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Identifying credit supply shocks with bank-firm data: methods and applications

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Abstract

Current empirical methods to identify and assess the impact of bank credit supply shocks rely strictly on multi-bank firms and ignore firms borrowing from only one bank. Yet, these single-bank firms are often the majority of firms in an economy and most prone to credit supply shocks. We propose and underpin an alternative demand control (using industry-location-size-time fixed effects) that allows identifying time-varying cross-sectional bank credit supply shocks using both single- and multi-bank firms. Using matched bank-firm credit data from Belgium, we show that firms borrowing from banks with negative credit supply shocks exhibit lower financial debt growth, asset growth, investments, and operating margin growth. Positive credit supply shocks are associated with bank risk-taking behaviour at the extensive margin. Importantly, to capture these effects it is crucial to include the single-bank firms when identifying the bank credit supply shocks.

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1. Introduction

How much do bank credit supply shocks impact credit availability, bank behaviour, and ultimately the real economy? This question is on top of research agendas since the 2007-2009 global financial crisis, when a substantial part of the credit market was disrupted and firms' investment and employment subsequently fell (e.g., Campello et al, 2010; Ivashina and Scharfstein, 2010; Aiyar, 2012; Chodorow-Reich, 2014; Iyer et al., 2014; Ongena et al., 2015; Amiti and Weinstein, 2018; Berton et al., 2018).

Two methodological choices may limit the generality of the conclusions that can be drawn from existing studies, however. First, current empirical methods to identify bank credit supply shocks rely only upon firms borrowing from multiple banks, as they require firm-time fixed effects to control for credit demand (i.e., since Khwaja and Mian, 2008). In most countries, such multi-bank firms represent the minority of borrowing firms (see, e.g., Ongena and Smith, 2001; Degryse et al., 2009; Kysucky and Norden, 2016). Second, the vast majority of papers in this strand of literature rely only on a one-off exogenous event (e.g., the Lehman collapse). However, bank credit supply shocks also occur during tranquil periods and their importance and impact might differ during these periods.

The main contribution of this paper is to propose and underpin an alternative demand control (industry-location-size-time (ILST) fixed effects) that allows to identify time-varying cross-sectional measures of bank credit supply using all firms (both single- and multi-bank firms), without the need to rely on a specific exogenous event. We obtain these measures by regressing bank-firm level credit growth on a set of bank-time fixed effects - which we interpret as bank credit supply shocks - and ILST fixed effects. ILST fixed effects allow for the inclusion of single-bank firms, which is essential for the identification of bank credit supply shocks, as well as for the assessment of their effects on firms' real-side policies and banks' risk-taking decisions over the business cycle.

To make this contribution, we employ monthly bank-firm credit register data from Belgium over the period 2002-2012. We progress in four steps. First, we group firms into industry-location-size-time clusters. For example, we assume that textile manufacturers (NACE-code 31) located in the Antwerp metropolitan area (postal code 20), which are of comparable size, have the same credit demand. We document that these ILST fixed effects are valid alternative demand controls for the traditional firm-time fixed effects. In order to show this, we rely on the sample of multi-bank firms, and find that the ILST approach leads to bank credit supply shocks that are highly correlated with bank credit supply shocks obtained using firm-time fixed effects.

Second, we move on from the sample of multi-bank firms and calculate bank credit supply shocks that are based on (and relevant for) all borrowing firms by using ILST fixed effects. Including single-bank firms leads to vastly different bank credit supply shock estimates. Analysing the month-by-month correlation between credit supply shocks identified using multi-bank firms (FT shocks) and shocks identified using all firms (ILST shocks), we find that the correlation coefficients vary substantially between 0.23 and 0.94. This implies that the FT shocks could be good proxies for the ILST shocks at some points in time but very bad proxies at other points in time.[1]

[1] In the remainder of the paper, we refer to bank credit supply shocks identified on the sample of multi-bank firms using firm-time fixed effects to control for credit demand as FT shocks; and refer to bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects to control for credit demand as ILST shocks.

Third, we use the ILST shocks and the FT shocks to study the impact of bank credit supply on firms' real outcomes and on bank risk taking, and compare the performance of ILST shocks with the performance of FT shocks. Using the ILST shocks, we observe that firms facing a negative credit supply shock experience lower financial debt growth, lower asset growth, lower investments, and lower operating margin growth. Additionally, we show that banks with positive credit supply shocks exhibit risk-taking behaviour. More firms and riskier firms enter a bank's portfolio following a positive credit supply shock. Importantly, researchers relying on FT shocks would come to vastly different conclusions.

Finally, we show that ILST shocks meaningfully relate to other often-used credit supply proxies. The ILST shocks correlate positively with interbank funding growth and with lending standards indicators based on the ECB Bank Lending Survey.

Our work has important implications for future empirical research and its associated policy recommendations. Information about a firm's industry, location and size is widely available in most datasets and therefore our ILST approach could be easily implemented. Policy recommendations can then be based on all borrowing firms and not only on the multi-bank firms, which may be the least likely to face bank credit supply shocks and to be adversely affected by them.

The remainder of the paper is structured as follows. Section 2 describes the related literature. Section 3 describes the data we use and explains our identification strategy. In Section 4, we use our bank credit supply shocks to analyse their impact on firm growth, investments and other firm outcomes, as well as on bank risk-taking behaviour. In Section 5 we test whether our estimates of bank credit supply shocks meaningfully relate to bank funding conditions and to banks' lending standards. In Section 6, we compare our bank credit supply measure to two alternative measures (including the extensive margin and incorporating a weighting structure). The final section concludes. An Online Appendix to the paper contains some additional results.

2. Related literature

Our paper relates closely to the literature employing bank-firm matched loan data to measure the (impact of the) bank lending channel (e.g., Gan, 2007; Khwaja and Mian, 2008; Jiménez et al., 2012). To identify credit supply, these influential papers rely only on multi-bank firms. This questions their external validity as single-bank firms are predominant in most countries; even more so when considering small and medium-sized enterprises. For example, at least half of the firms in the survey of small business finance (SSBF) in the US (e.g., Petersen and Rajan, 1995; Brick and Palia, 2007), and the median firm in countries such as Belgium, France, Germany, or Sweden maintain a single relationship. Single-bank firms are most prone and sensitive to bank credit supply shocks, as they are younger and smaller. Therefore, excluding them leads to biased inferences on the magnitudes of bank credit supply shocks and the assessment of their impact. Our ILST approach deals with these biases. Furthermore, while many of these papers rely on one-off events, our method can be applied in any time period.

Second, our paper relates to empirical work that implements different sets of fixed effects to control for credit demand, even industry-location-size-time effects (e.g., Popov and van Horen, 2015; Acharya et al., 2017; Berg et al., 2017). Our contribution is that we are the first to show (i) that industry-location-size-time fixed effects as demand controls yield bank credit supply shocks that are comparable to those obtained using firm-time fixed effects, and (ii) that restricting the analysis to multi-bank firms may lead to sample selection issues and accordingly affect overall results.

Third, our paper also relates to empirical work studying how credit supply shocks generate different real effects depending upon the time period, the stance of the business cycle, and across firms that are considered to be "almost identical". Berg (2018), for example, compares the impact of credit supply shocks to comparable firms just above and below a certain "cutoff" credit rating. Jiménez et al. (2017) study how demand or supply factors determine bank credit in good and crisis times. In general, our contribution is that we do not need to take a stance on the origin of the credit supply shock, and that our method is widely applicable also for single-bank firms.

Finally, our results on bank risk-taking are also highly related to a well-developed literature on the bank risk-taking channel. Banks facing shocks may alter their lending policies and accordingly adjust the riskiness and composition of their portfolio. This channel for example implies that banks adopt lower lending standards in prolonged periods of loose monetary policy, in particular when banks are subject to severe agency problems (e.g., Jiménez et al., 2014; Ioannidou et al., 2015; Dell'Ariccia et al., 2017). Related to this, positive supply shocks may reduce screening incentives, lead to a search-for-yield, and result in laxer lending standards (e.g., Ruckes, 2004). In general, these papers derive their results based on multi-bank firms. Our paper shows that this may be misleading as the impact on firm outcomes differs when credit supply shocks are obtained when including single-bank firms.

3. Data and methodology

We use a comprehensive dataset on monthly bank-firm level credit from the Central Corporate Credit Register (CCCR) in Belgium to measure bank credit supply shocks over the period 2002-2012. The availability of such detailed data on bank-firm relationships can be key in disentangling the bank-lending channel from the firm-borrowing channel. The credit register is maintained by the National Bank of Belgium (NBB) and is very comprehensive as all financial institutions established in Belgium are obliged to provide information to the credit register on all debtors to which they have an aggregate exposure exceeding 25,000 euro. We exclude banks with less than 30 firms in their lending portfolio at a given month in order to obtain reliable estimates of credit supply shocks. We also account for merger and acquisition activities in the banking sector when constructing bank-firm credit growth rates. Our final sample consists of 57 credit institutions. The Belgian banking market is quite concentrated, with four large banks capturing around 80% of the total market (see, e.g., NBB, 2006).

We combine the credit register data with the annual financial accounts filed by Belgian firms to the Central Balance Sheet Office (CBSO) at the NBB[2], and with monthly data from banks' balance sheet and income statements, also collected by the NBB. In our analysis we rely on bank-firm pairs for which information is available from all three data sources.

3.1 Disentangling the bank-lending and firm-borrowing channel: Frequently used methods for multi-bank firms

With detailed credit register data, we can disentangle the bank-lending and firm-borrowing channel at each time period without the explicit need for a general exogenous event or the

[2] We focus our attention on credit institutions granting credit in Belgium, thus excluding financial institutions such as leasing, insurance or factoring companies. We also exclude firms operating in sectors of Financial and insurance services (K), Public administration and defence services; compulsory social security services (O), Education services (P), Services of households as employers; undifferentiated goods- and services-products by households for own use (T) and Services provided by extraterritorial organisations and bodies (U).

occurrence of a particular bank-specific shock. For the sample of firms borrowing from more than one bank, we achieve this by regressing credit growth at the bank-firm level on a set of bank-time fixed effects while controlling for credit demand by including a set of firm-time fixed effects:

$$\Delta L_{fbt} = \alpha_{ft} + \beta_{bt} + \varepsilon_{fbt}. \tag{1}$$

We follow the existing literature and define $\Delta L_{fbt} = \frac{L_{fbt} - L_{fbt-1}}{L_{fbt-1}}$ as the firm-bank intensive margin annual growth rate of credit from bank b to firm f at time t. The credit growth rate is winsorized at the 1% level. α_{ft} is a firm-time fixed effect and captures the "firm-borrowing channel" and β_{bt} is a bank-time fixed effect and captures the "bank-lending channel" (Khwaja and Mian, 2008). The identifying assumption is that a firm's credit demand is homogeneous across banks. If this holds, then β_{bt} captures bank credit supply.[3]

In the existing literature, Equation 1 has often been estimated indirectly, when the interest of the researchers was on estimating the effect of bank characteristics and monetary policy on credit availability, while controlling for firm credit demand (e.g., Khwaja and Mian, 2008; Jiménez et al., 2012). Put differently, researchers typically use variables which are supposed to be correlated with the bank-fixed effects.

