The Effect of Unconventional Monetary Policy on Credit Flows*

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Abstract

This paper evaluates the quantitative effects of unconventional monetary policy on the flow of credit in the late 2000s and early 2010s when the federal funds rate hit the zero lower bound (ZLB). We compute credit flows using Compustat data and employ a factor augmented vector autoregression to analyze unconventional monetary policy's impact on the allocation of credit among firms. We find that unconventional monetary policy had a positive impact on credit reallocation, especially for long-term credit. We then inquire what groups of firms were affected, finding that during the ZLB, unconventional monetary policy reshuffled long-term credit towards firms typically viewed as financially constrained: high default probability and highly leveraged firms. We also show that during the ZLB, unconventional monetary policy brought about higher credit creation for firms of relatively high credit efficiency, suggesting this policy was key to fueling future economic growth.

Key words: Unconventional Monetary Policy, Credit Reallocation, Business Cycles

JEL codes: E44, E51, E52, E58

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1 Introduction

In December 2008, the Federal Open Market Committee established a target range for the federal funds rate of 0 to 1/4 percent. In the following years, with this rate effectively at the zero lower bound (ZLB), the Federal Reserve (Fed) resorted to unconventional policy methods to provide monetary accommodation. By November 2014, the Fed had purchased nearly $4 trillion of mortgage-backed securities, agency debt, and long-term U.S. Treasuries. Moreover, throughout the ZLB, Fed officials engaged in forward guidance to shape expectations of the course of future monetary policy. These unprecedented actions were intended to stabilize the financial system, which was hampering economic growth due to tight credit standards. Monetary policy accommodation was achieved, in part, through artificially boosting collateral prices. This improved the availability of credit to borrowers who pledge these assets as collateral for external financing. Further, through forward guidance and rounds of quantitative easing, the Fed managed to lower market expectations of long-term yields. This decrease – once the ZLB was reached – eased financial conditions for households and firms.[1]

Research on the effectiveness of unconventional monetary policy was significantly bolstered by the Financial Crisis of the 2000s. Indeed, lessons learned from this research appear to have been at the forefront of the Fed's effort to support the economy during the current COVID-19 crisis.[2] The central bank acted swiftly in the face of the Great Shutdown; the effective federal funds rate has hit the ZLB and aggressive unconventional policy measures have been implemented. While the effectiveness of these policies has been well documented in the literature, many aspects still need to be better understood.

There is increasing evidence that the allocation of physical and financial inputs across heterogeneous firms is central to economic growth. Yet, less is known regarding the role played by unconventional monetary measures on the dynamics of credit reallocation among firms. Do these policies intensify the process of credit reallocation? Can they boost economic activity by uphold-

[1]See Krishnamurthy and Vissing-Jørgensen (2011), Rodnyansky and Darmouni (2017), Fieldhouse, Mertens, and Ravn (2018), Chakraborty, Goldstein, and MacKinlay (2020), and Di Maggio, Kermani, and Palmer (2020).

[2]See, for instance, the statement from the unscheduled Federal Open Market Committee meeting on March 15, 2020, which states that the Fed is "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 "will use its tools and act as appropriate to support the economy." Similar wording is contained in subsequent statements.

ing and aiding the flow of credit towards more financially constrained firms? And, if so, is credit reshuffled towards more efficient uses?

To answer 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. Then, we estimate the effect of monetary policy shocks on credit flows using a factor-augmented vector autoregressive (FAVAR) model similar to that of Bernanke, Boivin, and Eliasz (2005). In addition, to study the effect of unconventional monetary policy during the ZLB, we follow Wu and Xia (2016). That is, we replace the effective federal funds rate with Wu and Xia's shadow rate and analyze two alternative counterfactuals. First, we explore the effect of shutting down the monetary policy shocks during the ZLB, which amounts to the Fed following a traditional monetary policy rule. Second, we inquire about the effect of unconventional monetary policy during the ZLB by forcing the monetary policy instrument to be constrained by the ZLB.

Our first key empirical result is that monetary policy easing increases both total credit creation and destruction, thus leading to increased fluidity in total credit reallocation. This increase in credit reallocation peaks three quarters after the shock and slowly declines over the following years. Our baseline estimates suggest credit creation is more responsive than credit destruction, which is consistent with the increase in aggregate net credit found in the literature. We estimate that a negative 25 basis point shock to monetary policy causes total net credit to rise 2.7 percentage points over the steady state level and credit reallocation to rise by nearly 7 percentage points.

We also provide empirical evidence that unconventional monetary policy had a heterogeneous impact on credit flows during the ZLB for groups of firms facing different financial constraints. Specifically, the boost provided by the Fed to promote credit creation tended to be markedly larger for financially constrained firms. This was most evident for the short-term credit of small firms, as well as long-term credit of high default probability firms and highly leveraged firms. We provide two additional pieces of evidence, which suggest this heterogeneity was driven by firms' response to unconventional monetary policy measures and not by the response to unexpected monetary policy shocks. First, differences in credit flow counterfactuals among groups of firms are negligible when the monetary policy shock is shut down during the rounds of quantitative easing (QE) and operation twist. Second, the fluidity of credit markets would have been considerably lower had the Fed been constrained by the ZLB. More specifically, unconventional monetary policy boosted long-term credit reallocation (0.98 percentage points), while having a substantially smaller effect on short-term credit reallocation (0.04 percentage points). The impact on long-term credit reallocation was larger for high default probability firms and highly leveraged firms than their counterparts (i.e. low default probability firms and low leverage firms).

Because long-term credit tends to finance long-term investment projects, our results suggest that unconventional monetary policy during the ZLB provided much needed stimulus to investment and growth. Although we do not have firm-level productivity measures for Compustat firms, we compute a measure of credit efficiency along the lines of Galindo, Schiantarelli, and Weiss (2007) investment efficiency index. We find that firms of high credit efficiency benefited from unconventional monetary policy during the ZLB. This policy led to an increase in long-term credit reallocation 2.12 percentage points for these firms, compared to a decline of -0.12 for low credit efficiency firms. In other words, there is a silver lining to the somewhat radical monetary policy measures needed in a "lower-for-longer" interest rate environment: such policies reshuffle credit towards more efficient firms.

Our paper contributes to two key strands of literature. The first explores how the impact of monetary policy shocks varies across firms. Starting with the work by Kashyap, Lamont, and Stein (1994), Gertler and Gilchrist (1994), and Kashyap and Stein (1994), several articles have argued that monetary policy has a greater impact on small firms, which are more likely to face credit constraints. We contribute to this literature by showing that short-term credit reallocation for small firms was more responsive to unconventional monetary policy measures, while long-term credit reallocation, and not just net credit, was more responsive for large firms. Among alternative measures of credit constraints, we show that credit reallocation responded more strongly for highly leveraged firms and high default probability firms. Moreover, we show that these responses were driven by long-term credit. Furthermore, our paper complements the work by Kudlyak and Sánchez (2017), who document a smaller decline in credit for small firms during the Great Recession and the start of the ZLB period and show that the tightening of collateral constraints did not play a notable role in describing credit markets of borrowing firms during the Great Recession. However, they do not quantify the impact of unconventional monetary policy to credit reallocation.

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, Boivin, and Eliasz, 2005; Gertler and Karadi, 2015; Wu and Xia, 2016) or has used firm-level data to investigate the impact on investment and credit spreads (see, e.g., Cloyne, Ferreira, Froemel, and Surico, 2018; Anderson and Cesa-Bianchi, 2020). 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 every insured U.S. commercial bank. Our paper is more closely related to work by Bianco (2020) that assesses the channels of monetary policy transmission to inter-firm credit flows.

This paper is organized as follows. Section 2 describes the data and the evolution of credit flows during the ZLB. Section 3 describes the empirical methodology. Section 4 provides the results of the counterfactual analysis during the ZLB, including the rounds of quantitative easing and Section 5 concludes.

2 Data and Measurement

2.1 Credit Flows

As in Herrera, Kolar, and Minetti (2011) –hereafter HKM–, we compute 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. Firms in finance, insurance, and real estate industry sectors are removed from the sample given our aim to study the impact of unconventional 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 large and less financially constrained. Thus, 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, recent work by Kudlyak and Sánchez (2017) finds that large firms exhibited a greater contraction in sales and short-term credit than small firms in 2008–09. Moreover, in the last three decades, the employment and revenue shares of large firms have increased greatly (Begenau, Farboodi, and Veldkamp, 2018), thus increasing the contribution of these firms to the aggregate dynamics of employment and output. Understanding how credit is reallocated among large firms is thus 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 historical decomposition to construct counterfactual scenarios (see, e.g., Wu and Xia, 2016).

We follow HKM's definition and measurement of credit flows in most aspects. In particular: (i) our 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;[3] (iv) only exits due to merger or acquisition, liquidation or bankruptcy are treated as credit subtractions.

We depart from HKM in employing quarterly, instead of annual, data and expand the sample to include the period of the ZLB.[4] While using annual data would permit the inclusion of earlier years –annual data is available since the early 1950s–, the use of higher frequency data is key for our identification strategy. Hence, 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 measure follows the rate of growth for job flows by Davis, Haltiwanger, and Schuh (1998) and is akin to quarterly job flow measures used in related studies (see, e.g., Davis and Haltiwanger, 2001; Davis, Faberman, and Haltiwanger, 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; Herrera, Kolar, and Minetti, 2011). In particular, $g_{it} \in [-2, 2]$, where -2 corresponds to debt growth of

[3]See Ramey and Shapiro (1998) for the use of a similar criteria applied to flows of physical capital and Herrera, Kolar, and Minetti (2011) for a detailed description.

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

firms that died in the current year and 2 is debt growth of newborn firms.

With the rate of growth defined as above, we proceed to compute aggregate credit creation and credit destruction for a set of firms s in quarter t. These are weighted sum 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 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

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

2.1.1 Aggregate Credit Flows

We start by examining the magnitude and volatility of aggregate credit flows. Table 1 reports the average credit creation, credit destruction, gross credit reallocation, net credit change, and excess credit reallocation for the 1974:Q1–2017:Q1 period. The first row of panel (a) shows that during this period, total credit creation averaged 5.4 percent and credit destruction 3.5 percent, amounting to an average net credit change of 1.9 percent and gross and excess credit reallocation of 8.9 percent and 6.9 percent, respectively. This confirms HKM's finding that the intensity of inter-firm credit flows for all firms far exceeds the reallocation needed to accommodate net credit changes. The table illustrates how the volatility of total credit creation has been substantially larger than that of total credit destruction; note how the coefficient of variation for POS in the first row (All firms) equals 40.2 whereas that for NEG is 27.6. Furthermore, the first rows of panels (b) and (c) reveal that average short-term credit creation and destruction for all firms (15.1 percent and 7.1 percent, respectively) are notably higher than long-term creation and destruction (5.9 percent and 3.6 percent, respectively).

Inspection of Figure 1 illustrates that the intensity of credit reallocation varies across quarters. Three characteristics of the intensity of reallocation stand out. First, credit reallocation intensified during the 1980s relative to the 1970s, which had been noted by HKM. Second, while the U.S. has experienced a secular decline in the pace of job reallocation since 1990 (Davis and Haltiwanger, 2014), this pattern in absent from credit flows. Third, the U.S. credit market became less fluid since the onset of the Great Recession in 2007. Credit reallocation rates fell from a pre-recession rate of more than 12 percent to 6.1 percent prior to 2010. Further, this reduction in credit reallocation and its fluidity was driven mainly through reduced activity in the long-term credit market.

To what extent does Figure 1 capture credit creation and destruction among continuing firms (the intensive margin), rather than credit flows due subtractions from dying firms or extension of credit to newborn firms (the extensive margin)? To answer this question, we plot credit flows for all firms as well as excluding entering and exiting firms in Figure 2. As the figure illustrates, credit creation for the aggregate and the continuing firms track strikingly close to one another, suggesting that entering firms do not account for a large part of the fluctuations in credit creation over time. The two exceptions occur in 1977:Q1 and 1984:Q1 when credit creation is flat at the intensive margin, but spikes dramatically for the aggregate. This behavior suggest that these spikes are driven by firms entering the database. In 1977:Q1, firms entering the database with positive debt tended to operate in utilities companies,[5] and in 1984:Q1, from the utilities and telecommunications sectors.[6] As seen in the third panel of Figure 2, the net credit change at the intensive margin alone is free of these two spikes.

[5]Companies entering the database with the largest debt in the quarter include Georgia Power, Alabama Power Company, Ohio Power, El Paso Corporation, and the Indiana Michigan Power Company.

[6]Companies entering the database with the largest debt in the quarter include Royal Dutch Shell, BellSouth, NYNEX Corporation, Pacific Telesis Group, and AT&T (reformation).

Unlike credit creation, credit destruction at the intensive margin differs from that at the intensive and extensive margin jointly, as shown the second panel of Figure 2. This indicates that much of credit destruction is due to bankruptcies, mergers, acquisitions, and liquidations as firms exit the database. The most drastic difference occurs in the late 1990s to the early 2000s. During this time, while the number of exiting firms was falling, the total amount of credit of these firms was at its highest level. Therefore, exiting firms tended to have larger weights in the measure of aggregate credit destruction. At the intensive margin, the peak of credit destruction occurs in the mid-2000s, prior to the financial crisis. During the Great Recession, credit destruction fell to a nadir not experienced before (1.78 percent), rising again during and after the Great Recession.

Excess credit reallocation was also high in the late 1990s and early 2000s. This alone suggests that credit creation and destruction were jointly elevated during this time. However, at the intensive margin alone, excess credit reallocation was flat. Instead, excess credit reallocation at the intensive margin was largest in 2006. This was followed by a considerably decrease prior to the start of the Great Recession in late 2007. It is unclear how much of the credit reallocation was due to refinancing of debt.[7] This is because Compustat only provides information on the dollar amount of short- and long-term debt. Yet, the decline in the intensity or reallocation among continuing firms suggest the loss of fluidity during the Great Recession was not only driven by entering and exiting firms.

