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Monetary Policy, Credit Constraints and SME Employment

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Abstract

Do financial constraints amplify or dampen the transmission of monetary policy to the real economy? To answer this question, we propose a simple empirical strategy that combines (i) firm-level employment and balance sheet data, (ii) identified monetary policy shocks and (iii) survey data on financing activities. The key novelty of our approach is a new proxy for the likelihood of being credit constrained, which is constructed using survey data on realized outcomes of financing requests. Leveraging cross-sectional heterogeneity in the proxy and the sensitivity of employment to monetary policy shocks, we find that credit constraints amplify the transmission of monetary policy. In the aggregate, credit constraints account for roughly a third of the employment response. Our findings are consistent with a strong financial accelerator, whereby accommodative monetary policy has the indirect effect of improving the ability of firms to obtain credit.

Topics: Credit and credit aggregates; Econometric and statistical methods; Firm dynamics; Labour markets; Monetary policy
JEL codes: E2, E3, E43, E52, G3

Résumé

Les contraintes financières amplifient-elles ou amortissent-elles la transmission des effets de la politique monétaire à l'économie réelle? Pour répondre à cette question, nous proposons une simple stratégie empirique combinant (i) des données relatives au niveau d'emploi et au bilan des entreprises, (ii) des chocs de politique monétaire ciblés et (iii) des données d'enquête sur les activités de financement. La principale nouveauté de notre approche est une variable d'approximation de la probabilité d'être soumis à des contraintes de crédit. Elle a été créée à partir de données d'enquête sur les résultats observés de demandes de financement. Nous exploitons l'hétérogénéité transversale de notre variable d'approximation ainsi que la sensibilité de l'emploi aux chocs de politique monétaire, et trouvons que les contraintes de crédit amplifient la transmission de la politique monétaire. Globalement, environ le tiers des effets de la politique monétaire se transmettent à l'emploi par l'intermédiaire des contraintes de crédit. Nos résultats sont cohérents avec l'idée d'un puissant accélérateur financier, par lequel une politique monétaire expansionniste a l'effet indirect d'accroître la capacité des entreprises à obtenir du crédit.

Sujets : Crédit et agrégats du crédit; Dynamique des entreprises; Marchés du travail; Méthodes économétriques et statistiques; Politique monétaire
Codes JEL : E2, E3, E43, E52, G3

1 Introduction

Do financial constraints faced by firms amplify or dampen the transmission of monetary policy to employment? 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—which 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, 2021; Bahaj, Foulis, Pinter, and Surico, 2020; 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. All in all, 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 those firms that are likely to face 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

[1]Similarly, other papers argue that interest rate covenants or floating rate debt amplify the effects of monetary policy to 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.

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 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 incremental 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) 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 response of 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 face financing constraints and then assess, in an agnostic manner, which firm characteristics matter to predict constraints. Importantly, our proxy has a cardinal interpretation (i.e., a value of 0.1 corresponds to a 10% probability of being credit constrained over the course of a year).

Finally, we 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 firm-level specification for employment growth where we interact the monetary shock with firm observables (i.e., size, age, and productivity) and with our proxy. By setting the coefficient on the interaction between the monetary policy shock and the proxy to zero, we thus obtain the counterfactual response of employment to monetary policy shutting down the effect of credit constraints. Aggregating these counterfactual firm responses, we obtain 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 one-third of the aggregate response of employment. It is worth emphasizing the fact that our approach allows the direct effect of monetary policy to vary with firm observables. We show that failure to do so implies a larger amplification effect of credit constraints, due entirely to an omitted variable bias. For instance, 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 new proxy measure 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. 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, consistent with the insights from the firm dynamics literature. 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.

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 curvature of the interest rate spread as a function of balance sheet health). Regarding 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., 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 marginal source of financing for SMEs). Regarding the final point, Leung, Meh, and Terajima (2008) provide evidence that Canadian lenders follow 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. We view this focus on the extensive margin as conservative (i.e., our results are a lower bound on the amplifying effect constraints), since 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 through intertemporal substitution (the interest rate channel), but also by changing the amount of credit that firms are able to obtain (the credit channel). The credit channel is thought to arise due to financial frictions, faced either by the banking sector or by entrepreneurs. 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). However, as discussed earlier, Farre-Mensa and Ljungqvist (2016) show that these celebrated proxies tend to perform poorly at identifying firms that are actually credit constrained. Compared to these studies, we construct our proxy using survey data on *observed* outcomes of requests for external credit and then assess which firm observables are relevant to predict whether or not a firm is financially constrained. Cao and Leung (2019) use the same survey and show that firm size, leverage, and cash flows are important predictors of being constrained.

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 dividend-paying status (Cloyne et al., 2021), liquidity

(Jeenas, 2019), credit rating (Ottonello and Winberry, 2020), leverage (Lakdawala and Moreland, 2021), and outstanding bank loans (Ippolito et al., 2018). 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, we build a proxy using survey data that contains 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 paper that also uses a representative sample of the economy covering SMEs is Bahaj et al. (2020). 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. (2020) 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.

Finally, our paper also relates to the firm dynamics literature, which documents that, for instance, small and young firms tend to have higher and more volatile growth rates (see, e.g., Haltiwanger, Jarmin, and Miranda, 2013, Fort, Haltiwanger, Jarmin, and Miranda, 2013, and Moscarini and Postel-Vinay, 2012). Our new proxy has interesting predictions for this literature: controlling for age, size, and productivity, our proxy predicts that firms with a higher likelihood of being constrained experience lower growth of employment and debt. These results provide new insights over traditional predictors of firm growth.

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 "macro channel" decomposition and estimate that credit constraints account for about one-third of the total effect of monetary policy on employment. Using a simple two-period model of firm financing and hiring, we describe how to map the decomposition into structural elasticities.

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.[2] With this new monetary policy shocks series, CS estimate the effect of monetary policy on real gross domestic

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

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 Appendix A.1, Equation 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:

$$y_{t+k} = \mu^k + \beta^k \varepsilon_t + \sum_{p=1}^{P} \rho_p^k y_{t-p} + \sum_{q=1}^{Q} \delta_q^k i_{t-q} + u_{t+k}. \tag{2.1}$$

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 horizon to three years (i.e., $K = 36$).

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).[3] 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. and Champagne and Sekkel, 2018 for Canada).

[3]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.

