

Supplemental Appendix

Monetary Policy and Employment: Do Financial Constraints Matter?

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A Data Construction

A.1 Monetary policy shocks: **Champagne and Sekkel (2018)**

Our monetary policy shocks series are based on the narrative approach by **Romer and Romer (2004)**, RR henceforth) and applied to Canada by **Champagne and Sekkel (2018)**, CS henceforth). The approach consists of constructing a series of intended changes in the central bank's policy rate and purging out the systematic component of monetary policy.

Methodology. The regression equation estimated by CS is

$$\begin{aligned} \Delta i_t = & \mu + \beta_1 i_{t-14} + \beta_2 i_{t-14}^{US} + \beta_3 e_{t-14} + \beta_4 \Delta i_{t-14}^{US} + \beta_5 \Delta e_{t-14} \\ & + \sum_{m=1}^3 \rho_m u_{m(t)-m} + \sum_{q=-1}^2 \left(\gamma_q \hat{y}_{q(t)+q} + \delta_j \hat{\pi}_{q(t)+q} \right) + \sum_{q=-1}^2 \left(\theta_q \Delta \hat{y}_{q(t)+q} + \phi_j \Delta \hat{\pi}_{q(t)+q} \right) \\ & + \epsilon_m, \end{aligned} \tag{A.1}$$

which we re-estimate for our period of interest (i.e., January 2000 through December 2016).

The dependent variable Δi_t is the change in the intended policy rate between two consecutive meetings. The subscript t denotes the day of the meeting while Δ denotes the change in a variable between two consecutive meetings. The regressors include the policy rate i_{t-14} , its U.S. counterpart i_{t-14}^{US} (i.e., the Fed funds rates), and the logarithm of the USD/CAD exchange rates e_{t-14} , where the variables are lagged by 14 days. We also include the Fed funds rate and the (log) exchange rate in changes (i.e., Δi_{t-14}^{US} and Δe_{t-14}).

The second set of regressors follows RR more closely and includes macroeconomic variables and forecasts. We include three lags of the monthly unemployment rate $u_{m(t)-1}$, $u_{m(t)-2}$, and $u_{m(t)-3}$, where $m(t)$ denotes the month in which the meeting occurred and $m(t) - 1$, $m(t) - 2$, and $m(t) - 3$ denote the previous three months. Then, we include one lag, the nowcast (forecast for the current quarter), and the one- and two-quarter-ahead forecasts of real output growth $\hat{y}_{q(t)+q}$ and CPI inflation $\hat{\pi}_{q(t)+q}$, where $q(t)$ denotes the quarter in which the meeting occurred and $q(t) - 1$, $q(t)$, $q(t) + 1$, and $q(t) + 2$ denote the previous, current, and subsequent two quarters. As in RR, we also include the revisions relative to the previous meeting (i.e., $\Delta \hat{y}_{q(t)+q}$ and $\Delta \hat{\pi}_{q(t)+q}$).

The error ϵ_m is the monetary policy shock. As in RR and CS, we collect the regression residuals and aggregate them into a monthly series by summing the shocks for those months with more than one meeting, and assign a zero value for those months without a meeting.

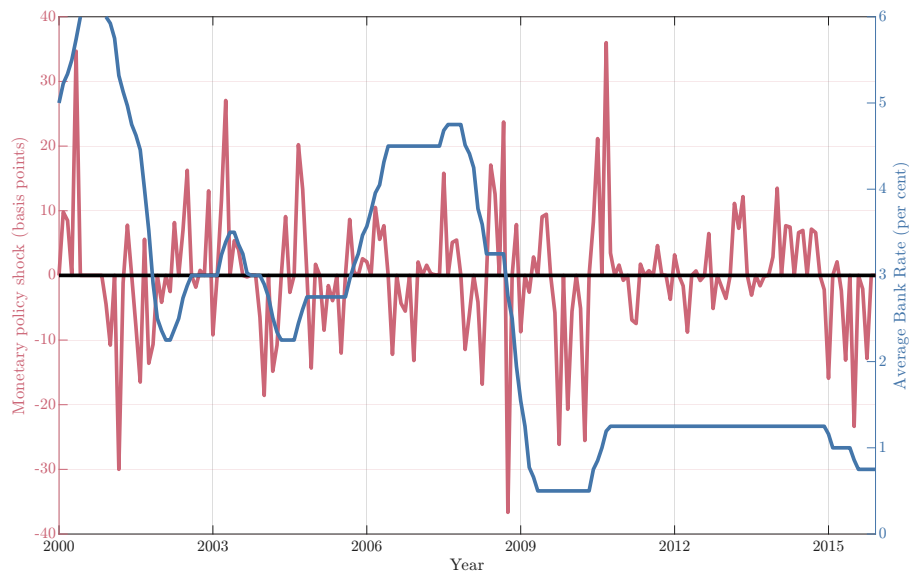


Figure 5: Monetary policy shocks (red line) and average monthly Bank Rate (blue line) (2000:M1–2015:M12).

Figure 5 plots the monthly monetary policy shocks series estimated for the 2000-15 period along with the average monthly Bank of Canada Bank rate for comparison. The series has a zero average (by construction), an average absolute shock of 6 basis points, and a standard deviation of 10 basis points.

Context. To add some narrative to some of these data points, we highlight a few examples:

1. There is a positive shock in May 2000 (roughly 30 basis points) where the 50 basis points increase in the policy rate was not warranted by the current and forecasted economic conditions at the time. Relative to the previous meeting in March, GDP nowcasts and forecasts were weaker, CPI inflation in 2000Q1 turned out slightly lower relative to 1999Q4, and CPI inflation forecasts were mildly higher. Despite this weaker GDP outlook, the Bank of Canada decided to increase rates by 50 bps.
2. The negative 30 basis point shock in March 2001 is due to the 50 basis points decrease in rates despite economic conditions being stable from the previous meeting two months before. The US Federal Reserve had lowered rates during that period, which might have prompted the Bank to follow course.²⁶
3. Another example are the two negative shocks observed in January 2015 and July 2015. These shocks are related to the surprise interest rate cuts that Governor Poloz characterized at the time as policy insurance: “Today’s action is intended to reduce the risk

²⁶CS’ specification takes into account the Bank of Canada’s reaction to US rates. But they break down their estimation before and after the introduction of inflation targeting in 1991 and find that the Bank of Canada was reacting strongly to movements in U.S. rates (and also exchange rates) prior to 1991, but not after, where monetary policy began mostly to respond to past, current and future GDP growth and inflation.

that our inflation path might move materially to the downside, as well as cushion the impact of lower oil prices and facilitate the economy's sectoral adjustment to its new circumstances." (see [Poloz, 2015](#))

A.2 Survey on Financing and Growth of SMEs

A.2.1 Survey questions

We now list the key survey questions from the survey that we use to construct the proxy. In particular, we use questions related to (i) credit requests over the last year and (ii) the outcome of these requests.

