Monetary Policy and Employment: Do Financial Constraints Matter?*

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Abstract

We propose a simple empirical strategy that combines (i) administrative firm-level data, (ii) identified monetary policy shocks, and (iii) survey data on financing activities. The key novelty is a firm-level proxy for the likelihood of being credit constrained, constructed using data on realized outcomes of financing requests. Leveraging heterogeneity in the proxy and employment responses to monetary policy shocks, we find that credit constraints *amplify* monetary policy transmission and account for roughly two thirds of the aggregate employment response to monetary policy. Our findings imply redistributive effects across firms (large firms barely respond to monetary policy) and a state-dependence to the current tightness of constraints.

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1 Introduction

Do financial constraints faced by firms amplify or dampen the transmission of monetary policy to employment? From a theoretical standpoint, the answer to this question is not obvious. Consider, for instance, the effect of a surprise interest rate cut. On the one hand, the existence of financially constrained firms—who are unable to obtain the financing they need to expand—dampens the stimulative effect of monetary policy. On the other hand, accommodative monetary policy might indirectly loosen financial constraints through a variety of channels (for instance, by raising collateral values), thus leading to a rise in hiring by initially-constrained firms. This second force is often referred to as the financial accelerator (Bernanke, Gertler and Gilchrist, 1999).

Following the work of Gertler and Gilchrist (1994), a large empirical literature has emerged that estimates the heterogeneous response of firms to monetary policy and the role of financial constraints in the transmission mechanism. On the one hand, many papers (e.g., Cloyne, Ferreira, Froemel and Surico, 2023; Bahaj, Foulis, Pinter and Surico, 2022; Caglio, Darst and Kalemli-Ozcan, 2021) show that small, young, or levered firms with unstable cash flows are more responsive to monetary policy, which they interpret as evidence that financial constraints amplify the transmission of monetary policy.[1] On the other hand, Ottonello and Winberry (2020) argue that highly levered firms with a low credit rating respond *less* to monetary policy, which they interpret as evidence that financial constraints dampen the effect of monetary policy on investment. Relatedly, Vats (2020) argues for a state-dependent effect: financial constraints dampen monetary transmission during normal times and amplify it during downturns. Nearly three decades after Gertler and Gilchrist (1994), the question of whether financial constraints amplify or dampen the transmission of monetary policy has remained somewhat unsettled.

Two data constraints have hindered progress on this question. First, firm-level data covering private firms and small and medium enterprises (SMEs) is scarce and often available only at the annual frequency. This is problematic, since private firms and SMEs are precisely the type of firms that are thought to face tight financing constraints. Moreover, annual data is not well suited to estimate dynamic responses to monetary shocks, which arrive at a higher frequency (i.e., several times per year). Second, existing firm-level proxies for the likelihood of being financially constrained tend to perform poorly in practice. Researchers have used proxies that combine information on firm size, age, and information from financial statements (i.e., dividend paying status, cash flows, leverage ratio, etc.) to identify which firms are likely to

[1] Similarly, other papers argue that interest rate covenants or floating rate debt amplify the effect of monetary policy on investment (e.g., Greenwald, 2019 and Ippolito, Ozdagli and Perez-Orive, 2018). While Crouzet and Mehrotra (2020) find that small firms in the U.S. manufacturing sector adjust investment more than large firms over the business cycle, they do not adjust their debt more, which points to factors other than access to credit to explain the excess *cyclicality* of small firms.

face financing constraints. However, Farre-Mensa and Ljungqvist (2016) review several popular proxies for measures of constraints based on firms' public statements and balance sheet information and find that they do not perform well at identifying firms that are plausibly constrained.

In this paper, we make progress on both fronts. First, we harmonize Canadian administrative data from different sources to construct a monthly panel dataset on firm employment, which covers the universe of firms in Canada over the 2000–2016 period. We combine this dataset with identified Canadian monetary policy shocks from Champagne and Sekkel (2018), which are constructed in the spirit of Romer and Romer (2004). This dataset is ideal for our investigation since it is both universal (i.e., it covers essentially all businesses operating in Canada) and our outcome variable (i.e., employment) is available at the monthly frequency, allowing us to trace out the dynamic response of firm-level employment following monetary policy shocks.

Second, we build a new firm-level proxy for the likelihood of being credit constrained using our administrative balance sheet data merged with a survey on SME financing activities and outcomes. The survey allows us to observe specifically the need *and* ability to obtain external financing at the firm level, which we can then relate to firm characteristics. We thus use the survey information on observed financing outcomes to identify precisely which firms are constrained in a given year and then assess, in an agnostic manner, which firm characteristics matter to predict the likelihood that a firm is constrained. Importantly, our proxy has a cardinal interpretation (i.e., a value of 0.1 corresponds to a 10% probability of being constrained), which is crucial for our empirical decomposition, as we discuss next.

We then provide a simple and easy-to-interpret empirical decomposition—which combines microdata, the proxy, and the identified monetary policy shocks—to estimate the contribution of credit constraints to the transmission of monetary policy. Conceptually, our goal is to decompose the transmission mechanism of monetary policy into a direct effect, which operates via changes in interest rates, and an indirect effect, which operates via changes in the tightness of credit constraints.

The implementation of our decomposition is simple: we estimate a panel local projection specification for firm-level employment, where we add an interaction of the monetary shock with our proxy. By setting the coefficient on this interaction to zero, we obtain the counterfactual response of employment to monetary policy shutting down the effect of credit constraints. We then aggregate those counterfactual firm-level responses using employment weights, hence obtaining an aggregate counterfactual. Overall, we find that credit constraints faced by SMEs amplify the response of employment to a monetary policy shock and account for roughly two thirds of the aggregate response of employment.[2]

[2]Note that there could be other "alternative channels" through which monetary policy differentially affects

Our proxy is key to uncovering the role of financial constraints in the transmission of monetary policy. We thus proceed with a thorough analysis of its properties. First, we show that it correlates strongly with several standard proxies from the literature, such as leverage and earnings-to-debt. Hence, we view our proxy as a data-driven approach that combines information on firm financials such that it optimally predicts the likelihood of a firm facing credit constraints. Interestingly, this suggests that both asset-based and earnings-based constraints might be important. Second, we show that, in the cross-section of firms, a higher likelihood of being constrained is associated with a lower growth rate of employment and debt. Finally, we provide non-parametric evidence that the response of employment to a monetary policy shock is decreasing monotonically in the likelihood of being credit constrained (as measured by our proxy). This piece of cross-sectional evidence is consistent with the amplification effect of financial constraints in the monetary transmission (Bernanke et al., 1999) and pins down the sign of the indirect effect in our decomposition.

The implementation of our empirical decomposition uses regression coefficients from a panel local projection model that leverages both the monetary policy shock and the proxy. We then provide a micro foundation for the empirical specification using a stylized model of firm employment. Through the lenses of the model, the regression coefficients map neatly to structural parameters.

Overall, our interpretation of the evidence is that stimulative monetary policy disproportionately affects the ability of some firms (e.g., those with a high probability of being constrained according to our proxy) to obtain credit, leading them to increase their employment (relative to the baseline case where there is no monetary policy shock). Consistent with this, we provide two pieces of evidence supporting this mechanism. First, we show that, on average, our proxy responds to monetary shocks. For instance, a tightening leads to a deterioration of firm balance sheets, which our proxy approach associates with a higher probability of being denied credit. Second, evidence from survey data that shows that, in response to a contractionary monetary policy shock, lenders and borrowers both report tightened lending standards. This is suggestive evidence that monetary policy operates not only via changes in the price of credit but also via changes in non-price credit conditions.

It is worth noting that our analysis of financial constraints focuses on (i) SMEs (rather than all firms), (ii) debt financing (rather than equity financing), and (iii) the extensive margin of financial constraints (i.e., the ability to access external credit) rather than the intensive margin (i.e., the sensitivity of the interest rate spread as a function of balance sheet health). Regarding

firms. For example, if young firms respond more to monetary policy irrespective of their ability to access credit, and young firms tend to be more constrained, then failing to account for the direct effect of age on the response to monetary policy will lead to an overestimation of the role of credit constraints. Our approach also allows us to let the direct effect of monetary policy vary with firm observables. We show that when controlling for different channels, such as age, labor productivity and size, the indirect decreases to about one half.

the first point, we focus on SMEs because they account for nearly all of the aggregate response of employment to monetary policy. Perhaps surprisingly, we find that large firms (i.e., those with more than 500 employees) do not respond at all to monetary policy shocks. Regarding the second point, we focus on debt financing because, as we show, SMEs rely almost exclusively on debt to raise funds (i.e., equity financing is a not a meaningful source of financing). Regarding the final point, Leung, Meh and Terajima (2008) provide evidence that Canadian lenders follow a more uniform pricing policies (i.e., conditional on obtaining credit, interest rate spreads are small) relative to U.S. lenders, suggesting that the intensive margin of credit constraints is less important in Canada.[3] Consequently, our focus on the extensive margin implies that our results are conservative (i.e., they provide a lower bound on the contribution the indirect effect), given that we ignore the fact that some firms could be constrained by high interest rate spreads.

Related literature. At a broad level, our paper builds on the idea that monetary policy can affect real economic activity not only via intertemporal substitution, but also by changing the amount of credit that firms are able to obtain (the credit channel). The credit channel is usually thought to arise due to financial frictions, faced either by the banking sector or by firms. These are old ideas (see Bernanke and Gertler, 1995 and Mishkin, 1995 for early literature reviews), yet they are still central to understanding the transmission mechanism of monetary policy.

More specifically, we contribute to several strands of literature. First, our proxy approach relates to papers that construct indirect proxies to identify firms that are most likely to be financially constrained. Early contributions build proxies by using commentary by public firm managers (e.g., see Kaplan and Zingales, 1997; Lamont, Polk and Saaá-Requejo, 2001; Hadlock and Pierce, 2010) or informed by structural models (Whited and Wu, 2006). As discussed earlier, these celebrated proxies tend to perform poorly at identifying firms that are actually credit constrained (see Farre-Mensa and Ljungqvist, 2016 and Moyen, 2004). Compared to these studies, we construct our proxy using survey data on *observed* outcomes of requests for external credit of SME firms, instead of qualitative and quantitative information in publicly-listed earnings reports, and then assess which firm observables are relevant to predict whether or not a firm is financially constrained.[4]

Our paper also contributes to the empirical literature on the role played by credit constraints in the transmission of monetary policy to firms. This literature has proposed various measures associated with credit constraints such as cash flows (Fazzari, Hubbard, Petersen, Blinder and Poterba, 1988), size (Gertler and Gilchrist, 1994; Caglio et al., 2021), age and

[3]Outside of Canada, there is existing evidence that the loan market tends to clears through quantities rather than prices (see Khwaja and Mian, 2008 for Pakistan and Pinardon-Touati, 2021 for France).

[4]Cao and Leung (2019) study the relationship between financial constraints and productivity using the same survey. They show that assets, leverage, and cash flows are important predictors of being constrained.

dividend-paying status (Cloyne et al., 2023), liquidity (Jeenas, 2019), credit rating (Ottonello and Winberry, 2020), leverage (Lakdawala and Moreland, 2021), outstanding bank loans (Ippolito et al., 2018), and credit line borrowing capacity Greenwald, Krainer and Paul (2021). Our work differs from these papers in some important dimensions. First, our sample of firms covers the non-farm private sector of the economy, including both privately held and publicly listed firms. Over 99 percent of firms in the Canadian economy are SMEs, and they are the ones most likely to be constrained. Second, while most papers cited above look at investment, we focus on employment, as SMEs account for half of total employment and almost all of the response of aggregate employment to a monetary policy shock. Third, our proxy is built using survey data that contains direct information on the observed need for credit and the outcome of credit requests. Fourth, we use a simple decomposition that combines our microdata and the proxy to quantify the effect of credit constraints in the transmission of monetary policy.

One related paper that also uses a representative sample of the economy covering SMEs is Bahaj et al. (2022). Using U.K. microdata, the authors assess the role of financial constraints in the transmission of monetary policy through a specific collateral channel that operates via real estate prices. They first show that young and more levered firms react more to monetary policy and find that these firms often use their directors' homes as a key source of collateral for corporate loans. They then show that firms whose employment is the most sensitive to monetary policy are the same firms that see more variation in the value of their directors' homes following changes in interest rates. Their main result is thus that real estate prices (i.e., collateral values) play a substantial role in the transmission of monetary policy to firms. Our paper differs from Bahaj et al. (2022) in the way we look at financial constraints. While they use a novel framework to assess the importance of a specific collateral constraint (i.e., real estate prices), we identify constrained firms irrespective of the source of the constraint.