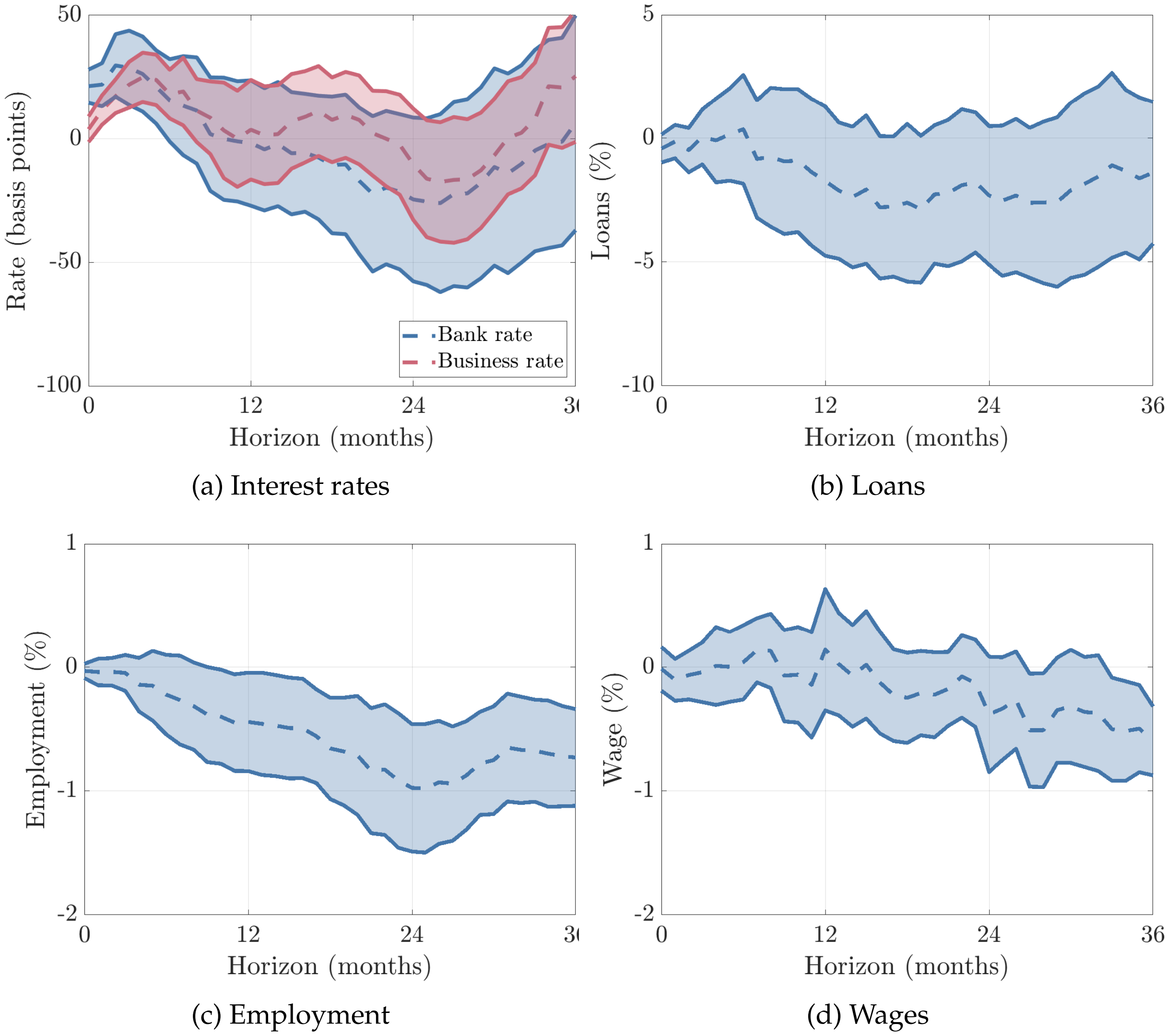


Figure 1: Response of financial and real variables to a monetary policy shock (25 basis points, 90% confidence intervals).

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.

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.[4]

The resulting dataset has a number of features that make it nicely suited for our analysis. 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).[5] 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.[6]

[4]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.

[5]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.

[6]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.[7] 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 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.

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

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

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 $y_{i,t}$ 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. For every monthly horizon $k \in \{0, \ldots, K\}$, we estimate the following local projection specification:

$$y_{i,t+k} = \mu^k_{g,j,m} + \sum_{p=1}^{P} \rho^k_{p,g} y_{i,t-p} + \sum_{q=1}^{Q} \delta^k_{q,g} i_{t-q} + \beta^k_g \varepsilon_t + u_{i,t+k}, \tag{2.2}$$

where subscript $g \in \{1, \ldots, G\}$ refers to a categorical variable that denotes groups of firms.[8] The term $\mu^k_{g,j,m}$ represents a fixed effect that is the interaction between industry j (NAICS 2-digit), month of the year m, and the group g. We weigh the observations by their employment at time $t - 1$ (i.e., weighted OLS) to preserve aggregation.

The estimated impulse response function for group g is $\{\hat{\beta}^k_g\}^K_{k=1}$, and we use Driscoll and Kraay (1998) standard errors to account for heteroscedasticity, autocorrelation, and cross-sectional dependence. As before, we set $P = 12$, $Q = 3$, and $K = 36$.

Consistency with agggregate 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 (2.2) are consistent with the aggregate IRFs estimated using specification (2.1) and publicly available data for the private non-farm economy.

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.

[8] For the application that we will consider shortly, g refers to a firm-size group. More generally, the groups can be based on any firm characteristic.

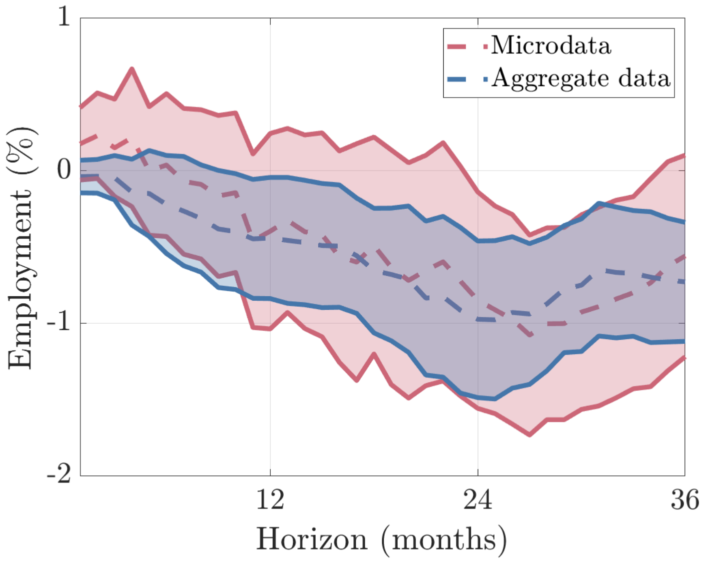
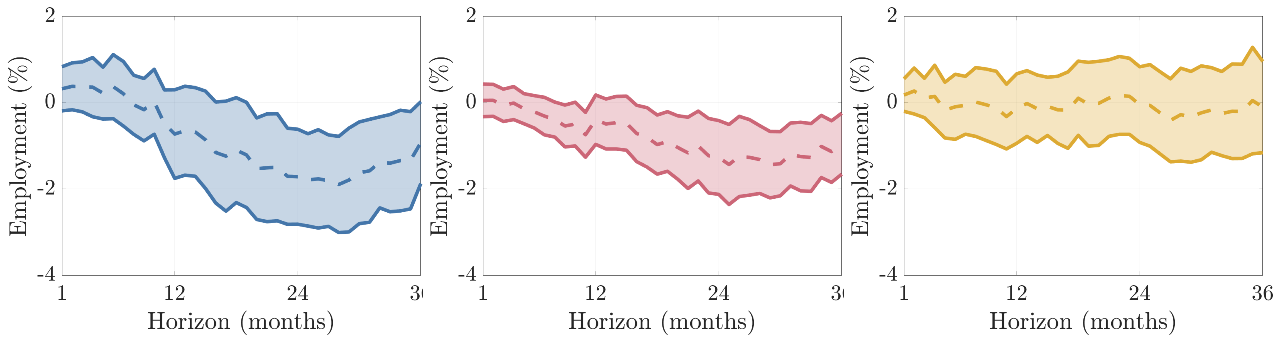


Figure 2: Employment impulse response function: microdata versus aggregate data (25 basis points monetary policy shock, 90% confidence intervals).