We take an alternative route and estimate Equation 1 using bank-time fixed effects and firm-time fixed effects. We then interpret the estimates of β_{bt} as the actual bank credit supply shock. A similar estimation strategy is also used by Greenstone et al. (2014) and Berton et al. (2018).

[3] One caveat that both the ILST and the FT approach may share is their reliance on the assumption that (similar) firms view their related banks as providers of a perfectly substitutable good. This assumption might be violated in case banks are specialized in market segments where demand shocks occur, leading to firm-bank specific loan demand (Paravisini et al., 2017). However, we believe this is unlikely to play an important role in a sample like ours where single-bank firms are plentiful. These firms cannot target their demand to a specific bank given that they borrow from only one bank.

When estimating Equation 1 it is also important to consider multicollinearity issues and to avoid the dummy variable trap. In an equation that includes two full sets of dummy indicators and no constant term, identification will only be possible if one dummy indicator from any of the two sets is excluded. To eliminate the omitted firm effect, the obtained series of bank-month credit supply estimates can be adjusted by deducting the time-specific mean from the estimate:

$$\tilde{\beta}_{bt} = \hat{\beta}_{bt} - \bar{\beta}_{t} \tag{2}$$

Such a measure has been shown to be useful when constructing firm-level indicators of exposure to bank-loan supply shocks (e.g., Greenstone et al., 2014; Amador and Nagengast, 2016; Amiti and Weinstein, 2018). Importantly, this implies that bank-credit supply shocks can only be compared within a time period.

3.2 Disentangling the bank-lending and firm-borrowing channels: Including single-bank firms

A severe drawback of estimating bank supply shocks (β_{bt}) using Equation 1 is the fact that it relies on firm-time fixed effects to control for credit demand. This limits the sample to multi-bank firms, implying that $\hat{\beta}_{bt}$ may not necessarily capture the representative supply shocks of banks in an economy. This is especially worrisome if single-bank firms represent a large share of the economy under investigation and if they differ substantially from multi-bank firms.

Panel A of Figure 1 illustrates this problem in our sample of over 17 million bank-firm-month observations on 234,392 Belgian firms. Around 84% of these firm-time observations represent firms that borrow from only one bank, and such single-bank firm-time combinations account for 46.1% of the total credit volume in the sample.

[FIGURE 1 HERE]

Although single-bank firms make up a non-negligible fraction of all borrowing firms in our sample, the Khwaja and Mian (2008) approach could still be justified if bank lending to multi-bank firms is very similar to bank lending to single-bank borrowers. However, if this assumption is violated, then ignoring single-bank firms when estimating Equation 1 undermines the external validity of these bank credit supply shocks.

To shed light on this, we compare the characteristics of firms that are always single-bank firms with those of firms that are always multi-bank firms throughout the entire sample period. For completeness, we also report the characteristics of firms that switched from single- to multi-bank borrower, or vice versa, at least once during the sample period. Unsurprisingly, Panel A of Table 1 indicates that multi-bank firms are on average older and larger (in terms of total assets and the number of employees). They also have fewer tangible assets and borrow larger credit amounts. This result suggests that there are non-negligible differences between multi-bank and single-bank firms.

[TABLE 1 HERE]

For that reason, we expand our methodology to include firms beyond the multi-bank firms. To include as many single-bank firms as possible into our estimations, we replace firm-time (FT) fixed effects with industry-location-size-time (ILST) fixed effects as a time-varying demand control. The industry bins are based on two-digit NACE classification codes; location bins are based on two-digit postal codes[4] and the size bins are based on deciles of total assets of the firms. Consequently, Equation 1 becomes:

$$\Delta L_{fbt} = \alpha_{ILSt} + \beta_{bt} + \varepsilon_{fbt} \tag{3}$$

The additional assumption that has to be made in order to progress from Equation 1 to Equation 3 is that the credit demand of firms belonging to the same industry-location-size group in a given time period is identical: $\alpha_{1t} = \alpha_{2t} = \cdots = \alpha_{Ft},\ (1..F)\ \epsilon\ ILS$. To give an example of our identifying assumption: we assume that textile manufacturers (NACE-code 31) of comparable size located in the Antwerp metropolitan area (postal code 20), have the same credit demand.

Using these ILST fixed effects instead of FT fixed effects allows us to include almost all single-bank firms (on top of the multi-bank firms) in the identification of the bank credit supply shocks. Panel B of Figure 1 shows that only a negligible number of firm-time observations cannot be included in the credit supply shock identification as only very few ILST clusters consist of firms borrowing from one and the same bank. More specifically, ILST shocks are identified using 97.3% of the borrowing firms, while FT shocks are identified using only 18.1% of the borrowing firms.

Figure 2 further illustrates the appropriateness of the ILST approach. It reports the weighted average intensive margin credit growth for all firms in Belgium (all firms IM), for all firms included in the ILST shock identification (ILST-sample firms IM), and for all firms in the FT shock identification (FT-sample firms IM). The credit growth for firms included in the ILST shock identification almost entirely overlaps with the credit growth for all firms in Belgium,

[4] There are 80 areas based on the two-digit postal codes. The average land area of one such zone is 382km², which is about seven times smaller than the land area of the average US county.

while the credit growth for firms included in the FT shock identification tends to overestimate the latter.

[FIGURE 2 HERE]

3.3 Measuring the bank-lending channel: The impact of methodology and sample choices

3.3.1 Controlling for credit demand: Moving beyond firm-time fixed effects

In order to motivate the use of industry-location-size-time fixed effects as controls for credit demand, we focus first on the sample of multi-bank firms. The reason for looking at this sample is that it allows us to compare supply shocks coming from a standard setup using firm-time fixed effects with supply shocks coming from our alternative setup within the same sample.

We first estimate bank supply shocks ($\hat{\beta}_{bt}^{F}$) using a setup with bank-time and firm-time fixed effects (see Equation 1). Next, we replace the firm-time fixed effects with eight alternative firm-cluster fixed effects as credit demand controls. We start from the least conservative setup (i.e., only including time fixed effects) and progress by making our credit demand controls more sophisticated (i.e., adding firm-specific information). The first two intermediate specifications consider location-time fixed effects (L) and industry-location-time fixed effects (IL) as credit demand control, where location is defined as the two-digit postal code and industry is defined as the two-digit NACE-code. To the latter specification, several other firm characteristics are added: age (ILA), availability of internal resources measured by the ratio of current assets to total assets (ILC), risk measured using the interest coverage ratio (ILR_1) as in Acharya et al. (2017), risk measured using the Altman Z score (ILR_2), and size in terms of total assets of firms (ILS). Each of these additional controls is incorporated using deciles of their annual distribution across firms to group firms into clusters. The equation of interest is the following:

$$\Delta L_{fbt} = \alpha_{it} + \beta_{bt}^{i} + \varepsilon_{fbt}, \quad where\ i = \cdot, L, IL, ILA, ILC, ILR_1, ILR_2, ILS, F \tag{4}$$

From these regressions we obtain nine sets of bank credit supply shocks ($\hat{\beta}_{bt}^{\cdot}, \hat{\beta}_{bt}^{L}, \hat{\beta}_{bt}^{IL}, \hat{\beta}_{bt}^{ILA}, \hat{\beta}_{bt}^{ILC}, \hat{\beta}_{bt}^{ILR_1}, \hat{\beta}_{bt}^{ILR_2}, \hat{\beta}_{bt}^{ILS} and\ \hat{\beta}_{bt}^{F}$) and use them in the second stage. Our rationale in the second stage is to investigate how similar the bank supply shocks are when using alternative controls for credit demand, compared to using firm-time fixed effects.

Table 2 reports the relation between bank credit supply shocks coming from the most conservative setup (using firm-time fixed effects) with each of the bank credit supply shocks coming from regressions with alternative demand controls. More specifically, Table 2 reports $\hat{\delta}$s from the following regression:

$$\hat{\beta}_{bt}^{F} = \delta \cdot \hat{\beta}_{bt}^{i} + \mu_t + \varepsilon_{bt}, \qquad where\ \ i = \cdot, L, IL, ILA, ILC, ILR_1, ILR_2, ILS \tag{5}$$

[TABLE 2 HERE]

Importantly, for every of the eight comparisons made, we are excluding clusters that are made up of only one multi-bank firm. Otherwise, to the extent that our new cluster fixed effects become identical to firm fixed effects, the results in Table 2 become spurious.

The results in Table 2 first of all indicate that bank credit supply shocks obtained using firm-time fixed effects as demand control are in strong positive co-movement with bank credit supply shock estimates obtained using other, less conservative demand controls. The coefficients range from 0.963 to 1.040, and are never significantly different from one.

The results also indicate that using industry-location-size-time fixed effects as demand control leads to bank credit supply shocks that are the closest (in terms of variation and ranking of banks) to the "standard" bank credit supply shocks obtained using firm-time fixed effects (Column 8). The Spearman rank correlation (0.818) and the adjusted R^2 (0.770) in Column 8 respectively show that the ranking of and the variation in FT shocks is most closely matched by the ILST shocks. The t-statistic reported in the lower half of the table indicates that the difference between the adjusted R^2 of this specification compared to the ones considered in the other columns is statistically significant.

Finally, Column 9 shows that the resemblance of these two series of bank credit supply shocks is also present during the '08-'09 financial crisis (September 2008 – December 2009). This shows that the industry-location-size-time fixed effects are proper demand controls both in normal and in crisis times.

3.3.2 (Why) Do single-bank firms matter?

The main advantage of using ILST fixed effects to control for credit demand is that they allow us to estimate bank credit supply shocks for the full sample of borrowing firms, i.e., including both single-bank borrowers and multi-bank borrowers. This is important as the ILST shocks are potentially very different compared to the FT shocks, given the differences in borrower characteristics (see Table 1).

In order to directly test for these differences, we calculate the correlation between the FT shocks stemming from Equation 1 and the ILST shocks coming from Equation 3. The average correlation coefficient over the full sample period is 0.68. The fact that this correlation coefficient is not close to 1 is a first indication that the two types of shocks are different. Additionally, Figure 3 illustrates that there is substantial variation in the correlation between the two sets of bank credit supply shocks over time. The figure plots the correlation coefficients between monthly ILST and FT shocks for each quarter in the sample and their 95% confidence intervals. The correlation coefficients vary substantially between 0.31 and 0.93. This implies that the FT shocks could be good proxies for the ILST shocks at some points in time, but very bad proxies at others. The important point here is that it is difficult – if not impossible – to know ex-ante how high the correlation will be.