Overview of the paper. In Section 2, we describe our administrative microdata and present macro and micro evidence on the effects on monetary policy. In Section 3, we describe the survey data on SME financing activities and the methodology used to construct the proxy. In Section 4, we present an empirical decomposition and estimate the contribution of credit constraints in the transmission of monetary policy to employment. Finally, we map our decomposition to a simple structural model and provide suggestive evidence for the indirect effect of monetary policy using survey data on firms and lenders.

2 Empirical Impulse Response Functions

In this section, we describe our empirical strategy to identify the effect of monetary policy on employment in Canada over the 2000–2016 period. First, we describe our series of monetary policy shocks. Second, we lay out our specification to estimate the dynamic response of aggregate employment (and other variables of interest) to monetary policy shocks. Third, we describe our firm-level microdata. Finally, we estimate impulse responses functions (IRFs) along the firm-size distribution (i.e., separately for small, medium, and large firms).

2.1 Monetary policy shocks

We construct our series of monetary policy shocks using the narrative approach pioneered by Romer and Romer (2004) and applied to the Canadian context by Champagne and Sekkel (2018, CS henceforth). The identification strategy consists of using historical documents to construct a series of intended changes in the target policy interest rate along with a database of real-time data and forecasts assembled from the Bank of Canada's staff economic projections. These real-time data and forecasts act as the policy-makers' information set and effectively isolate the innovations to the intended policy changes that are orthogonal to information about past, current, and future economic developments.

CS depart from Romer and Romer (2004) on two fronts: (i) by controlling for U.S. interest rates as well as the USD/CAD exchange rate in the policy-makers' information set, and (ii) by accounting for the structural break in the conduct of monetary policy caused by the announcement of inflation-targeting in 1991.[5] With this new monetary policy shocks series, CS estimate the effect of monetary policy on real gross domestic product (GDP) and the Consumer Price Index (CPI) in Canada. Overall, they find that while the effects on output are very similar to those found for the U.S., they are weaker for the price level. For our analysis, we re-estimate CS' monetary shocks for our period of interest (i.e., 2000–2016) using the same specification (see equation A.1 in Appendix A.1).

2.2 Aggregate data

We begin by describing how our monetary policy shock series affects macroeconomic aggregates. Let Y_t be the variable of interest while i_t and ϵ_t are respectively the nominal Bank rate (i.e., the interest rate that the Bank of Canada charges on short-term loans to financial institutions) and the monetary policy shock. We follow Ramey (2016) and estimate, for every monthly horizon $k = \{0, \ldots, K\}$, the following local projection specification:

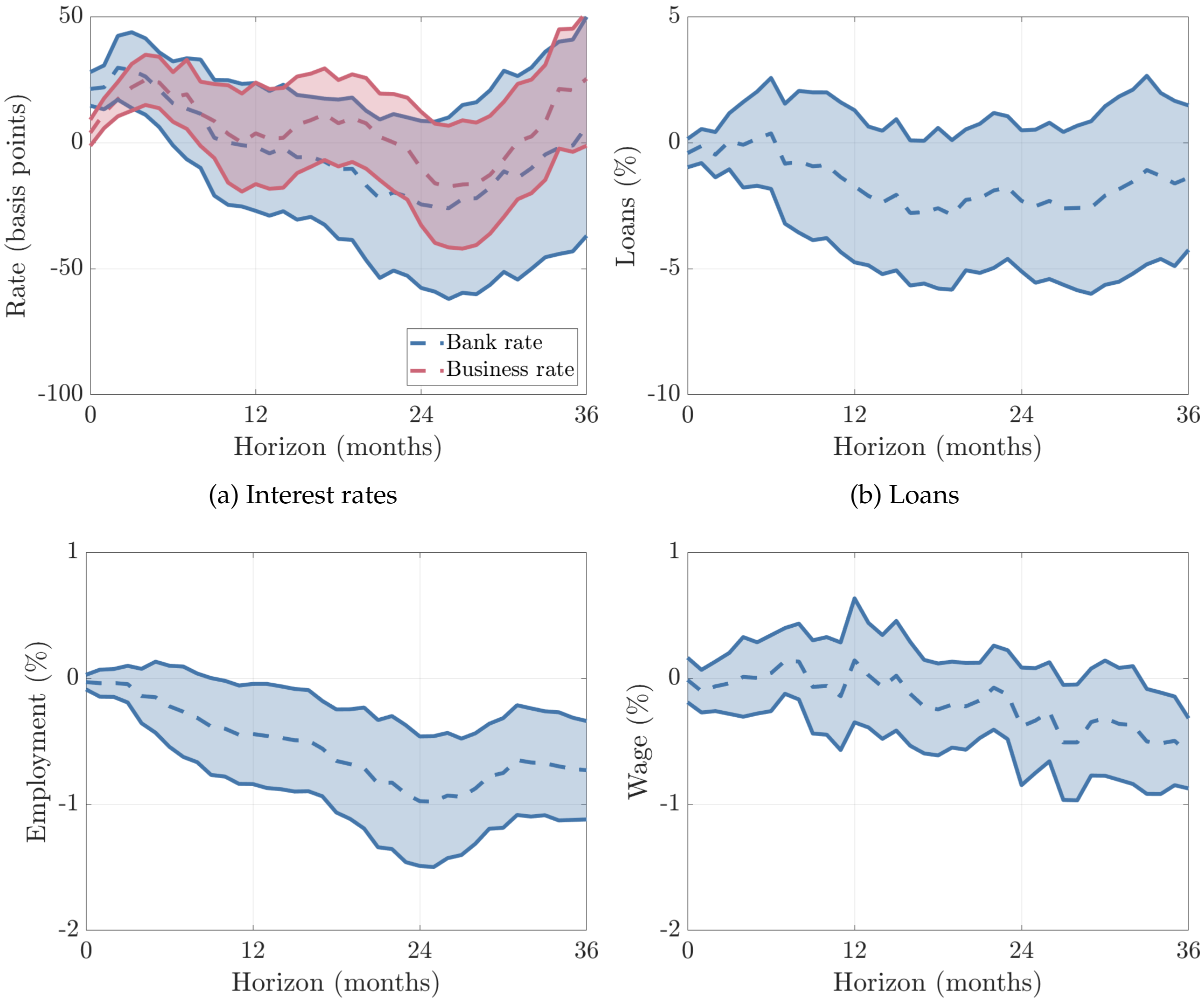
$$\underbrace{\log Y_{t+k}}_{\text{Aggregate variable}} = \underbrace{z_t'\lambda^k}_{\text{Controls}} + \underbrace{\beta^k \varepsilon_t}_{\text{Monetary shock}} + \underbrace{u_{t+k}}_{\text{Error}}, \tag{2.1}$$

[5] See Appendix A.1 for more details.

The controls are:

$$z_t' \lambda^k \equiv \mu^k + \sum_{p=1}^{P} \rho_p^k Y_{t-p} + \sum_{q=1}^{Q} \delta_q^k i_{t-q}, \tag{2.2}$$

where μ^k is the regression constant, and u_{t+k} is the regression residual with $E(u_{t+k}|\varepsilon_t) = 0$. The estimated IRF is $\{\hat{\beta}^k\}_{k=1}^{K}$, and we use Newey-West standard errors to account for serial correlation of the errors. We set the lags to $P = 12$, $Q = 3$ and the maximum projection horizon to three years (i.e., $K = 36$).



(a) Interest rates

(b) Loans

(c) Employment

(d) Wages

Figure 1: Response of financial and real variables to a monetary policy shock (25 basis points, 90% confidence intervals).

Notes: "Bank rate" is obtained from Statistic Canada's table 1010012201 and covers the 2000–2016 period; "Business rate" is an effective borrowing rate faced by businesses, which is obtained from the Bank of Canada's website and covers the 2000–2016 period; "Loans" is an aggregate measure of business loans outstanding obtained from Statistic Canada's table 1010011601 and covers the 2000–2016 period; "Employment" and "Wages" are obtained from Statistic Canada's table 1410022301 and cover the private non-farm economy (all industries excluding NAICS 00, 11, 22, 61, 62, and 92) over the 2001–2016 period. All data are at monthly frequency.

Figure 1 plots the IRF for the Bank rate, the business effective interest rate, as well as the logarithm of business loans, aggregate employment, and average weekly earnings. All IRFs are expressed as the response to an unexpected increase of 25 basis points (bps) in the policy rate (i.e., monetary policy shock).[6] As expected, the Bank rate increases by about 25 bps on impact, while the business effective borrowing rate follows with a lag. Business loans respond strongly, decreasing by two percent at peak and remain one percent lower after three years. Employment decreases by about one percent at peak (two years) while average weekly earnings do not react for 15 months before starting to decline, ending slightly lower than 0.5 percent after three years.

Overall, these responses are consistent with those found in the empirical monetary literature (see Coibion, 2012 and Ramey, 2016 for the U.S., Bahaj et al., 2022 for the U.K., and Champagne and Sekkel, 2018 for Canada), and relate to existing findings that credit shocks affect employment (e.g., Chodorow-Reich, 2014, Bottero et al., 2020, and Pinardon-Touati, 2021). While we find that a contractionary monetary policy shock causes both loans and employment to decline, our aggregate results do not necessarily imply a causal effect from the decline in loans to employment. In Appendix C.7, we provide suggestive evidence that lenders tighten their lending standards in response to an unexpected increase in interest rates, which leads to a rationing of credit.

2.3 Firm-level data

We use Statistics Canada's *National Accounts Longitudinal Microdata File* (NALMF), a dataset that comprises nearly all businesses operating in Canada, including incorporated and unincorporated businesses, non-profit organizations, government departments, and institutions for all industrial sectors in the economy.

The data is organized at the enterprise level. An enterprise is the business level associated with a complete set of financial statements. While a corporation can comprise several enterprises operating in different industries, an enterprise can itself comprise several establishments operating in different geographical locations. The financial information included in the NALMF draws from corporate income tax records (T2 form), which include annual balance sheets and income statements. In addition, we merge the NALMF with employment records from the "Statement of account for current source deductions" (PD7 form), which include the number of employees at the monthly frequency.[7]

The resulting dataset has a number of features that make it nicely suited for our analysis.

[6] The "Bank rate" is the rate of interest that the Bank of Canada charges on short-term loans to financial institutions. Since 1996, it is set at 25 bps over the target for the overnight rate. The "effective business borrowing rate" is a weighted-average borrowing rate for new lending to non-financial businesses, estimated as a function of bank and market interest rates. "Business loans" is the aggregate face value of outstanding loans issued by chartered banks to businesses. See the "notes" section under Figure 1 for the exact data sources.

[7] All Canadian employers must, by law, remit Canada Pension Plan contributions, Employment Insurance premiums, and income tax deductions to the Canadian Revenue Agency (usually bi-monthly) and report in the PD7 form the number of employees on their payroll.

First, it contains the universe of firms operating in Canada. This includes all sectors of the economy, all firm-size groups (i.e., SMEs as well as large firms), and all legal forms (i.e., unincorporated as well as private and publicly listed corporations). Second, the dataset contains many variables of interest for our analysis, such as employment, age, and financial information, allowing us to compute standard financial ratios (i.e., leverage, liquidity, and interest coverage) commonly used in the corporate finance literature. Third, the key variable for our analysis— employment—is available at the monthly frequency rather than at the annual frequency as in most administrative datasets. This is ideal to estimate IRFs to monetary policy shocks, which arrive at a high frequency. The dataset covers 17 years of data (from January 2000 to December 2016), giving us up to 204 monthly observations per firm.

We impose some restrictions to construct our "main sample." First, we focus on the private non-farm economy (i.e., we exclude businesses in agriculture and the government sector).[8] We also restrict attention to firms that have at least ten employees for at least one year. Finally, we construct a balanced panel by keeping only those firms that have non-missing values for employment over the full sample period. Using a balanced sample allows us to have a relatively stable set of firms and avoid entry and exit of very small firms, which can have highly volatile employment. This yields a balanced sample of 48,310 different firms, for a total of about 9.9 million monthly observations. Relative to the unbalanced sample, our balanced sample has, on average, about 22 percent of firms and 32 percent of total employment.