2.1.2 Group Credit Flows

A question that emerges from observing these patterns is whether the declines in reallocation observed since the Great Recession cut across firms facing varying degrees of financial frictions and efficiency. To address these questions, we borrow from Cloyne, Ferreira, Froemel, and Surico (2018) and group firms according to various proxies of financial constraints used in the corporate finance literature and compute credit flows for these subgroups. These proxies comprise (i) the value of total assets at the beginning of the quarter (Gertler and Gilchrist, 1994; Kudlyak and Sánchez, 2017), (ii) leverage, computed as the ratio of short-term debt to total assets following Kudlyak and Sánchez (2017), (iii) need for external financing defined as capital spending less cash flows as a

[7] That is, obtaining financing to pay off existing debt, resulting in increases in credit creation *and* destruction.

portion of capital spending as in Rajan and Zingales (1998), (iv) firm age computed as the number of years since the firm was incorporated in Compustat, and (v) default probability. The latter is computed as in Farre-Mensa and Ljungqvist (2016):

$$DD_{it} = Distance - to - default_{it} = \frac{log(\frac{E_{it}+F_{it}}{F_{it}}) + r_{it} - 0.5\sigma_{it}^2}{\sigma_{it}} \tag{7}$$

where

$$E_{it} = \frac{|prccq| \times cshoq}{10^3} \tag{8}$$

$$F_{it} = dlcq + \frac{1}{2} dlttq \tag{9}$$

$$\sigma_{it} = [\frac{E}{E+F} \times \sigma_{E,it}] + [\frac{F}{E+F} \times (0.05 + 0.25 \times \sigma_{E,it})] \tag{10}$$

where $\sigma_{E,it}$ is the rolling one-year standard deviation of *prccq* (stock price), r_{it} is the year-over-year stock return, *dlttq* is total long-term debt, *dlcq* is short-term debt, and *cshoq* is common shares outstanding. Default probabilities are obtained from the cumulative standard normal function.

In each quarter, we sort the firms along different characteristics that might reflect financial constraints (Farre-Mensa and Ljungqvist, 2016). We refer to firms that fall in the top tercile by leverage ratio and need for external financing, bottom tercile by value of assets and age, or whose default probability exceeds 25 percent as financially constrained.

Table 2 reports the percentage of time that firms are classified in a specific category at time t, conditional on classifications in time $t-1$. The table shows that these alternative proxies for financial constraints capture different aspects of a firm. For instance, default probabilities tend to fluctuate with equity prices and are therefore noisy measures. If a firm is classified as having a high default probability in $t-1$, then it is likely to remain in the same group in t 84.3 percent of the time. However, a firm that is classified as having a low default probability in $t-1$ is substantially more likely to remain in the low tercile in t (96.3 percent) than moving to the high default probability tercile. The distribution of firms' asset tends to be more stable over time, therefore, firms that are classified in the low tercile, small, in $t-1$ are 98.1 percent likely to stay in the same tercile in

t. Also, firms that are in the top tercile of asset value in $t-1$, which we classify as large, have a similar probability of staying in the same tercile in t.

Table 3 provides the change in the credit flow measures for financially constrained and non-financially constrained firms between 2009:Q3 and 2015:Q3, the period after the recession when unconventional monetary policy was conducted. Given that short- and long-term debt serve different purposes –financing current business operations versus long-term investment plans–, we report their evolution separately. For instance, at short-term maturities, the largest increase in net credit was for high default probability firms (10.05 percentage points). For this group, credit creation increased 10.95 percentage points and credit destruction increased 0.90 percentage points. While the change in credit reallocation was high for these firms (11.85 percentage points), the intensity of credit reallocation, as measured by excess credit reallocation, did not increase substantially.

Recall that Kudlyak and Sánchez (2017) find that median short-term credit for large firms contracted more than small firms during the Great Recession. After this time and during the ZLB, short-term net credit of firms for firms classified a large increased 2.20 percentage points, while net credit of small firms increased 3.31 percentage points. The change in net credit for small firms masks the large and intense reallocation of short-term credit during the ZLB. Short-term credit creation for small firms increased 6.68 percentage points, but short-term credit destruction increased 3.37 percentage points. This amounts to a 10.05 percentage points increase in small firms' credit reallocation, compared to a 2.06 percentage point decrease for large firms, who experienced a substantial decline in credit destruction. This is also evident by analyzing the changes in these groups' excess reallocation during the ZLB, increasing 6.74 percentage points for small firms and decreasing 4.26 percentage points for large firms.

Small firms also experienced a large rise in long-term credit creation (10.77 percentage points) relative to large firms (-0.08 percentage points). Long-term credit creation also increased disproportionately more for high default probability firms (4.22 percentage points) and young firms (2.51 percentage points). These results are consistent with easing of collateral constraints that likely occurred during the ZLB. However, we also document an increase in long-term credit creation for non-financially dependent firms (4.03 percentage points) and a decrease for financially dependent firms (-1.92 percentage points). Further, we find that highly leveraged firms' long-term credit creation decreased (-0.41 percentage points) but increased for low leverage firms (3.16 percent).

2.2 Monetary Policy Measure

Empirical investigations into the effect of monetary policy shocks on economic activity often identify the federal funds rate as the monetary policy instrument. However, from December 2008 until December 2015, the federal funds rate was effectively at the ZLB, thus limiting the use of the instrument to stimulate the economy and invalidating its use as the monetary policy variable in SVARs. An alternative measure of the monetary policy stance at the ZLB has been proposed by Wu and Xia (2016) –hereafter WX–, who develop an approximation to the forward rate in the multifactor shadow rate term structure model. This rate can be used to replace the effective federal funds rate in structural vector autoregressions (SVARs) during the ZLB period. As WX show, their proposed shadow rate contains relevant information monetary policy when the effective federal funds rate is bounded by zero. Moreover, it allows us to study the effect of unconventional monetary policy on credit flows during this time. We thus employ the effective federal funds rate as our measure of monetary policy for the period of time where it did not hit the ZLB and replace it with the Wu-Xia shadow rate during the ZLB period.

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. Figure 3 depicts the effective federal funds rate and the Wu-Xia shadow rate across time.

As WX note, the shadow federal funds rate became negative during the ZLB period and exhibited considerable variation. In fact, the shadow rate exhibited a negative trend until May of 2014, shortly before the Fed halted bond purchases after having accumulated $4.5 trillion in assets.

2.3 Other Variables

As in Bernanke, Boivin, and Eliasz (2005) –hereafter BBE– we include a large set of economic variables to capture the information available to Fed policymakers in determining the course of monetary policy. The variables included in this study cover broad markets such as labor, consumption, housing, exchange rates, etc. Following WX, we utilize 97 of the 120 original series used by BBE, and we update these series beyond the ZLB, through 2017:Q1. We also include aggregate credit creation and destruction measures, for a total of 99 series. When the variables are not expressed in rates or indices, we transform them into logged differences to induce stationarity.

3 Empirical Methodology

To study the effect of monetary policy shocks, we utilize a FAVAR model with three factors as in BBE and WX. Let r_t be the observed monetary policy instrument and let F_t be a vector of unobserved factors that jointly follow the vector autoregression:

$$\begin{bmatrix} F_t \\ r_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ r_{t-1} \end{bmatrix} + \upsilon_t \tag{11}$$

where $\Phi(L)$ is a lag polynomial of order four and υ_t is a normally distributed mean zero vector with covariance matrix, Ω. As in BBE, the unobserved factors are estimated from the large set of macroeconomic variables, X_t, described in the previous section. The observed variables are related to the unobserved factors and observed policy rate in the following manner:

$$X_t = \Lambda F_t + \lambda r_t + e_t \tag{12}$$

where Λ and λ are (98×3) and (98×1) matrices of factor loadings and policy rate loadings, respectively.[8]

Following BBE and WX, we extract the first three principal components from the observed macroeconomic variable, X_t, spanning the period between 1974:Q1 and 2017:Q1. We then purge the principal components to obtain factors that are orthogonal to the policy rate and employ these purged factors, $\widehat{F}_t$ to estimate the FAVAR in (11). Table 1 of the online Appendix provides details of the observed macroeconomic variables and their sources, including the factor loadings (link). The monetary policy shock, ε_t^r, is identified using a recursive scheme similar to BBE and WX. That is, we assume that the latent factors do not respond to monetary policy innovations contemporaneously. The response of the i^{th} macroeconomic variable at horizon h to a monetary

[8] We omit the constant for simplicity.

policy shock is given by

$$\Psi_h^{r,i} = b_i^{x^1} \frac{\partial F_{t+h}^1}{\partial \varepsilon_t^r} + b_i^{x^2} \frac{\partial F_{t+h}^2}{\partial \varepsilon_t^r} + b_i^{x^3} \frac{\partial F_{t+h}^3}{\partial \varepsilon_t^r} + b_i^r \frac{\partial r_{t+h}}{\partial \varepsilon_t^r} \tag{13}$$

where F_{t+h}^j denotes the $j = 1, 2, 3$ factor, $\frac{\partial F_{t+h}^j}{\partial \varepsilon_t^r}$ and $\frac{\partial r_{t+h}}{\partial \varepsilon_t^r}$ are the VAR impulse responses of factor j and the policy rate, respectively, to a monetary policy shock.

To study the effect of unconventional monetary policy, we follow Kilian and Lütkepohl (2017) in first expressing the paths of the variables of interest as a function of all the past shocks and initial conditions. We then compute the contribution of the monetary policy shocks[9] to the path of these variable across time. Second, we construct policy counterfactuals to describe the path that the economy would have taken had certain scenarios occurred, as in Sims and Zha (2006). We analyze the contribution of monetary policy shocks to credit flows over the period where the shadow rate was negative (2009:Q3–2015:Q3). We examine two policy counterfactuals as in WX. In the first counterfactual, we replace the column of the matrix of structural shocks that corresponds to the shadow federal funds rate with zero. In effect, this forces the actual shadow federal funds rate to a hypothetical rate that is fully determined by lagged macroeconomic variables. In other words, the monetary policy shock is shut down and policy is assumed to follow a rule that would have been expected given past observations of the macroeconomic variables. In the second counterfactual, we replace the monetary policy shock series with one that forces the shadow federal funds rate to the ZLB during the counterfactual period. This is achieved by adding the difference between the observed shadow rate and the ZLB rate, 0.25%, to the monetary shock series. Doing so allows us to quantify how credit flows would have responded had monetary policy been constrained by the ZLB. We proceed by creating artificial historical decompositions that show the contributions of these hypothetical monetary policy shocks to the creation and destruction of credit of borrowing firms. We compute wedges between the actual and counterfactual values of the variables of interest at time τ such that

$$wedge_\tau^i = Y_\tau^i - \sum_{s=t_1}^{\tau} \Psi_s^{r,i} \upsilon_s^{cf} \tag{14}$$

[9] See the Appendix for a plot of the monetary policy shock series throughout the ZLB.

where t_1=2009:Q3. In the first counterfactual, we let $\upsilon_s^{cf} = 0$. In the second counterfactual, we let $\upsilon_s^{cf} = \upsilon_s + 0.25 r_s$. Then, using the definitions for credit reallocation, net credit change, and excess credit reallocation in (4)-(6), we compute the counterfactuals for the remaining credit flow measures.

4 Monetary Policy and Credit Flows

4.1 The Effect of Monetary Policy Shocks

This section inquiries into the effect of monetary policy shocks on key macroeconomic variables and, especially, on aggregate credit flows. The solid lines in Figure 4 depict the responses of the variables of interest to a -25 basis point shock to the monetary policy rate along with the 90% confidence interval. For the sake of brevity, we plot the responses of the policy rate, the industrial production index (IP), the consumer price index (CPI), capacity utilization, the unemployment rate, housing starts, aggregate credit destruction, and aggregate credit creation. We find similar results to those obtained by WX using monthly data from January 1960 to December 2013, excluding credit flows. Namely, a -25 basis point shock to monetary policy leads to economic expansion over the following two years. This is illustrated in Figure 4 by the increase in industrial production, capacity utilization, and housing starts, and a lagged decline in the unemployment rate. For instance, the cumulative change in industrial production equaled 1.14 percentage points a year after the shock and 2.75 percent after two years. The effect of the monetary policy on most macroeconomic variables –with the exception of the unemployment rate– dies out after eight quarters. Finally, the response of the CPI reveals only a very slight decrease in inflation, which is suggestive of a slight price puzzle.

What would be the effect of a 25 basis point reduction in the monetary policy rate on credit flows? The bottom panel of Figure 4 show that monetary policy easing induces an increase in credit destruction and creation. More specifically, the rate of destruction rises from the third to the eighth quarter after the shock, while credit creation exhibits a statistically significant increase between the third and ninth quarters. At its peak, three quarters after the shock, credit creation rises 4.6 percentage points above its steady state level, while the increase in credit destruction reaches 2.4

percentage points at its peak. Credit reallocation accordingly increases 7 percentage points at its peak, while the net credit increases 2.2 percentage points after one year. While Compustat does not record the reason for firms' credit changes from one period to the next, our results suggest that monetary policy easing not only leads to an increase in credit creation – through lines of credit, bank loans, or bond issuance, for instance– but it 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).

To further illustrate monetary policy's impact on credit flows, Figure 5 shows the impulse responses of the net credit change, credit reallocation, and excess credit reallocation. Because of the magnitude of the relative increase in credit creation as the result of monetary easing compared to credit destruction, the net credit change increased nearly 3 percentage points seven quarters after the shock. Because credit destruction also increased, credit reallocation and excess credit reallocation (a measure of the intensity of credit reallocation) increased substantially two years after the monetary policy shock. We also plot the impulse responses of the 1-, 5-year, and 10-year Treasury spreads, consumer credit, and C&I loans outstanding. In a similar fashion, the latter credit aggregate increased substantially following the monetary policy shock. However, this is not able to capture any potential reallocation of credit.

4.2 Unconventional Monetary Policy at the ZLB

This section reports the results for the two counterfactuals described in Section 3. Recall that the first counterfactual quantifies the effect of shutting down the monetary policy shocks during the ZLB or, equivalently, of not deviating from a traditional monetary policy rule. The second counterfactual evaluates the impact of the unconventional monetary policy measures by assuming that the shadow rate remains at 0.25 percent during the period of analysis.