[FIGURE 3 HERE]

Next, we investigate why ILST shocks have a relatively low correlation with the FT shocks. Table 1 already documented that single-bank firms differ substantially from multi-bank firms through a number of characteristics (age, balance sheet size, asset tangibility, etc.). We now study whether the correlation between the two sets of bank supply shocks differs conditional on how different the single-bank firms are from the multi-bank firms. For instance, in case of firm size we calculate the size of the bank's average multi-bank borrower and the size of the bank's average single-bank borrower, for each bank-month observation. We then take the absolute value of the difference between the two values as an indicator of how much the two groups of borrowers differ from each other from the viewpoint of the bank in a given month. We undertake this exercise for firm size (measured by total assets), age, profitability, leverage and asset tangibility. We group bank-month observations in terciles of increasing differences (T1=small difference, T3=large difference).

[TABLE 3 HERE]

Table 3 reports the correlation coefficients within each group. Focusing on the first and the third tercile, we observe that the correlation between the FT shocks and the ILST shocks is lower when the single-bank firms and the multi-banks firms in a bank's portfolio differ more in terms of size, age, profitability, solvency risk (i.e., leverage), and collateral (i.e., asset tangibility). All these characteristics are known to be important determinants of loan approval/credit supply as they respectively proxy for opacity of the firm, the repayment capacity of the firm, the riskiness of the firm, and the available collateral in the firm. The p-values in Column 3 of Table 3 indicate that the difference in correlation coefficients between the first and third tercile is always significantly different from zero. Differences in firm characteristics thus (partly) explain the low correlation between ILST and FT shocks.

Apart from balance sheet characteristics, we also focus on the importance of single-bank firms in the bank's portfolio (in terms of total loan volume) for a given bank-month observation. We group bank-month observations in terciles according to the importance of single-bank firms (T1=low importance, T3=high importance). The correlation between the different FT shocks and ILST shocks is significantly lower when single-bank firms are more relevant for the bank.

These results show that including single-bank firms in the identification of bank supply shocks is essential to properly account for supply movements when single-bank firms are abundant.

4. The effects of credit supply shocks on firm outcomes and bank risk-taking

We now examine the impact of bank credit supply shocks on various firm outcomes and bank risk-taking behaviour. The advantage of identifying cross-sectional variation in bank credit supply in multiple periods is that it allows us to study the relation between supply shocks and outcome measures of interest not only during stress events, but also during other periods.

4.1. Real sector outcomes

We study how bank-credit supply shocks impact financial debt growth, firm growth (proxied by total asset growth), investments (proxied by fixed asset growth), and operating margin growth. The growth rates calculated for a given year are linked to supply shocks faced by the firms during that year. Given the annual nature of the firm balance sheet data, we adjust our bank credit supply shocks to reflect this frequency. In particular, we calculate the annual average of the demeaned monthly bank credit supply shocks faced by all lenders to a particular firm, weighted by the share of each bank in the firm's borrowing portfolio, and label it as $\bar{\bar{\beta}}_{ft}$. We run the following baseline regressions:

$$\Delta Y_{ft} \quad = \delta_1 \cdot \bar{\bar{\beta}}_{ft} + \delta_2 \cdot \gamma_{ft} + \mu_{it} + \varphi_f + \theta_b + \varepsilon_{ft} \tag{6}$$

where ΔY is either growth in financial debt, total assets, fixed assets or operating margin. Firm controls γ_{ft} include age, size (proxied by number of employees) and leverage of the firm. We also include industry-time fixed effects (μ_{it}), firm fixed effects (φ_f) and (main) bank fixed effects (θ_b). Standard errors are clustered at the (main) bank level.

Additionally, we run two other specifications. The first one investigates whether there is a differential impact during the global financial crisis, by adding an interaction term of $\bar{\bar{\beta}}_{ft}$ with a dummy, *crisis*. The crisis dummy is equal to one for annual accounts filed between September 2008 and December 2009. The second specification analyses whether the impact is different for multi-bank firms, by adding an interaction term of $\bar{\bar{\beta}}_{ft}$ with a dummy, *multiple borrower.* This dummy indicator is one if a firm borrows from more than one bank in year *t*, and zero otherwise. Summary statistics of the variables used in the regressions in this section are reported in Table 4.

[TABLES 4 AND 5 HERE]

Table 5 reports the impact of the credit supply shocks on firm behaviour. The first three columns show the impact of the ILST shocks, while Columns 4-6 report the results when using the FT shocks. Columns 1 and 4 show the findings for the supply shocks over the entire period; Columns 2 and 5 add an interaction term with *crisis*, whereas Columns 3 and 6 include an interaction term with *multiple borrower*.

Panel A of Table 5 focuses on how bank supply shocks influence growth in financial debt at the firm level. Financial debt is defined in the firms' balance sheets as the sum of bank loans and other financial debt (e.g., bonds). The results in Panel A are a first and natural step in understanding why bank credit supply shocks might have real effects, namely because they reduce the availability of financial debt on the affected firms' balance sheets. Although relatively few firms in our sample have access to bond markets, the results in Panel A also allow understanding whether or not firms can offset bank supply shocks by other financial debt sources.

The results in Column 1 of Table 5 (Panel A) show that the growth in financial debt drops by 0.609 percentage points when firms are facing a one standard deviation more negative credit supply shock (i.e., 0.194*3.138). The impact of credit supply shocks in crisis periods (Column 2) does not differ from the impact during normal times. In addition, the credit supply shocks only affect firms with single-bank relationships (Column 3), as the coefficient on the interaction term with the *multiple borrower* dummy is significant, has the opposite sign of the supply shock coefficient and is of similar magnitude. This implies that single-bank firms are not able to offset the supply shocks at their bank with credit from other banks or with other types of financial debt.

The results using the FT shocks are either not significant, or economically smaller than those using the ILST shocks. The point estimates of the bank credit supply shocks in Columns 4-6 of Table 5 (Panel A) are roughly half as large compared to the ones in the corresponding Columns 1-3. A t-test indicates that the coefficients in Column 1 and 4 are also statistically different from each other.[5] This shows that identifying bank credit supply shocks using the

[5] In order to perform this test, we estimate Column 1 and 4 together (by stacking the data), while including sample fixed effects. The stacking procedure leads to exactly the same coefficient and standard error estimates as in the current Table 5, but has the advantage that we can easily test whether (linear combinations of) the coefficients are statistically different from each other.

FT-methodology (and thus relying only on multi-bank firms) underestimates their impact on firms' financial debt.

In panels B to D of Table 5 we focus on the real effects of bank credit supply shocks. Panels B and C report the reaction on the asset side of the firms' balance sheets. The panels show the results for Equation 6 with total assets growth and fixed assets growth as a dependent variable, respectively. In a similar fashion to Panel A, the first three columns show the impact of the ILST shocks, while Columns 4-6 report the results when using FT shocks.

Looking at the average full-sample effect in Column 1 of Panels B and C, we observe a positive and significant relationship between bank credit supply shocks and both total assets growth and fixed assets growth. The coefficient of 0.055 in Column 1 of Panel B implies that a one standard deviation decrease in credit supply decreases the growth rate of total assets by 0.173 percentage points (i.e., 0.055*3.138), which corresponds with a 3.6% reduction in the growth for the average firm in our sample. The coefficient of 0.119 in Column 1 of Panel C implies that a standard deviation decrease in credit supply decreases fixed assets growth by 0.373 percentage points (i.e., 0.119*3.138). This corresponds with a 3.6% drop in investments for the average firm in our sample.

The calculations above also indicate that the reduction in assets is fully driven by a reduction in fixed assets: given that fixed assets represent 50.6% of total assets,[6] the two elasticities in Column 1 of Panel B and C roughly imply that other items on the assets side do not change with the bank credit supply shocks ($0.506 * -0.373 = -0.188 \approx -0.173$). At the same time, given that financial debt represents 33.1% of the financing of total assets for the average firm,

[6] This share is based on the observations for which the real effects regressions are estimated, which is why it differs slightly from the 47% reported in Table 1.

the two elasticities in Column 1 of Panel A and B are roughly equal (0.331 * -0.609 = -0.201 ≈ -0.173) and thus suggest that other items on the liabilities and equity side do not materially change with the bank credit supply shocks. We document the absence of a response of other items on the asset and liability side in Table A.2 in the Online Appendix. We do not find any significant impact on equity, accounts receivable, inventories, cash; and only a very weak reaction in non-financial debt.[7]

Furthermore, we find a positive and significant impact of the credit supply shocks on the growth rate of the operating margin. Column 1 of Panel D implies that a one standard deviation decrease in credit supply decreases the growth in operating margin with 0.34 percentage points (i.e., 0.107*3.138), which corresponds with a 2.3% decrease in the growth in operating margin for the average firm in our sample.

The results in Column 2 of Table 5 (all panels) indicate that there is no significant difference in the impact of shocks during crisis times versus normal times, as the interaction term with *crisis* is insignificant. Column 3 displays the results where we interact with the dummy variable *multiple borrower*. This interaction term is always negative but insignificant in two of the three panels that focus on the real impact (Panels B-D). Operating margin growth is the only dependent variable where we observe a statistically significant coefficient. If anything, the results in these three panels suggest that on average multi-bank borrowers react less to bank supply shocks, reinforcing our arguments to encompass single-bank borrowers in the analysis.

[7] This could indicate that firms that experience a more negative credit supply shock also have difficulties finding alternative financing sources. This is consistent with the idea that bank-supply shocks are transmitted along the supply chain (e.g., Bebchuk and Goldstein, 2011; Giannetti and Saidi, 2017).

Comparing the findings in Panel B-D of Table 5 obtained with the ILST shocks (Columns 1-3) with those obtained with the FT shocks (Columns 4-6) allows to answer whether including single-bank firms in the supply shock identification is relevant for the real effects. It leads to a number of interesting insights.

First, the FT shocks are only significant determinants of operating margin growth, but not of total assets growth and fixed assets growth (Column 4). Additionally, the coefficients in Column 1 and 4 are statistically different from each other in Panel B and C. This already shows that identifying credit supply shocks on a wider sample is relevant.