Summary statistics. Table 1 presents some statistics across different firm size (employment) categories for our main sample. Several observations stand out. First, as is typically the case, the firm-size distribution is highly skewed. While large firms (i.e., firms with more than 500 employees) represent only 1 percent of all firms in our sample, they account for 52 percent of aggregate employment. In contrast, small firms (i.e., firms with less than 100 employees) represent the vast majority of firms in Canada (94 percent) but account only for 33 percent of aggregate employment. Second, small firms are on average younger than larger firms.[9] Third, proxies for financial health are strongly related to firm size. Among SMEs (i.e., firms with less than 500 employees), there is no clear relationship between leverage and firms size; however, leverage of large firms is substantially larger. Liquidity is materially higher for small firms relative to large firms, as small firms have a larger share of short-term assets (e.g., cash) in their total assets. The earnings-to-debt ratio decreases with firm size (large firms borrow more relative to their cash flows), and large firms are almost twice as profitable as SMEs, with profit

[8]In addition to removing the public administration sector (NAICS 81), we also remove remove education, healthcare, and social services (NAICS 61 and 62) as well as utilities (NAICS 22), since most of the largest utilities in Canada are state-owned enterprises. We also remove unclassified business (NAICS 00) and businesses with no industry code.

[9]Because we use a balanced sample, the average firm in our sample is older than in the universe of firms in Canada.

margins at 13 percent on average in our sample.

Table 1: Summary statistics (administrative data, main sample)

Variables	Size groups					Total
	< 20	$20-100$	$100-250$	$250-500$	≥ 500	
Shares (%)						
Firm	64.3	29.8	3.7	1.0	1.1	100
Employment	12.5	20.4	9.5	6.1	51.7	100
Averages						
Employment	11.42	40.15	151.50	350.33	2,721.09	58.91
Age	16.8	17.9	19.6	19.2	19.2	17.3
Financial ratios						
Leverage	0.56	0.62	0.64	0.54	0.75	0.72
Liquidity	0.50	0.39	0.48	0.33	0.36	0.37
Earnings-to-debt	0.13	0.08	0.07	0.06	0.04	0.05
Profit margin	0.07	0.07	0.08	0.09	0.13	0.11

Notes: "Firm" and "Employment" shares are the share of the number of firms and total employment in each firm-size group in our main sample, respectively, averaged over the years 2000–2016. 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. The main sample includes 9,855,240 firm-month observations.

Empirical specification. We now describe the empirical specification that we use to estimate IRFs using the firm-level data. We first validate the representativeness of our main sample (i.e., show that the IRFs are consistent with evidence from aggregate data) and then describe the differential effect of monetary policy shocks along the firm-size distribution.

The specification for the firm-level data is a panel version of the one that we use with the aggregate data (see Equation 2.1). Let $\log L_{i,t}$ be the logarithm of the employment of firm i in month t, while i_t and ϵ_t are respectively the Bank rate and the monetary policy shock as above. For every monthly horizon $k \in \{0, \ldots, K\}$, we estimate the following local projection specification:

$$\underbrace{\log L_{i,t+k}}_{\text{Firm-level employment}} = \underbrace{z'_{i,t}\lambda^k}_{\text{Controls}} + \underbrace{\beta^k \varepsilon_t}_{\text{Monetary shock}} + \underbrace{u_{i,t+k}}_{\text{Error}}, \tag{2.3}$$

The controls are:

$$z'_{i,t}\lambda^k \equiv \mu^k_{j,m} + \sum_{p=1}^{P} \rho^k_p L_{i,t-p} + \sum_{q=1}^{Q} \delta^k_q i_{t-q}, \tag{2.4}$$

where $\mu^k_{j,m}$ is an industry-month fixed effect (i.e.two-digit NAICS), which captures seasonality. We set the number of lags to $P = 12$ lags of log employment and $Q = 3$ lags of the interest rates, as in the aggregate specification (2.1).

The estimated impulse response function is $\{\hat{\beta}^k\}_{k=1}^{K}$. We weigh the observations by their employment at time $t-1$ to preserve aggregation and we use Driscoll and Kraay (1998) standard errors to account for heteroskedasticity, autocorrelation, and cross-sectional dependence.

Consistency with aggregate evidence. As described above, our main sample is restricted to a balanced panel of firms within the private non-farm economy having at least ten employees on average per year. We first validate that despite these restrictions, our firm-level IRFs estimated using specification (2.3) are consistent with the aggregate IRFs estimated using specification (2.1) and publicly available data for the private non-farm economy.

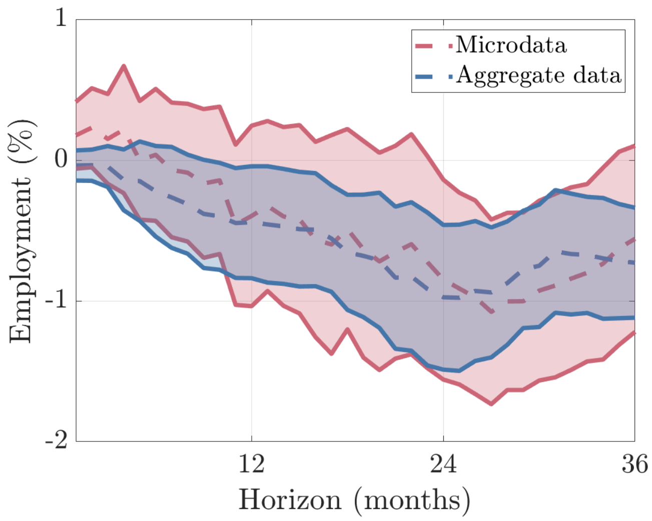


Figure 2: Employment impulse response function: microdata versus aggregate data (25 basis points monetary policy shock, 90% confidence intervals).

Notes: "Microdata" employment is the (weighted) average impulse response of firm-level employment in our main sample (9,855,240 firm-month observations over the 2000–2016 period). "Aggregate data" employment series is obtained from Statistic Canada's table 1410022301 and cover the private non-farm economy (all industries excluding NAICS 00, 11, 22, 61, 62, and 92) for the 2001–2016. All data are at monthly frequency.

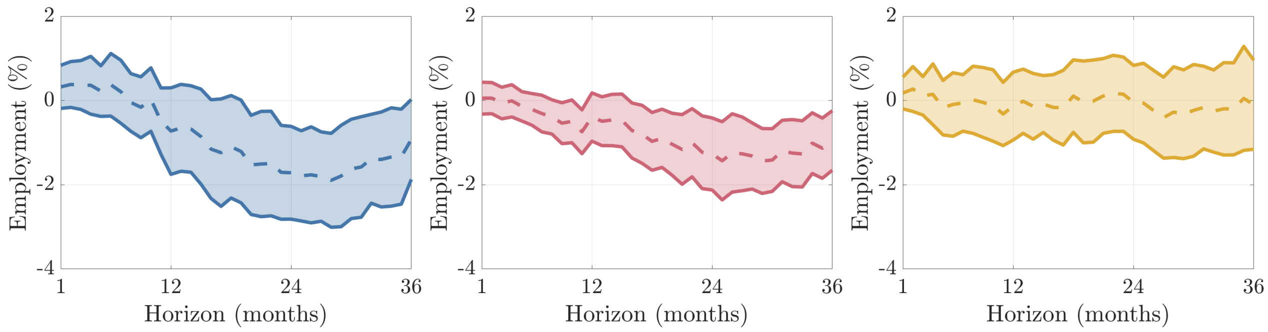
Figure 2 shows that both estimated IRFs track each other very well. While the response in the microdata declines more slowly, both IRFs imply employment declines of roughly -0.5 and -1.0 percent after 12 and 24 months, respectively. The response in the microdata has a slightly larger peak decline (after 28 months) and wider confidence intervals. Both IRFs end up after three years with employment levels that are slightly lower than 0.5 percent.

These results suggest that firm entry and exit are not key contributors to the response of aggregate employment to monetary policy. In Appendix C.3, we provide direct evidence on the response of firm entry and exit to monetary policy shocks and find small effects, suggesting that incumbent firms are likely driving the response of aggregate employment to monetary policy shocks.

IRFs along the firm-size distribution. We now estimate the employment response to monetary policy shocks for different firm-size groups. We classify firms into three size categories: small firms (less than 100 employees), medium firms (100 to 500 employees), and large firms (more than 500 employees).[10] These three size groups allow us to estimate whether the em-

[10]Firm size is determined at time t, consistent with the timing of the monetary policy shock in equation (2.3).

ployment response of SMEs (i.e., < 500 employees), which are the focus of this paper, differs from the response of large firms.



(a) Small (< 100 emp.) (b) Medium ($100 - 500$ emp.) (c) Large (> 500 emp.)

Figure 3: Response of employment to a monetary shock by firm-size groups (25 basis points, 90% confidence interval).

Figure 3 plots the impulse responses for the three size groups. Three observations stand out. First, SMEs exhibit a large and negative responses to contractionary monetary policy shocks, although the responses are not significant during the first 12 months. Second, the responses of employment for small- and medium-sized firms peak at around -1.9 percent and -1.4 percent, respectively, in both cases roughly 24 to 30 months following the shock. Both groups end up with employment that is 1.0 percent lower after three years. Third, large firms do not adjust their employment much following a monetary policy contraction. The response is not statistically different from zero at any point over the 36-month horizon.

Despite the fact that SMEs account for less than half of aggregate employment (see Table 1), this evidence implies that the aggregate response of employment to monetary policy is almost entirely accounted for by SMEs. Consequently, understanding why SME employment is more sensitive is key to the transmission mechanism of monetary policy to employment.

Heterogeneity beyond firm-size. A growing body of evidence documents heterogeneity in firm-level responses to monetary policy by age, industry, leverage, liquidity, earnings-to-debt, dividends (profitability), etc. In Appendix C.4, we provide a detailed assessment of employment responses along these dimensions. Individually, most of these variables have some explanatory power, a feature of the data that we leverage in the construction of our proxy in the next section.

3 The Proxy

We develop a proxy approach that assigns a time-varying probability (or "likelihood") of being financially constrained to all SMEs in our sample. We focus on SMEs for two reasons. First, as we show in the previous section, employment at large firms barely adjusts following a monetary policy shock. Second, as we will describe below, the construction of our proxy is based on a survey of financing activities of SME firms in Canada.

We proceed in two steps to construct our proxy. First, we use survey data—which contains information on credit requests and outcomes—to estimate the relationship between the event of being financially constrained and observable firm characteristics. Second, we use this estimated relationship to impute firm-level, time-varying probabilities of being constrained in our main sample (i.e., the administrative dataset described in the previous section).

3.1 Survey data

The *Survey on Financing and Growth of Small and Medium Enterprises* (SFGSME) is a cross-sectional dataset that reports detailed information on activities and outcomes of financing among Canadian SMEs (i.e., firms with 500 employees or less). It is conducted every three years and has a target sample size of roughly 10,000 firms. For our analysis, we will use the 2011, 2014, and 2017 waves of the survey. Importantly for the construction of our proxy, the survey is merged with the firm-level administrative tax records described in Section 2.3.

We are interested in a particular subset of survey questions that are related to external financing. In particular, firms are asked (i) whether they requested external financing in the past 12 months; (ii) which type of financing they requested; (iii) whether their request was fully accepted, partially accepted, or rejected; and (iv) the amount requested.[11] To the best of our knowledge, our proxy is one of the first to use direct evidence on observed outcomes of financing requests from a large cross-section survey of SMEs.[12]

We impose similar sample restrictions in the SFGSME as we did in the NALMF (see Section 2.3). First, we focus on firms that operate in the private non-farm sector with at least five employees. Then, we drop observations with missing values for age, total assets, short-term assets, total liabilities, short-term liabilities, revenues, or expenses. We pool the 2011, 2014, and 2017 waves of the survey together, yielding 13,604 observations.

Definition of a financially constrained firm. We say that a firm is financially constrained if its largest request for external financing within the last 12 months was denied or not fully accepted. Hence, to be financially constrained, a firm needs to (i) request financing and (ii) have its request denied. Table 2 shows that around 32 percent of respondents claim to have made a financing request in a given year (i.e., either a mortgage loan, a line of credit, a term loan, or a credit card loan) and that only about 2 percent of these requests are for equity financing. Since

[11] See Appendix A.2 for the detailed questions in the survey.

[12] One notable exception is Berg (2018), who studies the transmission of credit supply shocks using a sample of loan applications to SMEs by a large European lending institution.

SMEs rely almost exclusively on credit, from now on we refer to external financing as debt financing. Amongst debt financing requests, we can see that on average, larger SME firms request financing more often relative to smaller ones. Moreover, credit cards, term loans, and lines of credit are the most pervasive type of credit requests for SME firms.