Figure 6 plots the actual and counterfactual paths followed by the key macroeconomic variables as well as that of aggregate credit creation and destruction. The figures show that had the monetary policy shocks been shut down or if unconventional monetary policy measures had not been implemented in such a manner that the policy rate was bounded by the ZLB, unemployment and consumer prices would have been higher than observed. Additionally, industrial production, capacity utilization, and housing starts would have been lower. In other words, we find that both monetary policy shocks and unconventional monetary policy contributed to curb the economic contraction following the Great Recession. This is consistent with the results obtained by WX using a sample period ending in December 2013, which excludes the final round of quantitative easing (QE3).

The actual and the counterfactual paths for total credit creation and destruction reveal three important insights. First, credit creation would have been somewhat high, while credit destruction would have remained virtually unchanged, had the Fed avoided any deviations from the traditional monetary policy during the ZLB. Second, unconventional monetary policy during the ZLB led to a slight increase in credit destruction. Note how the dotted line (counterfactual 2) in the bottom left panel falls below the solid line (actual). Third, had the Fed not implemented the policy observed at the ZLB, credit creation would have fallen substantially (see the difference between the dotted and solid lines in the bottom right panel of Figure 6).

A question that arises when considering total credit flows is whether the change in credit reallocation stemmed from the impact of monetary policy on long-term or short-term credit. In particular, an increase in the dynamism of long-term credit reallocation would likely result in future investment and economic growth. To answer this question, we disaggregate credit flows into short- and long-term components, re-estimate the FAVAR by rotating in the credit flow measures of interest, and compute the contribution of monetary policy shocks under the two counterfactuals of interest. We weight the credit flow counterfactual wedges by the respective share of short- or long-term credit in total credit to get a better grasp of their contribution to the fluctuations in the total credit flows. The wedges between the actual and the counterfactual credit flows are reported in Table 4. Throughout the remainder of the paper we will refer to these counterfactuals as the "no monetary shock" and the "ZLB" counterfactuals.

The no monetary shock counterfactual leads to a negligible impact on short-term credit reallocation (0.02 percentage points), and only a 0.20 percentage point increase in long-term credit reallocation. The latter stems from 0.16 percentage point and 0.04 percentage point increases in credit creation and credit destruction, respectively. These results suggest that the impact of monetary policy shocks on credit flows is relatively small during the ZLB. In contrast, the effect of unconventional monetary policy on long-term credit flows during the ZLB was substantial (shown in Panel (b) of Table 4). Our estimates indicate that long-term credit creation (destruction) would have been 0.65 (0.33) percentage points lower if monetary policy had been bounded by the ZLB. The contribution of unconventional monetary policy to increasing the dynamism of long-term credit reallocation over this period was nontrivial. Unconventional monetary policy contributed 0.98 percentage points to long-term credit reallocation and 0.66 percentage points to long-term excess credit reallocation. The actual change in long-term gross and excess credit reallocation during the ZLB was 0.70 percentage points and 1.50 percentage points. Hence, the change in long-term credit reallocation would have been near zero and the intensity of credit reallocation would be substantially smaller had the shadow rate been kept at the ZLB.

Unconventional monetary policy led to a small increase in short-term credit creation (0.07 percentage points) and a small decline in short-term credit destruction (-0.03 percentage points). On the one hand, given that short-term credit mostly serves to cover the time lag between a firm's payment of its operational costs (e.g., wages) and the accrual of returns, the rise (decline) in credit creation (destruction) suggests unconventional monetary policy facilitated –albeit only slightly– firm's operations during the ZLB. On the other hand, because long-term debt typically finances long-term investment plans, the increased reallocation of long-term credit appears to have been a channel through which unconventional monetary policy had a positive impact on firm output and, thus, on aggregate economic activity.

Given that, large swings in credit flows may be linked to entry/exit of firms (see Figure 2), the reader may wonder whether our results are robust to considering only continuing firms. Comparing the first and second rows of panel (a) of Table 4 reveals minimal differences between the responses of all firms and continuing firms in the no monetary policy shock counterfactual. The only noticeable difference is a slightly larger rise in long-term credit creation for continuing firms, which is indicative of unconventional monetary policy re-shuffling more resources towards existing than entering firms. As for the zero lower bound counterfactual, we find the effect of unconventional monetary policy on credit creation to be similar for continuing and all firms, and smaller on continuing firms' long-term credit destruction. The latter implies that unconventional monetary policy contributed to credit destruction through mergers, acquisitions, liquidations, or bankruptcies to some extent. All in all, the impact of unconventional monetary on the reallocation of credit does not appear to be mainly driven by the response of entering and exiting firms.

4.3 Unconventional monetary policy, credit reallocation and financial frictions

Did unconventional monetary policy result in increased credit reallocation among firms that faced greater financial constraints? Was monetary policy during the ZLB able to foster the dynamism of the credit reallocation process among firms with different financial characteristics? Theoretical macroeconomic models suggest financial frictions play an important role in the transmission of monetary policy shocks. To answer these questions, we extend the counterfactual analysis carried out in the previous section. First, we divide Compustat firms into subgroups using the proxies described in Section 2.1.2. Then, we re-estimate the FAVAR rotating the sets of subgroups into Y_t, and compute the two counterfactual wedges during the ZLB, which are weighted by each group's share of short- or long-term credit in total credit.

We begin by analyzing the policy counterfactuals for small –usually more credit constrained– and large firms. The results in Table 4 reveal that monetary policy shocks caused similar, albeit small, increases in long-term credit destruction for both groups. Yet, it led long-term credit creation to rise 0.23 percentage points for large firms and to decrease 0.34 percentage points for small firms. Consequently, long-term credit reallocation increased 0.29 percentage points for large firms, whereas it decreased 0.26 percentage points for small firms. The ZLB counterfactual, on the other hand, indicates that unconventional monetary policy caused a greater boost on short-term credit creation for small firms (0.31 percentage points) relative to large firms (0.06 percentage points). The impact of unconventional monetary policy on short-term credit destruction was trivial for both groups. In contrast, the response of long-term credit reallocation was substantially stronger for large firms (1.1 percentage points) as credit creation and destruction rose by 0.72 and 0.38 percentage points, respectively. The net credit change and reallocation for small firms increased only slightly (0.06 and 0.20 percentage points, respectively).

Perhaps more striking than the results for small and large firms are the differences in the effects of unconventional monetary policy on high and low leverage firms. If external finance was more costly and marginally more difficult to obtain for the latter (Calomiris and Himmelberg, 1995), then the easing of credit constraints should play a greater role in channeling credit to low leverage firms. Conversely, if high leverage firms were financially constrained, we would expect credit to have flowed to these firms. Indeed, as illustrated by the results in Table 4, unconventional monetary policy caused increases in short- (0.14 percentage points) and long-term (0.91 percentage points) credit creation for high leverage firms. The estimated wedge for short-term (long-term) credit destruction was negative (positive) for both groups. Two results stand out when we compute the effects at the ZLB on net credit changes and credit reallocation of long-term credit. First, unconventional monetary policy led to an increase in net credit for high leverage firms, but it curtailed credit growth for low leverage firms. Second, while these policies resulted in greater long-term credit reallocation for high leverage firms (1.27 percentage points) and low leverage firms (0.47 percentage points), short-term credit reallocation fell for the latter. Our finding of increased reallocation for high leverage firms at both maturities is consistent with unconventional monetary policy's impact on credit markets working through the easing of financial constraints.

Were credit creation and destruction for financially dependent firms more sensitive to unconventional monetary policy than that of non-financially dependent firms? Not so, but with one exception: long-term credit destruction in the ZLB counterfactual increased more for non-financially dependent firms. Thus, had the Fed been constrained by the ZLB, the net change (excess reallocation) of long-term credit would have been 0.64 (0.82) and 0.33 (1.28) lower for financially and non-financially dependent firms, respectively (see Table 4). Similarly, when we split firms into young and old, we find that long-term credit destruction for old firms –which are likely to face lower financial constraints– was more responsive to unconventional monetary policy than that of young firms. Consequently, the net change (excess reallocation) of long-term credit for young and old firms was 0.70 (0.10) and 0.47 (0.42) for young and old firms, respectively.

Lastly, we split the sample into high and low default probability firms. We discuss the results for long-term credit flows in the ZLB counterfactual here since they comprise the bulk of the response to unconventional monetary policy measures but report all results in Table 4. The contribution of this policy to long-term credit creation was 1.03 percentage points for high default probability firms and 0.64 percentage points for low default probability firms. Both groups experienced similar increases in long-term credit destruction. These result in a larger increase in long-term net credit change and credit reallocation for high default probability firms, although the impact of this policy on excess credit reallocation was similar between the groups.

To summarize, we find that if, at the ZLB, the Fed had implemented monetary policy in accordance with a Taylor-type rule, the effect of the policy would have been rather homogeneous (and small) across different groups of firms. On the contrary, had the Fed been constrained by the ZLB, long-term credit reallocation would have been considerably lower for certain subsets of firms. Unconventional monetary policy brought about relatively large increases in long-term credit reallocation, especially for large, high default probability and high leverage firms.

4.4 The Contribution of the Different Rounds of Quantitative Easing

Between November 2008 and October 2014, the Fed conducted several rounds of QE, referred to as QE1 (Q3:2009–2010:Q1),[10] QE2 (2010:Q4–2011:Q2), operation twist (2011:Q3–2012:Q4), and QE3 (2012:Q3–2014:Q4). These rounds were intended to extend credit to certain financial institutions, provide liquidity to credit markets, and affect long-term interest rates via purchase of long-term securities. In this section, we quantify the contribution of these rounds of QE on the allocation of credit. We do so by creating wedges for each round of QE using (14), letting t_1 and τ be the start and end of each round. As we showed in the previous section, there is scant evidence that the no monetary policy shocks counterfactual had a sizeable effect. For this reason and for the sake of brevity, in the following sections, we solely focus on the ZLB counterfactual. The disaggregated results for the no monetary shock counterfactual are reported in Table A.1 of the Appendix.

4.4.1 QE1

The period known as QE1 began in November 2008 and ended in March 2010. During this time, the Federal Reserve Board established the Term Asset-Backed Securities Loan Facility (TALF). This facility was created to lend (non-recourse) to holders of AAA-rated asset-backed securities that were backed by new or recent loans. Initially, up to $180 billion was funded by the Fed and $20 billion from the Troubled Asset Relief Program (TARP). This amount later increased to $1 trillion with expanded acceptable collateral. The Fed also agreed to purchase up to $200 billion

[10] While QE1 started in 2008:Q4, we start the counterfactual period in 2009:Q3 as in Wu and Xia (2016) because the shadow rate does not become negative until this quarter.

in agency debt, \$1.25 trillion in agency mortgage-backed securities, and \$300 billion in long-term Treasury securities.

Table 5 reports the counterfactuals for each round of QE when Wu and Xia's shadow rate is negative, 2009:Q3–2010:Q1. As the table illustrates, the effect of unconventional monetary policy at the ZLB was small in magnitude for the aggregate and across most groups of firms. During QE1, unconventional monetary policy caused short-term credit creation to barely rise for small firms (0.06 percentage points), while it did not change for large firms. We do not observe striking differences in short-term credit creation among other groups during QE1. However, unconventional monetary policy led to larger increases in long-term credit creation for small, young, and high default probability firms compared to large, old, and low. default probability firms. Specifically, long-term credit creation for small, young, and high default probability firms increased 0.19, 0.12 and 0.10 percentage points, respectively. These firms are more likely to be financially constrained and impacted by the Fed's purchases of long-term Treasury securities, aimed at lowering long-term yields to stimulate long-term lending as these results suggest.

4.4.2 QE2

QE2 began in November 2010 and concluded in June 2011. This round of QE included monthly \$75 billion purchases of Treasury securities, up to a total of \$600 billion. At the end of QE2, the Fed continued to reinvest principal payments of their holdings. In a sense, QE2 was aimed at providing funding to lenders in the same manner as QE1. Hence, the question that arises is whether this policy effected the reallocation of credit among firms.

Table 5 indicates that unconventional monetary policy tended to have a slightly larger effect on long-term credit creation during QE2 compared to QE1 for nearly each group of firms. The largest is a 0.27 percentage point increase in the long-term credit creation of non-financially dependent firms, compared to 0.18 percentage points for financially dependent firms. We also observe a proportionally larger increase in the long-term credit creation for high default probability firms during QE2 (0.23 percentage points) compared to low default probability firms (0.10 percentage points). The contributions of monetary policy to aggregate short-term credit creation and destruction tended to be small and negative during QE2. In line with our findings for QE1, we estimate that unconventional monetary policy during QE2 generally exerted a larger stimulus on the reallocation of long-term credit than on short-term credit.

4.4.3 Operation Twist

In September 2011, the Fed announced that they would hold more long-term relative to short-term Treasuries, popularly referred to as operation twist. This would be achieved by simultaneously purchasing $400 billion of 6-30 year Treasuries and selling $400 billion of Treasuries with maturities of 3 years or less. This was to put downward pressure on long-term yields to boost credit markets beyond the stimulus provided by QE1 and QE2. The Fed also agreed to purchase additional agency mortgage-backed securities. While the simultaneous purchase and sale of Treasuries concluded in December 2012, the purchase of mortgage-backed securities continued beyond this time.

Even though these actions were intended to boost long-term credit, we find little evidence that unconventional monetary policy caused a notably larger increase in long-term credit reallocation during operation twist compared to QE1 and QE2. As Table 5 indicates, unconventional monetary policy caused aggregate long-term credit creation to increase only 0.08 percentage points and short-term credit creation to increase 0.03 percentage points. Furthermore, unconventional monetary policy also had only a minor impact on long-term credit destruction during operation twist.