Second, ignoring the statistical significance and looking at the economic importance of the coefficients, we also see a strong difference in the economic impact of the shocks. Comparing the impact between the ILST shocks (Column 1) and the FT shocks (Column 4) in Panel B for example, we get an increase in the growth rate of total assets of around 0.173 percentage points for a one standard deviation increase in credit supply when using the ILST shocks, while we would measure an increase of only 0.068 percentage points (i.e., 0.018*3.804) when using the FT shocks. The effects for the FT shocks are also lower in Panel C for fixed assets growth (i.e., 0.373 versus 0.270 percentage points). Relying upon FT shocks thus leads to an underestimation of the impact of credit supply shocks on firms' real outcomes.

Overall, our findings show that bank credit supply shocks impact the real economy regardless of the aggregate state of the economy. The propagation of financial shocks is not limited to crisis periods. The identification of the real effects of credit supply shocks will be affected by the choice of methodology to estimate these shocks. FT shocks are not necessarily representative of the credit supply shocks faced by single-bank firms.

4.2. Bank risk-taking

Bank credit supply shocks may induce banks to adjust their behaviour, which ultimately could be reflected in the riskiness of their lending portfolio. In this part, we show that banks with positive credit supply shocks take on more risk, while banks with negative credit supply shocks are more risk-mitigating. The choice of methodology used to identify credit supply shocks again seems to matter, in particular to identify the impact on risk-taking behaviour captured by differences in the quality of new and exiting borrowers.

4.2.1 Measuring bank risk taking

Our main risk measure is calculated as the difference between the average Altman Z-score of new borrowers at time *t* (weighted by the size of their loan) and the average Altman Z-score of borrowers that are leaving a bank`s portfolio at time *t* (weighted by the size of their loan). These differences capture the change in riskiness of the bank's loan portfolio that is driven by decisions taken by the bank, i.e., changes at the extensive margin. It abstracts from changes that are purely due to changes in the behaviour of firms that were already and remain in the bank's portfolio. Hence, these are ideal measures to capture the supply driven changes in bank risk-taking behaviour and we therefore relate them to our estimated bank credit supply shocks at time *t-1*. Our empirical setup looks as follows:

$$\bar{Z}_{bt}^{\ entry} - \bar{Z}_{bt}^{\ exit} = \delta \cdot \hat{\beta}_{bt-1} + \mu_t + \omega_b + \varepsilon_{bt} \tag{7}$$

where $\bar{Z}_{bt}^{\ entry}$ ($\bar{Z}_{bt}^{\ exit}$) is the weighted average riskiness of firms entering (exiting) the loan portfolio of bank *b* at time *t*. Regressions are run at the bank-month level as we observe at the monthly level when a bank has started or ended a relationship with a firm. We then link this to the most recent firm balance sheet information available. Bank-month observations in

Equation 7 are weighted by the total number of entering and exiting firms at time *t* for which the dependent variable is computed, given that a number of small banks in our sample only add or remove a limited number of firms to their loan portfolio. In this way, we avoid that potentially large (and uninformative) jumps in the riskiness of the portfolio of small banks bias our estimates. The main coefficient of interest is δ, which captures the impact of the credit supply shock ($\hat{\beta}_{bt-1}$) on bank risk-taking. We also control for bank and time fixed effects. In an additional robustness check, we employ a similar methodology, but focus on firm leverage (equity to debt ratio) as a measure of bank risk-taking.

We also analyse the share of entrants and exits. While the risk regressions will show us in which direction the riskiness of a bank's portfolio is changing, the share of entrants and exits will indicate how important these changes are in terms of total credit volume (or number of borrowers). Banks with a negative supply shock at the intensive margin are most likely also granting a lower volume of loans to new entrants and might be more likely to cut loans to existing borrowers. We calculate the total credit volume to new borrowers at time *t* and the total credit volume to exiting borrowers at time *t-1*, both relative to the size of the existing loan portfolio.

As with the risk measure, we analyse the net change in the shares by looking at the difference between the share of entries and the share of exits, and thus measure whether a bank's loan portfolio increases (a positive difference) or decreases (a negative difference) in size. As a robustness check, we calculate a similar measure based on the number (rather than the volume) of new relationships and the number of exiting relationships, both relative to the total number of existing relationships in the loan portfolio:

$$\sum LS_{bt}^{entry} - \sum LS_{bt}^{exit} = \delta \cdot \hat{\beta}_{bt-1} + \mu_t + \omega_b + \varepsilon_{bt} \tag{8}$$

where LS_{bt}^{entry} (LS_{bt}^{exit}) is the total credit volume of loans to new borrowers (exiting borrowers) by bank *b* at time *t* relative to the total credit volume to borrowers that stay in the portfolio between *t-1* and *t*. In Equations 7 and 8 we relate our dependent variables to two sets of bank supply shocks. First (and preferred), we use the set of ILST shocks ($\hat{\beta}_{bt-1}^{ILS}$) that are identified using the full sample of borrowers. Second, we use a set of FT shocks ($\hat{\beta}_{bt-1}^{FT}$) that are identified using the multi-bank borrowers.

4.2.2. Bank risk taking: Results

The first column of Table 6 shows the impact of the bank credit supply shocks on the total credit volume of entries vs. exits.[8] The bank supply shocks have been standardized in each specification to ease the comparison across columns. The results suggest that, during normal times, a positive bank credit supply shock leads to more credit being granted to new borrowers than there is credit being cut to firms that are being dropped, and vice versa for a negative bank credit supply shock.

[TABLE 6 HERE]

In economic terms, a one standard deviation negative bank credit supply shock leads to a reduction in the extensive margin change in credit volumes of 0.365 percentage points. Knowing that the average bank has a monthly net increase in credit volume at the extensive margin of about 0.46 percentage points, this implies a reduction in the monthly total extensive margin credit volume growth of almost 78 percent, which is a sizeable drop.

[8] The number of bank-month observations in this table is lower than in Table 1, as we cannot calculate our extensive margin and risk measures for bank-month combinations where there is no new loan granted or no borrower dropped from the bank`s portfolio.

We do not find a significant relation between the bank credit supply shock and the credit volume on the extensive margin during the crisis period. The negative and significant interaction of the credit supply shock with the crisis dummy of -0.442 leads to an insignificant effect of -0.08 during this period.

In Column 3 of Table 6, we confirm that positive bank credit supply shocks (which are calculated on the intensive margin) lead banks to expand their loan portfolios on the extensive margin by adding relatively more borrowers. The opposite holds for negative bank credit supply shocks. A one standard deviation drop in bank credit supply leads to a reduction in the extensive margin change in number of relationships added to the loan portfolio with 0.526 percentage points. In this setup, we do not find a significant difference between crisis and normal times. In Columns 1 and 3 of Table 6 we used our preferred ILST shocks, but the results in Columns 2 and 4 show that similar results would be obtained with FT shocks.

The results in Column 1 and 3 of Table 6 are particularly interesting when combined with the results on the changes in the riskiness of entering and exiting firms. Columns 5 and 7 of Table 6 show these results. Column 5 indicates that more negative bank credit supply shocks lead to a higher difference between the Altman Z-score of new borrowers relative to exiting borrowers: the weighted Altman Z-score of the pool of newly added firms is relatively higher compared to the weighted Altman Z-score of firms that leave the portfolio. Column 7 shows a similar result for the equity-to-debt ratio, i.e., the newly added firms are less risky for banks with a more negative credit supply shock.

Recall that Column 1 of Table 6 illustrated that banks with a negative credit supply decreased loan volume on the extensive margin. Combined with a smaller share of firms entering the banks' portfolio this suggests that, at the margin, banks facing a negative credit supply shock take only few new borrowers and simultaneously try to decrease the riskiness of their portfolio following the shock. As such, a negative credit supply shock leads to a reduction in bank risk-taking.

In economic terms, the negative and significant coefficient during non-crisis times in Column 5 of Table 6 implies that a one standard deviation decrease in the credit supply shock corresponds with an increase in the net Altman Z-score of 0.088, which is an increase of about 58% for the average bank month and is about 18% of the standard deviation of our risk measure. This result is quite sizeable and indicates that negative bank credit supply shocks lead to risk mitigating behaviour. Vice versa, the results also imply that positive bank credit supply shocks lead to more bank risk-taking as they will lead to a net increase if the banks' exposure to firms that have smaller equity buffers and are riskier.

In Columns 5 and 7 of Table 6 we used our preferred ILST shocks. Columns 6 and 8 of Table 6 show the results with FT shocks. In contrast to the results with the ILST shocks, the results with the FT shocks are not significantly different from zero. Hence, using FT shocks, one would incorrectly infer that banks' risk-taking behaviour is not affected by credit supply shocks.

5. External validity of the loan supply shock estimates

We now study whether the obtained ILST shocks are meaningfully correlated with several bank-specific variables. For that purpose, we look at bank variables that can be related to sources of funding for banks' lending activities (deposits, equity, and interbank liabilities); and at an alternative indicator of credit supply: bank lending standards from the ECB Bank Lending Survey (BLS).

5.1. Bank funding variables

We start our analysis by relating the estimated bank credit supply shocks to bank funding indicators – deposits, equity and interbank liabilities. The underlying idea is that when banks are hit by a funding shock, this will most likely impact their lending behaviour.

We use information from balance sheets of banks, filed with the NBB at a monthly frequency. The annual change of each of these bank characteristics was scaled by previous year's total assets, and these growth rates are winsorized at the 1% level. Table 7 reports the relation between our ILST shocks and these funding characteristics of banks. The results are reported for the full sample period (2002m1-2012m3), the period prior to the Lehman collapse (2002m1-2008m8), and for the post-Lehman period (2008m09-2012m3). The latter period we further decompose in the crisis (2008m9-2009m8) and post-crisis period (2009m9-2012m3).

[TABLE 7 HERE]

Across all periods, we find a positive and significant relation between the ILST shocks and the growth in interbank funding. The impact of a 10 percentage point increase in this funding variable leads to an average increase of the credit supply shock of 1.51 percentage points for the full period (Column 1). When looking at the sample split results, we observe that the economic and statistical significance of the relationship between interbank funding and bank credit supply shocks is fairly stable in all sub-periods. Of course, the variation in interbank liabilities growth is much more pronounced during the crisis period.

Over the full sample period, we do not find a significant relationship between the estimated bank credit supply shocks and the growth in equity and deposits. In the post-crisis period, we find a large negative relationship between equity growth and bank credit supply, which is statistically significant at the 5% level. While we do take into account capital injections, this might be indicative of a deleveraging spiral, possibly in response to tighter capital requirements.