We use three waves of the survey (i.e., 2011, 2014, and 2017). The questions related to financing slightly differ in the 2011 wave relative to the 2014 and 2017 waves. We explain below how we construct the variables $\text{Request}_{i,t}$ and $\text{Outcome}_{i,t}$.

Credit requests (2011 wave). In the 2011 wave of the survey, we use a question (Question 1) on whether the firm has made any credit request and a second question (Question 2) on the amount of credit requested. We list the exact questions below.

Question 1: *In 2011, did your business seek... (Mark all that apply):*

1. *Non-residential mortgage or refinancing of an existing non-residential mortgage.*
2. *Term loan.*
3. *Business line of credit or increase in the credit limit of current line of credit.*
4. *Business credit card or increase in the credit limit of current credit card.*
5. *Lease.*
6. *Trade credit (A trade credit involves purchasing goods or services from suppliers on account and paying the supplier at a later date. Trade credit debt is reported as "accounts payable" on your Financial Statements.)*
7. *Equity (This could be any request for new or additional financing from an investor, venture capital supplier, angel, or friend or family member in exchange for a share of the ownership of your business.)*
8. *Financing from government or a government lending institution (This includes direct loans, loan guarantees, grants, subsidies, no-interest loans, non-repayable contributions and equity.)*
9. *Other types of external finance.*

Question 2: *For your business' largest request for debt financing in 2011, what was the dollar amount requested? (Your largest request in 2011 is the one with the largest monetary value.) (Debt financing includes term loans, mortgages, lines of credit and credit cards. Please provide your best estimate.)*

For the wave 2011, we use Question 1 to create an indicator variable Request_i which takes the value of one if firm i answers yes to at least one of the answers (1) through (6).

Credit requests (2014 and 2017 waves). For 2014 and 2017 waves of the survey, there are specific questions for each of the types of debt financing (i.e., loans, mortgages, lines of credit, and credit cards). For each type of financing, we use a question (Question 1) on whether the

firm has made a request and a second question (Question 2) on the amount of credit requested. We list the exact questions below, where the type of credit instrument is mentioned in the brackets “[...]”.

Question 1: *In 2014, did your business request a [...] or increase in the credit limit of the [...]?*

Question 2: *For your business’ largest request for a [...] or increase in the credit limit of the [...] in 2014, what was the dollar amount requested? (Your largest request in 2014 is the one with the largest monetary value.)*

For the waves 2014 and 2017, we use Question 1 to create an indicator variable $\text{Request}_{i,t}$, which takes the value of one if firm i answers yes for at least one type of debt financing.

Outcome of credit requests (2011 wave). For 2011, the outcome of the request question is the following:

Question 3: *What was the outcome of this debt financing request? (Select one)*

1. *The full amount was authorized.*
2. *A partial amount was authorized.*
3. *Request was rejected.*
4. *Request still under review.*
5. *Request was withdrawn.*

For all firms that requested credit (i.e. $\text{Request}_{i,t} = 1$), we create a dummy variable $\text{Request}_{i,t}$ that takes the value of one if the largest request for external financing is fully accepted, and zero if it is rejected or partially accepted.

Outcome of credit requests (2014 and 2017 waves). In the 2014 and 2017 waves of the survey, the outcome of request question refers to the specific requests made (i.e., loans, mortgages, lines of credit and credit cards). We list the exact questions below, where the type of credit instrument is mentioned in the brackets “[...]”.

- *What was the outcome of this [...] or increase in the [...] credit limit request? (Select one only)*
 1. *The full amount was authorized.*
 2. *A partial amount was authorized.*
 3. *Request was rejected.*
 4. *Request still under review.*
 5. *Request was withdrawn.*

If a firm made multiple external financing requests, we first determine which request was the largest (using Questions 1 and 2) and then use the outcome of this particular credit request. As for 2011, we create a dummy variable $\text{Request}_{i,t}$ that takes the value of one if the largest request for external financing is fully accepted, and zero if it is rejected or partially accepted.

Definition of a constrained firm (2011, 2014, and 2017 waves). Finally, we construct our $Constrained_{i,t}$ variable as follows:

$$Constrained_{i,t} = \begin{cases} 1 & \text{if Request}_{i,t} = 1 \text{ \& Outcome}_{i,t} = 0 \\ 0 & \text{Otherwise} \end{cases} \quad (\text{A.2})$$

Alternative definition of constrained firm. In Equation (A.2), only firms who requested credit and were denied are considered to be constrained. As discussed in the main text, our definition of constrained firms may contain false negatives, i.e., firms that are financially constrained but were not denied credit. Here we provide an alternative definition of being constrained encompassing equation (A.2), by adding firms that did not request credit for the following reasons:²⁷

- (i) thought they would be turned down;
- (ii) applying for credit was too difficult or time consuming;
- (iii) the cost of financing was too high.

Table 11 presents the results from estimating the OLS regression from the survey data using this alternative definition of being constrained (see Section 3 in the main text).

Table 11: Determinants of credit constraints

Variable	Coefficient	Std error
Total liabilities	0.017***	0.003
Current liabilities	0.009***	0.003
Total assets	−0.0176***	0.003
Current assets	−0.010***	0.003
Revenue	−0.028***	0.008
Expense	0.014*	0.008
Age	−0.006***	0.002
Constant	0.056***	0.002

Notes: Survey on Financing and Growth of Small and Medium Enterprises sample (13,604 observations). Coefficients (2nd column) and robust standard errors (3rd column) for OLS regression; asterisks denote statistical significance (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$). $R^2 = 0.03$. The dependent variable of the regression is $Constrained_{i,t}$ as defined above.

²⁷See Table 4 in the main text for all the different reasons why firms did not request credit.

A.3 Summary statistics by firm age, survey data

We now extend Tables 2 and 3 sorted by firm age instead of firm size. Overall, the data points to older firms relying less on external financing (see Table 12), and having better balance sheets along all the financial ratios (see Table 13).

Table 12: Type of financing requests (%)

Variables	Age groups			Total
	0–10	11–20	21+	
Debt financing	34.4	33.2	29.4	31.7
Line of credit	18.8	15.8	14.1	15.8
Term loan	10.0	11.1	8.9	9.8
Mortgage	4.6	5.2	6.1	5.5
Credit card	13.9	12.7	11.0	12.2
Equity financing	2.7	2.0	1.4	1.9

Notes: Same sample and definitions as in Table 2.

Table 13: Summary statistics (survey data)

Variables	Age groups			Total
	0–10	11–20	21+	
Shares (%)				
Firm	25.8	27.0	47.2	100
Employment	22.6	25.7	51.8	100
Averages				
Size	17.5	19.1	22.0	20.1
Age	5.1	14.3	36.5	22.4
Financial ratios				
Leverage	0.57	0.62	0.57	0.58
Liquidity	0.27	0.49	0.48	0.43
Earnings-to-debt	0.04	0.08	0.12	0.09
Profit margin	0.03	0.03	0.05	0.04
Debt financing (%)				
Requested credit	34.4	33.2	29.4	31.7
Request accepted	82.2	88.7	89.9	87.4
Constrained	6.1	3.7	3.0	3.98

Notes: Same sample and definitions as in Table 3.

