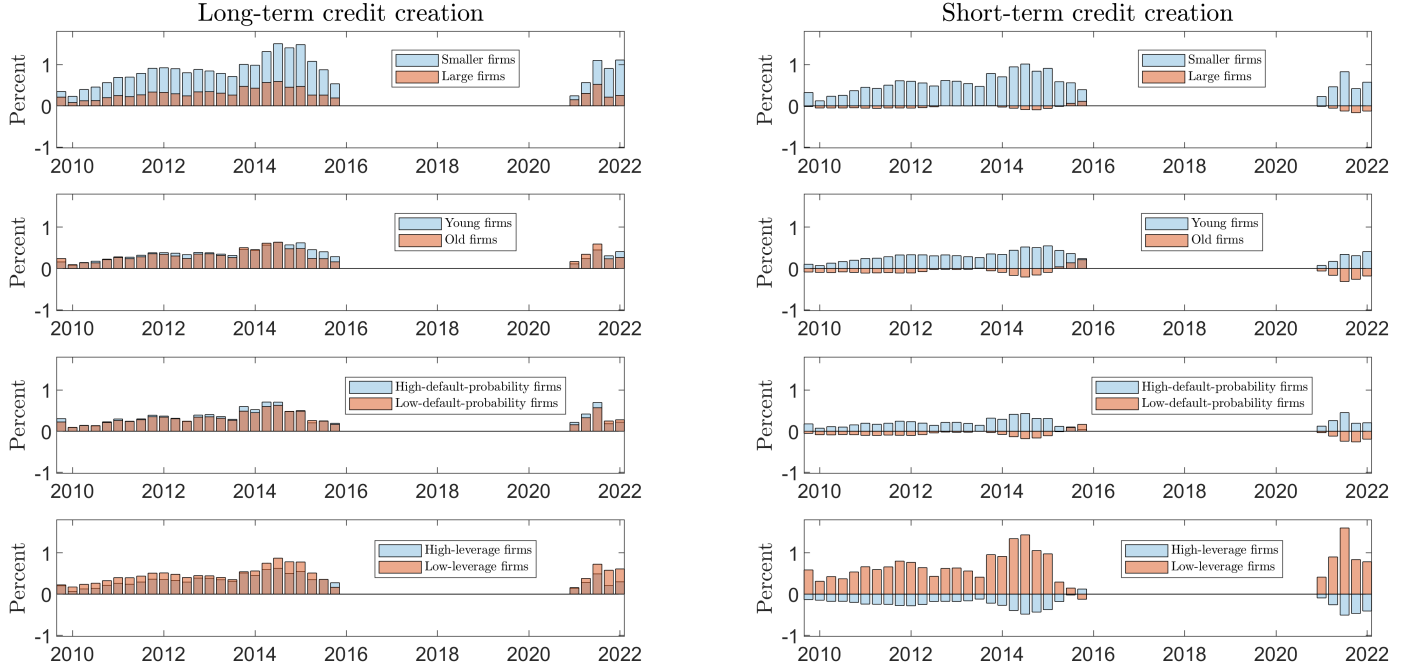
Note: The plots display the impulse responses of aggregate long-term credit flows to a -25 basis point monetary policy shock. These responses are estimated using a proxy SVAR framework utilizing federal funds futures as external instruments. Dots indicate the significance at a 68 percent level and diamonds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