5.2. Bank lending standards

Another potential measure of bank credit supply that has been used in empirical research is the bank lending standards indicator from the ECB's Bank Lending Survey (see, e.g, van der Veer and Hoeberichts, 2016). Research suggests that the measures of credit demand and supply provided in this and other similar bank surveys are credible indicators of actual credit demand and supply movements (e.g., Lown and Morgan, 2006; Ciccarelli et al., 2015). The BLS survey is conducted at a quarterly level since 2003, and surveys European banks on lending conditions. There are four respondent Belgian banks. In order to assess what the quarterly BLS survey has to say on credit supply conditions for these banks, we focus on the following question from the questionnaire:

“Over the past three months, how have your bank's credit standards as applied to the approval of loans or credit lines to enterprises changed”? Banks can choose between five answers: *“Tightened considerably”*, *“Tightened somewhat”*, *“Remained basically unchanged”*, *“Eased somewhat”*, and *“Eased considerably”*.

Based on the provided answer, we construct dummy indicators for the tightened and eased lending standards, respectively. These indicators should be interpreted as relative to the *“Remained basically unchanged”* answer.

We assess the validity of our bank credit supply estimates by correlating them with the dummy indicators on tightening and easing of bank lending standards. Additionally, we consider the number of banks tightening or easing their lending standards, since tightening or easing by more than one bank might imply that the related credit supply changes are more similar (or could even be part of a common shock, as was the case during the financial crisis). Hence it will be more difficult to disentangle one bank’s credit supply measure from estimates of the remaining three banks. The regressions we run, using the ILST shocks as dependent variable, are thus the following:

$$\hat{\beta}_{bt}^{ILS} = \delta^{T} \cdot BLS_{bt}^{T} + \delta^{E} \cdot BLS_{bt}^{E} + \mu_t + \omega_b + \varepsilon_{bt} \tag{9}$$

$$\hat{\beta}_{bt}^{ILS} = (\delta^{T} + \delta^{MT} \cdot M_t^{T}) \cdot BLS_{bt}^{T} + (\delta^{E} + \delta^{ME} \cdot M_t^{E}) \cdot BLS_{bt}^{E} + \mu_t + \omega_b + \varepsilon_{bt} \tag{10}$$

where superscripts T and E denote responses on tightening and easing of lending standards, respectively. Variables BLS_{bt}^{T} and BLS_{bt}^{E} represent the aforementioned dummy indicators for whether a bank tightened or eased its lending standards in a given period t, respectively; M_t^{T}

and M_t^E are dummy indicators for whether more than one bank tightened or eased its lending standards in a given period *t*, respectively.

[TABLE 8 HERE]

Table 8 shows that the bank credit supply indicators especially contain information on the tightening responses of banks: the credit supply estimates are on average 1.521 percentage points lower in the case of lending standard tightening in the pre-crisis period (Column 2, Panel A). However, note that the number of instances when banks report easing standards is very limited. As such, the non-result for the easing indicator could simply be due to a lack of observations to identify it.

In Panel B of Table 8 we consider the effects of more than one bank tightening their lending standards. As expected, in cases when a bank that tightens its standards is also the only bank that is tightening in a particular period, its credit supply estimate is on average 2.508 percentage points lower (Column 2, Panel B). Note that there have been no instances of multiple banks easing their lending standards during the whole period, and that there has not been any reported easing of lending standards in our post-crisis period.

Overall, the results of this section indicate that our bank-loan shock estimates are meaningfully correlated with bank funding conditions. This is not only true when using funding proxies based on bank balance sheet information, but also holds when comparing our bank-loan shock estimates with answers to lending condition surveys.

6. Alternative supply shocks

The bank credit supply shocks in the main part of our analysis are based on the estimates for the bank fixed effects in Equation 3, encompassing the intensive margin and giving equal weight to every bank-firm observation in the regression framework. Below, we study two alternative supply shock measures.

First, we take an alternative approach to compute the growth rates of lending to encompass both the intensive and extensive margin (see Davis and Haltiwanger, 1992 and Chodorow-Reich, 2014). We modify the growth rate calculation in Equation 3 as follows:

$$\Delta L_{fbt} = \frac{L_{fbt} - L_{fbt-1}}{0.5 \cdot (L_{fbt} + L_{fbt-1})} \tag{11}$$

The latter computation method implies that growth rate values belong to the bounded interval [-2,2]. Exits ($L_{fbt} = 0$) result in a growth rate of -2, whereas entries ($L_{fbt-1} = 0$) result in a growth rate of 2. The average weighted growth rate using this alternative approach moves very similar to our preferred growth measure (Figure A.1 in the online appendix). Based on this alternative approach, we re-estimate Equation 3 to obtain bank credit supply shocks that we label as "alternative approach", and compare them with our baseline ILST shocks. We find that the correlation between these shocks is 0.88.

Table A.3 in the Online Appendix reports the real effects of bank credit supply shocks using the shocks from the alternative approach. Given the high correlation between the alternative bank credit supply shocks and our baseline bank credit supply shocks, it is not surprising that using the alternative bank credit supply shocks leads to results that are very similar to the results in Table 5. We again observe that the main differences between ILST shocks and FT shocks arise when analysing financial debt growth, total assets growth, and fixed assets growth.

Second, following Amiti and Weinstein (2018), we calculate the bank credit supply shocks based on a weighted credit growth regression that takes into account the weight of each firm in the bank's lending portfolio. Conceptually, the main difference between the "average" credit supply shocks in the main analysis and the Amiti-Weinstein (AW) credit supply shocks is that the AW credit supply shocks rather capture the "overall shock to the banks' loan portfolio", as their methodology gives more weight to firms with larger loans. In contrast, our main analysis focuses on the credit supply shock that is received by the "average" firm in the sample, as every firm gets an equal weight in the estimation of the credit supply shocks.

We use these AW shocks and analyse their impact on firm behaviour. We again employ the industry-location-size-time fixed effects as demand controls to identify the AW shocks (i.e., similar to Equation 3) on the full sample of borrowers; and we also use firm-time effects as demand controls to identify the AW shocks (i.e., similar to Equation 1) on the sample of multi-bank firms. A more detailed explanation of the exact calculation of these shocks can be found in Section C of the Online Appendix.

The results for the impact on firm outcomes of these alternative AW credit supply shocks are shown in Table A.4 in the Online Appendix. As with our initial supply shocks, we again observe a strong difference in results depending on whether one uses AW-ILST shocks or AW-FT shocks. Focusing on the AW-ILST results, we get qualitatively similar results for financial debt growth, asset growth, and investments compared to our baseline setup in Table

5, though statistical significance sometimes differs. We do not find any significant relation between the AW bank credit supply shocks and operating margin growth.

Amiti and Weinstein (2018) apply their weighing methodology to Japanese publicly listed companies, of which almost all of them are multi-bank firms. These firms exhibit substantial heterogeneity in terms of loan exposures, making their weighing methodology highly important. In our setting, the impact of the weighing procedure is much less pronounced as we employ credit registry data covering all firms, and Belgium is an economy with many small and medium sized firms and few very large firms. Put differently, the supply shock as captured by the "average" firm may not be too different from the "overall shock to the banks' loan portfolio". This explains why we get fairly similar results when using the AW setup. It also indicates that the importance of the AW weights will depend on the structure of the credit market.

7. Conclusion

Current empirical methods to identify and assess the impact of bank credit supply shocks rely strictly on multi-bank firms and ignore firms borrowing from only one bank. Yet, these single-bank firms are plentiful and have significantly different characteristics than multi-bank firms. Our proposed methodology includes single-bank firms by replacing firm-time fixed effects as controls for the firm-demand with industry-location-size-time (ILST) fixed effects.

Using matched bank-firm credit data from Belgium between 2002 and 2012, we show that ILST fixed effects are solid alternative demand controls: using only the multi-bank borrowers sample, we show that bank credit supply shocks obtained with ILST fixed effects closely resemble bank credit supply shocks obtained with firm-time fixed effects (in terms of ordering and magnitude). However, taking into account the full sample of borrowers in Belgium (i.e., both multi-bank (18%) and single-bank borrowers (82%)) through the ILST fixed effects leads to vastly different bank credit supply shock estimates. This underlines the relevance of appropriately accounting for the structure of the credit register sample, and suggests that the "standard" approach (using firm-time fixed effects) to estimating the bank lending channel cannot be considered as a "one-size-fits-all" approach.

When analysing the impact of our bank credit supply shock estimates on firm outcomes, we find that firms' financial debt growth, asset growth, investments and operating margin growth are negatively affected if they borrow from banks with more negative credit supply shocks, both during normal times and in times of widespread financial distress. Importantly, in order to empirically capture these effects, it is crucial to include the single-bank firms when identifying bank credit supply shocks.

Our results also indicate that banks with more positive credit supply shocks take on more risk, whereas banks with negative credit supply shocks mitigate risk. This observation is especially useful for regulators, since it warns of potential negative consequences of policies encouraging banks' provision of credit on the degree of risk in the banking sector.

Our suggested control for firm credit demand (ILST fixed effects) trades-off the presence of single-bank firms and data availability against the potential use of firm-time fixed effects as credit demand controls. Our methodology is thus likely less appealing when the majority of borrowing firms are multi-bank firms or when single-bank firms are similar to multi-bank firms, in which case the implementation of firm-time fixed effects as demand control is still advised.