B Identification

To clarify the identification assumptions and characterize potential biases, we now consider a stripped down version of the empirical model without controls (i.e., $z_t = 1$ in equation 4.1).

Model. The model equations are:

$$\log L_{i,t+1} = \beta_p p_{i,t} + \beta_d \varepsilon_t + \beta_{id} p_{i,t} \varepsilon_t + u_{i,t+1}, \quad (\text{Employment})$$

$$p_{i,t} = p + x_{i,t-1}, \quad (\text{Proxy})$$

$$E(u_{i,t+1} | x_{i,t-1}, \varepsilon_t) = 0, \quad (\text{Identifying assumption})$$

The variables $(\log L_{i,t+1}, \varepsilon_t, x_{i,t})$ have an unconditional mean of zero. The constant p is a calibrated parameter.

Using the model assumptions, the structural parameters $(\beta_p, \beta_d, \beta_{id})$ can be expressed in terms of moments of $(\log L_{i,t+1}, \varepsilon_t, x_{i,t})$ as well as the parameter :

$$\begin{aligned} \begin{pmatrix} \beta_p \\ \beta_d \\ \beta_{id} \end{pmatrix} &= \begin{pmatrix} (\text{Var}(x_{i,t-1}) + p^2) & 0 & 0 \\ 0 & \text{Var}(\varepsilon_t) & p \text{Var}(\varepsilon_t) \\ 0 & p \text{Var}(\varepsilon_t) & (\text{Var}(x_{i,t-1}) + p^2) \text{Var}(\varepsilon_t) \end{pmatrix}^{-1} \begin{pmatrix} \text{Cov}(\log L_{i,t+1}, p_{i,t}) \\ \text{Cov}(\log L_{i,t+1}, \varepsilon_t) \\ \text{Cov}(\log L_{i,t+1}, p_{i,t} \varepsilon_t) \end{pmatrix}, \\ &= \frac{1}{\text{Var}(x_{i,t-1})} \begin{pmatrix} \frac{\text{Var}(x_{i,t-1})}{\text{Var}(x_{i,t-1}) + p^2} & 0 & 0 \\ 0 & \frac{\text{Var}(x_{i,t-1}) + p^2}{\text{Var}(\varepsilon_t)} & -\frac{p}{\text{Var}(\varepsilon_t)} \\ 0 & -\frac{p}{\text{Var}(\varepsilon_t)} & \frac{1}{\text{Var}(\varepsilon_t)} \end{pmatrix} \begin{pmatrix} \text{Cov}(\log L_{i,t+1}, p_{i,t}) \\ \text{Cov}(\log L_{i,t+1}, \varepsilon_t) \\ \text{Cov}(\log L_{i,t+1}, p_{i,t} \varepsilon_t) \end{pmatrix}, \\ &= \frac{1}{\text{Var}(x_{i,t-1})} \begin{pmatrix} \frac{\text{Var}(x_{i,t-1})}{\text{Var}(x_{i,t-1}) + p^2} & 0 & 0 \\ 0 & \frac{\text{Var}(x_{i,t-1}) + p^2}{\text{Var}(\varepsilon_t)} & -\frac{p}{\text{Var}(\varepsilon_t)} \\ 0 & -\frac{p}{\text{Var}(\varepsilon_t)} & \frac{1}{\text{Var}(\varepsilon_t)} \end{pmatrix} \begin{pmatrix} \text{Cov}(\log L_{i,t+1}, x_{i,t-1}) \\ \text{Cov}(\log L_{i,t+1}, \varepsilon_t) \\ p \text{Cov}(\log L_{i,t+1}, \varepsilon_t) + \text{Cov}(\log L_{i,t+1}, x_{i,t-1} \varepsilon_t) \end{pmatrix}, \\ &= \frac{1}{\text{Var}(x_{i,t-1})} \begin{pmatrix} \frac{\text{Var}(x_{i,t-1})}{\text{Var}(x_{i,t-1}) + p^2} & 0 & 0 \\ 0 & \frac{\text{Var}(x_{i,t-1})}{\text{Var}(\varepsilon_t)} & -\frac{p}{\text{Var}(\varepsilon_t)} \\ 0 & 0 & \frac{1}{\text{Var}(\varepsilon_t)} \end{pmatrix} \begin{pmatrix} \text{Cov}(\log L_{i,t+1}, x_{i,t-1}) \\ \text{Cov}(\log L_{i,t+1}, \varepsilon_t) \\ \text{Cov}(\log L_{i,t+1}, x_{i,t-1} \varepsilon_t) \end{pmatrix}, \\ &= \begin{pmatrix} \frac{\text{Var}(x_{i,t-1})}{\text{Var}(x_{i,t-1}) + p^2} & 0 & 0 \\ 0 & 1 & -p \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \frac{\text{Cov}(\log L_{i,t+1}, x_{i,t-1})}{\text{Var}(x_{i,t-1})} \\ \frac{\text{Cov}(\log L_{i,t+1}, \varepsilon_t)}{\text{Var}(\varepsilon_t)} \\ \frac{\text{Cov}(\log L_{i,t+1}, x_{i,t-1} \varepsilon_t)}{\text{Var}(x_{i,t-1} \varepsilon_t)} \end{pmatrix}. \end{aligned}$$

The first term is a matrix that depends only on p and $\text{Var}(x_{i,t-1})$. The second term is a vector of two data moments that do not depend on p . We can immediately see that β_{id} is invariant to the calibration of p , while β_d is not.

Bias due to omitted variables. Suppose that firms who are likely to be constrained also have a stronger response to monetary policy. To be precise, suppose that

$$u_{i,t} = \delta v_{i,t} \varepsilon_t + \tilde{u}_{i,t},$$

where $v_{i,t}$ is a firm characteristic and the new error satisfies $E(\tilde{u}_{i,t+1} | x_{i,t-1}, \varepsilon_t, v_{i,t}) = 0$.

In the baseline model, the exclusion restriction implies $\text{Cov}(u_{i,t+1}, p_{i,t} \varepsilon_t) = 0$. However, we

now have that

$$\text{Cov}(u_{i,t+1}, p_{i,t}\varepsilon_t) = \delta \text{Cov}(p_{i,t}, v_{i,t}) \text{Var}(\varepsilon_t).$$

Whenever the firm characteristic $v_{i,t}$ affects the transmission of monetary policy (i.e., $\delta \neq 0$) and it is correlated with the probability of being constrained (i.e., $\text{Cov}(p_{i,t}, v_{i,t}) \neq 0$), then the exclusion fails. This is the standard omitted variable bias. The solution is to include $v_{i,t}\varepsilon_t$ as a regressor.