Table 2: Type of financing requests in the last 12 months (annual frequency, %)

Variables	Size groups				Total
	< 20	$20 - 100$	$100 - 250$	$250 - 500$	
Debt financing	30.4	35.0	43.1	32.0	31.7
Line of credit	15.3	17.1	18.7	16.2	15.8
Term loan	9.2	11.2	17.7	9.4	9.8
Mortgage	4.9	7.3	7.9	5.7	5.5
Credit card	11.8	13.2	14.8	12.6	12.2
Equity financing	1.7	2.5	2.5	4.1	1.9

Notes: Percentage of firms in the *Survey on Financing and Growth of Small and Medium Enterprises* sample requesting credit by size groups. For example, "Mortgage" refers to the percentage of firms requesting a mortgage for each size group. We pool together the survey years 2011, 2014 and 2017, yielding 13,604 firm-year observations.

Descriptive statistics. Table 3 presents summary statistics across different firm-size categories in the survey (i.e., same variables as in Table 1), along with additional information regarding financing activities and outcomes over the past 12 months. The survey data aligns closely with the main sample described earlier (see Table 1).[13]

The bottom panel reports the percentage of (i) firms requesting credit (same as first row in Table 2); (ii) those requests accepted; and (iii) firms financially constrained (according to our definition above) across the size categories. About 32 percent of SMEs request credit, and 87 percent of those requests are on average accepted. The smallest SMEs (< 20) request somewhat less (30.4 percent) and have a substantially smaller acceptance rate than other SMEs. Overall, about 4 percent of SMEs are constrained. An issue one could raise is that some firms that need financing might not request credit because they believe that their request will be denied. Fortunately, the survey asks respondents who do not request credit the reason behind their choice. Panel A of Table 4 shows that the main reason (93 percent of the time) is indeed that they do not need financing. Less than 2 percent of firms that do not request financing claim that the reason is they thought they would be turned down.[14]

[13]First, the SFGSME sample is entirely composed of SME firms, most of which (98 percent) are less than 250 employees; SMEs with 250 to 500 employees comprise a small fraction of firms (0.3 percent) but about 5 percent of employment in the sample. Second, the average number of employees across firm-size categories is very similar to those found in our main NALMF sample (Table 1). Third, age increases with size, although average firm age is somewhat higher in the survey than in our main sample. Fourth, all the traditional financial proxies relate to firm size in the same way as found in our main sample. Overall, SME characteristics in the survey are very similar to those in our main sample.

[14]In Appendix A.2.1, as a robustness check we expand the definition of being constrained to include those firms that did not request credit due to: (i) thinking they would be turned down; (ii) applying for credit was too difficult or time consuming, and (iii) the cost of financing was too high. We come back to this below.

Panel B of Table 4 presents evidence on the reasons why SMEs' requests for external financing are denied. About 33 percent of requests have been turned down due to insufficient collateral, while 29 percent have been turned down because of insufficient cash flows. Poor credit history accounts for about 18 percent of denied requests. This evidence suggests that constraints based on asset and cash flows, as well as age, are important for SME firms when requesting credit.

Table 3: Summary statistics (survey data)

Variables	Size groups				Total
	< 20	$20-100$	$100-250$	$250-500$	
Shares (%)					
Firm	75.2	22.5	2.0	0.3	100
Employment	35.3	45.2	14.6	4.9	100
Averages					
Size	9.4	40.3	143.8	330.0	20.1
Age	21.5	24.8	28.7	30.8	22.4
Financial ratios					
Leverage	0.60	0.64	0.59	0.48	0.58
Liquidity	0.53	0.57	0.45	0.11	0.43
Earnings-to-debt	0.12	0.08	0.10	0.05	0.09
Profit margin	0.05	0.03	0.04	0.07	0.04
Debt financing (%)					
Requested credit	30.4	35.0	43.1	32.0	31.7
Request accepted	85.5	91.9	96.4	92.9	87.4
Constrained	4.40	2.83	1.57	2.29	3.99

Notes: *Survey on Financing and Growth of Small and Medium Enterprises*. "Firm" and "Employment" shares are the shares of the number of firms and total employment in each firm-size group, respectively, in the survey sample averaged over the survey years 2011, 2014, and 2017. The three survey years 2011, 2014 and 2017 pooled together yield a total of 13,604 firm-year observations. "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. "Requested credit" shows the percentage of SMEs that requested credit, and "Request accepted" is the percentage of SMEs' that saw their largest request accepted. "Constrained" is defined as in text as the percentage of firms that requested credit and were denied.

3.2 Proxy construction

The first step in the construction of our proxy is to estimate the relationship between observable firm characteristics and the probability of being financially constrained. We start by describing the firm characteristics we consider, and then we lay out the model selection procedure.

Predictive variables. We select seven variables that have been shown to correlate with financial constraints either directly or through a particular financial ratio: total liabilities; current liabilities; total assets; current assets; revenues; expenses; and age.

Table 4: Reason for not requesting financing and for being denied

A. Reason not requesting financing	Share (%)
Financing not required	92.6
Thought be turned down	1.8
Applying too difficult / time consuming	2.0
Cost of financing too high	1.2
Unaware of financial sources available	2.5
B. Reason denied financing	**Share (%)**
Insufficient cash flows	29.0
Insufficient collateral	33.0
Poor credit history	18.0
Others	20.0

Notes: *Survey on Financing and Growth of Small and Medium Enterprises*. Panel A shows the percentage of firms by reason for not requesting credit while Panel B shows the percentage of firms that were denied credit, by reason for being turned down. "Others" includes various reasons such as project too risky, unstable industry, or no specific reason given by credit provider. We pool together the survey years 2011, 2014 and 2017, yielding 13,604 firm-year observations.

All the variables are at the annual frequency. Total liabilities is the book value of all debts (i.e., it does not include shareholder's equity). Current liabilities is the book value of all debt whose remaining maturity is less than 12 months. Similarly, total assets represents the book value of all assets (including intangibles) and current assets represents assets with a maturity of less than 12 months (i.e., mostly cash and cash equivalents). Revenues and expenses represent, respectively, total annual sales and expenses (i.e., expenses includes all forms of compensation and input costs, but does not include investments). Finally, firm age is defined as the current year minus the business establishment data plus one. Note that the four financial ratios in Table 3 can be expressed as functions of our seven predictive variables (e.g., leverage is total liabilities divided by total assets, liquidity is current assets divided by total assets, etc.). For our analysis below, we take logarithms and demean each variable using cross-sectional year averages.

Model selection. Let $\text{Constrained}_{i,t} \in \{0,1\}$ be an indicator variable that denotes whether firm i is credit-constrained during year t, as defined above. The set of models we consider takes the form

$$\mathbb{P}(\text{Constrained}_{i,t} = 1) = F(x_{i,t-1}, \beta), \tag{3.1}$$

where $x_{i,t-1}$ denote the the observable characteristics of firm i at the end of year $t-1$ and β denotes a parameter vector, and F is an arbitrary function. What is the appropriate model (i.e., function F) for our predictive exercise? We take a pragmatic view and select our model to maximize out-of-sample forecasting performance.

We conduct a horse race using six different models: linear probability (OLS), logit, probit, random forest, and the "always-zero" and "sample-mean" models.[15] The parameters of our exercise are as follows. For each model and simulation, we estimate the parameter β on a "training set" of the survey data (i.e., a randomly drawn sub-sample with 90 percent of the observations) and forecast $\mathbb{P}(\text{Constrained}_{i,t} = 1)$ on a "prediction set" (i.e., the remaining 10 percent of observations not used for estimation). We repeat this exercise 1,000 times, and for each simulation, we compute the root mean squared error (henceforth, RMSE).

Table 5 presents the results of the model selection exercise. We find that the linear probability (OLS) model performs best, having the lowest RMSE 61 percent of the time, while the probit and logit models come second and third with the lowest RMSEs 23 percent and 14 percent of the time, respectively.

Table 5: Model selection results

Model	Average RMSE	Lowest RMSE (%)
Random forest	0.182	1.0
OLS	0.179	60.5
Logit	0.179	13.7
Probit	0.179	23.5
Always-zero	0.184	0.0
Sample-mean	0.181	1.3

Notes: *Survey on Financing and Growth of Small and Medium Enterprises*. "Average RMSE" is constructed by averaging the root mean squared errors across simulations; "Lowest RMSE" reports the percentage of simulations in which a particular model has the lowest root mean squared error. 1000 simulations.

Construction of the proxy. Given its relative performance and simplicity, we select the OLS model as our baseline predictive model and re-estimate the parameter vector β on the full survey data. Table 6 reports the estimated coefficients with their associated standard errors. A few observations stand out. First, the signs of the coefficients are consistent with standard theory: higher liabilities, lower assets, higher expenses, and lower revenues all increase the likelihood of being constrained. Second, younger firms are more likely to be constrained. Finally, the magnitudes of the coefficients are somewhat different: for instance, a 10 percent relative decrease in total revenues increases the probability of being constrained by 0.24 percentage points. Relative 10 percent decreases in total assets and total debt translate into 0.11 and -0.14 percentage point changes in the probability of being constrained, respectively —about twice as much as their short-term (current) counterparts.[16]

[15] "Linear probability" corresponds to $F(x, \beta) = x'\beta$; "Logit" corresponds to $F(x, \beta) = \frac{1}{1+e^{x'\beta}}$; "Probit" corresponds to $F(x, \beta) = \Phi(e^{x'\beta})$, where Φ is the CDF of a standard normal distribution. The "Random forest" model does not have a closed-form expression for F. It consists of a machine learning algorithm used for prediction. To implement it, we use the "classification problem" Stata function described in Schonlau and Zou (2020) with 500 trees. Finally, the "Always-zero" model corresponds to $F(x, \beta) = 0$ and the "sample-mean" model corresponds to $F(x, \beta) = \overline{\mathbb{P}(\text{Constrained} = 1)}$, i.e., the sample mean. These last two models are used as benchmarks.

[16] Because $Constrained_{i,t} \in [0, 1]$ and its sample average is about 0.039 (Table 3), these coefficients are not trivial. For example, consider a firm with balance sheet characteristics similar to the average firm, but with 10 percent

Table 6: Determinants of credit constraints

Variable	Coefficient	Std error
Total liabilities	0.014^{***}	0.003
Current liabilities	0.006^{**}	0.003
Total assets	-0.011^{***}	0.003
Current assets	-0.006^{**}	0.003
Revenue	-0.024^{***}	0.007
Expense	0.014^{*}	0.007
Age	-0.008^{***}	0.002
Constant	0.039^{***}	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 (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$). $R^2 = 0.02$. The dependant variable of the regression is $Constrained_{i,t}$ as defined in the text.

The next step is to impute the probability of being credit-constrained for each firm-year observation in our administrative dataset described in the previous section (i.e., the main sample). Using data on firm observables $x_{i,t}$ in the main sample and the parameter vector $\widehat{\beta}$ estimated in the survey data, we construct the probability of being credit constrained $p_{i,t}$ as

$$p_{i,t} = \overline{p} + x'_{i,t-1}\widehat{\beta}. \tag{3.2}$$

The value $\overline{p}$ is set to 2.9 percent so as to match the employment-weighted probability of being constrained in the survey.[17] In Appendix A.2.1, we provide a robustness exercise where we expand the definition of being constrained to include those firms that did not request credit due to: (i) thinking they would be turned down; (ii) applying for credit was too difficult or time consuming, and (iii) the cost of financing was too high. The employment-weighted probability of being constrained from this alternative definition is 4.3 percent. We re-estimate the coefficients from our OLS regression model and report the results in Appendix Table 11. Overall, coefficients are similar to those in Table 6, albeit larger in absolute terms. In Section 4, we come back to this alternative specification of being constrained when we assess the robustness of our empirical decomposition using our proxy variable.

3.3 Properties of the proxy

We now describe some properties of our proxy. In particular, we focus on (i) how our proxy relates to standard proxies for financial strength from the corporate finance literature and (ii) how it correlates with employment and debt growth.

lower expenses. This would imply a probability of being constrained that is 0.24 percentage points higher than the average probability (i.e. 4.14 vs. 3.9 percent).

[17] As just mentioned, the unweighted average of our $Constrained_{i,t}$ variable is 3.9 percent while the employment-weighted average is 2.9 percent. Note that the vector of firm observables $x_{i,t}$ in the administrative data is the same as in the survey data since the balance sheet information in the survey is obtained by merging the administrative tax information with the survey observations.