Operation twist made lenders' holding of long-term Treasuries less appealing because of their smaller yield. In effect, it may have induced lenders to seek higher returns elsewhere (Rajan, 2006). The counterfactual results in Table 5 do reveal some heterogeneity in the responses to unconventional monetary policy during operation twist. First, changes in short-term credit creation and destruction were negligible for all groups of firms. Second, for long-term credit, the ZLB counterfactual indicates unconventional monetary policy boosted creation for almost all groups – except for small and low leverage firms– and led only to small changes in destruction. As a result, long-term and short-term credit reallocation increased 0.12 and 0.03 percentage points, respectively, during operation twist.

4.4.4 QE3

In September 2012, during operation twist, the Fed announced their plans for the final round of quantitative easing (QE3). During this round, the Fed purchased \$40 billion of agency mortgage-backed securities and \$45 billion of long-term Treasuries per month. At this time, they also announced that these purchases would continue until economic conditions improved. By early 2014, the Fed reduced purchases by \$5 and \$10 billion each month, eventually concluding QE3 by October 2014.

A quick glance at Table 5 indicates that unconventional monetary policy caused a substantial larger reallocation of aggregate long-term credit during QE3 than in previous rounds. The estimated wedges for creation and destruction equaled 0.31 and 0.18 percentage points, respectively. These imply an increase of 0.49 (0.36) percentage points in gross (excess) long-term credit reallocation. The boost in long-term credit creation tended to be relatively larger for financially constrained firms, specifically for small, high leverage, young, and high default probability firms. The impact of unconventional monetary policy on short-term credit reallocation was negligible except for small firms, who are more likely to be financially constrained. For this group, unconventional monetary policy caused an increase of 0.32 percentage points in credit reallocation, which is considerably larger than any other round of QE.

4.5 Unconventional Monetary Policy and Credit Efficiency

A question that arises when studying the link between the 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 ought to lead to higher economic growth.

Because data required to calculate firm-level factor productivity is not available from Compustat, we inquire 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, Schiantarelli, and Weiss (2007) constructed as

$$CE_{it} = \frac{\frac{sales_{it}}{capital_{it}} \Delta debt_{it}}{\sum_i \frac{sales_{it}}{capital_{it}} \frac{debt_{it-1}}{debt_{t-1}} \Delta debt_{t-1}}. \tag{15}$$

This CE_{it} index measures the efficiency of the allocation of credit (debt) for firm i in quarter t relative to the total return obtained if credit had been allocated to the firm in proportion to its share in the economy's credit, $debt_{t-1}$.[11] Note that, as in Galindo, Schiantarelli, and Weiss (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's i debt stock at the end of quarter $t-1$ relative to the debt for all firms 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.

Table 6 describes the average asset size, leverage ratio, need for external financing, age, and default probability for firms whose index of credit efficiency falls in the top and bottom tercile (i.e. high credit efficiency firms and low credit efficiency firms, respectively). The most striking disparity between the groups is that high credit efficiency firms have, on average, substantially smaller default probabilities across time than low credit efficiency firms. We also find that high credit efficiency firms tend to have larger leverage ratios. In recent decades, we find that high credit efficiency firms are older and larger than low credit efficiency firms. Finally, we find, in recent decades, that high credit efficiency firms tend to have less need for external financing. Although, because the need for external financing ratio is negative, on average across time, this implies that firms on both ends of the credit efficiency index spectrum tend to generate a relatively large amounts of cash flow.

Averages and coefficients of variation for the credit flows of high and low credit efficiency firms are shown in Table 7. At short maturities, the average credit creation of high and low credit efficiency firms is similar, whereas at long maturities, credit creation is larger for high credit efficiency firms. Average long-term credit destruction is similar for both groups of firms, but short-term credit destruction for low credit efficiency firms (9.7 percent) exceeds that of high credit efficiency firms (5.6 percent). Consequently, we observe that: (a) average long-term net credit is positive for high credit efficiency firms, but negative for low credit efficiency firms; (b) gross and excess credit reallocation of long-term credit is greater for high credit efficiency firms; and (c) the

[11]See Galindo, Schiantarelli and Weiss (2007) for a discussion on why a sales-based index is preferable to a profit-based index.

intensity of short-term credit reallocation is greater among low-credit efficiency firms.

The Great Recession was characterized by large declines in aggregate net credit (5.36 percentage points) and credit reallocation (2.47 percentage points) compared to previous recessions. Furthermore, as Figure 7 illustrates, long-term credit reallocation increased during and after the Great Recession for low credit efficiency firms, but this pattern was absent for high credit efficiency firms. In fact, the recovery from the Great Recession was characterized by a less intense process of credit reallocation than the previous two recessions for this group.

How much of the reshuffling of credit towards more higher credit efficiency firms is explained by unconventional monetary policy? To answer this question, Table 8 reports the estimated wedges under the ZLB counterfactual during the rounds of QE. The methodology used to compute these wedges is like that used in the earlier sections with the differences that in the FAVAR, we rotate in the credit flows of high and low credit efficiency firms.

Four results stand out. First, during the ZLB, unconventional monetary policy contributed positively to the short- and long-term credit creation among high credit efficiency firms but contributed negatively for low credit efficiency firms. Second, the increase in long-term credit creation for high credit efficiency firms (1.69 percentage points) was larger than the contribution to any other group analyzed in this study. Third, long-term credit destruction of high credit efficiency firms exceeded that of low credit efficiency firms. The combined effect was substantially larger for long-term credit reallocation of high credit efficiency firms (2.12 percentage points) relative to low credit efficiency firms (-0.12 percentage points). We also split these contributions by round of monetary easing during the ZLB. Unsurprisingly, we find that the largest contribution of unconventional monetary policy to the long-term credit creation of high credit efficiency firms occurred during QE3.

What do these results imply about the effect of unconventional monetary policy on economic growth? Recall first that we uncovered a positive effect of unconventional monetary policy on industrial production during the ZLB. In addition, work by HKM suggests that the net change of credit is procyclical as the contraction in credit supply that takes place during economic downturns outweighs the expansion in credit demand that stems from a decline in internal funds. Moreover, consider the cyclical behavior of the reallocation of credit for high and low credit efficiency firms –computed as the correlations with the unemployment rate as in HKM– reported in Table 9. First, long-term net credit change and credit reallocation are procyclical for high credit efficiency firms. The contemporaneous correlation with the unemployment rate is -0.203 and -0.415, respectively. The lag and lead correlations are also negative and increase with the leads.[12] In contrast, both long-term net credit creation and reallocation are acyclical for low credit efficiency firms. In other words, the procyclical behavior of credit flows uncovered by HKM is driven by the cyclical behavior of high credit efficiency firms. Hence, the positive effect of the unconventional monetary policy on economic growth that we document appears to be due to the reshuffling of credit towards this group of firms.

All in all, our results suggest that the persistence in unemployment during the Great Recession was linked to the low intensity of long-term credit reallocation of high credit efficiency firms. Yet, had the Fed not resorted to unconventional policy methods to provide monetary accommodation, the decline in economic growth would have been more severe.

5 Conclusion

In this paper, we showed that unconventional monetary policy had a large and persistent impact on the allocation of credit among borrowing firms during the ZLB. Unconventional monetary policy led to a 0.65 (0.33) percentage points increase in long-term credit creation (destruction) during this period. Our methodology highlighted the ability of unconventional monetary policy to reshuffle long-term credit and, thus, foster investment and growth.

We computed credit flows of financially constrained and non-financially constrained firms and investigated whether the effect of unconventional monetary policy was heterogeneous. While Kudlyak and Sánchez (2017) showed, using data from Compustat and the Quarterly Financial Reports for Manufacturing, Mining, and Wholesale Trade, that large firms' short-term credit contracted more than small firms during the Great Recession, our results indicated that both short- and long-term credit for the larger firms covered by Compustat would have contracted even further during the ZLB period had the Fed not implemented unconventional policy measures. In fact, these policies led to greater dynamism in the reallocation of long-term credit among the largest firms. We found that

[12] Our results are robust to computing the correlations between these credit flows and other macroeconomic variables, such as real GDP and industrial production.

unconventional monetary policy caused relatively large increases in long-term credit reallocation for firms facing high default probabilities and leverage ratios. These surges in credit reallocation were due mainly to relatively large increases in credit creation rather than credit destruction, thus suggesting that unconventional monetary policy was effective at easing financial constraints during the ZLB.

Because unconventional monetary policy was conducted in rounds of QE, we inquired into the contribution of monetary policy shocks to credit flows measures during these periods. We showed that QE3 exerted the largest stimulus on credit reallocation. Indeed, it led to more long-term credit creation and destruction (0.31 and 0.18 percentage points, respectively) than it would have been observed in the absence of unconventional monetary policy measures. We found that long-term credit creation tended to increase more for groups of firms classified as financially constrained during this round of QE, implying that unconventional monetary policy was effective at easing financial constraints of borrowing firms.

Finally, our results revealed that the long-term credit creation of firms whose credit was allocated in a more efficient manner was more responsive to unconventional monetary policy during the ZLB. Our results provide important insights into the transmission of unconventional monetary policy to credit flows and the aggregate economy. First, they imply that the measures taken by the Fed once the federal funds rate had hit the ZLB were effective in reshuffling credit toward financially constrained firms. Second, unconventional monetary policy fostered the allocation of credit towards those better equipped to invest and grow. In brief, unconventional monetary policies implemented near the ZLB are an effective tool to boost economic activity as they increase the intensity of credit reallocation by enhancing the fluidity of long-term credit markets.

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Tables

Table 1: Descriptive Statistics for Financially Constrained and Non-Financially Constrained Firms' Credit Flows (1974:Q1–2017:Q1)

		Average					Coefficient of variation				
		POS	*NEG*	*NET*	*SUM*	*EXC*	*POS*	*NEG*	*NET*	*SUM*	*EXC*
(a) **Total credit**	All firms	5.4	3.5	1.9	8.9	6.9	40.2	27.6	108.8	29.9	27.2
	Small firms	12.3	9.5	2.8	21.8	18.0	29.1	25.9	152.9	20.3	22.3
	Large firms	5.3	3.4	1.9	8.7	6.6	42.2	29.9	110.7	31.7	29.3
	High leverage firms	5.5	3.0	2.5	8.5	5.9	51.6	36.3	112.9	38.4	36.4
	Low leverage firms	8.0	9.3	-1.3	17.2	13.0	62.9	58.7	-455.0	50.2	49.3
	Financially dependent firms	6.7	3.5	2.5	9.5	5.9	61.6	61.5	180.8	43.3	49.1
	Non-financially firms	7.8	5.1	1.6	11.8	8.1	52.5	54.1	300.2	34.3	41.6
	Young firms	7.8	2.6	5.2	10.4	5.2	72.8	32.8	113.6	53.7	30.4
	Old firms	5.0	2.9	2.0	7.9	5.7	47.7	28.4	118.1	33.0	25.5
	High default probability firms	7.7	4.3	3.4	12.1	6.7	88.6	104.7	252.1	65.1	53.2
	Low default probability firms	5.2	3.6	1.5	8.8	7.0	37.6	30.8	123.1	28.9	27.8
(b) **Short-term credit**	All firms	15.1	7.1	8.0	22.2	14.1	29.7	23.9	55.7	22.9	23.3
	Small firms	24.2	12.8	11.5	37.0	25.4	21.1	27.4	54.4	16.6	26.1
	Large firms	14.7	6.9	7.9	21.6	13.7	30.7	24.4	58.5	23.4	23.5
	High leverage firms	15.1	6.2	8.9	21.4	12.4	41.8	31.4	69.3	32.9	31.4
	Low leverage firms	20.0	11.6	8.4	31.6	21.1	56.1	45.1	139.4	41.3	40.0
	Financially dependent firms	15.9	7.1	8.8	23.1	12.8	62.6	76.6	133.0	47.9	53.2
	Non-financially firms	18.3	9.0	9.3	27.3	16.3	46.8	48.8	110.3	32.7	40.5
	Young firms	16.7	5.5	11.2	22.2	10.9	56.2	45.3	86.2	43.9	44.1
	Old firms	14.9	6.8	8.1	21.7	13.5	41.1	29.6	76.1	30.9	28.4
	High default probability firms	16.0	7.9	8.1	23.8	13.7	59.1	69.4	132.6	46.5	54.6
	Low default probability firms	15.1	7.1	8.0	22.2	14.2	33.1	25.7	63.0	25.3	25.0
(c) **Long-term credit**	All firms	5.9	3.6	2.3	9.5	7.1	40.7	31.7	90.5	32.9	31.8
	Small firms	16.2	8.3	7.9	24.6	16.5	32.8	26.6	70.9	24.2	25.7
	Large firms	5.8	3.5	2.3	9.3	6.9	42.5	33.7	93.8	34.6	33.9
	High leverage firms	6.2	3.3	2.8	9.5	6.6	49.9	39.5	98.1	40.4	39.7
	Low leverage firms	7.1	7.2	-0.1	14.3	10.4	69.4	66.1	-4884.4	52.8	49.7
	Financially dependent firms	7.0	3.7	3.4	10.7	6.3	78.6	54.9	177.9	54.0	52.3
	Non-financially firms	6.9	4.9	2.0	11.8	7.8	52.9	65.7	257.5	38.8	46.6
	Young firms	8.3	2.6	5.7	11.0	5.2	66.1	30.9	99.0	50.0	29.7
	Old firms	5.4	3.0	2.4	8.4	5.8	44.8	30.6	91.8	34.5	30.3
	High default probability firms	8.5	4.1	4.4	12.7	6.7	99.8	91.7	223.6	69.5	46.1
	Low default probability firms	5.6	3.7	1.9	9.3	7.3	37.3	33.7	93.2	31.7	32.2

Note: Firms are small (large) if the value of their total assets is in the bottom (top) tercile of firms in a given quarter. High (low) leverage firms are those for which the leverage ratio is in the top (bottom) tercile of firms in a given quarter. Financially dependent (non-financially dependent) firms are those which the need for external financing (Rajan and Zingales,1998) is in the top (bottom) tercile in a given quarter. Young (old) firms are those whose number of years listed in Computstat is in the bottom (top) tercile in a given quarter and old firms are those in the top tercile in a given quarter. Following Farre-Mensa and Ljungqvist (2016), high default probability firms are those which the default probability exceeds 25 percent at a point in time and all others are low default probability firms.