IRFs along the firm-size distribution. We now estimate the employment response to monetary policy shocks across 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). These three size groups allow us to estimate whether the employment 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.

3 The Proxy

We now shift our focus to SMEs. Ultimately, our goal is to assess whether financial constraints amplify the transmission of monetary policy to employment. We develop a proxy approach, which assigns a time-varying probability (or "likelihood") of being financially constrained to all SMEs in our sample. To do so, we proceed in two steps.

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.[9]

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 over 13,600 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 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, mortgages, credit cards, 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
Mortgage	15.5	17.1	18.7	21.5	16.0
Line of credit	9.4	11.2	17.7	14.7	10.0
Term loan	5.1	7.3	7.9	11.0	5.7
Credit card	12.1	13.2	14.8	17.9	12.4
Equity financing	2.0	2.5	2.5	9.4	2.1

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.

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 in-

[9] See Appendix B for the detailed questions in the survey.

formation regarding financing activities and outcomes over the past 12 months. The survey data aligns closely with the main sample described earlier (see Table 1).[10]

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."

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.

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

[10]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 less than 2 percent of firms but 15 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.

Table 3: Summary statistics (survey data)

Variables	Size groups				Total
	< 20	$20 - 100$	$100 - 250$	$250 - 500$	
Shares (%)					
Firm	54.8	32.3	11.1	1.8	100
Employment	12.8	32.5	39.9	14.9	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	0.54	0.57	0.61	0.45	0.53
Liquidity	0.50	0.54	0.50	0.21	0.39
Earnings-to-debt	0.12	0.11	0.10	0.06	0.09
Profit margin	0.05	0.04	0.04	0.07	0.05
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: "Firm" and "Employment" shares are the shares of the number of firms and total employment in each firm-size group, respectively, in the main sample 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. "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.

Table 4: Reason for not requesting financing and 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: Panel A shows the percentage of firms by reason for not requesting credit in the *Survey on Financing and Growth of Small and Medium Enterprises* sample. 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.

liabilities; current liabilities; total assets; current assets; revenues; expenses; and age.

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 over total assets, liquidity is current assets over total assets, etc.). For our analysis below, we take logarithms and demean each variable using cross-sectional year average.

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.[11] 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 subsample with 90 percent of the observations) and forecast $\mathbb{P}(\text{Constrained}_{i,t} = 1)$ on a

[11]"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.

"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: "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.

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 1.0 percent relative decrease in total revenues increases the probability of being constrained by 2.4 percentage points. Relative decreases in total assets and total debt translate into 1.1 and -1.4 percentage point changes in the probability of being constrained, respectively —about twice as much as their short-term (current) counterparts.

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

Table 6: Determinants of credit constraints

Predictive variables	Coefficient	Standard error
Total liabilities	0.0136***	0.0026
Current liabilities	0.0058**	0.0025
Total assets	−0.0112***	0.0031
Current assets	−0.0061**	0.0026
Revenue	−0.0236***	0.0073
Expense	0.0138*	0.0070
Age	−0.0080***	0.0020
Constant	0.0387***	0.0018

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

credit constrained $\widehat{p}_{i,t}$ as

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

The value $\overline{p}$ is set to 2.1 percent so as to match the employment-weighted probability of being constrained in the survey.[12]

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) what our proxy predicts in terms of firm dynamics.

Relationship with standard proxies. Table 7 reports the correlation structure 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.

Several interesting observations stand out. First, notice that 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

[12]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.

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.

each other (i.e., all but three correlations are below 0.1 in absolute value). In Appendix B.2, we report "heatmaps" (Figure 8) describing the correlation structure in a non-parametric way by plotting deciles of our proxy by deciles of the standard financial proxies. Overall, Figure 8 corroborates the correlations in Table 7 nicely.

While we do not take a stand on the particular form of constraint faced by SMEs, Table 7 and Appendix Figure 8 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. (2021) 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.

Properties of the proxy (unconditional). How does our proxy correlate with firm dynamics in the data? Standard theory predicts that, all else equal, firms that face credit constraints have lower growth rates for employment and debt. To summarize these dynamic correlations in the data, we estimate local projection models of the form

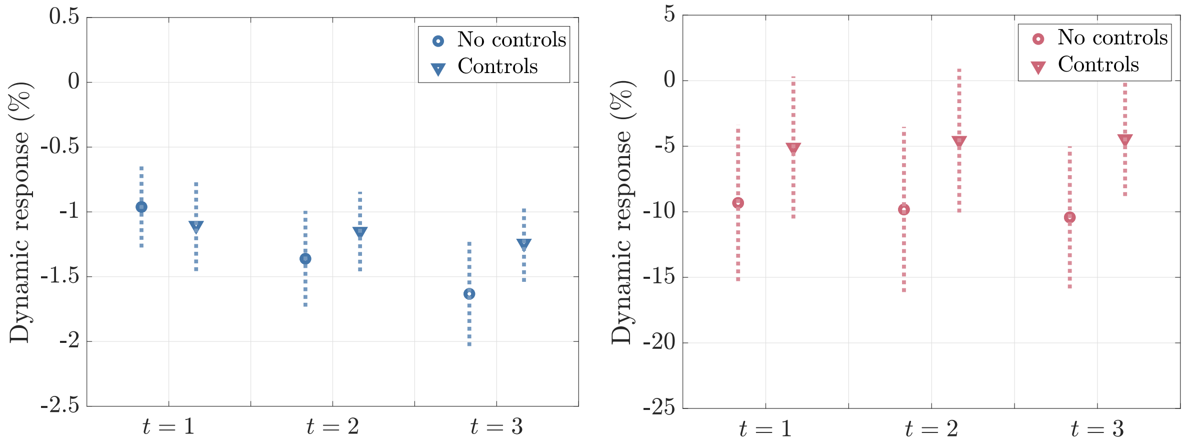
$$y_{i,t+k} = \mu^k_{j,t} + \rho^k y_{i,t-1} + \beta^k \widehat{p}_{i,t} + z'_{i,t}\theta^k + u_{i,t+k}, \tag{3.3}$$

where t denotes years, $\mu^k_{j,t}$ is an industry-year fixed effect (i.e., NAICS two digit), $y_{i,t}$ is the variable of interest in logarithm, $\widehat{p}_{i,t}$ is the proxy; and $z_{i,t}$ is a vector of firm-level controls. The coefficient of interest is β^k. It measures the difference in the path of $y_{i,t+k}$ for firms with different probabilities of being constrained, *conditional* on its lag $y_{i,t-1}$ and the controls $z_{i,t}$. 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.[13] We include these three variables in logs, and productivity is proxied by sales per worker.