Bias due to false negatives We now assess the effect of changing the calibration of p on the decomposition ω . Recall that $\omega \equiv \frac{\beta_{id}p}{\beta_d + \beta_{id}p}$. Using the analytical derivation of $(\beta_p, \beta_d, \beta_{id})$, we therefore have that

$$\omega = p \frac{\frac{\text{Cov}(\log L_{i,t+1}, x_{i,t-1}\varepsilon_t)}{\text{Var}(\varepsilon_t x_{i,t-1})}}{\frac{\text{Cov}(\log L_{i,t+1}, \varepsilon_t)}{\text{Var}(\varepsilon_t)}}$$

Since the second term on the left does not depend on p , we have that doubling p implies a doubling of ω .

Bias due to measurement error in proxy Suppose that $x_{i,t}$ is observed with error. To be precise, suppose that we observe firm characteristics with noise:

$$\tilde{x}_{i,t} = x_{i,t} + v_{i,t},$$

where $v_{i,t}$ is unconditionally mean zero, but potentially correlated with future employment $E(v_{i,t-1}|u_{i,t+1}) = 0$. This is a direct violation of the exclusion restriction.

C Additional specifications

C.1 Nonlinear relationship of proxy with standard financial ratios

Figure 6 provides a non-parametric summary of the joint distribution of our proxy with other standard proxies for financial health. For each of the standard proxies (i.e., size, leverage, liquidity, debt-to-earnings, and profit margin), we report a “heatmap”, where each cell corresponds to the fraction (in percent) of observations in a given decile of likelihood to be credit constrained $\times$ a given decile of the variable of interest.

We also report the annual transition probability matrix for the firm-level proxy (Figure 6, first panel). We find a low level of mobility, as the probability of a firm staying in its decile in the next year is much higher than transitioning to any other decile. This result is particularly strong in the lowest and highest deciles of the distribution. This likely reflects the fact that balance sheet items used to construct the proxy themselves evolve slowly over time.

C.2 Dynamic relationship between the proxy and firm-level outcomes

As mentioned in Section 3, we estimate local projection models of the form

$$\log Y_{i,t+k} = \mu_{j,t}^k + \rho^k \log Y_{i,t-1} + \beta_p^k p_{i,t} + \beta_{ch}^k \text{controls}_{i,t} + u_{i,t+k}, \quad (\text{C.1})$$

where t denotes years, $\mu_{j,t}^k$ is an industry-year fixed effect (i.e., two-digit NAICS as above), $Y_{i,t}$ is the variable of interest in logarithm, and $\hat{p}_{i,t}$ is the proxy, as in the main text. Here we control for observable firm characteristics ($\text{controls}_{i,t}$) that could be correlated with our proxy and drive firm employment and debt dynamics: labor productivity, age and size. We include these three variables in logs, size is defined as employment and productivity is computed as sales per worker. Our choice of controls is informed by the firm dynamics literature, which highlights the fact that size, age, and productivity are key determinants of growth (e.g., Haltiwanger et al., 2013, Fort et al., 2013, and Moscarini and Postel-Vinay, 2012, Ilut, Kehrig and Schneider, 2018 and Decker, Haltiwanger, Jarmin and Miranda, 2020).

Figure 7a shows the dynamic impulse response of employment to an increase in the likelihood of being credit constrained over a three-year period (i.e., the estimated coefficients $\hat{\beta}^k$ for $k = 0, 1, 2, 3$), controlling for alternative channels. As in the main text, firms that are more likely to be constrained experience a lower growth rate of employment. Quantitatively, a 10 percentage point increase in the likelihood of being credit constrained in year t is associated with a roughly 12 percent decline in employment in year $t + 2$ (i.e., $\hat{\beta}^2 \approx 1.2$).

Figure 7b replicates the exercise but focuses on total debt (i.e., the sum of short- and long-term liabilities) as the variable of interest, again controlling for alternative channels. Qualitatively, the results are similar as in the main text: firms that are more likely to be constrained experience a lower growth rate of debt. However, the results are less precisely estimated than in the employment specification and lower than in the specification without these additional controls. Quantitatively, we find that a 10 percentage point increase in the likelihood of being credit constrained in year t is associated with a roughly 46 percent decline in total liabilities in year $t + 2$ (i.e., $\hat{\beta}^2 \approx 4.6$).