Table 2: Transitions Between Classifications

t-1\t	Small	Large	High leverage	Low leverage	Financially dependent	Non-financially dependent	Young	Old	High default probability	Low default probability
Small	0.981	0.000								
Large	0.000	0.981								
High leverage			0.918	0.012						
Low leverage			0.011	0.930						
Financially dependent					0.787	0.054				
Non-financially dependent					0.051	0.736				
Young							1.000	0.000		
Old							0.000	0.985		
High default probability									0.843	0.037
Low default probability									0.157	0.963

Note: This table provides probabilities that a firm belongs to a certain classification in time t conditional on the classification in $t-1$. In classifying firms by terciles, the omitted probability corresponds to the probability of being in the middle tercile conditional on being in the top or bottom tercile in the previous quarter. Firms are small (large) if the value of their total assets is in the bottom (top) tercile of firms in a given quarter. High (low) leverage firms are those for which the leverage ratio is in the top (bottom) tercile of firms in a given quarter. Financially dependent (non-financially dependent) firms are those which the need for external financing (Rajan and Zingales,1998) is in the top (bottom) tercile in a given quarter. Young (old) firms are those whose number of years listed in Computstat is in the bottom (top) tercile in a given quarter and old firms are those in the top tercile in a given quarter. Following Farre-Mensa and Ljungqvist (2016), high default probability firms are those which the default probability exceeds 25 percent at a point in time and all others are low default probability firms.

Table 3: Percentage Point Change in Credit Flows During the Zero Lower Bound (2009:Q3–2015:Q3)

	Short-term credit					Long-term credit				
	POS	*NEG*	*NET*	*SUM*	*EXC*	*POS*	*NEG*	*NET*	*SUM*	*EXC*
Small firms	6.68	3.37	3.31	10.05	6.74	10.77	-0.17	10.94	10.60	-0.34
Large firms	0.07	-2.13	2.20	-2.06	-4.26	-0.08	0.82	-0.90	0.74	1.64
High leverage firms	-1.64	-0.29	-1.35	-1.93	-0.58	-0.41	1.32	-1.73	0.91	2.64
Low leverage firms	2.43	6.07	-3.64	8.50	12.14	3.16	7.56	-4.40	10.72	6.32
Financially dependent firms	2.01	0.56	1.45	2.57	1.12	-1.92	0.98	-2.90	-0.94	1.96
Non-financially dependent firms	-0.84	-3.13	2.29	-3.97	-6.26	4.03	-1.41	5.44	2.62	-2.82
Young firms	2.48	4.22	-1.74	6.70	8.44	2.51	0.49	2.02	3.00	0.98
Old firms	3.67	-4.50	8.17	-0.83	-6.94	1.24	0.01	1.23	1.25	0.02
High default probability firms	10.95	0.90	10.05	11.85	1.80	4.22	-0.69	4.91	3.53	1.30
Low default probability firms	0.15	-2.52	2.67	-2.37	-5.04	-0.29	0.74	-1.03	0.45	1.48

Note: This table provides the percentage point change in credit flow measures over the period 2009:Q3–2015:Q3. Firms are small if the value of their total assets is in the bottom tercile of firms in a given quarter and are large if the value of their total assets is in the top tercile of firms in a given quarter. High leverage firms are those which the leverage ratio is in the top tercile of firms in a given quarter and low leverage are those for which the leverage ratio is in the bottom tercile of firms in a given quarter. Financially dependent firms are those which the need for external financing (Rajan and Zingales,1998) is in the top tercile in a given quarter and are non-financially dependent if this ratio is in the bottom tercile of firms in a given quarter. Young firms are those whose number of years listed in Computstat is in the bottom tercile in a given quarter and old firms are those in the top tercile in a given quarter. Following Farre-Mensa and Ljungqvist (2016), high default probability firms are those which the default probability exceeds 25 percent at a point in time and all others are low default probability firms.

Table 4: Policy Counterfactuals During the Zero Lower Bound (2009:Q3–2015:Q3)

(a) Counterfactual 1: no monetary shock

	Short-term credit					Long-term credit				
	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
All firms	0.00	0.02	-0.02	0.02	0.00	0.16	0.04	0.12	0.20	0.08
Continuing firms	0.01	0.01	0.00	0.02	0.02	0.20	0.02	0.18	0.22	0.04
Small firms	-0.02	0.07	-0.09	0.05	-0.04	-0.34	0.08	-0.42	-0.26	-0.68
Large firms	0.01	0.01	0.00	0.02	0.02	0.23	0.06	0.17	0.29	0.12
High leverage firms	0.01	0.02	-0.01	0.03	0.02	0.26	0.06	0.20	0.32	0.12
Low leverage firms	-0.03	-0.08	0.05	-0.11	-0.16	-0.03	0.00	-0.03	-0.03	-0.06
Financially dependent firms	0.11	0.02	0.09	0.13	0.04	0.24	0.09	0.15	0.33	0.18
Non-financially dependent firms	0.04	0.07	-0.03	0.11	0.08	0.51	0.37	0.14	0.88	0.74
Young firms	-0.04	0.00	-0.04	-0.04	-0.08	0.01	0.03	-0.02	0.04	0.02
Old firms	0.00	0.01	-0.01	0.01	0.00	0.22	0.03	0.19	0.25	0.06
High default probability firms	0.00	0.03	-0.03	0.03	0.00	0.30	-0.14	0.44	0.16	-0.28
Low default probability firms	0.01	0.02	-0.01	0.03	0.02	0.20	0.08	0.12	0.28	0.16

(b) Counterfactual 2: zero lower bound

	Short-term credit					Long-term credit				
	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
All firms	0.07	-0.03	0.10	0.04	-0.06	0.65	0.33	0.32	0.98	0.66
Continuing firms	0.06	-0.06	0.12	0.00	-0.12	0.63	0.17	0.46	0.80	0.34
Small firms	0.31	0.01	0.30	0.32	0.02	0.13	0.07	0.06	0.20	0.14
Large firms	0.06	-0.04	0.10	0.02	-0.08	0.72	0.38	0.34	1.10	0.76
High leverage firms	0.14	-0.04	0.18	0.10	-0.08	0.91	0.36	0.55	1.27	0.72
Low leverage firms	-0.42	-0.04	-0.38	-0.46	-0.84	-0.04	0.51	-0.55	0.47	-0.08
Financially dependent firms	-0.05	-0.07	0.02	-0.12	-0.14	1.05	0.41	0.64	1.46	0.82
Non-financially dependent firms	0.01	-0.06	0.07	-0.05	-0.12	0.97	0.64	0.33	1.61	1.28
Young firms	0.06	-0.03	0.09	0.03	-0.06	0.75	0.05	0.70	0.80	0.10
Old firms	0.10	-0.06	0.16	0.04	-0.12	0.68	0.21	0.47	0.89	0.42
High default probability firms	-0.01	0.05	-0.06	0.04	-0.02	1.03	0.38	0.65	1.41	0.76
Low default probability firms	0.11	-0.04	0.15	0.07	-0.08	0.64	0.39	0.25	1.03	0.78

Note: This table shows the percentage point difference in how credit creation (POS), credit destruction (NEG), net credit change (NET), credit reallocation (SUM), and excess credit reallocation (EXC) would respond in monetary policy counterfactuals. Counterfactual 1 is a scenario absent of monetary policy innovations and Counterfactual 2 is a scenario whereby monetary policy innovations are such that the monetary policy rate is at the zero lower bound. The table presents the wedge between the contribution of the counterfactual monetary policy innovations and the actual innovations weighed by each groups share of short- and long-term credit to total credit. A positive number indicates that the actual monetary policy contributed positively to the credit flow measure relative to the counterfactual. Firms are small if the value of their total assets is in the bottom tercile of firms in a given quarter and are large if the value of their total assets is in the top tercile of firms in a given quarter. High leverage firms are those which the leverage ratio is in the top tercile of firms in a given quarter and low leverage are those for which the leverage ratio is in the bottom tercile of firms in a given quarter. Financially dependent firms are those which the need for external financing (Rajan and Zingales,1998) is in the top tercile in a given quarter and are non-financially dependent if this ratio is in the bottom tercile of firms in a given quarter. Young firms are those whose number of years listed in Computstat is in the bottom tercile in a given quarter and old firms are those in the top tercile in a given quarter. Following Farre-Mensa and Ljungqvist (2016), high default probability firms are those which the default probability exceeds 25 percent at a point in time and all others are low default probability firms.

Table 5: Policy Counterfactual During Rounds of Quantitative Easing

			Short-term credit					Long-term credit				
			POS	*NEG*	*NET*	*SUM*	*EXC*	*POS*	*NEG*	*NET*	*SUM*	*EXC*
(a)	All firms	QE1	0.00	-0.01	0.01	-0.01	-0.02	0.03	0.04	-0.01	0.07	0.06
		QE2	0.00	-0.01	0.01	-0.01	-0.02	0.12	0.06	0.06	0.18	0.12
		Op. twist	0.03	0.00	0.03	0.03	0.00	0.08	0.04	0.04	0.12	0.08
		QE3	0.02	-0.03	0.05	-0.01	-0.06	0.31	0.18	0.13	0.49	0.36
(b)	Small firms	QE1	0.06	-0.04	0.10	0.02	-0.08	0.19	-0.01	0.20	0.18	-0.02
		QE2	0.09	0.02	0.07	0.11	0.04	0.12	0.05	0.07	0.17	0.10
		Op. twist	-0.02	-0.01	-0.01	-0.03	-0.04	-0.10	-0.02	-0.08	-0.12	-0.20
		QE3	0.32	0.00	0.32	0.32	0.00	0.36	0.04	0.32	0.40	0.08
	Large firms	QE1	0.00	-0.01	0.01	-0.01	-0.02	0.01	0.04	-0.03	0.05	0.02
		QE2	0.00	-0.01	0.01	-0.01	-0.02	0.12	0.06	0.06	0.18	0.12
		Op. twist	0.03	-0.01	0.04	0.02	-0.02	0.12	0.05	0.07	0.17	0.10
		QE3	0.02	-0.03	0.05	-0.01	-0.06	0.29	0.19	0.10	0.48	0.38
(c)	High leverage	QE1	0.01	-0.02	0.03	-0.01	-0.04	0.04	0.04	0.00	0.08	0.08
		QE2	-0.01	-0.01	0.00	-0.02	-0.02	0.13	0.06	0.07	0.19	0.12
		Op. twist	0.07	0.00	0.07	0.07	0.00	0.15	0.05	0.10	0.20	0.10
		QE3	0.04	-0.04	0.08	0.00	-0.08	0.37	0.18	0.19	0.55	0.36
	Low leverage firms	QE1	-0.07	0.03	-0.10	-0.04	-0.14	0.01	0.09	-0.08	0.10	0.02
		QE2	0.00	0.05	-0.05	0.05	0.00	0.05	0.11	-0.06	0.16	0.10
		Op. twist	-0.12	-0.07	-0.05	-0.19	-0.24	-0.05	0.01	-0.06	-0.04	-0.10
		QE3	-0.16	0.05	-0.21	-0.11	-0.32	0.04	0.36	-0.32	0.40	0.08
(d)	Financially dependent firms	QE1	-0.11	-0.03	-0.08	-0.14	-0.22	0.02	0.00	0.02	0.02	0.00
		QE2	-0.03	-0.02	-0.01	-0.05	-0.06	0.18	0.07	0.11	0.25	0.14
		Op. twist	0.03	-0.01	0.04	0.02	-0.02	0.14	0.05	0.09	0.19	0.10
		QE3	-0.18	-0.05	-0.13	-0.23	-0.36	0.49	0.20	0.29	0.69	0.40
	Non-financially dependent firms	QE1	-0.02	-0.04	0.02	-0.06	-0.08	0.01	0.04	-0.03	0.05	0.02
		QE2	-0.02	-0.02	0.00	-0.04	-0.04	0.27	0.22	0.05	0.49	0.44
		Op. twist	0.03	0.00	0.03	0.03	0.00	0.04	-0.05	0.09	-0.01	-0.10
		QE3	-0.04	-0.05	0.01	-0.09	-0.10	0.50	0.42	0.08	0.92	0.84
(e)	Young firms	QE1	0.05	-0.01	0.06	0.04	-0.02	0.12	-0.01	0.13	0.11	-0.02
		QE2	0.01	0.00	0.01	0.01	0.00	0.17	-0.01	0.18	0.16	-0.02
		Op. twist	0.01	0.00	0.01	0.01	0.00	0.03	0.04	-0.01	0.07	0.06
		QE3	0.08	-0.02	0.10	0.06	-0.04	0.53	-0.02	0.55	0.51	-0.04
	Old firms	QE1	0.02	-0.02	0.04	0.00	-0.04	0.01	0.02	-0.01	0.03	0.02
		QE2	0.00	-0.01	0.01	-0.01	-0.02	0.10	0.03	0.07	0.13	0.06
		Op. twist	0.04	-0.01	0.05	0.03	-0.02	0.12	0.03	0.09	0.15	0.06
		QE3	0.04	-0.04	0.08	0.00	-0.08	0.25	0.11	0.14	0.36	0.22
(f)	High default probability firms	QE1	-0.01	0.03	-0.04	0.02	-0.02	0.10	0.15	-0.05	0.25	0.20
		QE2	0.00	0.00	0.00	0.00	0.00	0.23	-0.03	0.26	0.20	-0.06
		Op. twist	-0.01	0.00	-0.01	-0.01	-0.02	0.05	0.09	-0.04	0.14	0.10
		QE3	-0.01	0.04	-0.05	0.03	-0.02	0.46	0.10	0.36	0.56	0.20
	Low default probability firms	QE1	0.01	-0.01	0.02	0.00	-0.02	0.01	0.03	-0.02	0.04	0.02
		QE2	0.00	-0.01	0.01	-0.01	-0.02	0.10	0.06	0.04	0.16	0.12
		Op. twist	0.04	0.00	0.04	0.04	0.00	0.11	0.05	0.06	0.16	0.10
		QE3	0.03	-0.03	0.06	0.00	-0.06	0.26	0.20	0.06	0.46	0.40

Note: This table shows the percentage point difference in credit flows as in Panel (b) of Table 4 for the four rounds of quantitative easing. QE1 spans Q3:2009–2010:Q1, QE2 spans 2010:Q4–2011:Q2, operation twist spans 2011:Q3–2012:Q4, and QE3 spans 2012:Q3–2014:Q4.