Figure 4a shows the "dynamic 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 $k = 1, 2, 3$) with and without controls. Whether we include controls or not, the results are similar: 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., $\widehat{\beta}^2 \approx 1.2$ both with and without controls).

Figure 4b replicates the exercise but focuses on total liabilities (i.e., the sum of short-

[13] See Haltiwanger et al. (2013), Fort et al. (2013), and Moscarini and Postel-Vinay (2012) for evidence on the link between size, age, and firm growth. For evidence on the link between productivity and growth, see Ilut, Kehrig, and Schneider (2018) and Decker, Haltiwanger, Jarmin, and Miranda (2020)



(a) Employment

(b) Liabilities

Figure 4: Properties of the proxy (estimated coefficients $\widehat{\beta}^k$ in specification 3.3)

and long-term debt) as the variable of interest. Qualitatively, the results are similar: firms that are more likely to be constrained experience a lower growth rate of debt. However, the results are less precisely estimated and are somewhat less pronounced in the specification with controls. Focusing on the specification with controls, we find that a 10 percentage point increase in the likelihood of being credit constrained in year t is associated with a roughly 50 percent decline in total liabilities in year $t + 2$ (i.e., $\widehat{\beta}^2 \approx 5$).

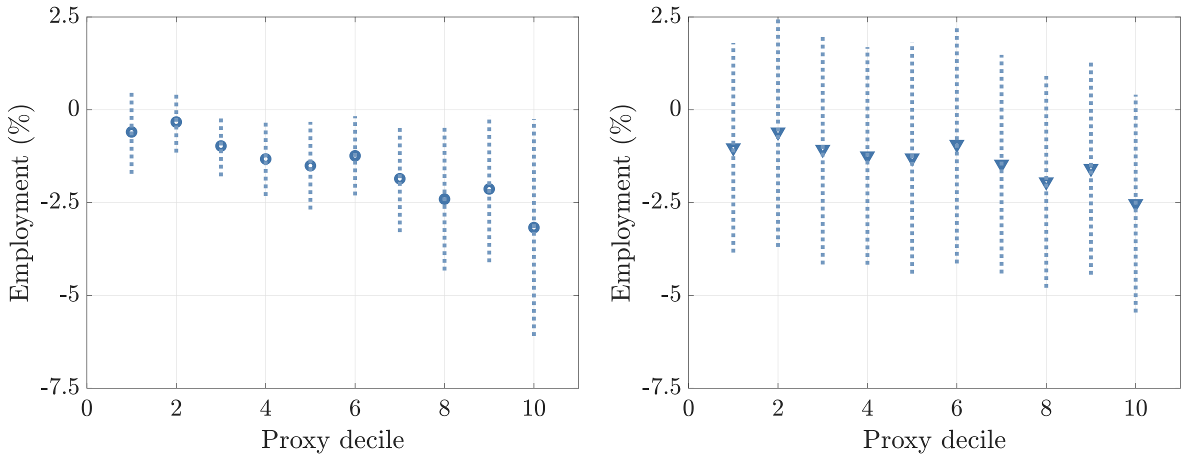
Overall, the properties of the proxy are consistent with what one would expect from standard theory: constrained firms experience a lower growth rate of employment and debt. Moreover, the fact that our results hold after controlling for differences in age, size, and productivity suggests that our proxy contains information that is orthogonal to the traditional predictors of firm growth in the firm dynamics literature.

Properties of the proxy (conditional on monetary shock). 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. Instead of tracing out the full IRF, we use a "peak response" specification that is designed to estimate the average employment response over the 12–24 month horizon. The specification is

$$\bar{l}_{i,t\in(12,24]} = \mu_{j,m} + \sum_{p=1}^{P} \rho_p l_{i,t-p} + \sum_{q=1}^{Q} \delta_q i_{t-q} + \beta_g \varepsilon_t + z_{i,t}\varepsilon_t'\theta + u_{i,t\in(12,24]}, \tag{3.4}$$

where the coefficient of interest is β_g and the subscript g refers to a categorical variable that denotes the proxy-implied deciles. Equation (3.4) is similar to Equation (2.2), except that (i) the left-hand-side variable is the log of the average employment over the 12 through 24 months ahead (which we denote $\bar{l}_{i,t+12,t+24}$), and (ii) we include a vector of firm dynamics controls $z_{i,t}$ interacted with the monetary policy shock. The standard errors are computed as before, using the Driscoll-Kraay approach.



(a) No controls (b) Controls

Figure 5: Response of employment to a monetary policy shock by likelihood of being constrained (25 basis points, 90% confidence intervals).

Figure 5a presents the results for the specification without controls, 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 the response is roughly -3% for firms in the tenth decile (i.e., the 10 percent of firms most likely to be credit-constrained).

Figure 5b reproduces the results but with controls. The same qualitative pattern occurs, but the magnitudes are less pronounced (i.e., the response is roughly -2.5 percent for firms in the tenth decile) and the coefficients are estimated with less precision. Since our specification controls for firm observables $z_{i,t}$ interacted with the monetary policy shock, this means that the excess sensitivity to monetary policy of employment in likely constrained firms is driven partly by the fact that these firms differ in terms of age, size, and productivity. Overall, this evidence on the cross-sectional relationship between sensitivity of employment to monetary policy and likelihood of being constrained points to an amplification mechanism of credit constraints to monetary policy. We turn next to a decomposition that will allow us to quantify how much financial constraints actually amplifies the transmission of monetary policy.

4 Quantifying the Contribution of Credit Constraints

We now provide a simple and easy-to-interpret empirical decomposition to quantify the contribution of credit constraints in the transmission of monetary policy to employment.

4.1 The decomposition

The key idea underlying our decomposition is to use cross-sectional heterogeneity in firm exposure to the credit constraint channel by using our proxy. Our goal is to decompose the firm-level response of employment to a monetary policy shock into (i) the *direct effect* of monetary policy that operates via changes in the cost of credit, and (ii) the *indirect effect* of monetary policy that operates via changes in the tightness of credit constraints.

Our decomposition can be implemented by estimating a single local projection model. In particular, we estimate the following version of the "peak response" specification (3.4) that includes the monetary policy shock, its interaction with the proxy $\widehat{p}_{it}$, and its interaction with firm-level observable characteristics $z_{i,t}$:

$$\bar{l}_{i,t\in(12,24]} = \mu_{j,m} + \sum_{p=1}^{P} \rho_p l_{i,t-p} + \sum_{q=1}^{Q} \delta_q i_{t-q} + \beta_d \varepsilon_t + z_{i,t}\varepsilon_t'\theta_d + \beta_{id}\widehat{p}_{it}\varepsilon_t + u_{i,t\in(12,24]}. \quad (4.1)$$

For firm i in month t, the direct effect is obtained by shutting down the contribution of credit constraints (i.e., $\beta_{id} = 0$). We thus obtain

$$\text{Direct effect}_{i,t} = \beta_d + z_{i,t}'\theta_d. \quad (4.2)$$

The indirect effect captures the additional effect of credit constraints on the response of employment to the monetary policy shock:

$$\text{Indirect effect}_{i,t} = \beta_{id}\widehat{p}_{i,t}. \tag{4.3}$$

Note that our specification allows both the direct (4.2) and indirect effect (4.3) to be heterogeneous in the cross-section of firms. In particular, we allow the direct effect to depend on observable firm characteristics $z_{i,t}$ (i.e., age, size, and productivity), while the indirect effect is proportional to the ex-ante probability of being constrained $\widehat{p}_{it}$.