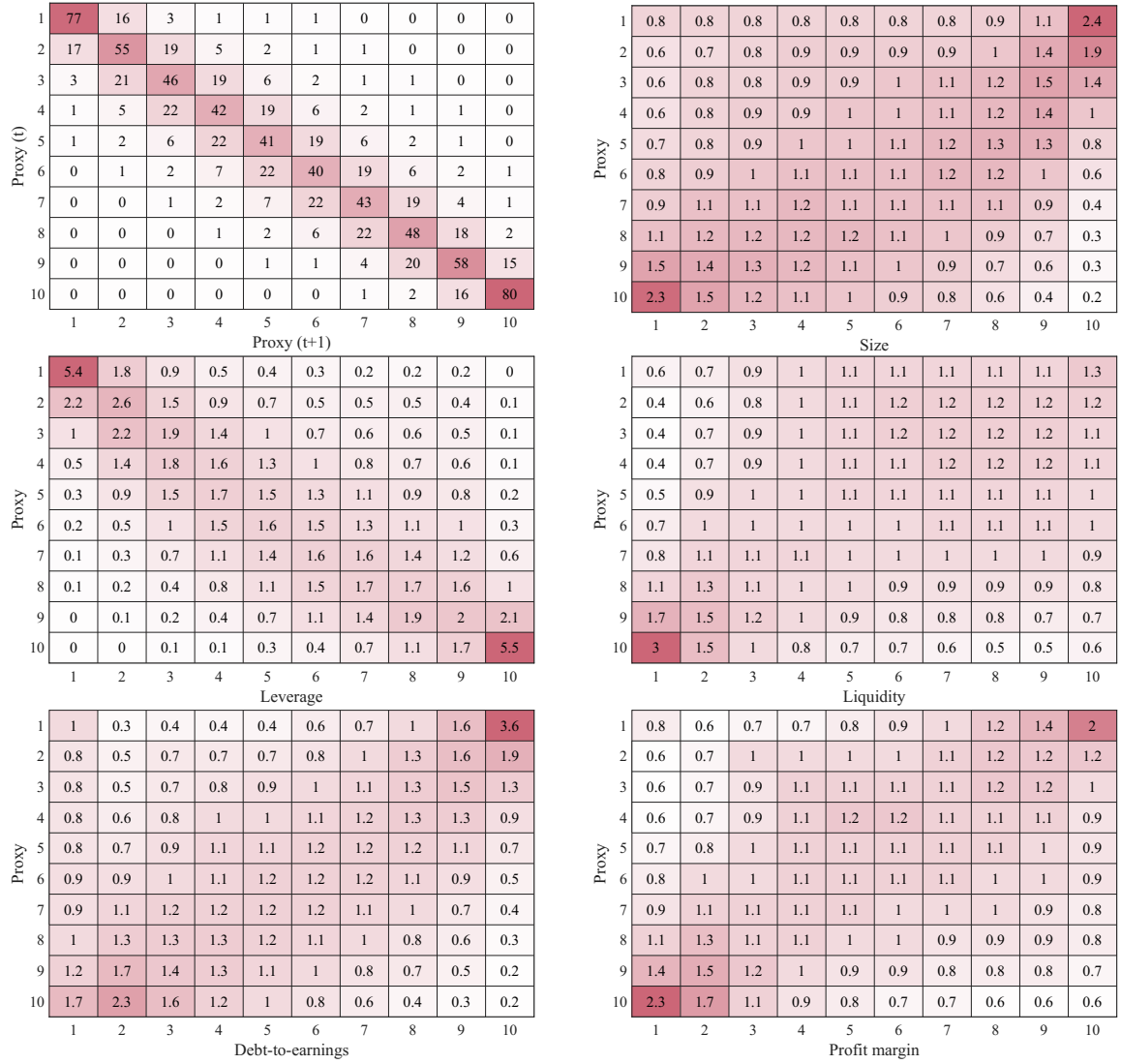


Figure 6: Relationship with standard proxies

Notes: The first panel (upper left) presents the Markov transition matrix of the proxy between two years. Each cell represents a probability (in percent). For the next five panels, each cell corresponds to the fraction (in percent) of observations in a particular decile of the probability of being constrained $\times$ decile of the standard financial proxy. “Size” is the number of employees; “Leverage” is computed as the ratio of total liabilities over total assets; “Liquidity” is short-term assets over total assets; “Earnings-to-debt” and “Profit margin” are defined as total revenues minus total expenses over total liabilities and total revenues, respectively.

C.3 Employment response to monetary policy: firm entry and exit

The results in the paper are based on a balanced sample of firms (e.g., our firm-level panel local projections, Equation 2.3, or our main decomposition, 4.1). This means that we do not measure the contribution of entry and exit to the aggregate employment response to monetary policy. Figure 2 in the paper suggests that the net entry margin is not an important contributor to the aggregate employment response: the aggregate employment response implied by our balanced-sample is almost identical to the aggregate employment response.

To investigate this further, we use quarterly estimates of business entry and exit in Canada from Statistics Canada Table 33-10-0165-01 (Statistics Canada, 2020). We quantify the importance of entry and exit to the transmission of monetary policy to employment using this addi-

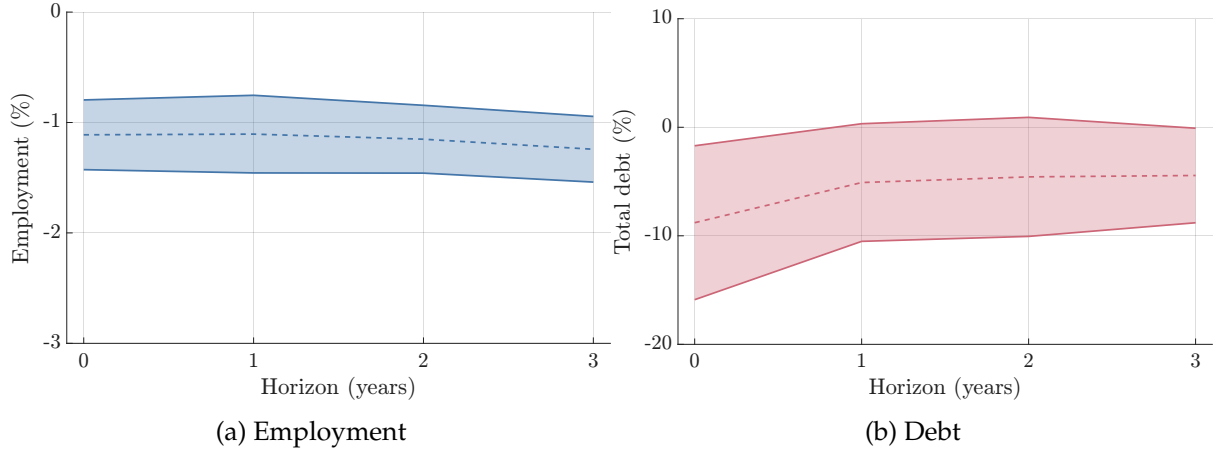


Figure 7: Impulse response of employment (panel a) and debt (panel b) to a monetary policy shock (25 bps, 90% confidence intervals).

tional data. We start with a simple accounting decomposition:

$$L_{t+1} - L_t = C_{t+1} + E_{t+1} - X_{t+1}.$$

It says that the quarterly change in aggregate employment between time t and $t + 1$ can be expressed as the contribution of continuers C_{t+1} , entrants E_{t+1} , and exiters X_{t+1} . Continuers are firms that exist over the period from $t - 1$ to $t + 1$; entrants are firms that exist from t to $t + 1$; exiters are firms that exist over $t - 1$ to t .

We now estimate the cumulative contribution of each term to monetary policy shocks. To accommodate the quarterly frequency of the data, we sum the monetary policy shocks within each quarter. The specification is

$$\begin{aligned} \frac{L_{t+k} - L_t}{L_t} &= \mu_{q,L}^k + \beta_L^k \varepsilon_t + \sum_{q=1}^Q \delta_{q,L}^k i_{t-q} + u_{L,t+k}, \\ \frac{\sum_{h=1}^k C_{t+h}}{L_t} &= \mu_{q,C}^k + \beta_C^k \varepsilon_t + \sum_{q=1}^Q \delta_{q,C}^k i_{t-q} + u_{C,t+k}, \\ \frac{\sum_{h=1}^k E_{t+h}}{L_t} &= \mu_{q,E}^k + \beta_E^k \varepsilon_t + \sum_{q=1}^Q \delta_{q,E}^k i_{t-q} + u_{E,t+k}, \\ \frac{\sum_{h=1}^k X_{t+h}}{L_t} &= \mu_{q,X}^k + \beta_X^k \varepsilon_t + \sum_{q=1}^Q \delta_{q,X}^k i_{t-q} + u_{X,t+k}, \end{aligned}$$

where $\mu_{q,\cdot}^k$ is a quarterly dummy; ε_t is the monetary policy shock, and i_t is the bank rate. We use $Q = 4$ lags for the bank rate. The time period is from 2000Q1 to 2016Q4. The δ_q^k are the coefficient of interest and the standard errors are calculated using Newey-West.

Because employment growth is exactly the sum of the contribution of continuers, entrants, and exiters, our coefficients satisfy $\beta_L^k = \beta_C^k + \beta_E^k + \beta_X^k$ at all horizon k . We can decompose the aggregate employment IRF into the contributions of continuers, entry, and exit.