Table 6: Characteristics of High and Low Credit Efficiency Firms

	High credit efficiency firms				
	Asset size (2014 dollars)	Leverage ratio	Need for external financing	Age (years)	Default probability (percent)
1970s	81,519,520	1.14	-2.45	12.27	1.80
1980s	240,274,768	0.79	-3.93	11.45	3.46
1990s	744,006,848	0.61	-10.06	11.63	5.30
2000s	2,294,684,160	0.60	-12.59	14.04	6.86
2010s	4,776,571,392	0.67	-18.64	16.06	7.42

	Low credit efficiency firms				
	Asset size (2014 dollars)	Leverage ratio	Need for external financing	Age (years)	Default probability (percent)
1970s	219,595,664	0.53	-2.04	14.00	16.90
1980s	428,873,568	0.24	-4.23	12.27	24.45
1990s	456,044,256	0.12	-6.62	11.09	41.58
2000s	913,920,000	0.06	-9.05	12.54	52.03
2010s	2,039,897,216	0.08	-12.98	16.01	49.93

Note: This table provides the 1 percent trimmed means of high and low credit efficiency firms' real assets size (2014 dollars), leverage ratio (short-term debt as a percentage of total assets), need for external financing (capital spending less cash flow from operations as a percentage of capital spending), age, and default probability. High (low) credit efficiency firms are those whose index of credit efficiency is in the top (bottom) tercile of firms at a point in time. A firm's credit efficiency index is computed as $(\frac{sales_{it}}{capital_{it}}\Delta debt_{it})/(\Sigma_i \frac{sales_{it}}{capital_{it}}\frac{capital_{it-1}}{capital_{t-1}}\Delta debt_{t-1})$

Table 7: Descriptive Statistics of Credit Flows (1974:Q1–2017:Q1)

		Average				
		POS	*NEG*	*NET*	*SUM*	*EXC*
High credit efficiency firms	Short-term credit	14.4	5.6	8.8	20.1	11.2
	Long-term credit	9.7	4.2	5.5	14.0	8.4
Low credit efficiency firms	Short-term credit	15.2	9.7	5.5	24.9	17.8
	Long-term credit	3.6	4.3	-0.7	7.9	5.9

		Coefficient of variation				
		POS	*NEG*	*NET*	*SUM*	*EXC*
High credit efficiency firms	Short-term credit	47.3	40.0	77.0	37.8	38.6
	Long-term credit	51.6	37.9	91.4	39.6	38.1
Low credit efficiency firms	Short-term credit	38.4	38.8	137.2	25.0	30.0
	Long-term credit	58.8	49.4	-414.8	40.5	43.8

Note: A firm's credit efficiency index is computed as $(\frac{sales_{it}}{capital_{it}}\Delta debt_{it})/(\Sigma_i \frac{sales_{it}}{capital_{it}}\frac{capital_{it-1}}{capital_{t-1}}\Delta debt_{t-1})$.

Table 8: Zero Lower Bound Policy Counterfactual for High and Low Credit Efficiency Firms (2009:Q3–2015:Q3)

		Short-term credit					Long-term credit				
		POS	*NEG*	*NET*	*SUM*	*EXC*	*POS*	*NEG*	*NET*	*SUM*	*EXC*
Zero lower bound	High credit efficiency firms	0.12	-0.07	0.19	0.05	-0.14	1.69	0.43	1.26	2.12	0.86
	Low credit efficiency firms	-0.17	0.02	-0.19	-0.15	-0.34	-0.38	0.26	-0.64	-0.12	-0.76
QE1	High credit efficiency firms	0.01	-0.03	0.04	-0.02	-0.06	0.07	0.01	0.06	0.08	0.02
	Low credit efficiency firms	-0.06	0.00	-0.06	-0.06	-0.12	-0.05	0.08	-0.13	0.03	-0.10
QE2	High credit efficiency firms	0.00	-0.02	0.02	-0.02	-0.04	0.19	0.05	0.14	0.24	0.10
	Low credit efficiency firms	-0.01	0.00	-0.01	-0.01	-0.02	-0.02	0.05	-0.07	0.03	-0.04
Operation twist	High credit efficiency firms	0.06	-0.01	0.07	0.05	-0.02	0.30	0.09	0.21	0.39	0.18
	Low credit efficiency firms	-0.03	0.00	-0.03	-0.03	-0.06	-0.08	-0.02	-0.06	-0.10	-0.16
QE3	High credit efficiency firms	0.05	-0.06	0.11	-0.01	-0.12	0.72	0.18	0.54	0.90	0.36
	Low credit efficiency firms	-0.10	0.01	-0.11	-0.09	-0.20	-0.21	0.15	-0.36	-0.06	-0.42

Note: This table shows the percentage point difference in how credit destruction (NEG) and credit creation (POS) would respond to the monetary policy counterfactual whereby monetary policy innovations are such that the policy rate (shadow federal funds rate as in Wu and Xia (2016)) is at the zero lower bound. The table presents the wedge between the contribution of the counterfactual monetary policy innovations and the actual innovations, weighted by each group's share of short- and long-term debt as a percentage of total debt. A positive number suggests that the actual monetary policy contributed positively to the credit flow measure relative to the counterfactual. High credit efficiency firms are those whose credit efficiency index is in the top tercile of firms at a point in time, and low credit efficiency firms are those in the bottom tercile at a point in time.

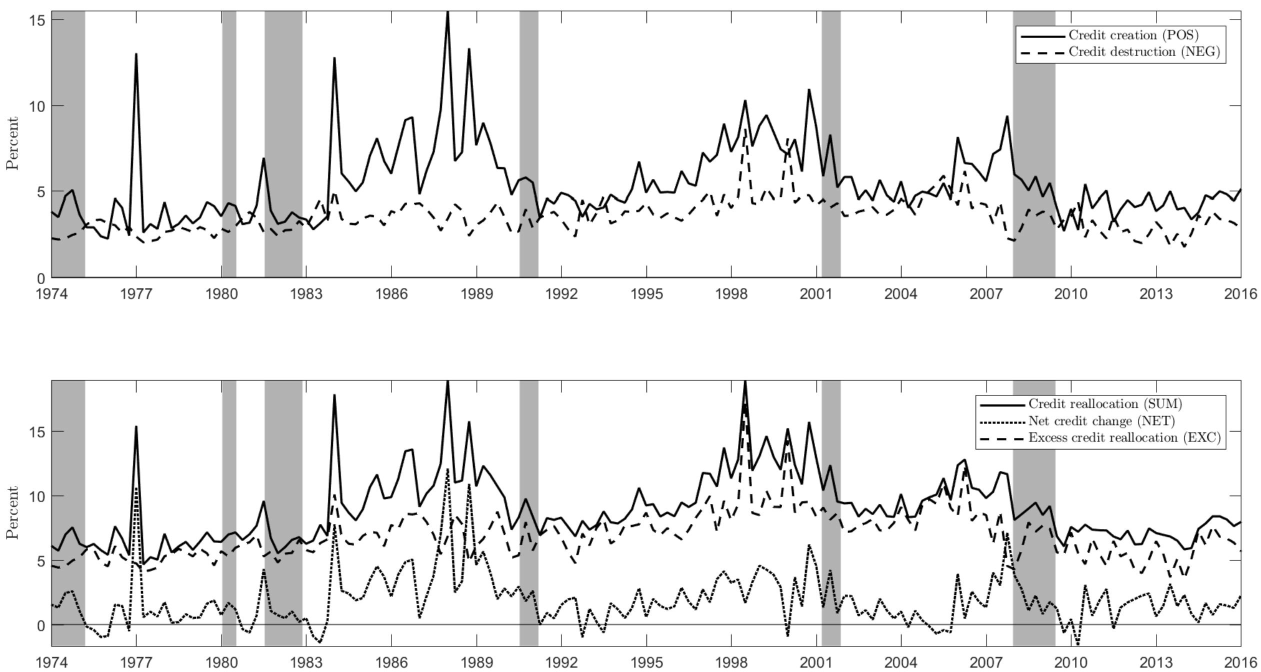
Table 9: Cross Correlations of Credit Flows and the Unemployment Rate

		Unemployment rate								
		$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
High credit efficiency firms										
Long-term credit	POS_t	-0.157	-0.217	-0.270	-0.309	-0.329	-0.359	-0.377	-0.387	-0.386
		(0.137)	(0.136)	(0.128)	(0.122)	(0.115)	(0.109)	(0.104)	(0.102)	(0.102)
	NEG_t	-0.351	-0.354	-0.369	-0.380	-0.396	-0.403	-0.412	-0.413	-0.407
		(0.101)	(0.101)	(0.097)	(0.095)	(0.091)	(0.089)	(0.084)	(0.082)	(0.080)
	NET_t	-0.045	-0.103	-0.152	-0.187	-0.203	-0.230	-0.245	-0.255	-0.255
		(0.125)	(0.127)	(0.121)	(0.115)	(0.107)	(0.101)	(0.099)	(0.100)	(0.101)
	SUM_t	-0.245	-0.300	-0.354	-0.392	-0.415	-0.444	-0.463	-0.472	-0.470
		(0.136)	(0.131)	(0.122)	(0.116)	(0.111)	(0.104)	(0.098)	(0.095)	(0.095)
	EXC_t	-0.369	-0.382	-0.398	-0.411	-0.424	-0.430	-0.439	-0.441	-0.431
		(0.100)	(0.098)	(0.094)	(0.092)	(0.089)	(0.087)	(0.082)	(0.078)	(0.078)
Short-term credit	POS_t	0.211	0.190	0.140	0.095	0.058	0.042	0.052	0.066	0.078
		(0.109)	(0.118)	(0.110)	(0.111)	(0.103)	(0.107)	(0.111)	(0.114)	(0.114)
	NEG_t	0.147	0.177	0.219	0.287	0.330	0.362	0.382	0.371	0.360
		(0.134)	(0.136)	(0.130)	(0.125)	(0.120)	(0.115)	(0.110)	(0.106)	(0.106)
	NET_t	0.164	0.133	0.068	-0.001	-0.052	-0.079	-0.075	-0.058	-0.042
		(0.116)	(0.120)	(0.114)	(0.117)	(0.114)	(0.115)	(0.112)	(0.110)	(0.109)
	SUM_t	0.233	0.223	0.190	0.170	0.150	0.145	0.160	0.170	0.178
		(0.099)	(0.110)	(0.104)	(0.104)	(0.095)	(0.100)	(0.106)	(0.110)	(0.112)
	EXC_t	0.169	0.194	0.225	0.277	0.312	0.348	0.373	0.370	0.360
		(0.130)	(0.135)	(0.132)	(0.125)	(0.116)	(0.114)	(0.111)	(0.110)	(0.111)
Low credit efficiency firms										
Long-term credit	POS_t	-0.230	-0.216	-0.195	-0.160	-0.110	-0.060	-0.037	-0.018	-0.015
		(0.170)	(0.180)	(0.178)	(0.176)	(0.176)	(0.186)	(0.200)	(0.204)	(0.202)
	NEG_t	-0.221	-0.204	-0.190	-0.206	-0.227	-0.253	-0.275	-0.284	-0.288
		(0.210)	(0.202)	(0.195)	(0.178)	(0.160)	(0.147)	(0.138)	(0.136)	(0.132)
	NET_t	-0.007	-0.009	-0.004	0.035	0.089	0.147	0.182	0.203	0.208
		(0.217)	(0.212)	(0.203)	(0.184)	(0.165)	(0.155)	(0.151)	(0.151)	(0.147)
	SUM_t	-0.298	-0.279	-0.255	-0.242	-0.223	-0.207	-0.206	-0.200	-0.200
		(0.158)	(0.163)	(0.164)	(0.163)	(0.166)	(0.176)	(0.185)	(0.190)	(0.188)
	EXC_t	-0.358	-0.340	-0.319	-0.298	-0.264	-0.234	-0.226	-0.208	-0.191
		(0.141)	(0.148)	(0.151)	(0.150)	(0.152)	(0.155)	(0.154)	(0.153)	(0.150)
Short-term credit	POS_t	-0.101	-0.114	-0.116	-0.100	-0.071	-0.040	0.028	0.085	0.137
		(0.169)	(0.167)	(0.161)	(0.164)	(0.168)	(0.163)	(0.165)	(0.163)	(0.153)
	NEG_t	-0.001	0.011	0.033	0.039	0.028	0.024	-0.007	-0.036	-0.061
		(0.156)	(0.163)	(0.168)	(0.165)	(0.160)	(0.159)	(0.154)	(0.149)	(0.151)
	NET_t	-0.077	-0.093	-0.105	-0.096	-0.069	-0.042	0.025	0.083	0.136
		(0.175)	(0.174)	(0.170)	(0.169)	(0.168)	(0.160)	(0.157)	(0.152)	(0.143)
	SUM_t	-0.094	-0.099	-0.089	-0.071	-0.050	-0.023	0.022	0.058	0.092
		(0.151)	(0.154)	(0.152)	(0.154)	(0.160)	(0.162)	(0.170)	(0.172)	(0.170)
	EXC_t	-0.078	-0.093	-0.090	-0.076	-0.064	-0.032	-0.037	-0.037	-0.040
		(0.143)	(0.142)	(0.142)	(0.140)	(0.142)	(0.152)	(0.155)	(0.159)	(0.160)

Note: This table reports the correlations between credit flows and the unemployment rate lagged up to four quarters ($t-4$), the contemporaneous correlations (t), and correlations with the lead unemployment rate up to four quarters ($t+4$). The standard errors, reported in parantheses, are corrected for heteroscedasticity and autocorrelation.