We believe that allowing for the direct effect to differ across firms with different age, size, and productivity is important and failing to do so can lead to important biases. For instance, suppose that the direct effect is decreasing in size (perhaps because larger firms face more important labor adjustment costs) and that the proxy p is positively correlated with size (perhaps because smaller firms have worse balance sheets). In a specification that does not control for the interaction between size and the monetary policy shock, the estimates will spuriously rationalize all of the excess response of small firms via their higher probability of being constrained. Hence, the contribution of the indirect effect will be overestimated (upward biased in absolute value). This is the classic omitted variable bias.

Aggregation. Denoting by $\overline{p}$ the employment-weighted probability of being constrained and $\overline{z}$ the employment-weighted average of firm-level observables, we have the following expression for the *aggregate* direct and indirect effects:

$$\text{Direct effect} = \beta_d + \overline{z}'\theta_d, \tag{4.4}$$

$$\text{Indirect effect} = \beta_{id}\overline{p}, \tag{4.5}$$

$$\text{Total effect} = \beta_d + \overline{z}'\theta_d + \beta_{id}\overline{p}. \tag{4.6}$$

Note that these three quantities can be constructed using only the estimated parameters from (4.1) (i.e., $\widehat{\beta}_d, \widehat{\theta}_d, \widehat{\beta}_{id}$) and cross-sectional weighted averages (i.e., $\overline{z}, \overline{p}$).[14]

Results. Table 8 presents the results of the decomposition, where the indirect effect (4.5) is expressed as a share of the total effect (4.6). We also estimate a 90 percent confidence interval on this ratio using the Delta method. The first row contains the

[14] Recall that all of our firm-level specifications are estimated using employment weights, which ensures that they aggregate to the corresponding macro IRF (see discussion around Figure 2).

baseline specification. We find that the indirect effect accounts for 29 percent of the total response of SME employment to a monetary policy shock, albeit with a high degree of estimation uncertainty (i.e., the confidence interval covers roughly 0 to 0.6).

Table 8: Contribution of credit constraints

Specification	$\frac{\text{Indirect effect}}{\text{Total effect}}$	90% confidence interval
Baseline	0.29	$[-0.03, 0.62]$
No controls	0.60	$[-0.08, 1.29]$

Notes: The 90 percent confidence interval is constructed using the Delta method where standard errors are estimated using Driscoll-Kray.

The second row of Table 8 contains the results of the decomposition when we impose a homogeneous direct effect $\theta_d = 0$ (i.e., no firm-level controls interacted with the shock). In this case, we find that the indirect effects account for 60 percent of the total response, which is twice as large as in the baseline specification. Given the above discussion, we believe that the specification without controls overstates the indirect effect for the reasons that we discussed earlier (i.e., it is more prone to an omitted variable bias).

From an accounting standpoint, we thus find that credit constraints materially amplify the transmission of monetary policy to employment. Why is that? In Section 4.3, we study a textbook two-period model of firm hiring augmented with an ad-hoc credit constraint. We show that if monetary policy has a strong effect on the tightness of credit constraints, in addition to its usual effect on the cost of credit, then the presence of credit constraints amplifies the response of monetary policy. Before we study the economic mechanism that can rationalize our results, it is worth discussing further the implicit assumptions behind our decomposition.

4.2 Implicit assumptions and interpretation

Our decomposition has the straightforward interpretation of "zero-ing out" the contribution of credit constraints (i.e., $\beta_{id} = 0$) in order to obtain an estimate of the direct effect of monetary policy. We now discuss the interpretation of our decomposition more formally.

First, it is worth emphasizing the fact that our empirical specification (4.1) does not include a time fixed effect, and therefore does not suffer from the missing intercept problem. We thus estimate the employment response of firms to a monetary policy shock taking into account the effect of the shock on aggregate objects, such as wages and labor market tightness.

Second, the direct effect (4.4) 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 $\beta_{id} = 0$). However, doing so does not shut down the contribution of credit constraints to the response of aggregate objects (i.e., wages and labor market tightness), which themselves affect firm-level hiring. To be concrete, suppose that the indirect effect is negative, so that the presence of credit constraint amplifies the decline in employment associated with a rise in the interest rate. This means that wages fall more in the economy with credit constraints than in the economy without credit constraints. When we shut down the contribution of credit constraints in the firm-level employment equation (4.1), we do not shut down the effect they have on aggregate wages.

Huber, Paul, and Wolf (2022) study the type of decomposition that we implement in detail. They call these "micro-channel decompositions" as opposed to "macro-channel decompositions," where the researcher shuts down all of the general equilibrium effects induced by the amplification channel studied.

Finally, for our decomposition to be valid, it must be the case that our proxy correlates with the tightness of credit constraints but not with other channels of transmission of monetary policy. While this assumption is not testable, we believe that the construction of our proxy, which is based on realized instances of credit constraints binding, is uniquely suited to satisfy this assumption. Moreover, and as discussed earlier, we believe that our inclusion of firm observables (i.e., size, age, and productivity) interacted with the monetary policy shock goes a long way in mitigating omitted variable biases that would generate a spurious correlation between our proxy and the sensitivity of employment to monetary policy.

4.3 Interpretation of results in stylized model

We now provide a fully-specified, albeit stylized, model of firm employment. We use the model to (i) clarify which structural parameters govern the direct and indirect effects of monetary policy, (ii) show that the presence of credit constraints can either amplify or dampen the transmission of monetary policy, and (iii) 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 $t = 1$. The wage is the numéraire and goods prices are sticky and normalized to one. Workers supply labor perfectly elastically. Firms discount cash flows at the gross nominal interest rate R. Firms are ex-ante identical and have an initial level of cash $C > 0$. With probability p, they are credit-constrained (i.e., they do not have access to credit).

Firm problem. Firms maximize the present discounted value of cash flows. With probability $1 - p$, the firm is unconstrained and solves:

$$\max_{L \geq 0} -L + R^{-1} L^{1-\frac{1}{\sigma}},$$

which has the solution $L^{\mathrm{uc}} = (1 - \frac{1}{\sigma})^{\sigma} R^{-\sigma}$. With probability p, the firm is constrained and can hire at most C workers using its cash, which means that the level of employment of constrained firms is $L^{\mathrm{c}} = \min\{L^{\mathrm{uc}}, C\}$. We denote the employment gap of unconstrained firms by $\Delta \equiv \log(L^{\mathrm{uc}}/L^{\mathrm{c}})$, which is non-negative by construction.