Figure 8: Counterfactual Wedges



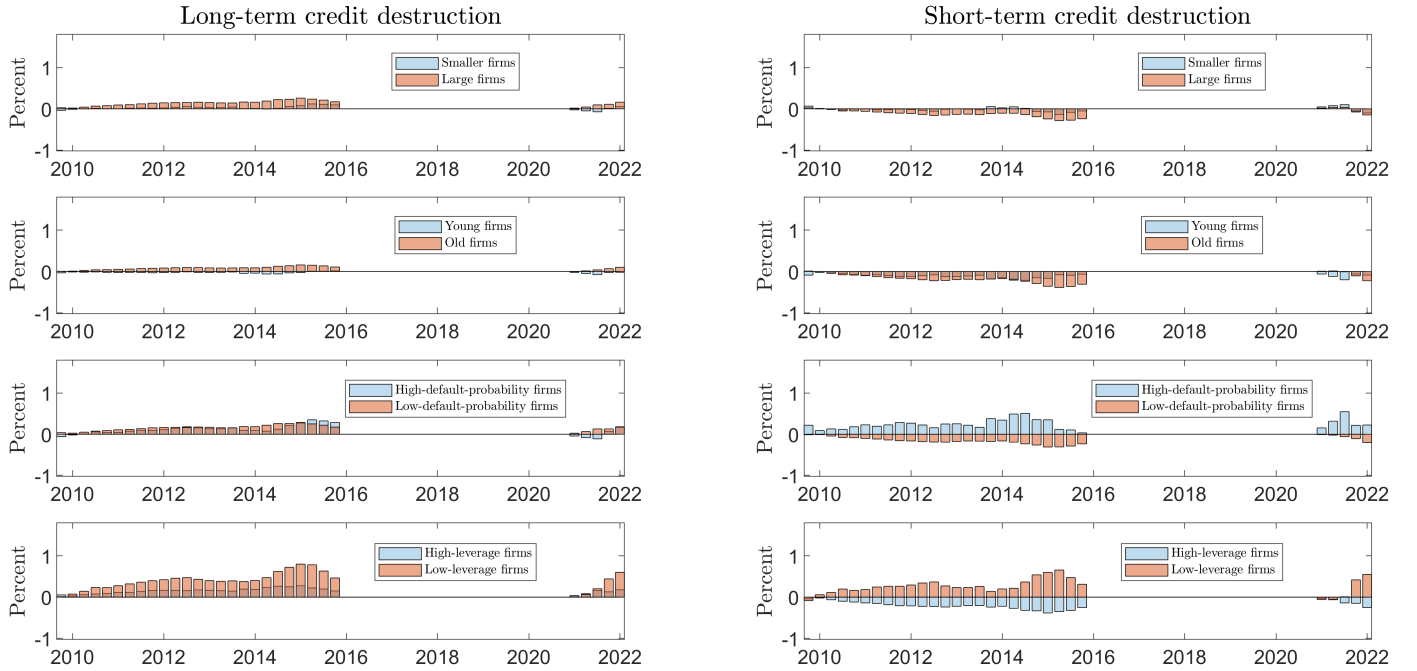
Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 9: Counterfactual Wedges for Credit Creation (*POS*) by Firm Groups



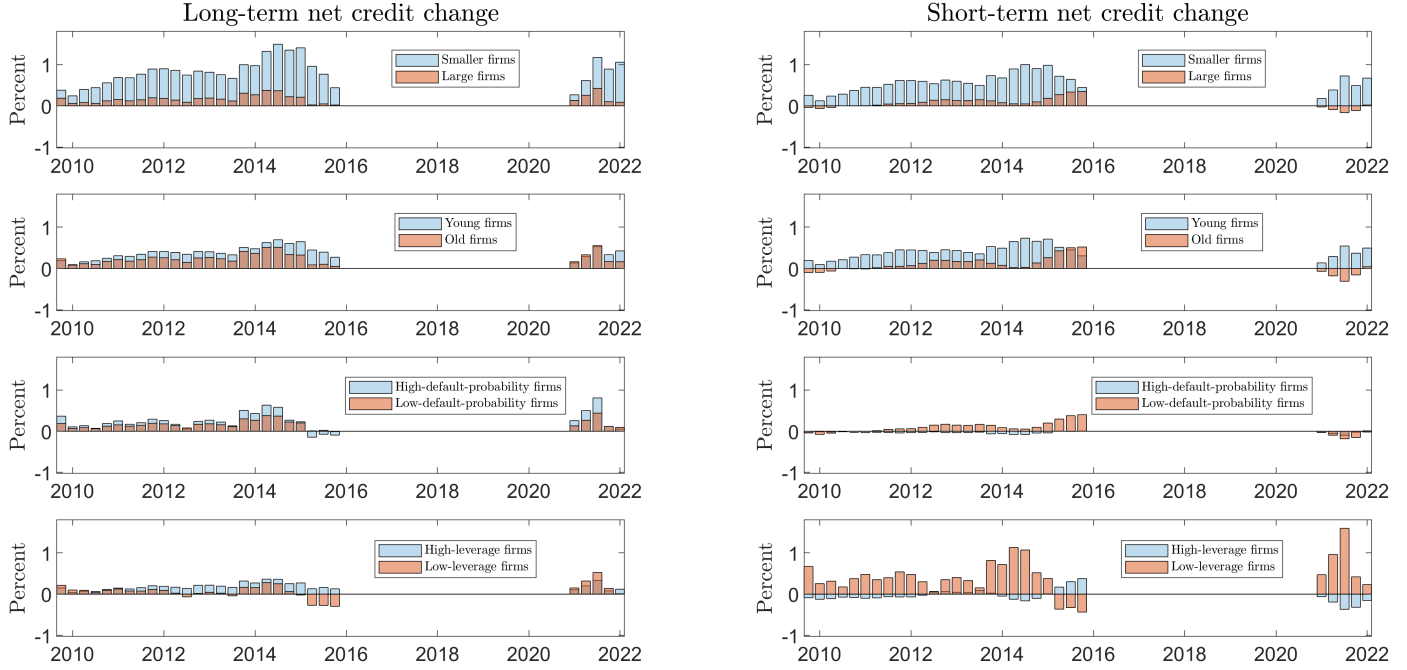
Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 10: Counterfactual Wedges for Credit Destruction (*NEG*) by Firm Groups