Relationship with standard proxies. Table 7 reports the correlation matrix between our proxy and six "standard proxies" that have been shown to relate to financial constraints: age, size, leverage, liquidity, earnings-to-debt, and profit margin.

Table 7: Correlation with standard proxies

	Proxy	Age	Size	Lev.	Liq.	E/D	Prof.
Proxy	1.00						
Age	−0.20	1.00					
Size	−0.24	0.09	1.00				
Leverage	0.62	−0.07	0.01	1.00			
Liquidity	−0.23	0.01	−0.05	−0.03	1.00		
Earnings-to-debt	−0.35	0.02	−0.05	−0.29	0.07	1.00	
Profit margin	−0.20	0.01	−0.00	−0.22	−0.01	0.51	1.00

Notes: "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. The cross-sectional correlations reported in this table represent average over all years in the main sample (9,855,240 firm-month observations).

Several interesting observations stand out. First, the proxy correlates strongly with all the variables (i.e., correlation above 0.2 in absolute value for all the variables). Second, the sign of the correlations are intuitive for all the variables. For instance, firms that are likely to be constrained according to our proxy are younger and smaller, have high leverage, have low liquidity, and have low earnings-to-debt and profitability. Third, the standard proxies tend to be only weakly correlated with each other (i.e., all but three correlations are below 0.1 in absolute value).

In Appendix C.1, we report "heatmaps" (Figure 6) describing the correlation structure in a non-parametric way by plotting deciles of our proxy by deciles of the standard financial proxies. Overall, Figure 6 corroborates the correlations in Table 7. We also report the annual transition probability matrix of the proxy itself (Figure 6, first panel). The transition matrix exhibits a high level of persistence: firms have a higher probability of staying in their decile the following year than moving to any other decile. For example, firms in the top decile (the most likely to be constrained) have a 80 percent probability of remaining in this decile the following year.

While we do not take a stand on the particular form of constraint faced by SMEs, Table 7 and Appendix Figure 6 show that our proxy has strong correlations will all the traditional proxies. These correlations are consistent with Table 4 above, which showed that collateral, cash flows, and age are important reasons why firms were denied access to credit (i.e., constrained) in the SFGSME data. This evidence aligns well with several papers using these standard financial proxies to identify financially constrained firms. For instance, the strong correlation of our proxy with leverage and earnings-to-debt is consistent with Lian and Ma (2021), who find that both asset-based and cash-flow-based constraints are important determinants in the U.S.

lending market. It also relates to Lakdawala and Moreland (2021), who find that stock prices of high- versus low-leverage firms respond differently to an unexpected change in monetary policy. Greenwald (2019) notes that interest coverage covenants, which set a maximum ratio of interest payments to earnings, are among the most popular provision in debt contracts (i.e., earnings-to-debt ratio) and finds that they amplify the transmission of interest rates to borrowing and investment. Our proxy is also closely related to firm age and profitability, which are found to be important determinants of the transmission of monetary policy to capital expenditures and borrowing among U.S. publicly listed firms. Specifically, Cloyne et al. (2023) find that young firms not paying dividends adjust significantly more relative to older firms that pay dividends following changes in interest rates. They interpret this as younger non-dividend paying firms being more more likely to be constrained by the value of their assets relative to older ones with steady cash flows. Finally, our proxy also suggests that firms with low liquidity are more likely to be financially constrained, in line with the evidence in Jeenas (2019), who finds that firms with few liquid (short-term) assets reduce investment relative to others following an unexpected increase in interest rates. Our interpretation of these correlations is that our proxy relates to the traditional proxies for financial constraints, but it combines them in a way that maximizes its ability to detect constrained SMEs in Canada.

In Appendix C.2, we also investigate the dynamic correlations between the proxy and firm-level outcomes. Specifically, we estimate how future employment and debt dynamics evolve for firms with different probabilities of being constrained $p_{i,t}$. We find that an increase in the proxy $p_{i,t}$ translates to lower employment and lower debt over the next three years.

Proxy-sorted monetary policy response. Does employment of constrained firms respond more or less to monetary policy shocks? As discussed in the introduction, theory does not have a definitive answer to this question, as it depends on how much monetary policy affects the tightness of financial constraints.

To answer, we combine our proxy with the IRF approach in described in Section 2. First, we sort firms in each year into ten deciles ($g \in \{1, \ldots, 10\}$) according to their likelihood of being constrained. For example, group $g = 1$ contains the 10 percent of firms that are the least likely to be financially constrained, while group $g = 10$ includes the 10 percent of firms that are most likely to be constrained. We define $g_{i,t}$ as the group in which firm i is at time t and $1\{g_{i,t} \in g\}$ is an indicator variable that takes a value of one if the firm is in group g and zero otherwise. Instead of tracing out the full IRF, we use a "peak response" specification designed to estimate the average employment response over the 13–24 month horizon for each decile

g.[18] The specification is

$$\log L_{i,t+24} = z'_{i,t}\lambda^k + \sum_{g=1}^{10} 1\{g_{i,t} \in g\}\beta_g \cdot \varepsilon_t + u_{i,t+24}, \tag{3.3}$$

where $\log L_{i,t+24} \equiv \log(\frac{L_{i,t+13}}{12} + \cdots + \frac{L_{i,t+24}}{12})$ is the log of the average employment over the 13 through 24 months ahead, and $u_{i,t+24}$ is the error term. Note that equation (3.3) is the same as Equation (2.3), except that (i) the left-hand-side variable is a 12-month average, and (ii) the coefficient of interest β_g varies across the deciles of the firm-level proxy $g_{i,t}$. Standard errors are computed using Driscoll-Kraay as before.

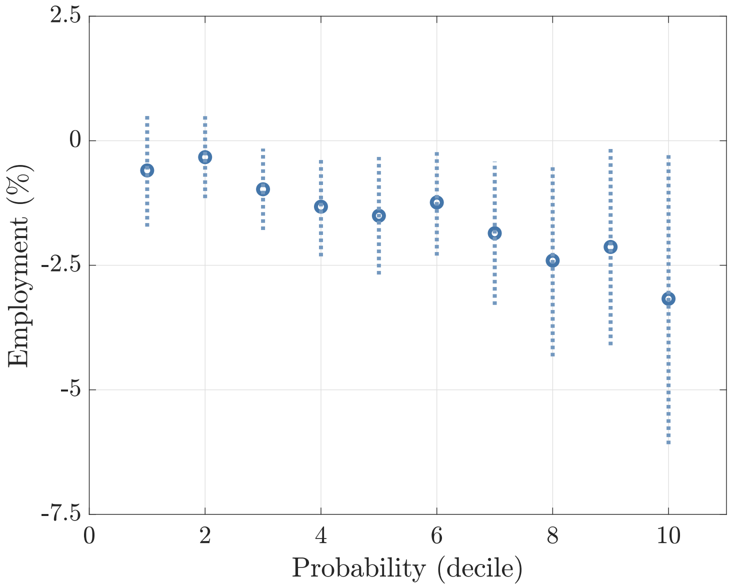


Figure 4: Response of employment to a monetary policy shock by probability of being constrained (25 basis points, 90% confidence intervals).

Figure 4 presents the results where the coefficients of interest $\{\widehat{\beta}_g\}_{g=1}^{10}$ are scaled to correspond to a 25 bps monetary policy shock. Notice that the employment response across firms is decreasing in the probability of being constrained. For instance, the peak response of employment is nearly zero for firms in the first decile while firms in the tenth decile (i.e., the 10 percent of firms most likely to be credit-constrained) decrease their employment on average by more than -3 percent (in absolute terms).[19]

[18] This is equivalent to the average employment response during the second year following the shock.

[19] In Appendix C.5, we construct standard errors for the *relative* effect of each employment response relative to the top decile (i.e., the top 10% of firms ranked by their likelihood of being constrained). We implement this construction by simply adding a time fixed effect to the specification. The findings are consistent with Figure 4: large point estimates with important sampling uncertainty.

4 Quantifying the Contribution of Credit Constraints

We start by laying out a simple and easy to interpret empirical decomposition to quantify the contribution of credit constraints in the transmission of monetary policy to employment. We then write down a fully-specified, albeit stylized model of firm employment and monetary policy, which we use to provide a microfoundation for the empirical decomposition, as well as to clarify the theoretical transmission mechanism.

4.1 Empirical decomposition

The core idea is to decompose the response of aggregate employment to a monetary policy shock into (i) a *direct effect* of monetary policy that operates via changes in the interest rate, and (ii) an *indirect effect* of monetary policy that operates via changes in the tightness of credit constraints.[20]

We implement our decomposition by estimating a single employment-weighted local projection as in equation (2.3), using the "peak response" specification introduced in equation (3.3). Firm-level employment is projected on the usual controls $z_{i,t}$, the monetary policy shock ε_t, as well as its interaction with the proxy p_{it} :

$$\log L_{i,t+24} = \underbrace{z_{i,t}'\lambda + \beta_p p_{i,t}}_{\text{Controls}} + \underbrace{\beta_d \varepsilon_t}_{\text{Direct effect}} + \underbrace{\beta_{id} p_{i,t} \varepsilon_t}_{\text{Indirect effect}} + u_{i,t+24}. \tag{4.1}$$

The identifying assumption is that firm-level employment shocks are exogenous with respect to monetary policy shocks as well as the controls:

$$\mathrm{E}(u_{i,t+24} | \varepsilon_t, p_{i,t}, z_{i,t}) = 0. \tag{4.2}$$

The controls $z_{i,t}'\lambda$ are the same as in equation (2.3) and include an industry-month fixed effect (i.e., two-digit NAICS), 12 lags of log employment and 3 lags of the Bank rate. We also include our proxy variable $p_{i,t}$ to control for systematic differences in employment trajectories that are due credit constraints, but not its interaction with monetary policy. The direct effect $\beta_d \varepsilon_t$ accounts for the (counterfactual) response of firm i if it were to be completely unconstrained (i.e., its probability of being constrained in the next year is equal to zero, $p_{i,t} = 0$). The indirect effect $\beta_{id} p_{i,t} \varepsilon_t$ accounts for the additional employment response of firm i due to the fact that its probability of being constrained is positive. In Section 4.4, we provide a microfoundation for equation (4.1).

[20]This type of conceptual decomposition has its origins in the financial accelerator literature, which posits that the "direct effects of monetary policy on interest rates are amplified by endogenous changes in the external finance premium" (Bernanke and Gertler, 1995), which we will refer to hereon as the indirect effect.

Aggregate decomposition. Equation (4.1) implies that the response of aggregate employment to a monetary policy shock is

$$\frac{\mathrm{E}(\log L_{t+24}|p,\varepsilon)}{\partial\varepsilon} = \beta_d + \beta_{id}p.$$

The aggregate response of employment to a monetary policy shock can thus be constructed using two regression parameters β_d, β_{id} and the estimated employment-weighted probability p from the survey data. Recall that all our firm-level specifications are estimated using employment weights, which ensures that they aggregate to the corresponding macro IRF (see discussion around Figure 2).

Finally, we report the results of this decomposition simply as the share of indirect effects in the total response of employment to monetary policy:

$$\omega \equiv \frac{\text{Indirect effect}}{\text{Direct effect} + \text{Indirect effect}}.$$

For instance, if $\omega = 1/2$, it means that half of the transmission of monetary policy to employment operates via credit constraints.

Empirical decomposition versus GE counterfactual. Our decomposition has the straightforward interpretation of "zero-ing out" the contribution of credit constraints (i.e., setting $p = 0$) in order to obtain an estimate of the direct effect of monetary policy (i.e., absent any credit constraints).

However, it is worth emphasizing that the direct effect β_d in our decomposition does not exactly correspond to the aggregate response of employment in an economy without credit constraints. The reason is that our decomposition is based on the idea of shutting down the contribution of credit constraints at the *firm-level* (i.e., setting $p_{i,t} = 0$). However, doing so does not shut down the contribution of credit constraints on equilibrium wages, which themselves affect firm-level hiring. Therefore, our decomposition quantifies the effect of shutting down the effect of credit constraints on employment, while holding everything else constant (as in Kaplan, Moll and Violante, 2018).

4.2 Empirical results

We begin by reporting the regression results for specification (4.1). Table 8 contains the baseline results as well as a number of robustness exercises and extensions, which we describe shortly. First, we estimate a value of around $\beta_d = -0.016$ in the baseline specification for the direct effect coefficient. The interpretation is that a 100 bps contractionary shock has a direct effect on firm employment of -1.6 percent. Second, we estimate a value of around -1.16 for the indirect effect coefficient β_{id}. This means that firms with a probability of being constrained of 5 percent (i.e., $p = 0.05$) see an additional 6 percent decline in employment. Finally, we estimate a coefficient β_p on the probability of being constrained of roughly -1, which is consistent with the evidence on employment trajectories across firms reported in the appendix (see Figure 7a).