Monetary policy. We are interested in the employment effect of a shock to the nominal interest rate (dR, henceforth a monetary policy shock). In addition to the standard cost of credit 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 constrained).[15] In particular, we assume that the probability of being constrained is given by

$$p = \overline{p} R^{\theta},$$

where $\overline{p} > 0$ governs the level of credit constraints in the economy and θ governs the sensitivity of constraints to the interest rate.

[15]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 sheets by increasing their collateral values, thus leading them to loosened lending standards. Second, a lower R could also improve firm balance sheets, thus leading lenders to lend more without loosening their lending standards.

Decomposition in the model. Without using any of the model's assumptions, we have that average log employment is given by

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

Totally differentiating, we obtain

$$\frac{\mathrm{d}\mathbb{E}(\log L)}{\mathrm{d}R} = \underbrace{\frac{\partial \log L^{\text{uc}}}{\partial R}}_{\text{Direct effect}} + \underbrace{p\left[\frac{\partial \log(L^{\text{uc}}/L^{\text{c}})}{\partial R} - \frac{\partial \log p}{\partial R}\log(L^{\text{uc}}/L^{\text{c}})\right]}_{\text{Indirect effect}}$$

The response of log employment is thus given by by the direct effect (i.e., the response of unconstrained firms) and the indirect effect, which is defined residually.

Using the assumptions of the model, we have that

$$\frac{\mathrm{d}\mathbb{E}(\log L)}{\mathrm{d}R} = \underbrace{-\sigma}_{\text{Direct effect}} + \underbrace{p \times (\sigma - \theta\Delta)}_{\text{Indirect effect}}. \tag{4.7}$$

The direct effect is negative and governed by the inverse curvature of the production function σ. However, notice that the sign of the indirect effect is ambiguous.

For instance, if monetary policy does not affect the probability of being constrained ($\theta = 0$), then the indirect effect is positive. In this case, 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 underlying the main result in Ottonello and Winberry (2020).

If, instead, the effect of monetary policy on the tightness of constraints is sufficiently large (i.e., $\theta\Delta > \sigma$), then the indirect effect is negative, meaning that 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 their employment by $\Delta > 0$ log points. This is precisely the financial accelerator mechanism proposed by Bernanke et al. (1999).

Back-of-the-envelope calibration of the model. The decomposition in the model (4.7) has four structural parameters $(\sigma, p, \theta, \Delta)$. We now provide a simple mapping between structural parameters and moments in the data. The main takeaway is that the model can rationalize the data with a moderate sensitivity of credit constraints to monetary policy. Given that this exercise is for illustrative purposes, we use round numbers.

Two structural parameters have direct empirical counterparts. First, the parameter σ in the model, which governs the curvature of the production function, can be mapped directly to the direct effect of monetary policy. In the data, we have that the elasticity of employment to the interest rate amongst SMEs is roughly -6 at the two-year horizon (see Figure 3), with two-thirds of it being the direct effect (see Table 8). We thus have that $\sigma \approx 4$. This is a reasonable value, as it implies a production function with a moderate amount of decreasing returns to scale in the short run (i.e., $L^{1-\frac{1}{\sigma}} \approx L^{0.75}$). Second, the probability p in the model can be mapped directly to the (employment-weighted) probability of being constrained in the survey data, which is roughly $p \approx 2\%$.

Then, the product of the semi-elasticity of the constraint θ and the employment gap Δ can be obtained residually by using the fact that $p \times (\sigma - \theta\Delta)$ is equal to the direct effect of -2. Using the fact that $\sigma \approx 4$, this gives us that $\theta\Delta \approx 100$. Finally, we can separately identify θ and Δ by using a direct estimate of Δ. Recall that we estimated that a 1 percent rise in the probability of being constrained is associated with a decline in employment of roughly 1 log point at the two-year horizon (see Figure 4a). Scaling up, we thus have that the implied log employment gap is $\Delta = 1$. Residually, we have that $\theta \approx 100$.

Is a semi-elasticity of $\theta \approx 100$ (or alternatively a local elasticity of $\theta \times p \approx 2$) reasonable? As a concrete example, it means that a 25 bps monetary policy shock increases the fraction of firms that are constrained by 0.5 percent:

$$\mathrm{d}p = \underbrace{p}_{2\%} \times \underbrace{\theta}_{100} \times \underbrace{\mathrm{d}\log R}_{0.25\%} = 0.5\%. \tag{4.8}$$

The key takeaway is as follows. Even if a 25 bps monetary policy has only a small effect on the probability of being constrained (i.e., $\mathrm{d}p \approx 0.5\%$), it can have a large effect on employment if being credit constrained is associated with a large decline in employment, as we find in the data (i.e., $\Delta \approx 1$ implies that constrained firms are 65 percent smaller than large firms).

4.4 Monetary policy and non-price credit conditions

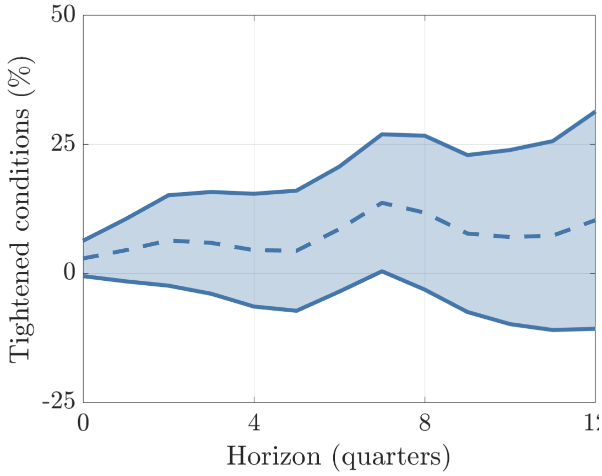
Guided by the model, our interpretation of the evidence is that the transmission of monetary policy to employment is amplified by the fact that monetary policy affects not only the price of credit (i.e., the interest rate), but also the ability of firms to obtain credit (i.e., the probability of being constrained). Ideally, we would present 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 is not suitable for 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).[16]

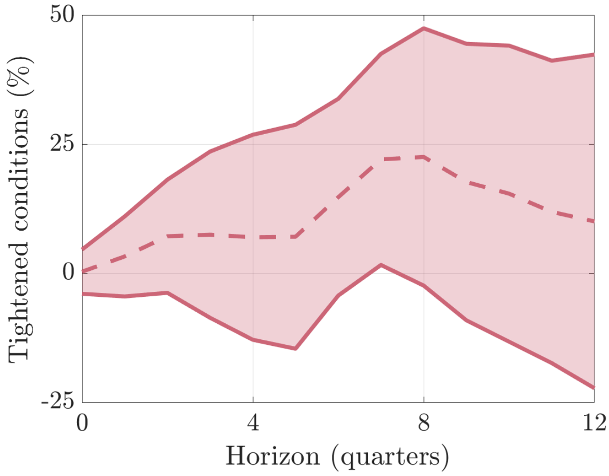
The BOS asks firms: *"How have the terms and conditions for obtaining financing changed over the last three months compared to the previous three months?"* Examples of tightened terms and conditions given to the survey participants are increased collateral requirements or capital markets being less receptive 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

[16] 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 6: Non-price credit conditions following a monetary policy shock where positive values indicates tightening (25 basis points, 90% confidence intervals).

bps monetary policy shock.[17] Figure 6a reports the results from the BOS (i.e., from the perspective of borrowers). The balance of opinion responds positively, meaning that a rising share of firms report that credit conditions are tightening. Figure 6b reports the results from the SLOS (i.e., from the perspective of lenders). Similarly, the response is positive, signifying a tightening. 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.