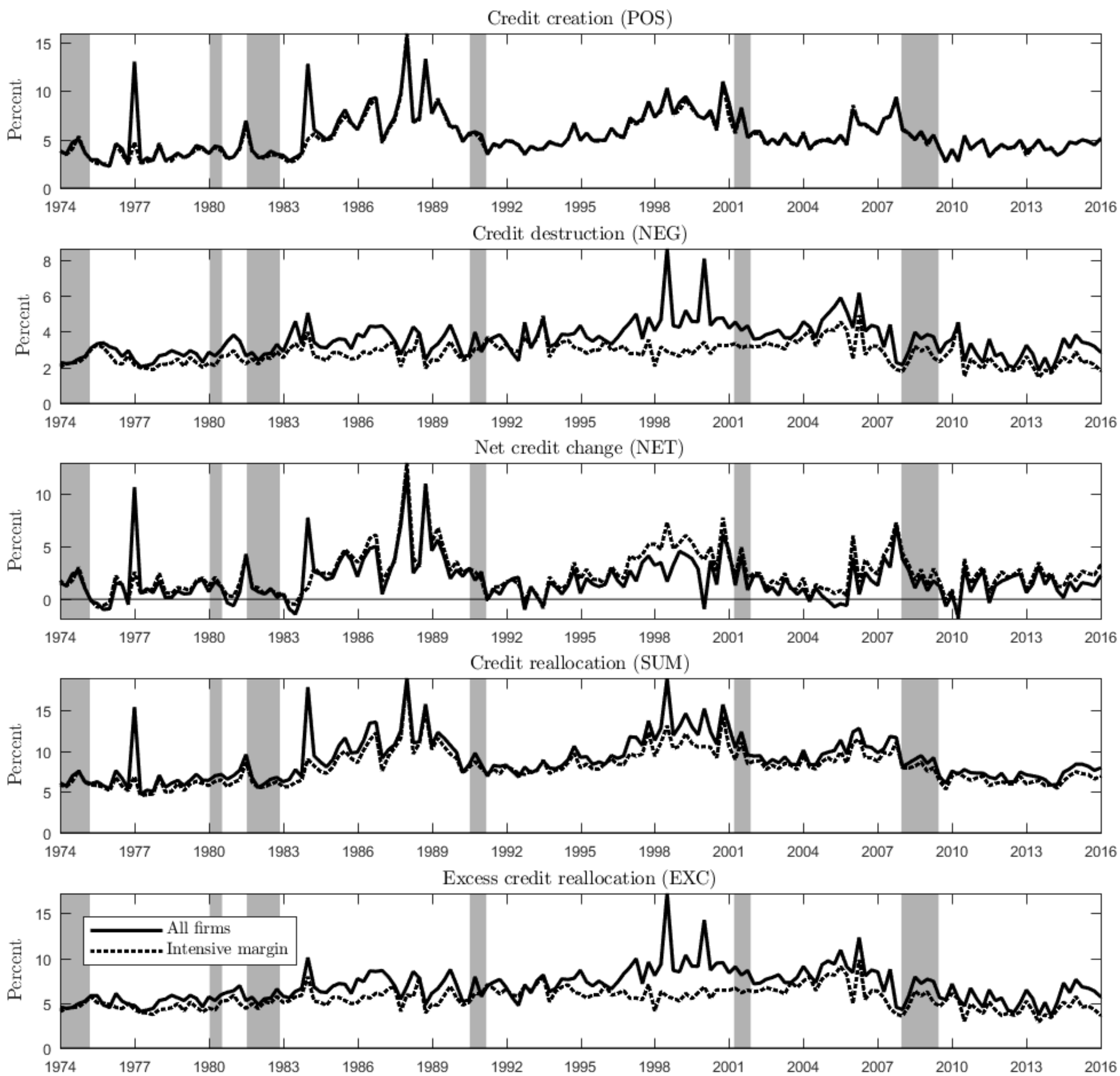
Figures

Figure 1: Total Credit Measures of All Publicly Traded Firms



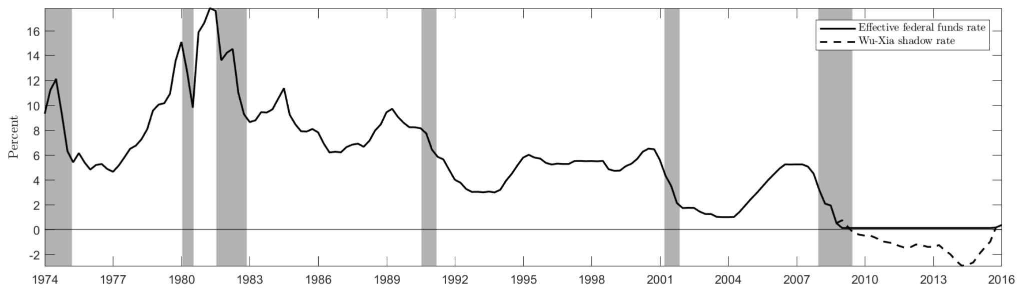
Note: POS refers to credit creation, NEG is credit destruction, NET is net credit change ($NET_{st} = POS_{st} - NEG_{st}$), SUM is credit reallocation ($SUM_{st} = POS_{st} + NEG_{st}$), and EXC is excess credit reallocation ($EXC_{st} = SUM_{st} - |NET_{st}|$) for total credit of all firms. Shaded bars indicate NBER recessions.

Figure 2: Credit flows - Intensive Margin



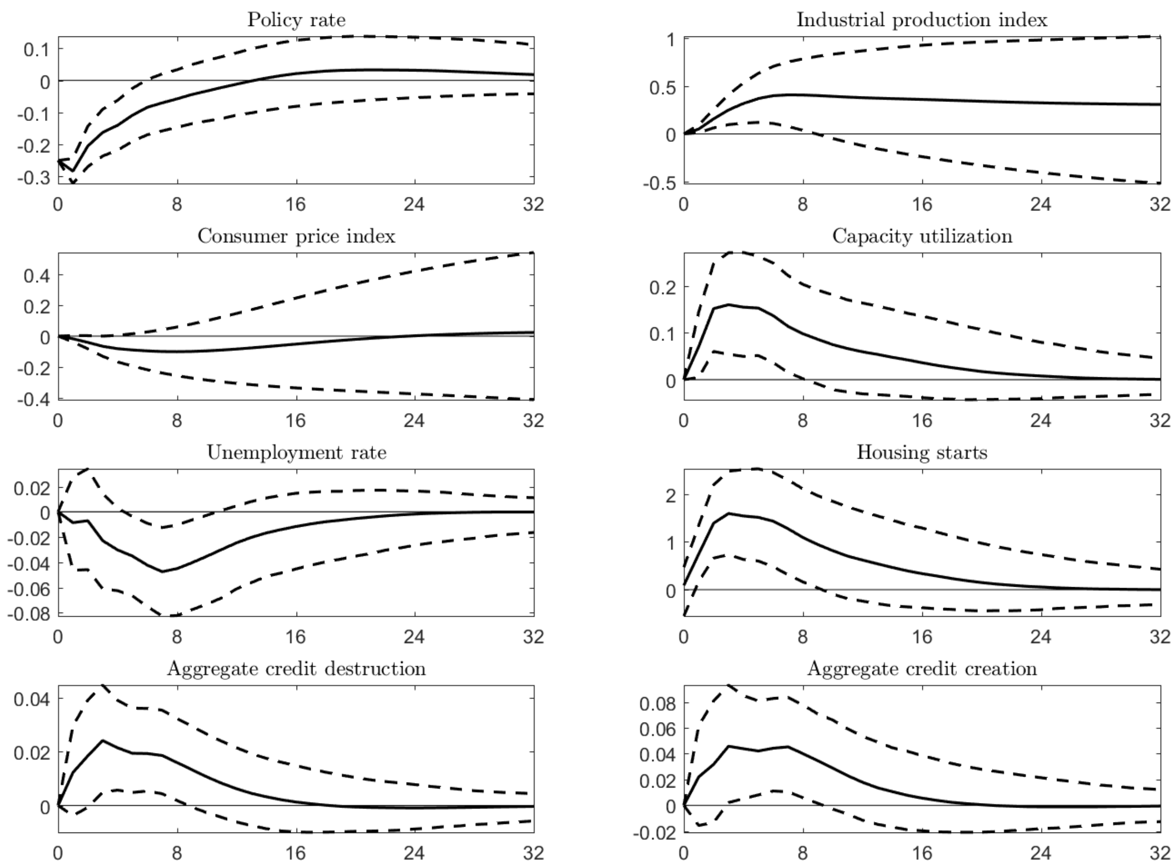
Note: The solid lines are credit flow measures for all firm, including firms entering and exiting the database. The dotted line (intensive margin) are firms that are neither entering or exiting the database in the current quarter. Shaded bars indicate NBER recession.

Figure 3: Effective Federal Funds Rate and Shadow Rate



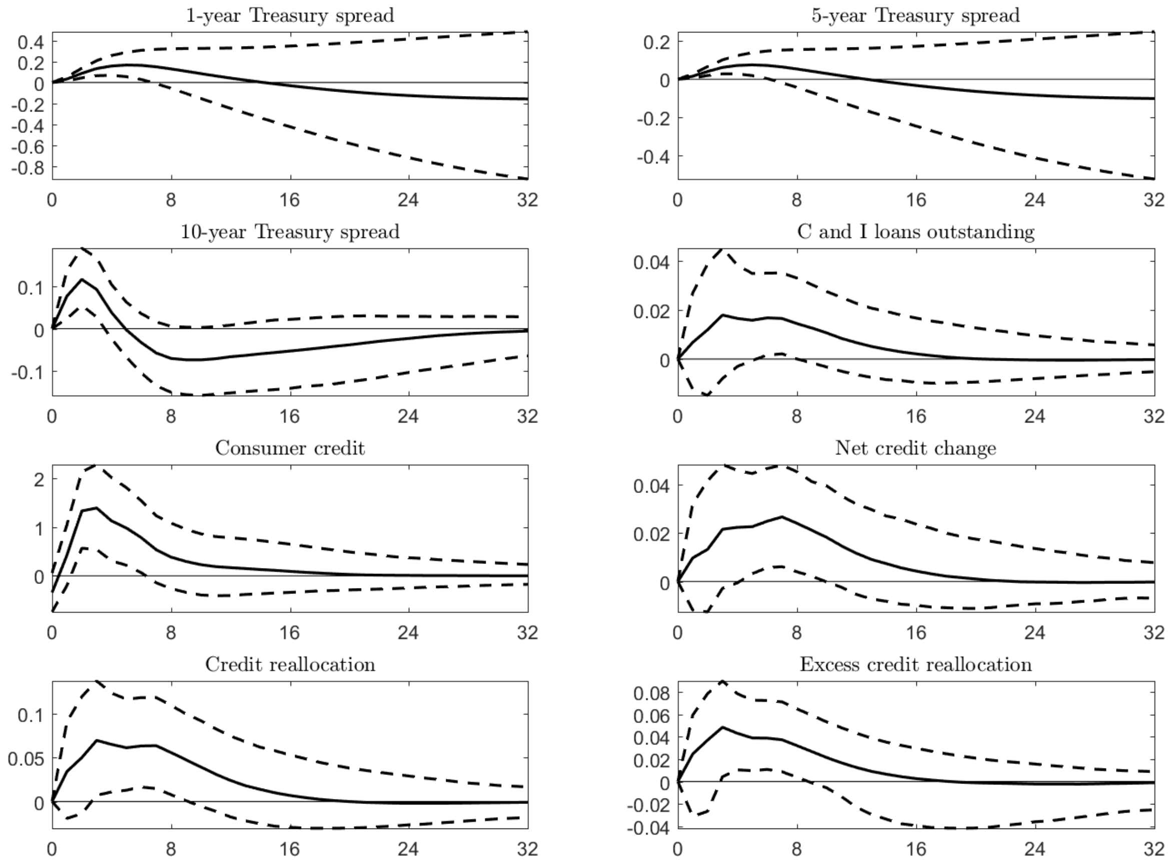
Source: Federal Reserve Board; Federal Reserve Bank of Atlanta.

Figure 4: Impulse Responses to an Expansionary Monetary Policy Shock



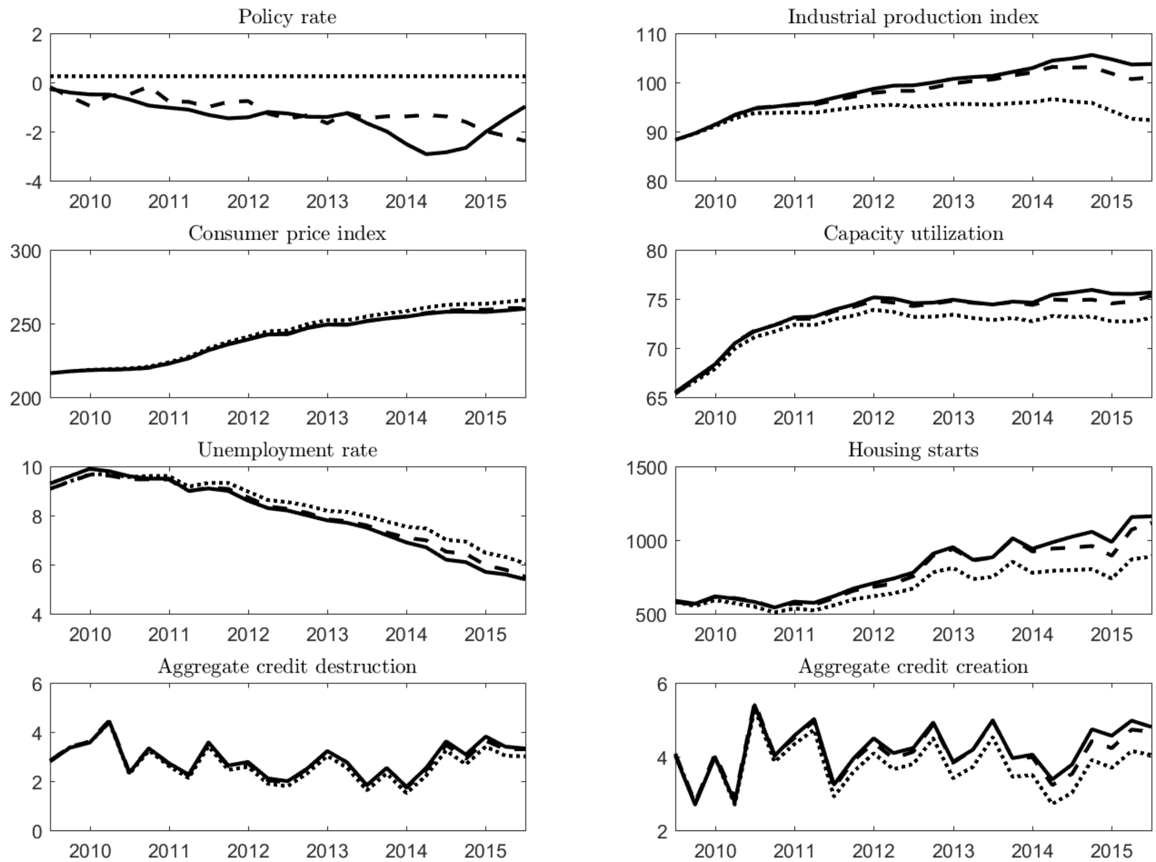
Note: These graphs plot quarterly impulse responses to a -25 basis point monetary policy shock using the sample, 1974:Q1–2017:Q1, in a FAVAR(4) setting. The x-axis is number of quarters following the monetary easing shock. The policy rate, aggregate credit destruction, and aggregate credit creation are percentage points and all remaining are percentage deviations from the steady state.