Table 8: Regression results for Equation (4.1).

Employment ($\log L_{i,t+24}$)	Baseline	Robustness checks				
		Alt. channels	False neg.	Between	Time FE	Firm FE
Monetary shock (ε_t)	-0.016	-0.023	-0.022	-0.038	not ID	-0.002
	(0.022)	(0.001)	(0.022)	(0.034)		(0.011)
Interaction ($p_{i,t} \times \varepsilon_t$)	-1.16	-0.78	-0.64	-0.67	-1.31	-0.72
	(0.099)	(0.44)	(0.064)	(1.479)	(1.04)	(0.61)
Probability ($p_{i,t}$)	-1.01	-0.04	-1.06	-1.51	-0.96	-1.35
	(0.018)	(0.074)	(0.017)	(0.379)	(0.184)	(0.018)
Controls ($z_{i,t}$)	✓	✓	✓	✓	✓	✓
Time fixed effect					✓	
Firm fixed effect						✓
Age, size, productivity		✓				
Sample size	7.34M	7.34M	7.34M	7.63M	7.34M	7.34M
R^2	0.933	0.935	0.933	0.945	0.934	0.296

Notes. Estimated coefficients from local projection of $\log L_{i,t+24}$ on the listed variables. Standard errors in parentheses are computed using Driscoll–Kraay.

Robustness exercise: Alternative channels. A key threat to identification is the presence of alternative channels in the transmission of monetary policy to employment that are heterogeneous across firms. For example, suppose that large firms face more important adjustment costs to employment relative to small firms, so they respond less to any shocks. Moreover, suppose that large firms are also less likely to be credit constrained. This situation would lead to a violation of the identification assumption: a classic omitted variable bias.[21] In practice, this would lead us to attribute the true size effect (due to differences in adjustment costs) to credit constraints, when in reality it is not.

We focus on three alternative channels that could explain why firms respond differently to (monetary policy) shocks. We use three commonly-used determinants of growth emphasized by the firm dynamics literature : labor productivity, age and size (e.g., Haltiwanger et al., 2013; Fort et al., 2013; Moscarini and Postel-Vinay, 2012; Ilut et al., 2018; Decker et al., 2020). We control for these variables in Equation (4.1) by adding them both in levels and interacted with the monetary policy shock. The three variables are in logs; size is defined as employment, and productivity is computed as sales per worker. The second column of Table 8 reports the

[21] In Appendix B, we characterize the resulting violation of the exclusion restriction more formally.

coefficients for this specification. The estimate for the indirect effect is about one third lower in absolute value than in the baseline (0.8 versus 1.2), indicating that our baseline specification could overestimate the indirect effect. However, note that the standard errors are more than four times larger than in the baseline, reflecting the fact that there is a high cross-sectional correlation between the additional controls (i.e., age, size, productivity) and the proxy (see Table 7).

Robustness exercise: False negatives in the survey. One concern regarding the construction of our proxy is that our definition of a constrained firm in the survey data contains false negatives: some firms could be financially constrained although they did not report being denied credit. For instance, some firms could request a lower loan amount in order to be accepted, somewhat analogous to mortgage borrowers bunching at institutional limits (e.g., Greenwald, 2018).

To assess the impact of false negatives on our empirical decomposition, we leverage the information in the survey regarding the reasons why firms did not request credit described in Table 4. We construct an alternative definition of begin constrained by adding firms that did not request because (i) thought they would be turned down; (ii) applying for credit was too difficult or time consuming; and (iii) the cost of financing was too high. See Appendix A.2.1 for details. We use this alternative definition in our empirical decomposition and evaluate the robustness of our baseline results.

Using this alternative definition of a constrained firm has two implications. First, the employment-weighted probability of being constrained p, which enters our decomposition formula, increases from 2.9 percent to 4.3 percent. In Appendix B, we show that this higher p has, by itself, the mechanical effect of increasing the decomposition ω by about 50% (i.e., $4.3/2.9 \approx 1.5$). Second, with this alternative definition of constrained firms in the survey data, the proxy changes, which affects the estimated coefficients β_d and β_{id}.

In the false negative specification (Table 8, third column), the estimated indirect effect is about half that of the baseline (0.64 versus 1.16). We interpret the importance of this change in the context of the aggregate decomposition below (Table 9).

Robustness exercise: Between-firm. Our proxy approach delivers a firm-level probability of being constrained for every year. One concern would be the presence of (potentially non-classical) measurement error. In addition to standard attenuation bias, this could lead to a violation of the exclusion restriction, in the case where the measurement error in $p_{i,t}$ is correlated with future firm-level employment $\log L_{i,t+k}$. For instance, if our construction of the proxy spuriously picks up annual changes in some balance sheet item that is associated with future employment growth rather than decreased financial constraints.

To limit the noise in our proxy, we conduct a robustness check where we replace $p_{i,t}$ by its within-firm average (i.e., $\frac{1}{T}\sum_{t=1}^{T} p_{i,t}$). This way, the identification is between-firms: we compare the employment response of firms with a high versus low proxy on average. Consequently, there is no yearly fluctuation in the proxy in this specification. Table 8 (fourth column) presents the coefficients; the estimated indirect effect is about half that of the baseline (0.67 versus 1.16). Again, we interpret the importance of this change shortly, in the context of our aggregate decomposition.

Robustness exercise: Fixed effects. As a final robustness check, we assess how our parameter of interest β_{id}, which captures indirect effects changes when we add fixed effects. First, we add a time fixed effect to the baseline specification, as in Ottonello and Winberry (2020). The indirect effects do not change much, and if anything are a bit higher in absolute value: roughly -1.3 compared to -1.1 in the baseline. (Note that the direct effect β_d is not identified, due to the fact that the time effect is perfectly collinear with the shock ε.)

Second, we add firm fixed effects. The idea is to focus on within-firm variations in the proxy $p_{i,t}$ to identify β_{id}. For instance, we are comparing the response of a single firm to monetary policy in periods where it has a bad balance sheet (high $p_{i,t}$) versus when it has a strong balance sheet (low $p_{i,t}$). This is a very stringent test since most balance sheet items, which are used to construct $p_{i,t}$ move slowly over time. Nevertheless, we estimate an indirect effect of similar magnitude as in the baseline: roughly -0.7 compared to -1.1 in the baseline.

4.3 Aggregate decomposition

Table 9 presents the results of the empirical decomposition. We construct standard errors for the ratio ω by combining the Delta method and Driscoll-Kray standard errors. The first row contains the baseline specification. We find that the indirect effect accounts for about two thirds (68 percent) of the total response of SME employment to a monetary policy shock, albeit estimated with considerable uncertainty (i.e., the standard error is 0.44). Since SMEs account for almost all of the aggregate response of employment to a monetary policy shock (see Figure 3), our results can be interpreted as the contribution of indirect effects in the *aggregate* response of monetary policy, not just amongst SMEs.

We also implement the decomposition using the parameters (β_d, β_{id}) from the "alternative channels", "false negatives", and "between-firm" specifications described earlier. When adding alternative channels, the indirect channel decreases to about one half (49 percent), implying that firm-level characteristics seem to pick up some of the transmission of monetary policy allocated to indirect effects in our baseline specification. When we substitute our proxy with the "false negative" alternative definition, the indirect effect decreases slightly to 56 percent. The between-firm specification has an indirect half as large as in the baseline (34 percent),

Table 9: Contribution of credit constraints to the aggregate employment response

Specification	Indirect effect ω	Standard error
Baseline	0.68	0.44
Robustness check: Alternative channels	0.49	0.26
Robustness check: False negatives	0.56	0.44
Robustness check: Between-firm	0.34	0.67

Notes: The 90 percent confidence interval is constructed using the Delta method where standard errors are estimated using Driscoll-Kray. The second and third rows correspond to the robustness checks described above.

with significant sampling uncertainty (standard error of 0.67).

Our interpretation of the decomposition is that while only a small fraction of employees work at financially-constrained firms ($\overline{p} \approx 3\%$, see discussion around equation 3.2), those firms account for roughly two thirds of the transmission of monetary policy to employment in our baseline specification (between one third and one half in the alternative specifications).

To go from accounting decomposition to a more structural interpretation, Section 4.4 maps our estimates to an equilibrium model of firm hiring under credit constraints. Through the lens of the model, we show that our empirical evidence is consistent with a "strong financial accelerator" (i.e., financial constraints amplify the effect of monetary policy on employment).

4.4 Decomposition in a stylized equilibrium model

We now provide a fully-specified, albeit stylized, model of firm employment and monetary policy. We use the model to (i) clarify which structural parameters govern the direct and indirect effects of monetary policy and (ii) provide a back-of-the-envelope mapping between our empirical evidence and the structural model parameters.

Environment. We consider a two-period deterministic model where firms hire labor L at time $t = 0$ and produce at time $t = 1$. Prices are fully sticky and the consumption good is the numéraire. We assume that workers supply labor perfectly elastically such that firms are able to hire as much as they want at the wage level w. Firms discount cash flows at the gross interest rate R. Firms differ in their credit worthiness (i.e., balance sheet health, credit history, etc.) and therefore their access to credit, but are otherwise identical.

Firm problem. Each firm $i \in [0, 1]$ maximizes the present discounted value of cash flows. With probability $1 - p_i$, the firm is unconstrained and solves:

$$\Pi = \max_{L \geq 0} -wL + R^{-1} \frac{L^{1-\alpha}}{1-\alpha},$$

which has the solution $L^{\text{uc}} = (wR)^{-\frac{1}{\alpha}}$. With probability p_i, the firm is constrained and can hire at most C/w workers (i.e., using its available cash), meaning that the level of employment of constrained firms is $L^{\text{c}} = \min\{L^{\text{uc}}, C/w\}$. We denote the employment gap of unconstrained firms by $\Delta \equiv \log(L^{\text{uc}}/L^{\text{c}})$, which is weakly positive by construction.

Credit constraint. We are interested in the employment effect of a small shock to the nominal interest rate (i.e., $\mathrm{d}\log R$). In addition to the standard interest rate channel of monetary policy, which increases employment by reducing the cost of borrowing, we allow for monetary policy to have an additional effect on the tightness of credit constraints (i.e., the ex-ante probability that a firm is unable to obtain credit).[22] In particular, we assume that the probability of the type i firm being constrained is given by

$$p_i = \overline{p}_i \cdot R^{\theta},$$

where $\overline{p}_i > 0$ governs the level of constraints faced by firm i, while θ is a structural elasticity that governs the sensitivity of constraints to the interest rate.[23] The aggregate probability of being constrained as $p \equiv (\int p_i \,\mathrm{d}i) \cdot R^{\theta}$.

Decomposition in the model. Let $\log L$ be aggregate employment. In Appendix D.1, we show that the total effect of a monetary policy shock on aggregate employment is given by

$$\frac{\partial \log L}{\partial \log R} = \underbrace{\frac{\partial \log L^{\text{uc}}}{\partial \log R}}_{\substack{\text{Direct effect} \\ = -\frac{1}{\alpha}}} + \underbrace{p \cdot \left(\frac{\partial \log(L^{\text{c}}/L^{\text{uc}})}{\partial \log R} - \frac{\partial \log p}{\partial \log R} \log(L^{\text{uc}}/L^{\text{c}}) \right)}_{\substack{\text{Indirect effect via change in } p \\ = \; p\,\left(\frac{1}{\alpha} - \theta\Delta\right)}}. \tag{4.3}$$

The direct effect is the employment elasticity to R of unconstrained firms. In the model, the direct effect is always negative and the magnitude is governed by the parameter α, which governs the curvature of the production function.

The sign of the indirect effect, however, is ambiguous. For instance, if monetary policy does not affect the probability of being constrained (e.g., $\theta = 0$), then the indirect effect is positive (i.e., financial constraints *dampen* the effect of monetary policy on employment). The reason is that constrained firms, by definition, do not respond to monetary policy, so that an economy with a high level of financial constraints (i.e., p is high) will be less responsive to monetary policy. This is the logic that underlies the main result in Ottonello and Winberry (2020).

[22] Two mainstream theories have been suggested to explain why the tightness of credit constraints might depend on the level of R. First, a lower R could improve lenders' balance sheet health, thus leading them to loosened lending standards (bank-lending channel). Second, a lower R could also improve firm balance sheets, thus leading lenders to lend more without loosening their lending standards (balance-sheet channel).