5 Concluding Remarks

Do financial constraints faced by firms amplify or dampen the transmission of monetary policy to macroeconomic aggregates such as employment? And if so, by how

[17] To accommodate the quarterly frequency of the survey, we sum the monetary policy shocks within each quarter. The exact specification is

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

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 the Driscoll-Kray method.

much? 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 paper makes incremental progress on two data issues that have hindered progress on these questions. 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. This dataset is ideal for our investigation since it is both universal (i.e., it covers private and smaller firms which are not covered in datasets using publicly listed corporations) and our outcome variable (i.e., employment) is available at the monthly frequency.

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 *observed* SME financing activities and outcomes. We use the survey information on the need *and* ability to obtain external credit to identify precisely which firm faces financing constraints and then to assess, in an agnostic manner, which firm characteristic matters to predict constraints.

Finally, we 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.

Our results highlight an important role for a financial accelerator in the transmission of monetary policy to employment. Given that our analysis of financial constraints focuses on (i) SME firms (rather than all firms), (ii) debt financing (rather than both equity and debt 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 curvature of the interest rate spread as a function of balance sheet health), we are confident that our estimates provide a lower bound on the effects of financial constraints in the transmission of monetary policy to employment.

References

BAHAJ, S. A., A. FOULIS, G. PINTER, AND P. SURICO (2020): "Employment and the collateral channel of monetary policy," *Journal of Monetary Economics*, Forthcoming.

BERNANKE, B. S. AND M. GERTLER (1995): "Inside the black box: The credit channel of monetary policy transmission," *Journal of Economic Perspectives*, 9, 27–48.

BERNANKE, B. S., M. GERTLER, AND S. GILCHRIST (1999): "The financial accelerator in a quantitative business cycle framework," *Handbook of Macroeconomics*, 1, 1341–1393.

CAGLIO, C. R., R. M. DARST, AND S. KALEMLI-OZCAN (2021): "Risk-taking and monetary policy transmission: Evidence from loans to SMES and large firms," Tech. rep., National Bureau of Economic Research.

CAO, S. AND D. LEUNG (2019): "Credit constraints and productivity of SMEs: Evidence from Canada," *Economic Modelling*.

CHAMPAGNE, J. AND R. SEKKEL (2018): "Changes in monetary regimes and the identification of monetary policy shocks: Narrative evidence from Canada," *Journal of Monetary Economics*.

CLOYNE, J., C. FERREIRA, M. FROEMEL, AND P. SURICO (2021): "Monetary Policy, Corporate Finance and Investment," *Journal of the European Economic Association*, Forthcoming.

COIBION, O. (2012): "Are the effects of monetary policy shocks big or small?" *American Economic Journal: Macroeconomics*, 4, 1–32.

CROUZET, N. AND N. R. MEHROTRA (2020): "Small and large firms over the business cycle," *American Economic Review*, 110, 3549–3601.

DECKER, R. A., J. HALTIWANGER, R. S. JARMIN, AND J. MIRANDA (2020): "Changing business dynamism and productivity: Shocks versus responsiveness," *American Economic Review*, 110, 3952–90.

DRISCOLL, J. C. AND A. C. KRAAY (1998): "Consistent covariance matrix estimation with spatially dependent panel data," *Review of Economics and Statistics*, 80, 549–560.

FARRE-MENSA, J. AND A. LJUNGQVIST (2016): "Do measures of financial constraints measure financial constraints?" *The Review of Financial Studies*, 29, 271–308.

FARUQUI, U., P. GILBERT, AND W. KEI (2008): "The Bank of Canada's Senior Loan Officer Survey," *Bank of Canada Review*, 2008, 57–64.

FAZZARI, S. M., R. G. HUBBARD, B. C. PETERSEN, A. S. BLINDER, AND J. M. POTERBA (1988): "Financing constraints and corporate investment," *Brookings Papers on Economic Activity*, 141–206.

FORT, T. C., J. HALTIWANGER, R. S. JARMIN, AND J. MIRANDA (2013): "How firms respond to business cycles: The role of firm age and firm size," *IMF Economic Review*, 61, 520–559.

GERTLER, M. AND S. GILCHRIST (1994): "Monetary policy, business cycles, and the behavior of small manufacturing firms," *The Quarterly Journal of Economics*, 109, 309–340.

GREENWALD, D. (2019): "Firm debt covenants and the macroeconomy: The interest coverage channel," Tech. rep., Working paper.

HADLOCK, C. J. AND J. R. PIERCE (2010): "New evidence on measuring financial constraints: Moving beyond the KZ index," *The Review of Financial Studies*, 23, 1909–1940.

HALTIWANGER, J., R. S. JARMIN, AND J. MIRANDA (2013): "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 95, 347–361.

HUBER, K., P. PAUL, AND C. WOLF (2022): "Identifying channels of macroeconomic shock propagation," Tech. rep., Working paper.

ILUT, C., M. KEHRIG, AND M. SCHNEIDER (2018): "Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news," *Journal of Political Economy*, 126, 2011–2071.

IPPOLITO, F., A. K. OZDAGLI, AND A. PEREZ-ORIVE (2018): "The transmission of monetary policy through bank lending: The floating rate channel," *Journal of Monetary Economics*, 95, 49–71.

JEENAS, P. (2019): "Firm balance sheet liquidity, monetary policy shocks, and investment dynamics," Working paper.

KAPLAN, S. N. AND L. ZINGALES (1997): "Do investment-cash flow sensitivities provide useful measures of financing constraints?" *The Quarterly Journal of Economics*, 112, 169–215.

LAKDAWALA, A. AND T. MORELAND (2021): "Monetary policy and firm heterogeneity: The role of leverage since the financial crisis," Available at SSRN 3405420.

LAMONT, O., C. POLK, AND J. SAAÁ-REQUEJO (2001): "Financial constraints and stock returns," *The Review of Financial Studies*, 14, 529–554.

LEUNG, D., C. MEH, AND Y. TERAJIMA (2008): "Are There Canada-US Differences in SME Financing?" *Bank of Canada Working Paper*, 2008-41.

LIAN, C. AND Y. MA (2021): "Anatomy of corporate borrowing constraints," *The Quarterly Journal of Economics*, 136, 229–291.

MISHKIN, F. S. (1995): "Symposium on the monetary transmission mechanism," *Journal of Economic Perspectives*, 9, 3–10.

MOSCARINI, G. AND F. POSTEL-VINAY (2012): "The contribution of large and small employers to job creation in times of high and low unemployment," *American Economic Review*, 102, 2509–39.