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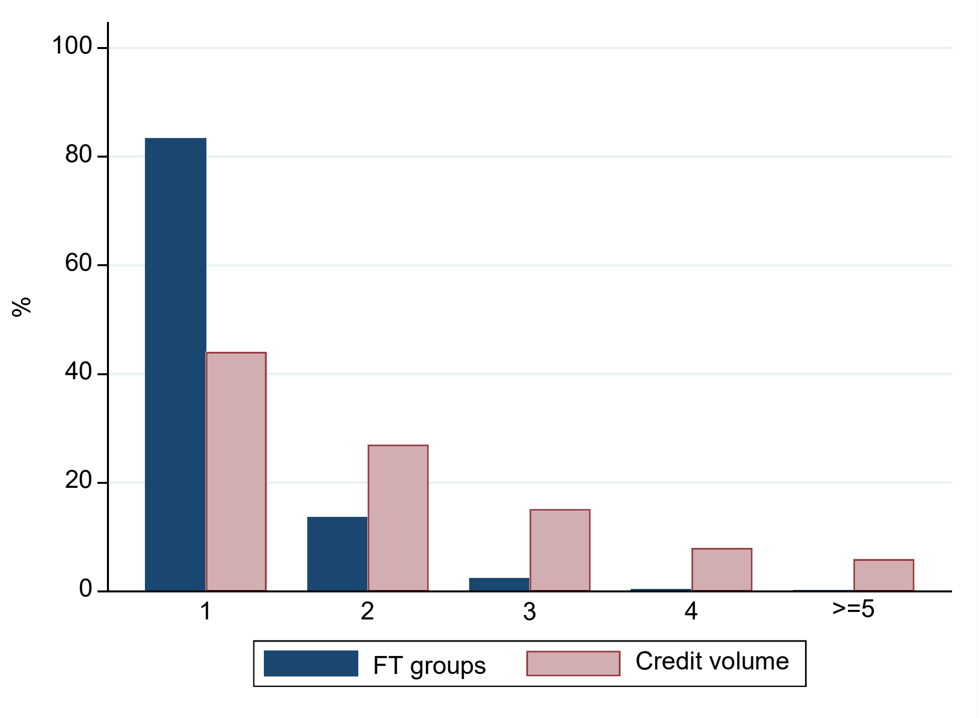
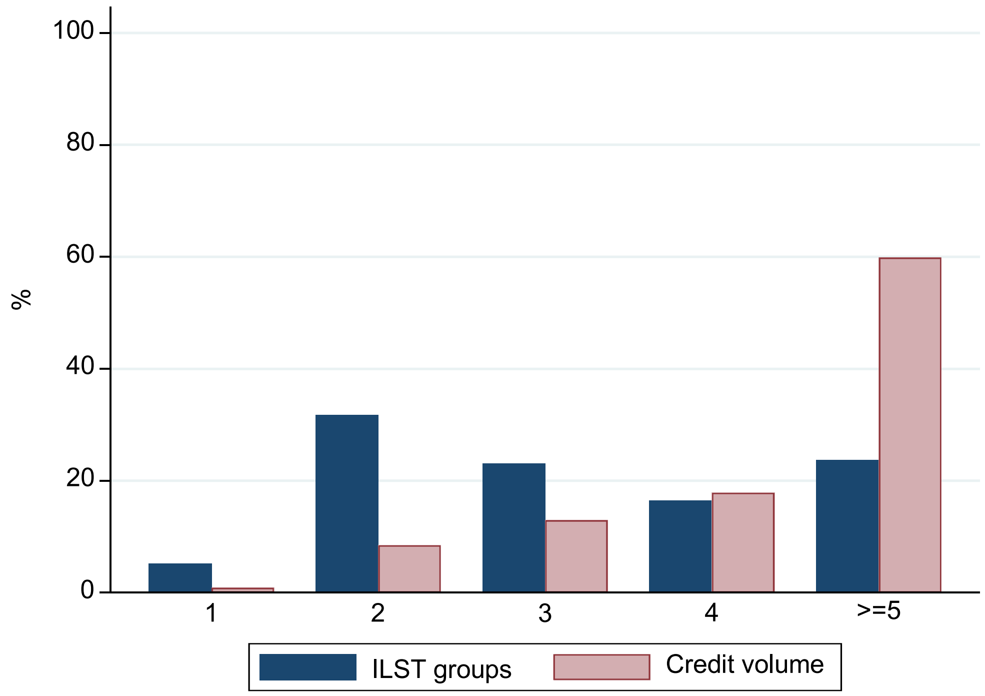
Figures and tables

Figure 1. The number of borrowing relationships

Panel A: Firm-Time groups

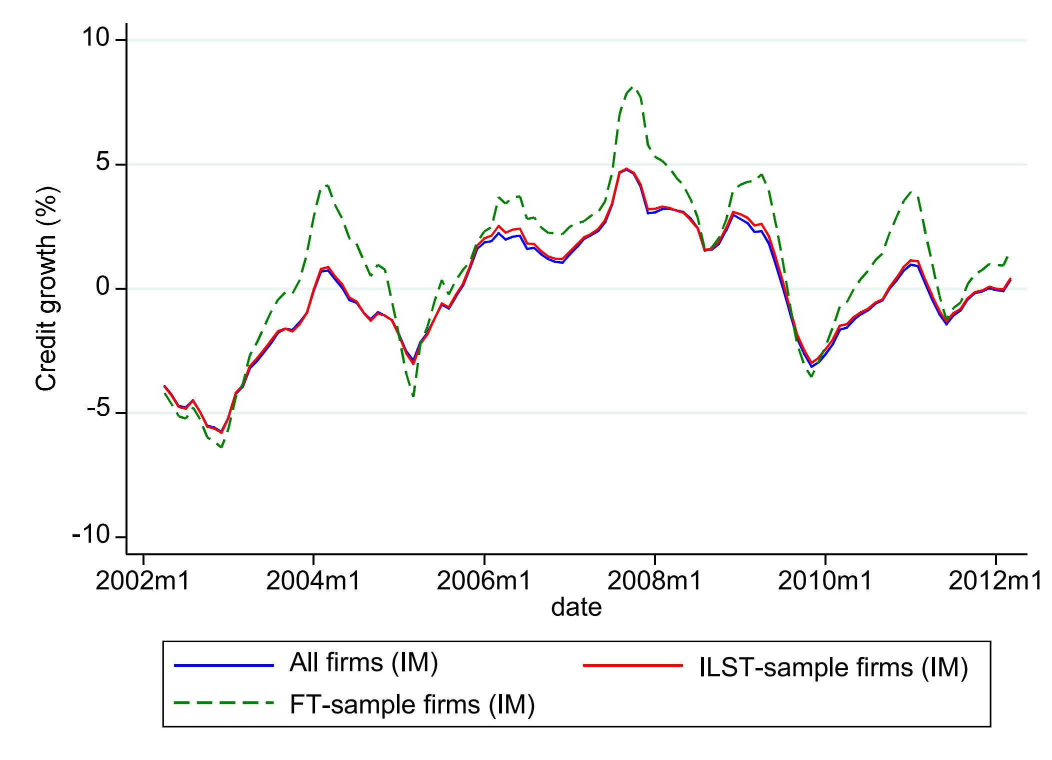


Panel B: Industry-Location-Size-Time groups



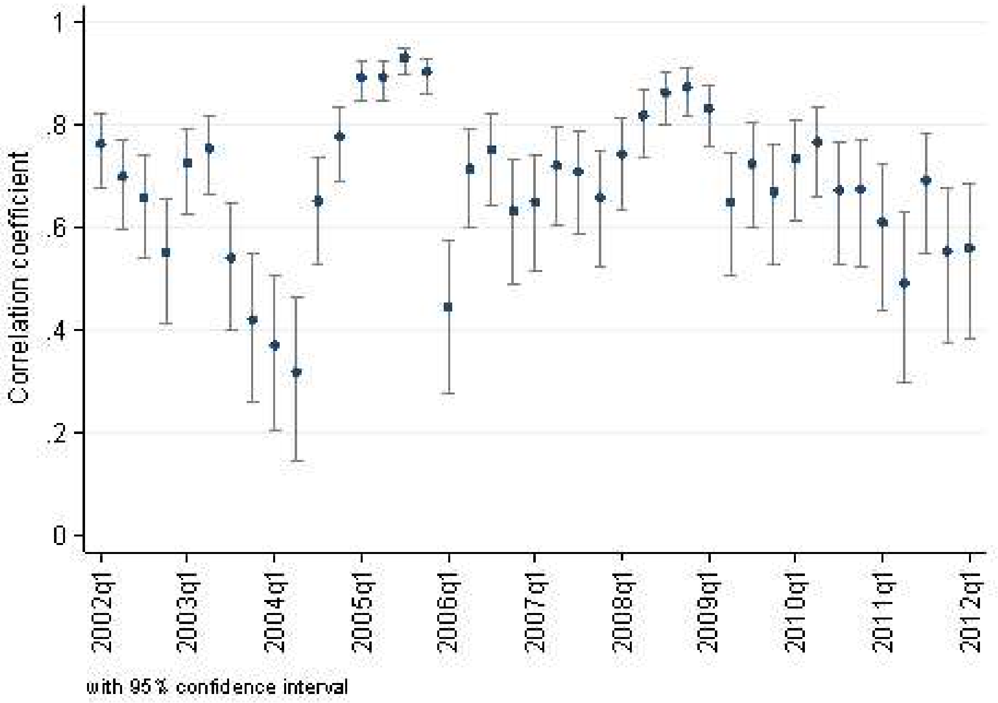
Note: Panel A of Figure 1 shows the percentage of firm-time combinations in the full sample with 1, 2, 3, 4, and 5 or more banking relationships as well as the percentage of loan volume that these firm-time combinations represent in the total loan volume. Panel B shows the same indicators for Industry-Location-Size-Time (ILST) groups.

Figure 2. Credit growth: all firms *vs* multi-bank firms *vs* single- and multi-bank firms



Note: Figure 2 shows the weighted average credit growth rate over the sample period. We plot weighted average credit growth for (1) the overall credit register sample (solid blue line), (2) the subsample of both single-bank and multi-bank firms used in the identification of ILST shocks (solid red line), and (3) the subsample of the multi-bank firms used in the identification of FT shocks (green dashed line). Credit growth rates in this graph are based on the intensive margin only, such that it corresponds with the bank-firm observations included in the regression analyses.

Figure 3. Correlation between ILST shocks and FT shocks



Note: Figure 3 shows the correlation coefficients of bank credit supply shocks from Equation 3 (ILST shock) and Equation 1 (FT shock) for each quarter in the sample. FT shocks are bank credit supply shocks identified on the sample of multi-bank firms using firm-time fixed effects as demand control. ILST shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control.

Table 1. Characteristics of single-bank and multiple-bank firms

	Mean	Firm-bank-month observations	Firm-year observations	Firms	T-stat (p-value) of difference in means
Age (in years)					
Permanently single-bank firms	12.70	9,705,534	973,368	183,885	
Permanently multiple-bank firms	24.01	1,367,672	48,419	5,752	166.36 (0.000)
Both single- and multiple-bank firms	16.81	6,015,943	378,097	44,755	191.12 (0.000)
Total assets (in mil. EUR)					
Permanently single-bank firms	1.74	9,705,534	973,368	183,885	
Permanently multiple-bank firms	29.44	1,367,672	48,419	5,752	10.98 (0.000)
Both single- and multiple-bank firms	9.90	6,015,943	378,097	44,755	18.87 (0.000)
Number of employees, FTE					
Permanently single-bank firms	4.17	9,705,534	973,368	183,885	
Permanently multiple-bank firms	57.67	1,367,672	48,419	5,752	18.30 (0.000)
Both single- and multiple-bank firms	16.58	6,015,943	378,097	44,755	40.89 (0.000)
Fixed assets/total assets					
Permanently single-bank firms	0.52	9,705,534	973,368	183,885	
Permanently multiple-bank firms	0.36	1,367,672	48,419	5,752	-132.69 (0.000)
Both single- and multiple-bank firms	0.47	6,015,943	378,097	44,755	-94.43 (0.000)
Loan size (in mil. EUR)					
Permanently single-bank firms	0.30	9,705,534	973,368	183,885	
Permanently multiple-bank firms	1.33	1,367,672	48,419	5,752	32.77 (0.000)
Both single- and multiple-bank firms	0.60	6,015,943	378,097	44,755	44.10 (0.000)

Note: Table 1 provides summary statistics on firm age, size, investments and credit amounts authorized for three subsamples of firms: (1) firms that never borrow from more than one bank at the same time ("permanently single-bank firms"), (2) firms that always borrow from more than one bank ("permanently multiple bank firms"), and (3)firms that borrow from more than one bank at some point in time and from only one bank during other periods ("both single and multiple-bank firms"). In the last column, we report the t-statistic and p-values of the test of the difference in means between "permanently single bank firms" and each of the two other subgroups.