[23] This setup implicitly assumes proportional hazard: the ratio of probabilities between two firms does not depend on the level of the interest rate.

If, instead, the effect of monetary policy on the tightness of constraints is sufficiently large (i.e., $\theta\Delta > \frac{1}{\alpha}$), then the indirect effect is negative (i.e., financial constraints *amplify* the effect of monetary policy on employment). The idea is that accommodative monetary policy allows more firms to access credit, which increases aggregate employment. This is analogous to the financial accelerator mechanism proposed by Bernanke et al. (1999).

Identification using firm-level data in the model. We now show that our empirical model in Section 4.1 correctly recovers direct and indirect effects, under the assumptions of the model. First, we state the result.

Proposition 4.1 (Identification)**.** *Denote the monetary policy shock by* $\varepsilon = \mathrm{d}\log R$*. The model implies the following approximate regression model*

$$\log L_i \approx \lambda + \beta_p p_i + \beta_d \varepsilon + \beta_{id} p_i \varepsilon + u_i$$
$$\mathrm{E}(u_i | p_i, \varepsilon) = 0.$$

The mapping from regression coefficients to structural parameters is invertible and given by

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

Proof. Appendix D.2 □

Proposition 4.1 says that, as long as we have enough variation in the data to estimate $(\lambda, \beta_p, \beta_d, \beta_{id})$, we can recover the structural parameters (α, θ, Δ).[24] What this means is that under the assumptions of the model, our empirical decomposition formula ω is indeed equal to the contribution of credit constraints in the aggregate employment response to a monetary policy shocks.

Calibration that rationalizes the data. The model can generate either small or large indirect effects, depending on the calibration. Using Proposition 4.1, we now provide a simple mapping between structural parameters and regression evidence to assess the plausibility of our proposed mechanism. In short, we find that the model can rationalize the data with: (i) an inelastic demand curve for labor, (ii) a large effect of constraints on employment, and (iii) a moderate sensitivity of credit constraints to monetary policy. Table 10 reports the calibration of the model that rationalizes the regression evidence from Section 4.2. We report round numbers for simplicity.

[24] By "enough variation," we mean at least two time periods and two firms. Otherwise, one could not compute variances and covariances.

Table 10: Calibration that rationalizes the data

Parameter	Map to reduced form	Value
α	$-\frac{1}{\beta_d}$	60
Δ	$-\beta_p$	1
θ	$(\beta_d + \beta_{id})/\beta_p$	1

First, the curvature of the production function needs to be high: $\alpha \approx 60$. In the model, this implies that the response of unconstrained firms to the interest rate is small (i.e., $\mathrm{d}\log L^{\mathrm{uc}} = -\frac{1}{\alpha}\,\mathrm{d}\log R$). In contrast, a standard long-run calibration calibration to $\alpha = 1/3$ (i.e., steady-state capital share) would instead imply a much more elastic demand curve for labor. However, we are interested in the short-run response of firms to monetary policy, where adjustment costs and other factors might lead firms to be unresponsive.[25]

Second, the employment gap between constrained and unconstrained firms needs to be quite high: $\Delta \approx 1$. This means that a one percentage point increase in the share of constrained firms (e.g., an increase from $p = 0.03$ to $p = 0.04$), leads to a 1 percent decline in employment.

Finally, and most importantly, the elasticity of the probability with respect to the interest rate needs to be $\theta \approx 1$. Is that a reasonable value? As a concrete example, it means that a 1 percentage point monetary policy shock causes an increase in the aggregate probability of being constrained of

$$\frac{\mathrm{d}p}{\mathrm{d}r} = \underbrace{p}_{0.03} \times \underbrace{\theta}_{1} = 0.03 \tag{4.4}$$

The key takeaway is as follows. Even if a 1 percentage point monetary policy shock has only a small effect on the probability of being constrained (i.e., $\mathrm{d}p \approx 0.03$ percent), it can have a large effect on employment if being credit constrained is associated with a sharp reduction in employment growth, as we find in the data (i.e., $\Delta = 1$).

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.

Testing the mechanism. Our proposed channel of monetary policy transmission predicts that the probability of being constrained increases in response to a monetary tightening. We provide two empirical tests (see Appendices C.6 and C.7).

[25] As suggestive evidence in favor of this high curvature, recall that large firms firms in the data (who are typically believed to be unconstrained) appear to be unresponsive to monetary policy (see Figure 3).

First, we use publicly available data from the Bank of Canada *Business Outlook Survey* (BOS) and *Senior Loan Officer Survey* (SLOS) to trace the effect of monetary shocks on the non-price credit conditions. We find that a contractionary shock predicts a rise in the share of firms reporting a tightening in credit conditions, and similarly a rise in the share of financial institutions that report a tightening of lending conditions. This suggests that the transmission of monetary policy to firms is amplified not only by the level of interest rates themselves, but also the ability of firms to obtain credit altogether (see Appendix Figure 9). Second, Appendix Table 17 provides the predicted response of our proxy itself to a monetary policy shock (aggregated to the annual frequency). We find that our proxy increases following the monetary policy shock, suggesting that balance sheets deteriorate in a way that is associated with a higher probability of being denied credit.

5 Conclusion

Do financial constraints faced by firms amplify or dampen the transmission of monetary policy to macroeconomic aggregates such as employment? Using an empirical framework based on a new proxy for the likelihood of being credit-constrained, we find that credit constraints amplify the effects of monetary policy and that one-third of the transmission can be attributed to these constraints.

Our results highlight an important role for a financial accelerator in the transmission of monetary policy to employment. Theoretically, it has been known for decades that the presence of financial constraints can amplify the transmission of monetary policy (see the introduction for a review of the literature). However, direct empirical evidence is scarce, mainly due to (i) a lack of high-frequency firm-level data and (ii) the difficulties involved in identifying constrained firms in the data. Our paper makes progress on both fronts. Notably, our study has two important implications. First, monetary policy has a distributive effect on the firm side: it affects employment mostly at small firms. Second, it generates state-dependent aggregate responses: when the corporate sector has a weak balance sheet, only a small rate hike is needed to bring down employment.

Given that our analysis of financial constraints focuses on (i) SMEs (rather than all firms), (ii) debt financing (rather than equity *and* debt financing), and (iii) the extensive margin of financial constraints (the ability to access external credit) rather than the intensive margin (the curvature of the interest rate spread as a function of balance sheet health), we view our findings as providing a conservative estimates of the importance of financial constraints in the transmission of monetary policy to employment.

Finally, a limitation of our study is that we cannot distinguish between two variants of the financial accelerator. On the one hand, our proxy could be identifying firms who are collateral dependent, consistent with a firm balance sheet channel of monetary policy. On the other hand, our proxy could be identifying bank-dependent firms, consistent with a bank lending channel of monetary policy. While this distinction does not affect our main result (i.e., in both cases, amplification is due to credit constraints faced by firms), future work should attempt to further disentangle the channels at play, perhaps by combining our proxy approach with matched borrower-lender data.

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Online Appendix (not for publication)

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

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

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^{US}_{t-14} (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^{US}_{t-14} 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 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:

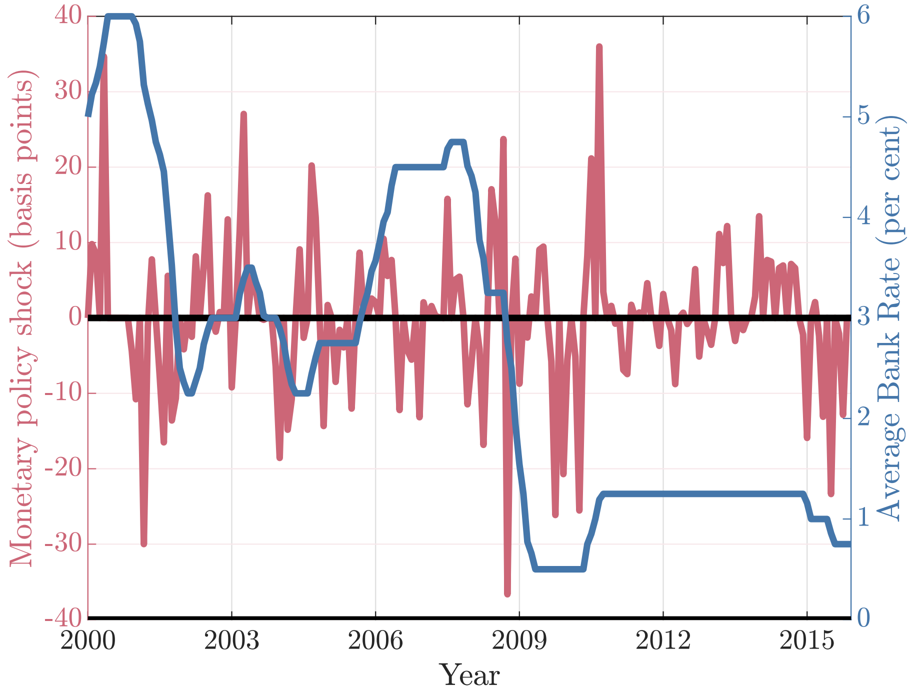


Figure 5: Monetary policy shocks (red line) and average monthly Bank Rate (blue line) (2000:M1–2015:M12).

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 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)

[26]CS' 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.

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 Request$_i$, 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. Request$_{i,t} = 1$), we create a dummy variable 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 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 $\text{Constrained}_{i,t}$ variable as follows:

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

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 my 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	-0.009^{***}	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.

[27] See 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 0–10	11–20	21+	Total
Debt financing	34.4	33.2	29.4	31.7
Line of credit	18.8	15.8	14.1	16.0
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 0–10	11–20	21+	Total
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	14.4	36.5	22.4
Financial ratios				
Leverage	0.58	0.63	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	87.5
Constrained	6.1	3.8	3.0	3.99

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:

$$\log L_{i,t+1} = \beta_p p_{i,t} + \beta_d \varepsilon_t + \beta_{id} p_{i,t} \varepsilon_t + u_{i,t+1}, \qquad \text{(Employment)}$$
$$p_{i,t} = p + x_{i,t-1}, \qquad \text{(Proxy)}$$
$$\mathrm{E}(u_{i,t+1} | x_{i,t-1}, \varepsilon_t) = 0, \qquad \text{(Identifying assumption)}$$

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 :

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

The first term is a matrix that depends only on p and $\mathrm{Var}(x_{i,t-1})$. 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

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

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

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

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

where $v_{i,t}$ is unconditionally mean zero, but potentially correlated with future employment $\text{E}(v_{i,t-1} | u_{i,t+1}) = 0$. 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 in Section 3, we estimate local projection models of the form

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

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 $\widehat{p}_{i,t}$ is the proxy, as in the main text. Here we control for observable firm characteristics (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 $\widehat{\beta}^k$ 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., $\widehat{\beta}^2 \approx 1.2$).

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., $\widehat{\beta}^2 \approx 4.6$).