Figure 8 plots the impulse responses for total continuers (left), entrants (middle), and exiters (right). We highlight three observations: (i) the only group with a meaningfully negative

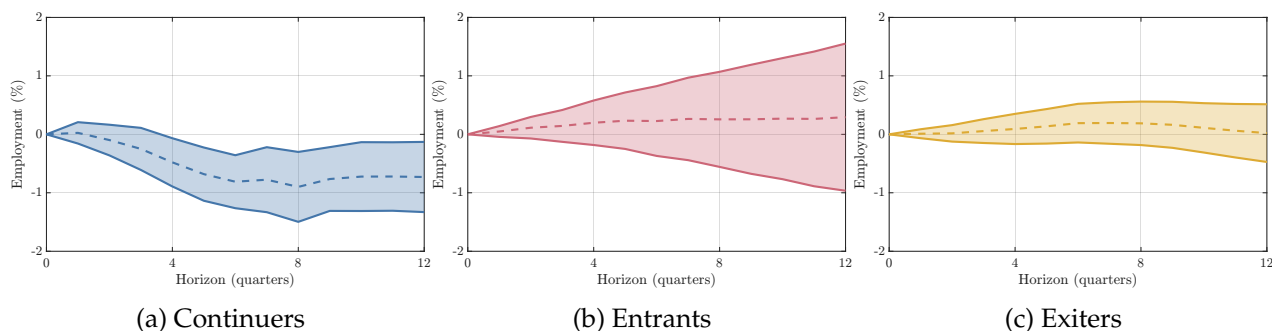


Figure 8: Impulse responses of employment to a monetary policy shock (contribution, 25 basis points, 90% confidence interval).

response is the continuers; (ii) the response of entry and exit is not statistically different from zero at all horizons; and (iii) the peak response of continuers (about 1 percent after two years) is roughly equal to the aggregate response of employment found in Figure 2 in the paper.

We note that impulse responses at horizons $k \geq 2$ have to be interpreted cautiously, since the contribution of continuers includes employment growth at firms born between $t + 1$ and $t - k - 1$. Hence, our estimate of the contribution of continuers to aggregate response at the two-year horizon includes the contribution of firms born in the first 7 quarters after the shock.

C.4 Employment response to monetary policy: age, financial ratios, and industries

For each firm characteristic, we compute the “peak-response” specification, introduced in Equation 3.3, which corresponds to the average employment response between months 12 and 24 after the shock. We now report the peak-response by firm characteristics in Table 14 and by industry in Table 15.

The first rows of Table 14 show the employment response by firm size. Consistent with the earlier evidence (see Figure 3), we have that small and medium firms response strongly, while large firms have a near zero (but negative) response.

We then report the response by age groups: young 1 (0 – 10 year old), young 2 (11 – 20), and old (> 20). We find that age heterogeneity is important for employment response: young firms have a much larger employment response than old firms, who have a near zero response. The pattern of impulse responses across age groups is very similar to size, as it is well understood that size and age are positively correlated. To tease out the marginal effect of size, we create size groups for both young and old firms. We find a monotone relationship within age groups: larger firms have a lower response conditional on their age.

We then report employment responses by (within-year) terciles of leverage, liquidity, earnings-to-debt and net profit margin, the standard financial ratios discussed in Section 3. For each financial ratio, the “group 1” is defined as those with the lowest leverage, lowest liquidity, lowest earnings-to-debt, and lowest net profit margin. For leverage and interest coverage, the effect appears to be non-monotonic: firms in the high and low groups respond more strongly than firms in the middle group. We do not have a clear answer for this pattern, but for instance, a financially-constrained firm could have low leverage because it has difficult to borrow, or a firm that has borrowed a lot might be experiencing financial distress when interest rates move up. In contrast, the employment response is monotonically decreasing in liquidity (i.e., high-

liquidity firms respond more) and net profit margin (i.e., firms with low profit margins respond more).

Table 15 reports the employment peak-response by industry.²⁸ All but three industries have a negative response (i.e., transportation, Information & cultural, arts & entertainment, and two of them are not statistically significant at the 10 percent level). The industries with the largest negative response are: mining, construction, administrative & support services, and manufacturing. Note that while these impulse responses are significant at the 10 percent level, the response for the mining response is not.

²⁸We have 15 industries at the NAICS 2-digit level. Note that we removed the same industries as in our main sample (see Section 2).

Table 14: Employment response to monetary policy shock, by firm characteristics (25 bps)

Specification	Size	Age	Age×Size	Leverage	Liquidity	Int. coverage	Net profit marg.
Small	−1.43** (0.65)						
Medium	−1.0** (0.40)						
Large	−0.23 (0.50)						
Young 1		−3.11** (1.40)					
Young 2		−0.71** (0.35)					
Old		0.16 (0.29)					
Young, small			−1.61** (0.80)				
Young, medium			−1.31*** (0.43)				
Young, large			−0.77 (0.56)				
Old, small			−0.57* (0.32)				
Old, medium			−0.26 (0.31)				
Old, large			0.54 (0.42)				
Leverage 1				−1.56** (0.74)			
Leverage 2				−0.51 (0.45)			
Leverage 3				−1.19* (0.68)			
Liquidity 1					−0.25 (0.49)		
Liquidity 2					−0.91** (0.44)		
Liquidity 3					−1.69*** (0.61)		
Earnings-to-debt 1						−1.84*** (0.49)	
Earnings-to-debt 2						−0.38 (0.45)	
Earnings-to-debt 3						−1.50*** (0.51)	
Net prof margin 1							−1.86*** (0.51)
Net prof margin 2							−0.50 (0.45)
Net prof margin 3							−0.57 (0.55)
N	8,116,100	8,116,100	8,116,100	7,538,500	7,504,800	7,525,200	7,523,800

Notes. Impulse responses to a monetary policy shock by different category groupings (25 basis points). Driscoll–Kraay standard errors reported in parentheses. Asterisks denote statistical significance (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$).

Table 15: Employment response to monetary policy shock, by industry (25 bps)

Industry	Coefficient	Industry	Coefficient
Mining	−2.22 (2.44)	Real estate	−0.45 (1.23)
Construction	−2.54** (1.00)	Professional services, technical	−1.36 (1.08)
Manufacturing	−1.89** (0.89)	Management of companies	−0.81 (1.60)
Wholesale	−0.13 (0.49)	Administrative & support services	−2.22* (1.21)
Retail	−0.02 (0.72)	Arts, entertainment, etc.	0.66 (0.90)
Transportation	0.53 (0.79)	Accommodation	−0.13 (1.00)
Information & cultural	2.50** (1.40)	Other services	−0.85 (0.93)
Finance & Insurance	−0.80 (0.91)		
N		8,116,100	

Notes. Impulse responses to a monetary policy shock by industry (25 basis points). Driscoll–Kraay standard errors reported in parentheses. Stars (*, **, ***) denote statistical significance at the 10%, 5%, and 1%, respectively.

C.5 Employment response to monetary policy shock, by decile of proxy

Figure 4 of the paper presents the estimated effects of monetary policy on employment for each decile of our proxy (firms ranked by deciles of the proxy, where the 10th decile is comprised of the 10 per cent most likely to be constrained firms). Here, we use the exact same specification but we add a time fixed effect. As a result, we estimate relative effects for the first nine decile, relative to the top decile (the 10 per cent of firms that are the most likely to be constrained is the reference group). Table 16 reports the results.

Table 16: Employment response to monetary policy shock, by decile of proxy (relative effect).