Figure 5: Impulse Responses of Credit Market Indicators to a Monetary Easing Shock



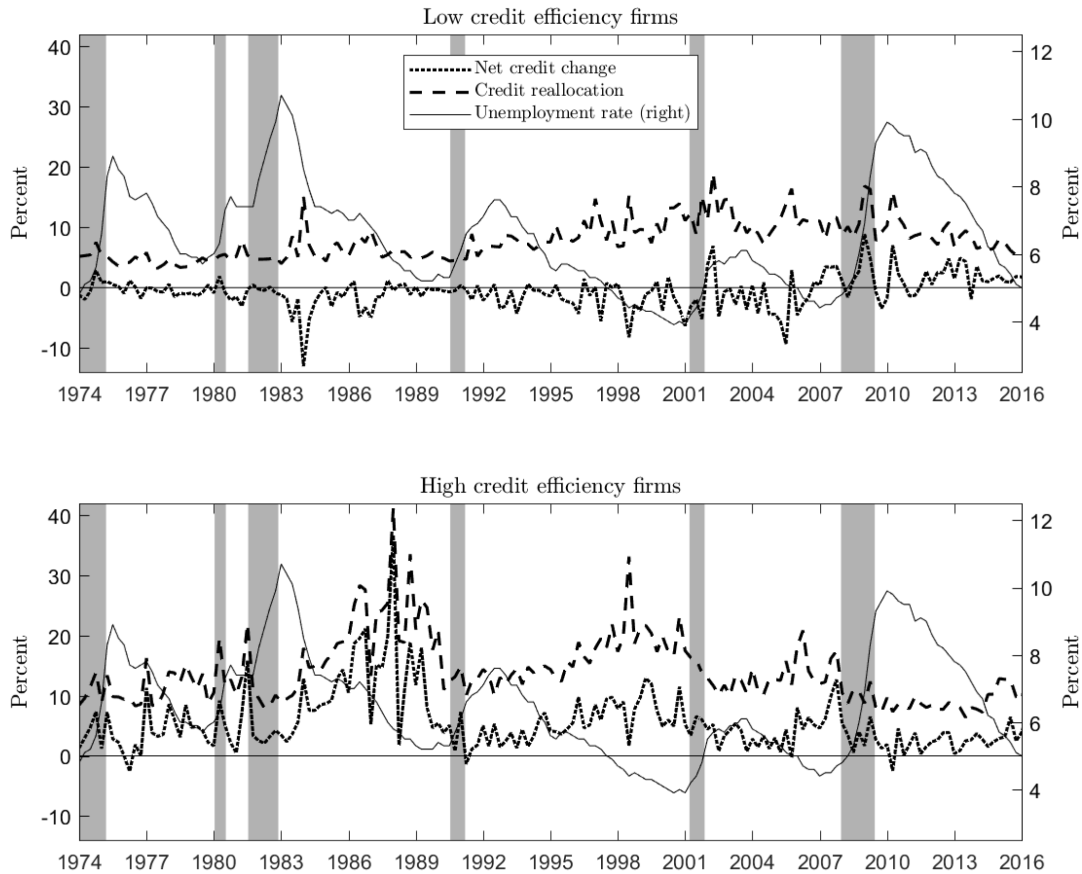
Note: These graphs plot quarterly impulse responses to a -25 basis point monetary policy shock using the sample, 1974:Q1–2017:Q1, in a FAVAR(4) setting. The x-axis is number of quarters following the monetary easing shock. C and I loans outstanding and consumer credit outstanding are percentage deviations from the steady state and all remaining variables are percentage points.

Figure 6: Policy Counterfactuals During the Zero Lower Bound



Note: The solid lines are the observed economic variables between 2009:Q3 and 2015:Q3. The dashed lines are the values if the monetary shocks were shut down and the dotted lines are the values of these variables if the shadow policy rate were at the zero lower bound.

Figure 7: Long-term Credit Flows and the Unemployment Rate



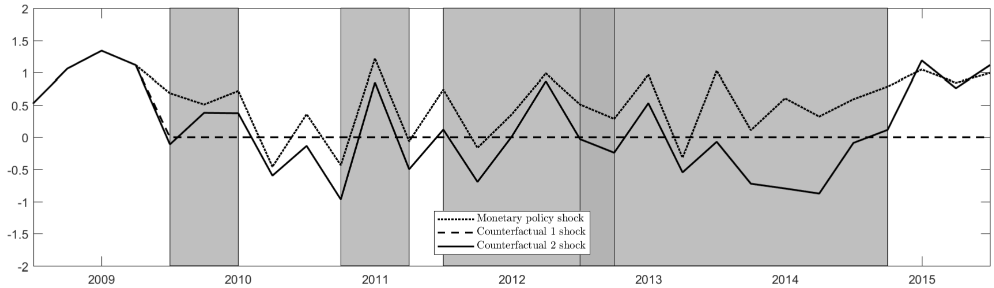
Note: Shaded bars indicate NBER recessions.

Appendix

Table A.1: No Monetary Shock Policy Counterfactual During the Zero Lower Bound (2009:Q3–2015:Q3)

		Short-term credit					Long-term credit				
		POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
QE1	All firms	0.00	0.00	0.00	0.00	0.00	-0.02	-0.01	-0.01	-0.03	-0.04
	Continuing firms	0.00	0.00	0.00	0.00	0.00	-0.03	0.00	-0.03	-0.03	-0.06
	Small firms	-0.03	-0.01	-0.02	-0.04	-0.06	-0.03	0.00	-0.03	-0.03	-0.06
	Large firms	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	-0.02	-0.02	-0.04
	High leverage firms	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	-0.01	-0.02
	Low leverage firms	-0.01	-0.02	0.01	-0.03	-0.04	-0.02	-0.02	0.00	-0.04	-0.04
	Financially dependent firms	0.00	0.00	0.00	0.00	0.00	-0.06	-0.03	-0.03	-0.09	-0.12
	Non-financially dependent firms	0.00	0.01	-0.01	0.01	0.00	0.01	0.05	-0.04	0.06	0.02
	Young firms	-0.01	0.00	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01	-0.03	-0.04
	Old firms	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	-0.02	-0.02	-0.04
	High default probability firms	-0.01	0.02	-0.03	0.01	-0.02	0.05	0.05	0.00	0.10	0.10
	Low default probability firms	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	-0.01	-0.02
	High credit efficiency firms	-0.01	0.01	-0.02	0.00	-0.02	-0.04	-0.02	-0.02	-0.06	-0.08
	Low credit efficiency firms	-0.01	0.00	-0.01	-0.01	-0.02	0.00	0.01	-0.01	0.01	0.00
QE2	All firms	0.00	-0.01	0.01	-0.01	-0.02	0.09	0.05	0.04	0.14	0.10
	Continuing firms	0.00	-0.01	0.01	-0.01	-0.02	0.08	0.02	0.06	0.10	0.04
	Small firms	0.09	0.01	0.08	0.10	0.02	0.22	0.04	0.18	0.26	0.08
	Large firms	0.00	-0.01	0.01	-0.01	-0.02	0.09	0.05	0.04	0.14	0.10
	High leverage firms	-0.01	-0.01	0.00	-0.02	-0.02	0.10	0.06	0.04	0.16	0.12
	Low leverage firms	0.00	0.06	-0.06	0.06	0.00	0.05	0.12	-0.07	0.17	0.10
	Financially dependent firms	-0.06	-0.02	-0.04	-0.08	-0.12	0.17	0.07	0.10	0.24	0.14
	Non-financially dependent firms	-0.02	-0.02	0.00	-0.04	-0.04	0.20	0.19	0.01	0.39	0.38
	Young firms	0.02	0.00	0.02	0.02	0.00	0.19	-0.02	0.21	0.17	-0.04
	Old firms	0.00	-0.02	0.02	-0.02	-0.04	0.07	0.03	0.04	0.10	0.06
	High default probability firms	0.00	0.01	-0.01	0.01	0.00	0.15	-0.04	0.19	0.11	-0.08
	Low default probability firms	0.00	-0.01	0.01	-0.01	-0.02	0.07	0.06	0.01	0.13	0.12
	High credit efficiency firms	0.00	-0.02	0.02	-0.02	-0.04	0.13	0.03	0.10	0.16	0.06
	Low credit efficiency firms	-0.03	0.00	-0.03	-0.03	-0.06	-0.02	0.04	-0.06	0.02	-0.04
Operation twist	All firms	0.01	0.01	0.00	0.02	0.02	-0.04	-0.04	0.00	-0.08	-0.08
	Continuing firms	0.02	0.02	0.00	0.04	0.04	0.00	-0.01	0.01	-0.01	-0.02
	Small firms	-0.10	0.01	-0.11	-0.09	-0.20	-0.34	-0.02	-0.32	-0.36	-0.68
	Large firms	0.01	0.01	0.00	0.02	0.02	0.00	-0.03	0.03	-0.03	-0.06
	High leverage firms	0.03	0.02	0.01	0.05	0.04	0.00	-0.03	0.03	-0.03	-0.06
	Low leverage firms	-0.03	-0.10	0.07	-0.13	-0.20	-0.07	-0.13	0.06	-0.20	-0.26
	Financially dependent firms	0.11	0.03	0.08	0.14	0.06	-0.02	-0.01	-0.01	-0.03	-0.04
	Non-financially dependent firms	0.05	0.05	0.00	0.10	0.10	-0.07	-0.11	0.04	-0.18	-0.22
	Young firms	-0.03	0.01	-0.04	-0.02	-0.06	-0.17	0.03	-0.20	-0.14	-0.34
	Old firms	0.01	0.02	-0.01	0.03	0.02	0.00	-0.02	0.02	-0.02	-0.04
	High default probability firms	0.00	-0.01	0.01	-0.01	-0.02	-0.07	-0.01	-0.06	-0.08	-0.14
	Low default probability firms	0.02	0.01	0.01	0.03	0.02	0.00	-0.03	0.03	-0.03	-0.06
	High credit efficiency firms	0.02	0.03	-0.01	0.05	0.04	0.04	0.02	0.02	0.06	0.04
	Low credit efficiency firms	0.04	0.00	0.04	0.04	0.00	-0.01	-0.10	0.09	-0.11	-0.20
QE3	All firms	-0.01	-0.02	0.01	-0.03	-0.04	0.16	0.11	0.05	0.27	0.22
	Continuing firms	-0.01	-0.03	0.02	-0.04	-0.06	0.09	0.05	0.04	0.14	0.10
	Small firms	0.27	0.00	0.27	0.27	0.00	0.46	0.02	0.44	0.48	0.04
	Large firms	-0.01	-0.02	0.01	-0.03	-0.04	0.13	0.11	0.02	0.24	0.22
	High leverage firms	-0.01	-0.03	0.02	-0.04	-0.06	0.16	0.11	0.05	0.27	0.22
	Low leverage firms	-0.03	0.10	-0.13	0.07	-0.06	0.09	0.29	-0.20	0.38	0.18
	Financially dependent firms	-0.21	-0.03	-0.18	-0.24	-0.42	0.26	0.11	0.15	0.37	0.22
	Non-financially dependent firms	-0.06	-0.07	0.01	-0.13	-0.14	0.27	0.28	-0.01	0.55	0.54
	Young firms	0.08	-0.01	0.09	0.07	-0.02	0.41	-0.04	0.45	0.37	-0.08
	Old firms	0.00	-0.03	0.03	-0.03	-0.06	0.09	0.07	0.02	0.16	0.14
	High default probability firms	-0.01	0.03	-0.04	0.02	-0.02	0.23	0.02	0.21	0.25	0.04
	Low default probability firms	0.00	-0.03	0.03	-0.03	-0.06	0.10	0.11	-0.01	0.21	0.20
	High credit efficiency firms	0.00	-0.04	0.04	-0.04	-0.08	0.33	0.08	0.25	0.41	0.16
	Low credit efficiency firms	-0.09	0.01	-0.10	-0.08	-0.18	-0.12	0.09	-0.21	-0.03	-0.24

Figure A.1: Monetary Policy Shock throughout the Zero Lower Bound



Note: This graph shows the monetary policy shocks during the zero lower bound. These shocks come from a FAVAR(4) that includes three purged factors and the monetary policy rate. The shaded boxes represent individual rounds of quantitative easing.