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 for Net Credit Change (NET) by Firm Groups



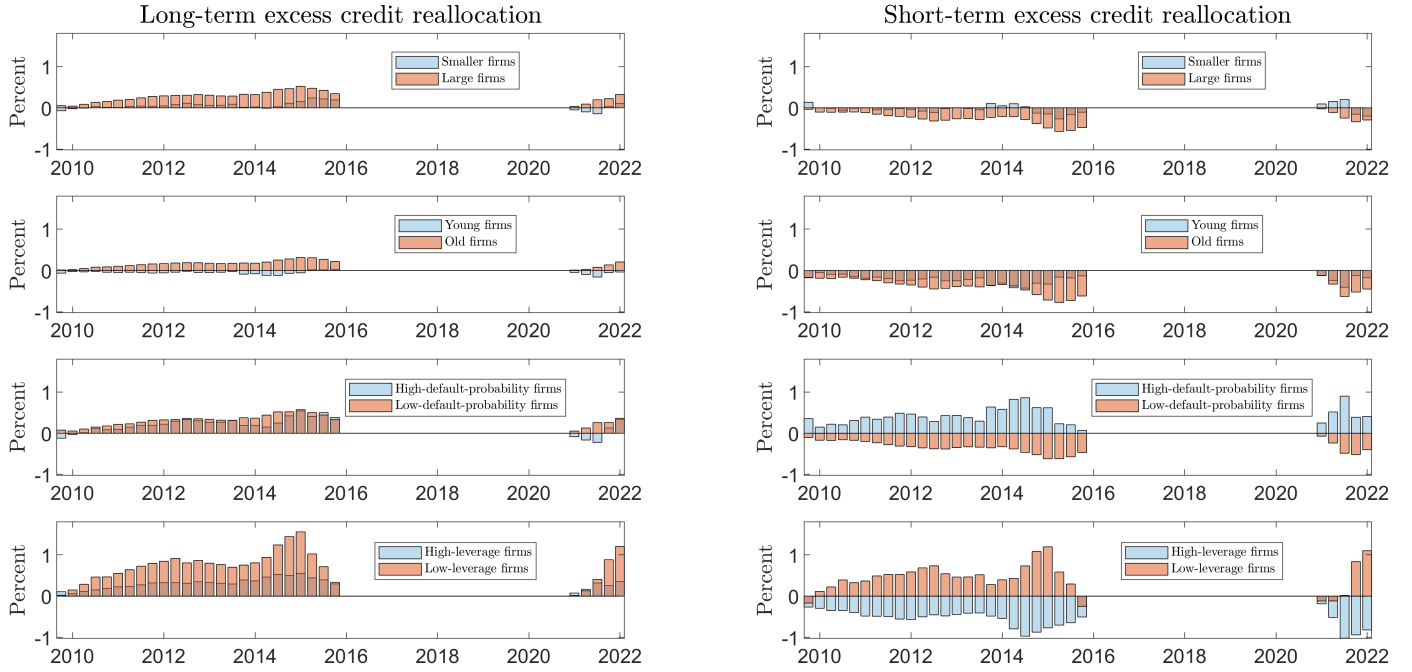
Note: The counterfactual wedges are the differences between the counterfactual credit flows and the actual credit flows during the two ELB periods (Q3:2009 – Q3:2015 and Q4:2020 – Q4:2021).

Figure 12: Counterfactual Wedges for Credit Reallocation (SUM) by Firm Groups



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 for Excess Credit Reallocation (EXC) by Firm Groups



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).