OTTONELLO, P. AND T. WINBERRY (2020): "Financial heterogeneity and the investment channel of monetary policy," *Econometrica*, 88, 2473–2502.

RAMEY, V. A. (2016): "Macroeconomic shocks and their propagation," *Handbook of Macroeconomics*, 2, 71–162.

ROMER, C. D. AND D. H. ROMER (2004): "A new measure of monetary shocks: Derivation and implications," *American Economic Review*, 94, 1055–1084.

SCHONLAU, M. AND R. Y. ZOU (2020): "The random forest algorithm for statistical learning," *The Stata Journal*, 20, 3–29.

WHITED, T. M. AND G. WU (2006): "Financial constraints risk," *The Review of Financial Studies*, 19, 531–559.

Online Appendix (not for publication)

A Data

A.1 Monetary policy shocks

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.

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 2015).

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.

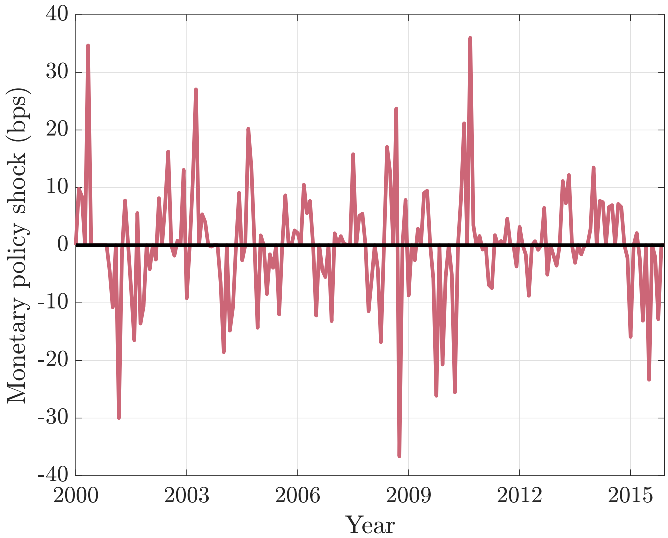


Figure 7: Monetary policy shocks (2000–2015).

Figure 7 plots the monthly monetary policy shocks series estimated for the 2000-15 period. The series has a zero average (by construction), an average absolute shock of 6 basis points, and a standard deviation of 10 basis points.

B Survey on Financing and Growth of SMEs (SFGSME)

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

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

- *What was the outcome of this [...] or increase in the [...] credit limit request? (Select one only)*

1. *The full amount was authorized.*
2. *A partial amount was authorized.*

3. *Request was rejected.*
4. *Request still under review.*
5. *Request was withdrawn.*

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

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

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

B.2 Relationship with standard proxies

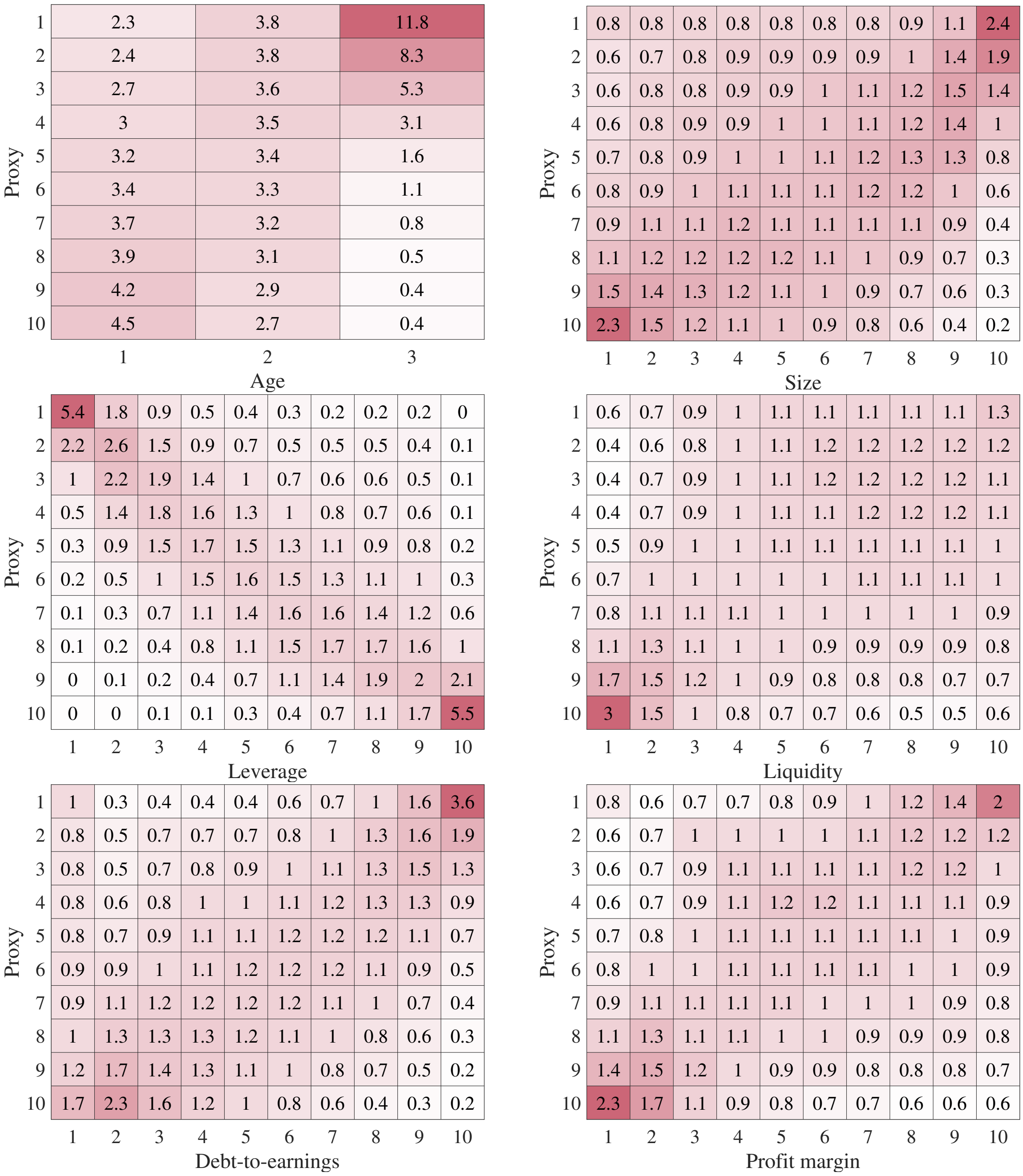


Figure 8: Relationship with standard proxies (heatmaps)

Notes: Each cell corresponds to the fraction of observations in a particular decline of likelihood to be credit constrained × decile of the standard proxy. For the variable "Age," we construct three groups (the first group includes firms < 15 years old, the second group comprises firms between 15 to 29 years old, and the third group includes firms 30 years or older). Since the three age groups do not have the same number of firms (unlike the deciles), we rescale each column so that it sums up to 1/3. "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.