Proxy (t) \ Proxy (t+1)	1	2	3	4	5	6	7	8	9	10
1	77	16	3	1	1	1	0	0	0	0
2	17	55	19	5	2	1	1	0	0	0
3	3	21	46	19	6	2	1	1	0	0
4	1	5	22	42	19	6	2	1	1	0
5	1	2	6	22	41	19	6	2	1	0
6	0	1	2	7	22	40	19	6	2	1
7	0	0	1	2	7	22	43	19	4	1
8	0	0	0	1	2	6	22	48	18	2
9	0	0	0	0	1	1	4	20	58	15
10	0	0	0	0	0	0	1	2	16	80

Proxy \ Size	1	2	3	4	5	6	7	8	9	10
1	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	1.1	2.4
2	0.6	0.7	0.8	0.9	0.9	0.9	0.9	1	1.4	1.9
3	0.6	0.8	0.8	0.9	0.9	1	1.1	1.2	1.5	1.4
4	0.6	0.8	0.9	0.9	1	1	1.1	1.2	1.4	1
5	0.7	0.8	0.9	1	1	1.1	1.2	1.3	1.3	0.8
6	0.8	0.9	1	1.1	1.1	1.1	1.2	1.2	1	0.6
7	0.9	1.1	1.1	1.2	1.1	1.1	1.1	1.1	0.9	0.4
8	1.1	1.2	1.2	1.2	1.2	1.1	1	0.9	0.7	0.3
9	1.5	1.4	1.3	1.2	1.1	1	0.9	0.7	0.6	0.3
10	2.3	1.5	1.2	1.1	1	0.9	0.8	0.6	0.4	0.2

Proxy \ Leverage	1	2	3	4	5	6	7	8	9	10
1	5.4	1.8	0.9	0.5	0.4	0.3	0.2	0.2	0.2	0
2	2.2	2.6	1.5	0.9	0.7	0.5	0.5	0.5	0.4	0.1
3	1	2.2	1.9	1.4	1	0.7	0.6	0.6	0.5	0.1
4	0.5	1.4	1.8	1.6	1.3	1	0.8	0.7	0.6	0.1
5	0.3	0.9	1.5	1.7	1.5	1.3	1.1	0.9	0.8	0.2
6	0.2	0.5	1	1.5	1.6	1.5	1.3	1.1	1	0.3
7	0.1	0.3	0.7	1.1	1.4	1.6	1.6	1.4	1.2	0.6
8	0.1	0.2	0.4	0.8	1.1	1.5	1.7	1.7	1.6	1
9	0	0.1	0.2	0.4	0.7	1.1	1.4	1.9	2	2.1
10	0	0	0.1	0.1	0.3	0.4	0.7	1.1	1.7	5.5

Proxy \ Liquidity	1	2	3	4	5	6	7	8	9	10
1	0.6	0.7	0.9	1	1.1	1.1	1.1	1.1	1.1	1.3
2	0.4	0.6	0.8	1	1.1	1.2	1.2	1.2	1.2	1.2
3	0.4	0.7	0.9	1	1.1	1.2	1.2	1.2	1.2	1.1
4	0.4	0.7	0.9	1	1.1	1.1	1.2	1.2	1.2	1.1
5	0.5	0.9	1	1	1.1	1.1	1.1	1.1	1.1	1
6	0.7	1	1	1	1	1	1.1	1.1	1.1	1
7	0.8	1.1	1.1	1.1	1	1	1	1	1	0.9
8	1.1	1.3	1.1	1	1	0.9	0.9	0.9	0.9	0.8
9	1.7	1.5	1.2	1	0.9	0.8	0.8	0.8	0.7	0.7
10	3	1.5	1	0.8	0.7	0.7	0.6	0.5	0.5	0.6

Proxy \ Debt-to-earnings	1	2	3	4	5	6	7	8	9	10
1	1	0.3	0.4	0.4	0.4	0.6	0.7	1	1.6	3.6
2	0.8	0.5	0.7	0.7	0.7	0.8	1	1.3	1.6	1.9
3	0.8	0.5	0.7	0.8	0.9	1	1.1	1.3	1.5	1.3
4	0.8	0.6	0.8	1	1	1.1	1.2	1.3	1.3	0.9
5	0.8	0.7	0.9	1.1	1.1	1.2	1.2	1.2	1.1	0.7
6	0.9	0.9	1	1.1	1.2	1.2	1.2	1.1	0.9	0.5
7	0.9	1.1	1.2	1.2	1.2	1.2	1.1	1	0.7	0.4
8	1	1.3	1.3	1.3	1.2	1.1	1	0.8	0.6	0.3
9	1.2	1.7	1.4	1.3	1.1	1	0.8	0.7	0.5	0.2
10	1.7	2.3	1.6	1.2	1	0.8	0.6	0.4	0.3	0.2

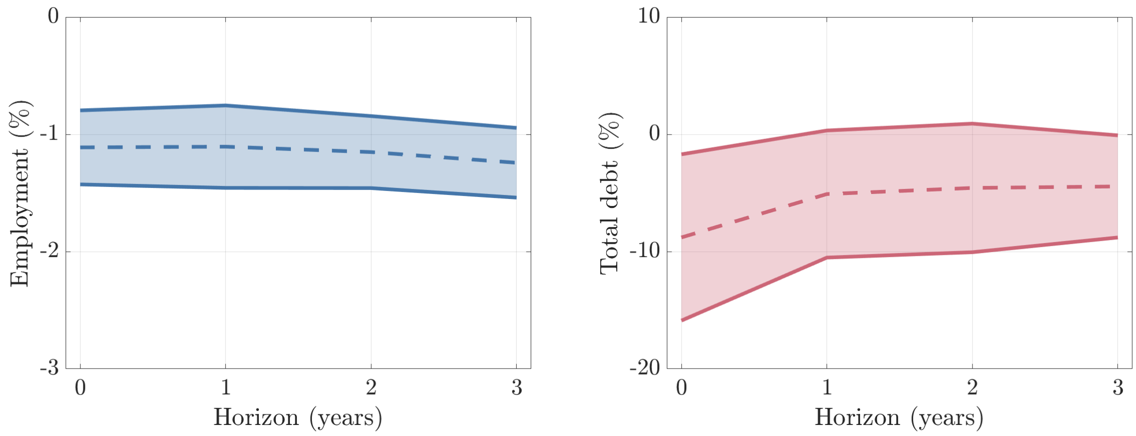
Proxy \ Profit margin	1	2	3	4	5	6	7	8	9	10
1	0.8	0.6	0.7	0.7	0.8	0.9	1	1.2	1.4	2
2	0.6	0.7	1	1	1	1	1.1	1.2	1.2	1.2
3	0.6	0.7	0.9	1.1	1.1	1.1	1.1	1.2	1.2	1
4	0.6	0.7	0.9	1.1	1.2	1.2	1.1	1.1	1.1	0.9
5	0.7	0.8	1	1.1	1.1	1.1	1.1	1.1	1	0.9
6	0.8	1	1	1.1	1.1	1.1	1.1	1	1	0.9
7	0.9	1.1	1.1	1.1	1.1	1	1	1	0.9	0.8
8	1.1	1.3	1.1	1.1	1	1	0.9	0.9	0.9	0.8
9	1.4	1.5	1.2	1	0.9	0.9	0.8	0.8	0.8	0.7
10	2.3	1.7	1.1	0.9	0.8	0.7	0.7	0.6	0.6	0.6

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 × 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



(a) Employment

(b) Debt

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

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.[28] We quantify the importance of entry and exit to the transmission of monetary policy to employment using this additional 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

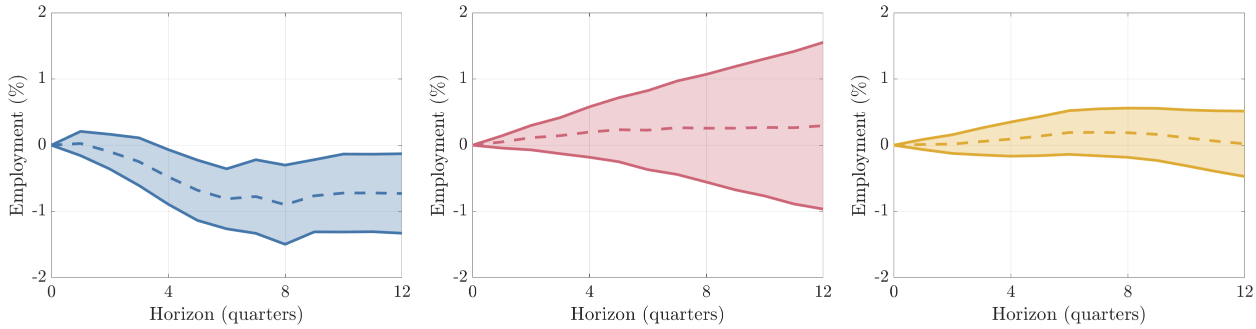
$$\begin{aligned}
\frac{L_{t+k} - L_t}{L_t} &= \mu^k_{q,L} + \beta^k_L \varepsilon_t + \sum_{q=1}^{Q} \delta^k_{q,L} i_{t-q} + u_{L,t+k}, \\
\frac{\sum_{h=1}^{k} C_{t+h}}{L_t} &= \mu^k_{q,C} + \beta^k_C \varepsilon_t + \sum_{q=1}^{Q} \delta^k_{q,C} i_{t-q} + u_{C,t+k}, \\
\frac{\sum_{h=1}^{k} E_{t+h}}{L_t} &= \mu^k_{q,E} + \beta^k_E \varepsilon_t + \sum_{q=1}^{Q} \delta^k_{q,E} i_{t-q} + u_{E,t+k}, \\
\frac{\sum_{h=1}^{k} X_{t+h}}{L_t} &= \mu^k_{q,X} + \beta^k_X \varepsilon_t + \sum_{q=1}^{Q} \delta^k_{q,X} i_{t-q} + u_{X,t+k},
\end{aligned}$$

where $\mu^k_{q,\cdot}$ 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^k_q are the

[28]See Statistic Canada, Cansim Table 3310016501.

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 existers, 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.



(a) Continuers (b) Entrants (c) Exiters

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

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 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 that 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.[29] All but three industries have a negative response (i.e., transportation, Information & cultural, arts & entertainment, and two of them are not statistically significant att 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.

[29] We have 15 industries, at the NAICS 2-digit level. Note that some removed some industries 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^{**}				
			(0.79)				
Young, medium			-1.31^{***}				
			(0.43)				
Young, large			-0.77				
			(0.56)				
Old, small			-0.57^{*}				
			(0.31)				
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^{***}	
						(0.48)	
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
							(0.51)
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^{**} (0.99)	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 (0.99)
Information & cultural	2.50^{**} (1.40)	Other services	-0.85 (0.92)
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 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

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

The controls are the same as in Equation C.3:

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

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	0.004*	0.004*
	(0.002)	(0.002)	(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.7 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) and (ii) the *Senior Loan Officer Survey* (henceforth SLOS). 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).[30]

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.

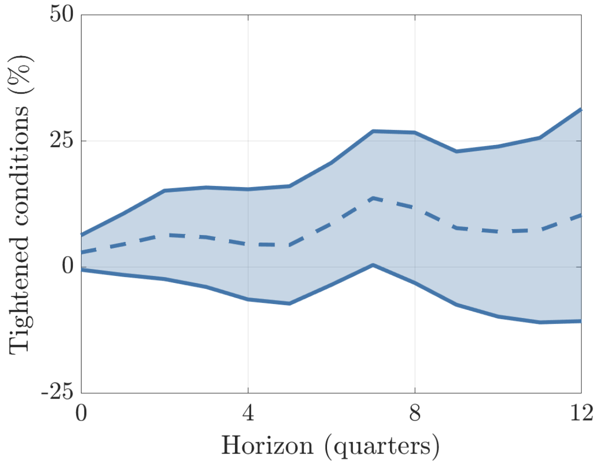
We conduct a simple exercise where we estimate the response of the cumulative balance of opinion to a monetary policy shock. We use the same specification that we used with the aggregate data (see Equation 2.1) and report IRFs associated with a 25 bps monetary policy shock. To accommodate the quarterly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

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

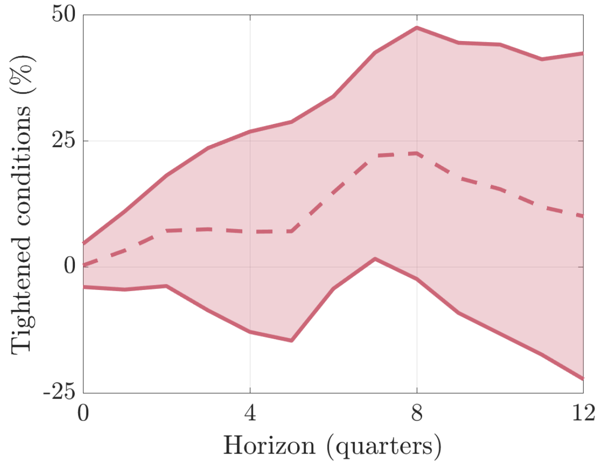
where BOO_t is the balance of opinion (in percentage points) in quarter t, μ_q^k is a quarterly dummy; ε_t is the monetary policy shock, and i_t is the bank rate. We use $Q = 4$ lags for the bank rate. The time period is from 2000 to 2016. Standard errors are calculated using Newey-West.

Figure 9a reports the results from the BOS (i.e., from the perspective of borrowers). The

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



(a) Firms



(b) Financial insitutions

Figure 9: Non-price credit conditions following a monetary policy shock where positive values indicates tightening (25 basis points, 90% confidence intervals).

balance of opinion responds positively, meaning that a rising share of firms report that credit conditions are tightening. Figure 9b 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

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

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

Differentiating with respect to R, we obtain

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

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

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

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 $\varepsilon \equiv \log(R'/R)$:

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

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

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

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

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

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 $\mathrm{E}(u_i|p_i, \varepsilon) = 0$. The mapping between parameters $(\lambda, \beta_p, \beta_d, \beta_{id})$ is

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