Decile	Coefficient	Decile	Coefficient
1	2.83 (2.05)	6	1.93 (1.38)
2	2.95 (1.89)	7	1.29 (1.00)
3	2.24 (1.67)	8	0.788 (0.689)
4	1.88 (1.33)	9	1.04 (0.641)
5	1.69 (1.29)		
N		7337900	

Notes. Impulse responses to a monetary policy shock by deciles of the proxy. Group 10 is omitted category. (25 basis points). Driscoll-Kraay standard errors reported in parentheses. Asterisks denote statistical significance (**: $p < 0.01$, *: $p < 0.05$, $p < 0.1$).

First, all the point estimates are positive and generally large, meaning that all nine groups react *less* to a monetary policy shock, in a relatively monotonic relationship with the deciles of the proxy. Second, the standard errors reveal large sampling uncertainty. For instance, the point estimate for the top versus bottom decile has a 90% confidence interval of $2.83 \pm 1.645 \cdot 2.05 = [-0.54, 6.20]$.

C.6 Alternative proxy approach

As mentioned in the main text, an earlier version of the paper experimented with a probit approach to classify firms into three groups: those likely (i) to have requested credit and be denied (i.e., constrained), (ii) to have requested credit and be accepted, and (iii) not to have requested credit, in the spirit of [Attanasio et al. \(2002\)](#). That approach estimated our linear probability model specification separately for the probabilities of requesting credit and being accepted or requesting credit and being denied in the survey, which we then carried into our main dataset in each year using the estimated coefficients. To categorize the firms in each group in the main dataset, we used a fixed cut-off equal to the average share of firms that requested credit and were denied, and the share of firms not requesting credit in the pooled survey (those are the shares shown in Table 3.)

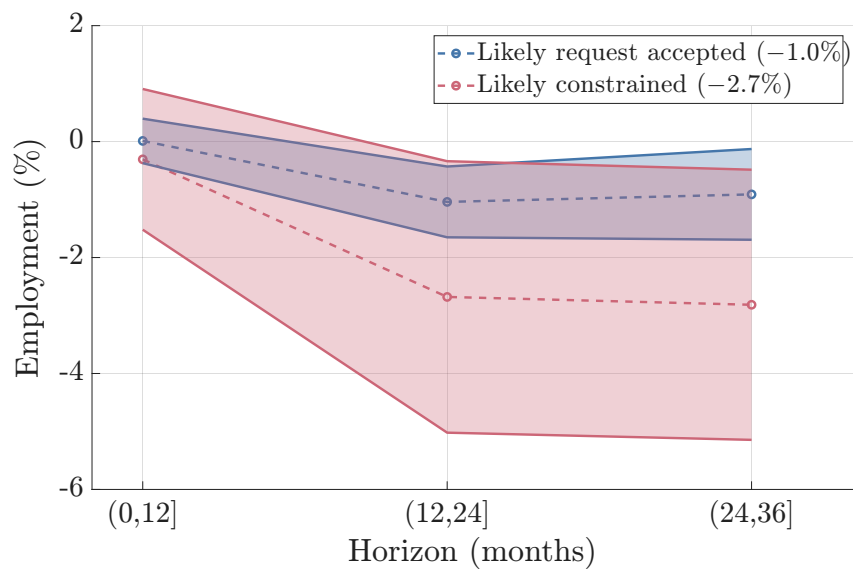


Figure 9: Employment response to monetary policy shock (25 bps).

C.7 Does the proxy responds to monetary policy?

Our model in Section 4.4 contains an exogenous function that maps interest rate to probability of being constrained. In the real world, one potential mechanism is that monetary policy leads to a deterioration of firm balance sheets over time, making firms overall less likely to obtain credit in the future.

To test this channel, we estimate how the empirical proxy $p_{i,t+k}$ responds to a monetary policy shock at time t . Since the proxy is constructed using annual information on firm characteristics, we need to aggregate the monetary shocks at the annual level. We keep the same structure as our specification Equation 2.3, where t and horizon k are in years as the data is in annual terms. Specifically, we estimate

$$\underbrace{p_{i,t+k}}_{\text{Firm-level proxy}} = \underbrace{z'_{i,t}\lambda^k}_{\text{Controls}} + \underbrace{\beta^k \varepsilon_t}_{\text{Monetary shock}} + \underbrace{u_{i,t+k}}_{\text{Error}} \quad (\text{C.2})$$

The controls are the same as in Equation 2.4:

$$z'_{i,t}\lambda^k \equiv \mu_j + \rho_p p_{i,t-1} + \delta_q i_{t-1}, \quad (\text{C.3})$$

Table 17 presents the results associated with a monetary policy shock of 25 basis points. A 25 basis point shock raises the firm-level proxy by about 0.2 percentage points after one year, and by about 0.4 percentage points in the second and third year. While the impulse response in one year after the shock is not statistically significant, those at two and three years are significant at the 10 percent level. Note that those responses might appear small, but recall that the unconditional probability of being constrained is only 3 percent, so in relative term those are meaningful responses.

Table 17: Percentage points response of proxy to 25 bps monetary policy shock.

Firm-level proxy ($p_{i,t+k}$)	$k = 1$	$k = 2$	$k = 3$
Monetary policy shock (ε_t)	0.002 (0.002)	0.004* (0.002)	0.004* (0.002)
N	648,100	603,100	558,200

Notes. Impulse responses of the proxy to a monetary policy shock (25 basis points). Driscoll–Kraay standard errors reported in parentheses. Asterisks denote statistical significance (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$). Annual data.

C.8 Credit market response to monetary policy: survey evidence

Guided by the model, our interpretation of the evidence is that the transmission of monetary policy to employment is amplified by the fact that monetary policy affects not only the price of credit (i.e., the interest rate), but also the ability of firms to obtain credit (i.e., the probability of being constrained). Ideally, one would obtain direct evidence on the response of the fraction of firms p that are constrained to a monetary policy shock. While our survey data contains rich cross-sections, it only covers three years, which rules out time series analysis. We now provide suggestive evidence that monetary policy indeed affects “non-price” credit conditions using publicly available data.

The Bank of Canada conducts two quarterly surveys designed to provide measures of credit conditions in the Canadian economy from the perspective of (i) lenders (financial institutions) and (ii) borrowers (firms): (i) the *Business Outlook Survey* (henceforth BOS; Bank of Canada, 2026a) and (ii) the *Senior Loan Officer Survey* (henceforth SLOS; Bank of Canada, 2026c). The BOS surveys Canadian firms of all sizes and industries, while the SLOS surveys major Canadian financial institutions. In both cases, we focus on the question related to whether non-price credit conditions have tightened in the current quarter. Both surveys report a balance of opinion (i.e., the share of respondents reporting a tightening versus the share that reports an easing).²⁹

The BOS asks firms: “How have the terms and conditions for obtaining financing changed over the last three months compared to the previous three months?” Examples of tightened terms and conditions given to the survey participants are increased collateral requirements or capital markets being less receptive to new issues of debt. The SLOS asks financial institutions about their commercial lending operations: “How have your institution’s general standards (i.e., your appetite for risk) and terms for approving credit changed in the past three months?” Examples of terms given to the survey participants include collateral requirements and covenants. Importantly, both survey questions are meant to isolate changes the non-price credit conditions in the economy (i.e., how hard is it to obtain credit) from the cost of credit.