Table 2. Comparison of bank-credit supply shock estimates: comparing credit demand controls

	Firm-time fixed effects								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Time fixed effects	0.963***								
	(0.0371)								
Location-time fixed effects (L)		0.965***							
		(0.0374)							
Industry-location-time fixed effects (IL)			0.986***						
			(0.0273)						
Industry-location-age-time fixed effects (ILA)				1.025***					
				(0.0271)					
Industry-location-CA-time fixed effects (ILC)					1.015***				
					(0.0335)				
Industry-location-risk-time fixed effects (Interest coverage, ILR1)						0.981***			
						(0.0225)			
Industry-location-risk-time fixed effects (Altman, ILR2)							1.040***		
							(0.0258)		
Industry-location-size-time fixed effects (ILS)								1.014***	
								(0.0171)	
Industry-location-size-time fixed effects (ILS) 2008m9-2009m12									1.065***
									(0.0407)
Observations	4,478	4,478	4,478	4,478	4,478	4,478	4,478	4,478	531
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value coef.=1	0.325	0.348	0.607	0.360	0.650	0.401	0.122	0.419	0.120
Adjusted R-squared	0.670	0.675	0.713	0.735	0.727	0.730	0.735	0.770	0.813
Difference with ILST adjusted R-squared	-0.0999	-0.0950	-0.0568	-0.0343	-0.0426	-0.0396	-0.0347		0.0433
T statistic for R-squared difference	-34.78	-33.52	-22.66	-14.93	-17.38	-16.92	-14.94		17.31
Spearman's rank correlation coef.	0.744	0.748	0.787	0.805	0.803	0.806	0.804	0.818	0.862

Note: Table 2 documents the relationships between credit supply estimates obtained from the sample of multi-bank firms, but with altering credit demand controls. The dependent variable in each regression is the series of bank supply shocks obtained when estimating Equation 1 using firm-time fixed effects. Dependent variables are series of supply shocks obtained by estimating Equation 1 with various alternative demand controls, ranging from time fixed effects in Column 1 to industry-location-size-time fixed effects in Column 8 (Column 9 reports the results for the crisis period September 2008-December 2009). For every of the nine comparisons made, we are excluding groups of firms that are made up of only one (multi-bank) firm when calculating the right-hand side variables. Groups that are based on firm characteristics are constructed using yearly deciles of these firm characteristics. All regressions include time fixed effects. Standard errors clustered at the bank level are reported in parentheses.

Table 3. FT shock and ILST shock correlation: the role of borrower composition

Difference between single-bank and multi-bank firms in terms of:	Tercile	Correlation	Test diff with T1 (p-value)	Test diff with T2 (p-value)
Firm size (total assets)	T1	73.9%		
	T2	72.5%	0.41	
	T3	68.5%	0.00	0.03
Firm age (in years)	T1	70.7%		
	T2	76.1%	0.00	
	T3	67.2%	0.07	0.00
Profitability (EBIT / total assets)	T1	74.3%		
	T2	74.4%	0.33	
	T3	68.2%	0.00	0.00
Solvency risk (financial debt / total assets)	T1	75.5%		
	T2	73.9%	0.96	
	T3	68.3%	0.00	0.00
Collateral (fixed assets / total assets)	T1	80.1%		
	T2	67.3%	0.00	
	T3	63.2%	0.00	0.05
Share of singles in total loan volume	T1	79.4%		
	T2	72.7%	0.00	
	T3	65.2%	0.00	0.00

Note: Table 3 displays the correlation coefficients of bank supply shocks from Equation 3 (ILST shock) and Equation 1 (FT shock) for each bank-month in the sample, conditional on how different these borrowers are in terms of a specific balance sheet characteristics (as indicated in the first column). More specifically, for each month and bank in our sample, we calculate the average of a firm characteristic (size, age, profitability, solvency risk and collateral) for all single-bank borrowers and all multi-bank borrowers in a bank's loan portfolio. Next, we calculate, for each month and bank, the absolute value of the difference between the average value of that firm characteristic of the single-bank borrowers and the multi-bank borrowers. Subsequently, we divide the sample of bank-month observations in three terciles based on this computed difference (T1, T2, T3, where T3 contains the bank-month observations with the largest difference). We report the correlation between the ILST shock and the FT shock for each tercile in Column 3. The last two columns report the p-value for a t-test on the difference between the correlations.

Table 4. Descriptive statistics: Supply shocks, real effects and risk-taking

Panel A: Main variables for real effects regressions

	N	Mean	St. dev.	p5	p95
Bank supply shock ILST	1,026,426	0.292	3.138	-3.712	3.616
Bank supply shock FT	1,026,426	1.918	3.804	-3.249	5.802
Total assets growth (in %)	1,026,426	4.833	31.12	-27.92	53.23
Operating margin growth (in %)	1,026,426	15.07	104.5	-89.98	113.9
Fixed assets growth (in %)	1,026,426	10.29	94.38	-43.49	95.37
Financial debt growth (in %)	1,026,426	13.93	134.9	-84.84	161.0
Leverage	1,026,426	0.738	0.310	0.263	1.197
Ln (Number of employees)	1,026,426	1.023	1.174	0	3.367
Ln (Firm age)	1,026,426	2.580	0.628	1.386	3.584

Panel B: Main variables for bank risk-taking regressions

	N	Mean	St. dev.	p5	p95
Bank supply shock ILST	2,663	4.744	10.07	-8.958	19.08
Bank supply shock FT	2,663	4.364	12.13	-13.31	22.88
New - exit (Loan volume)	2,663	0.826	3.095	-2.356	5.99
New - exit (Number of loans)	2,663	0.502	2.65	-2.8	5.08
New - exit (Altman Z-score)	2,663	0.118	0.81	-1.316	1.435
New - exit (Equity/debt ratio)	2,663	0.0926	0.749	-1.16	1.309

Note: Table 4 provides descriptive statistics of key variables in the analysis of bank credit supply shock effects. Panel A shows the summary statistics for the main variables in the real effects regressions which thus vary at the firm-year level. Panel B shows the summary statistics for the main variables in the bank risk-taking regressions which thus vary at the bank-month level.

Table 5. Real effects of bank credit supply shocks

	(1)	(2)	(3)		(4)	(5)	(6)
Panel A	**Dependent variable = Financial debt (growth in %)**						
	ILST shock				FT shock		
Bank credit supply shock	0.194***	0.208**	0.230**		0.088	0.129*	0.115*
	(0.072)	(0.080)	(0.094)		(0.058)	(0.070)	(0.068)
Bank credit supply shock * crisis		-0.056				-0.151	
		(0.101)				(0.098)	
Bank credit supply shock * multiple borrower			-0.275*				-0.201
			(0.150)				(0.122)
Panel B	**Dependent variable = Total assets (growth in %)**						
	ILST shock				FT shock		
Bank supply shock	0.055***	0.048**	0.055**		0.018	0.020	0.011
	(0.019)	(0.022)	(0.022)		(0.020)	(0.021)	(0.023)
Bank credit supply shock * crisis		0.026				-0.010	
		(0.034)				(0.042)	
Bank credit supply shock * multiple borrower			-0.011				0.034
			(0.034)				(0.033)
Panel C	**Dependent variable = Fixed assets (growth in %)**						
	ILST shock				FT shock		
Bank credit supply shock	0.119**	0.124*	0.123**		0.071	0.078	0.082*
	(0.057)	(0.069)	(0.054)		(0.051)	(0.059)	(0.048)
Bank credit supply shock * crisis		-0.019				-0.026	
		(0.073)				(0.058)	
Bank credit supply shock * multiple borrower			-0.052				-0.085
			(0.091)				(0.085)
Panel D	**Dependent variable = Operating margin (growth in %)**						
	ILST shock				FT shock		
Bank credit supply shock	0.107**	0.109**	0.143**		0.087**	0.077*	0.091**
	(0.047)	(0.051)	(0.060)		(0.034)	(0.042)	(0.043)
Bank credit supply shock * crisis		-0.005				0.035	
		(0.086)				(0.074)	
Bank credit supply shock * multiple borrower			-0.231*				-0.024
			(0.128)				(0.099)
Observations	1,026,426	1,026,426	1,026,426		1,026,426	1,026,426	1,026,426
Bank FE	Yes	Yes	Yes		Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes		Yes	Yes	Yes
Firm FE	Yes	Yes	Yes		Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes		Yes	Yes	Yes

Note: Table 5 relates bank credit supply estimates to firms' financial debt growth (Panel A), total assets growth (Panel B), fixed assets growth (Panel C) and growth in operating margin (Panel D). We report results for ILST shocks (Columns 1-3) and for FT shocks (Columns 4-6). FT shocks are bank credit supply shocks identified on the sample of multi-bank firms using firm-time fixed effects as demand control. ILST shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control. Regressions are on the firm-year level. For each firm, we calculate the average bank credit supply shock during year *t* and relate that to the dependent variable in year *t*. If a firm borrows from more than one bank, we calculate the weighted average bank credit supply shock, with weights depending on the relative size of the different loans. *Crisis* is a dummy equal to 1 for annual accounts filed between September 2008 and December 2009. *Multiple borrower* is a dummy equal to one for firms that borrow from more than one bank. Each regression includes firm-time level control variables (firm employment, age and leverage, all for year *t-1*) and bank, firm and industry-time fixed effects. Standard errors are clustered at the main bank level. The sample period is January 2003-April 2012.