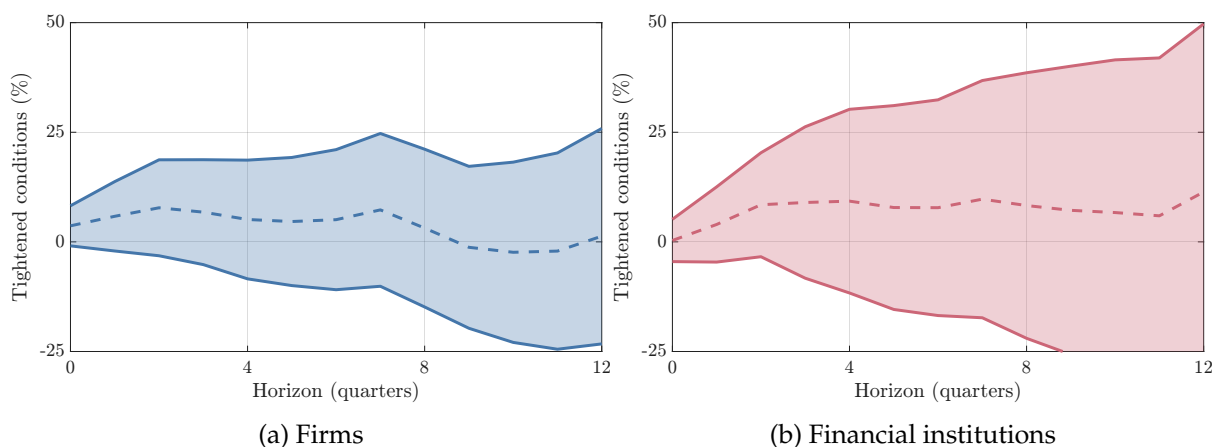


Figure 10: Non-price credit conditions following a monetary policy shock where positive values indicates tightening (25 basis points, 90% confidence intervals).

²⁹Faruqui, Gilbert and Kei (2008) show that the two survey questions we are focusing on are highly correlated and (inversely) predict future investment.

We conduct a simple exercise where we estimate the response of the cumulative balance of opinion to a monetary policy shock. We use the same specification that we used with the aggregate data (see Equation 2.1) and report IRFs associated with a 25 bps monetary policy shock. To accommodate the quarterly frequency of the survey, we sum the monetary policy shocks within each quarter. The exact specification is

$$\sum_{h=0}^k \text{BOO}_{t+h} = \mu_q^k + \beta^k \varepsilon_t + \sum_{q=1}^Q \delta_q^k i_{t-q} + u_{t+k}, \quad (\text{C.4})$$

where BOO_t is the balance of opinion (in percentage points) in quarter t , μ_q^k is a quarterly dummy; ε_t is the monetary policy shock, and i_t is the bank rate. We use $Q = 4$ lags for the bank rate. The time period is from 2000 to 2016. Standard errors are calculated using Newey-West.

Figure 10a reports the results from the BOS (i.e., from the perspective of borrowers). The balance of opinion responds positively, meaning that a rising share of firms report that credit conditions are tightening. Figure 10b reports the results from the SLOS (i.e., from the perspective of lenders). Similarly, the response is positive, signifying a tightening of lending. In both cases, the response peaks around two years and the estimation uncertainty is high (i.e., the peak responses are barely significant at the 10 percent level).

Despite the caveats, we view this evidence as supporting the credit constraint channel of monetary policy that we emphasize in this paper. In particular, both borrowers and lenders report a tightening of non-price credit conditions following a monetary tightening.

D Stylized Model

D.1 Aggregate decomposition

Aggregate log employment can be expressed as

$$\log L = (1 - p) \log L^{\text{uc}} + p \log L^{\text{c}},$$

where $p \in (0, 1)$ is the fraction of firms who are (ex-post) constrained.

Differentiating with respect to R , we obtain

$$\begin{aligned} \frac{\partial \log L}{\partial \log R} &= (1 - p) \frac{\partial \log L^{\text{uc}}}{\partial \log R} + p \frac{\partial \log L^{\text{c}}}{\partial \log R} + \frac{\partial p}{\partial \log R} \log(L^{\text{c}}/L^{\text{uc}}) \\ &= \frac{\partial \log L^{\text{uc}}}{\partial \log R} + p \left(\frac{\partial \log L^{\text{c}}/L^{\text{uc}}}{\partial \log R} + \frac{\partial \log p}{\partial \log R} \log(L^{\text{c}}/L^{\text{uc}}) \right) \end{aligned}$$

So far, this is an accounting decomposition (i.e., it does not use equilibrium restrictions). Using the formulas for $L^{\text{uc}}, L^{\text{c}}, p$ from the model, we have that

$$\frac{\partial \log L}{\partial \log R} = -\frac{1}{\alpha} + p \left(\frac{1}{\alpha} - \theta \Delta \right).$$

D.2 Proof of Proposition 4.1

In the model, firm employment can be expressed as

$$\mathbb{E}(\log L_i | p_i, R) = (1 - p_i) \log L^{\text{uc}}(R) + p_i \log L^{\text{c}}. \quad (\text{D.1})$$

Denote R the initial interest rate and R' the new one. We will use now use a first-order approximation to express the conditional expectation as a linear function of the monetary policy shock $\varepsilon \equiv \log(R'/R)$:

$$\mathbb{E}(\log L_i | p_i, \varepsilon) \approx \mathbb{E}(\log L_i | p_i, R) + \frac{\partial \mathbb{E}(\log L_i | p_i, R)}{\partial \log R} \varepsilon. \quad (\text{D.2})$$

Using the same logic as in the aggregate decomposition, we have that

$$\frac{\partial \mathbb{E}(\log L_i | p_i, \varepsilon)}{\partial \log R} = -\frac{1}{\alpha} + p_i \left(\frac{1}{\alpha} - \theta \Delta \right) \quad (\text{D.3})$$

Combining (D.1), (D.2), and (D.3), we obtain

$$\mathbb{E}(\log L_i | p_i, \varepsilon) \approx \log L^{\text{uc}} - \Delta p_i - \frac{1}{\alpha} \varepsilon + \left(\frac{1}{\alpha} - \theta \Delta \right) p_i \varepsilon.$$

We can therefore write

$$\log L_i \approx \lambda + \beta_p p_i + \beta_d \varepsilon + \beta_{id} p_i \varepsilon + u_i$$

where u_i captures the randomness of the event of being constrained and satisfies $E(u_i|p_i, \varepsilon) = 0$. The mapping between parameters $(\lambda, \beta_p, \beta_d, \beta_{id})$ is

$$\lambda = \log L^{\text{uc}}, \quad \beta_p = -\Delta, \quad \beta_d = -\frac{1}{\alpha}, \quad \beta_{id} = \frac{1}{\alpha} - \theta\Delta.$$