Table 6. Bank credit supply estimates, loan risk and loan volumes on the extensive margin

	Credit volume				Credit quality			
	Loan volume		Number of loans		Altman Z		Equity/debt ratio	
	ILST shock	FT shock	ILST shock	FT shock	ILST shock	FT shock	ILST shock	FT shock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank credit supply shock	0.365**		0.526***		-0.0881*		-0.0995**	
	(0.142)		(0.120)		(0.0487)		(0.0480)	
Bank credit supply shock * crisis	-0.442*		-0.238		0.108		0.0789	
	(0.238)		(0.180)		(0.121)		(0.128)	
Bank credit supply shock		0.337***		0.455***		-0.0464		-0.0607
		(0.0993)		(0.107)		(0.0370)		(0.0406)
Bank credit supply shock * crisis		-0.278		-0.181		-0.0734		-0.120
		(0.216)		(0.279)		(0.0824)		(0.0868)
Observations	2,663	2,663	2,663	2,663	2,663	2,663	2,663	2,663
Adjusted R-squared	0.450	0.449	0.691	0.688	0.387	0.387	0.357	0.356
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 6 contains information on how banks change the size of their loan portfolio (measured by loan volume or number of exposures) and the riskiness of their portfolio (measured by the Altman Z-score and the equity-to-debt ratio of the firms) at the extensive margin (i.e. comparing new borrowers with exiting borrowers) in response to a bank credit supply shock. In Columns 1 and 2, we analyse how a credit supply shock in the previous period affects the extensive margin change in firm entries, measured as the difference between the volume of loans entering the bank`s portfolio and the volume of loans exiting the portfolio, scaled by the volume of existing firms in the portfolio. As such, bank-month observations where there is no new loan granted or no borrower dropped from the bank`s portfolio are dropped from the sample, which leads to a lower amount of observations compared to Table 1. The dependent variable in Columns 3 and 4 is the difference between the number of new loans and the number of exiting loans, scaled by the number of existing loans. The dependent variable in Columns 5(7) and 6(8) is the difference in the weighted Altman Z-score (equity/debt ratio) of the firms entering the banks' loan portfolio and those exiting, weighted by the volume of the loan. We report results for ILST shocks (Columns 1/3/5/7) and for FT shocks (Columns 2/4/6/8). FT shocks are bank credit supply shocks identified on the sample of multi-bank firms using firm-time fixed effects as demand control. ILST shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control. All regressions are on the bank-month level for the period 2002-2012. The regression observations are weighted by the number of new and exiting loans in the banks' portfolio to make sure that the relatively small number of exits and entries in each period for some small banks (and the corresponding noisy estimates of the riskiness) are not biasing our estimates. All specifications contain time and bank fixed effects and include controls for bank M&As (two quarters following an M&A for the acquiring bank and one quarter prior for the acquired bank), and dummies for months of capital injections for the recipient banks. Standard errors are clustered at the bank level.

Table 7. Bank credit supply shock estimates and bank sources of funding

	(1)	(2)	(3)	(4)
	Full period	Pre-crisis	Crisis	Post-crisis
		2002m1-2008m8	2008m9-2009m8	2009m9-2012m3
Deposit growth	0.00552	-0.0121	0.111	0.0225
	(0.0439)	(0.0595)	(0.0856)	(0.0632)
Equity growth	0.0780	0.167	0.974	-0.468**
	(0.312)	(0.368)	(1.055)	(0.226)
Interbank liabilities growth	0.151***	0.192***	0.186*	0.184***
	(0.0366)	(0.0586)	(0.0923)	(0.0638)
Observations	4,354	3,045	411	898
Adjusted R-squared	0.332	0.316	0.760	0.526
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes
Number of banks	57	55	37	34

Note: Table 7 shows regression results of specifications in which we relate our main bank credit supply measure (ILST shocks) to three observable sources of bank funding growth: growth in deposits, growth in equity and growth in interbank funding. ILST shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control. The results are reported for the full sample period (2002m1-2012m3), the period prior to the Lehman collapse (2002m1-2008m8), and for the post-Lehman period (2008m09-2012m3). The latter period we further decompose in the crisis (2008m9-2009m8) and post-crisis period (2009m9-2012m3). All specifications contain time and bank fixed effects. All regressions include controls for bank M&As (two quarters following an M&A for the acquiring bank and one quarter prior for the acquired bank), and dummies for months of capital injections for the recipient banks. Robust standard errors clustered at the bank level are reported in parentheses.

Table 8. Bank credit supply shock estimates and BLS supply indicators

Panel A: BLS lending standards

	(1)	(2)	(3)
	Full period	2002m1-2008m9	2008m10-2012m3
Supply tightening	-0.721	-1.521**	0.904
	(0.694)	(0.607)	(0.891)
Supply easing	-0.854	-1.024	
	(1.984)	(1.855)	
Observations	152	96	56
R-squared	0.907	0.914	0.970
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes

Panel B: BLS lending standards, multiple tightening/easing

	(1)	(2)	(3)
	Full period	2002m1-2008m9	2008m10-2012m3
Supply tightening	-1.909**	-2.508***	0.904
	(0.815)	(0.581)	(0.891)
Tightening * Multiple banks	1.938*	1.791**	
tightening	(1.044)	(0.649)	
Supply easing	-0.900	-1.044	
	(1.979)	(1.849)	
Observations	152	96	56
R-squared	0.909	0.916	0.970
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes

Note: Table 8 shows regression results of specifications in which we relate our main bank credit supply measure (ILST shocks) to an alternative bank credit supply indicator obtained from the Bank Lending Survey, i.e. the bank's response to the question on how credit standards have changed over the past three months (Panel A). ILST shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control. To further control for the informativeness of the answer, we also interact the dummy variables (tightening and easing) with an indicator variable that is equal to one if multiple banks were either tightening or easing in that time period (Panel B). Monthly data on credit supply estimates refer to end-of-quarter months. We report results for the full period, as well as for two sample splits (using September 2008, the month of the Lehman collapse, to define the sample split). All specifications contain time and bank fixed effects. All regressions include controls for bank M&As (two quarters following an M&A for the acquiring bank and one quarter prior for the acquired bank), and dummies for months of capital injections for the recipient banks. Robust standard errors are reported in parentheses.

Online Appendix

Identifying credit supply shocks with bank-firm data: methods and applications

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Abstract

This Online Appendix accompanies the paper "Identifying credit supply shocks with bank-firm data: methods and applications". Section A of the Appendix depicts the growth rate of credit at the intensive and extensive margin. Section B shows the real effects of bank supply shocks on other asset and liability items in the balance sheets of firms. Section C describes the Amiti and Weinstein (2018) method of estimating bank supply shocks. Section D provides results on the real effects of two alternative bank supply shocks: (i) including the extensive margin in the estimation of the shocks, and (ii) using the Amiti and Weinstein (2018) approach.

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A. Credit growth in Belgium: 2002-2012

Figure A.1 Credit growth: intensive margin vs intensive + extensive margin

Note: This figure shows the weighted average credit growth rate over the sample period. We plot the weighted average credit growth for all firms in the credit register sample on the intensive margin (IM) only (solid blue line), as well as the weighted average credit growth for all firms in the credit register sample on the intensive and extensive margin (IM+EM) (dashed red line).

B. Real effects: additional dependent variables

Table A.1: Summary statistics

	N	Mean	St. dev.	p5	p95
Equity growth (in %)	1,026,407	20.56	109.10	-90	115.9
Non-financial debt growth (in %)	1,026,426	15.99	79.48	-50.96	113.5
Trade receivables growth (in %)	979,421	41.57	172.8	-82.29	277.8
Inventories growth (in %)	578,607	16.07	103.5	-70.35	114.9
Cash and equivalent growth (in %)	976,726	89.80	258.8	-90	979.2

Note: This table provides descriptive statistics of additional variables used in the analysis of bank credit supply shock effects. In particular, it shows the summary statistics for growth in accounts receivable, inventories, cash and equivalents, non-financial debt and equity. These variables vary at the firm-year level.

Table A.2: Real effects of credit supply shocks – other balance sheet items

Panel A1	**Dependent variable = Equity (growth in %)**					
	ILST supply shock			FT supply shock		
Bank supply shock	0.049	0.088	0.017	0.104	0.153	0.045
	(0.065)	(0.082)	(0.056)	(0.085)	(0.116)	(0.066)
Bank supply shock * crisis		-0.151			-0.180	
		(0.122)			(0.146)	
Bank supply shock * multiple borrower			0.202			0.353*
			(0.152)			(0.176)
Observations	1,026,407	1,026,407	1,026,407	1,026,407	1,026,407	1,026,407
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes
Panel A2	**Dependent variable = Non-Financial debt (growth in %)**					
	ILST supply shock			FT supply shock		
Bank supply shock	0.072*	0.039	0.038	0.033	0.028	0.012
	(0.041)	(0.049)	(0.038)	(0.034)	(0.045)	(0.036)
Bank supply shock * crisis		0.125			0.016	
		(0.092)			(0.086)	
Bank supply shock * multiple borrower			0.211***			0.123*
			(0.066)			(0.066)
Observations	1,026,426	1,026,426	1,026,426	1,026,426	1,026,426	1,026,426
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes
Panel A3	**Dependent variable = Accounts receivable (growth in %)**					
	ILST supply shock			FT supply shock		
Bank supply shock	0.011	-0.036	-0.006	0.011	-0.029	-0.026
	(0.088)	(0.107)	(0.090)	(0.059)	(0.075)	(0.072)
Bank supply shock * crisis		0.188			0.150	
		(0.136)			(0.127)	
Bank supply shock * multiple borrower			0.095			0.209
			(0.163)			(0.169)
Observations	979,421	979,421	979,421	979,421	979,421	979,421
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes
Panel A4	**Dependent variable = Inventories (growth in %)**					
	ILST supply shock			FT supply shock		
Bank supply shock	0.027	-0.041	0.014	0.033	0.013	-0.009
	(0.043)	(0.055)	(0.040)	(0.043)	(0.049)	(0.048)
Bank supply shock * crisis		0.297***			0.079	
		(0.102)			(0.135)	
Bank supply shock * multiple borrower			0.055			0.201*
			(0.131)			(0.106)
Observations	578,607	578,607	578,607	578,607	578,607	578,607
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel A5	Dependent variable = Cash and equivalent (growth in %)					
	ILST supply shock			FT supply shock		
Bank supply shock	-0.194	-0.113	-0.268	-0.095	-0.085	-0.105
	(0.144)	(0.184)	(0.163)	(0.117)	(0.146)	(0.127)
Bank supply shock * crisis		-0.316			-0.036	
		(0.209)			(0.192)	
Bank supply shock * multiple borrower			0.448			0.044
			(0.311)			(0.240)
Observations	976,726	976,726	976,726	976,726	976,726	976,726
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table relates bank credit supply estimates to growth rates of various firm characteristics. The dependent variables are the growth rate of equity, non-financial debt, accounts receivable, inventories, and cash and equivalents, respectively. We report results for ILST shocks (Columns 1-3) and for FT shocks (Columns 4-6). FT shocks are bank credit supply shocks identified on the sample of multi-bank firms using firm-time fixed effects as demand control. ILST shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control. Regressions are on the firm-year level. For each firm, we calculate the average credit supply shock during year *t* and relate that to the dependent variable in year *t*. If a firm borrows from more than one bank, we calculate the weighted average credit supply shock, with weights depending on the relative size of the different loans. *Crisis* is a dummy equal to 1 for annual accounts filed between September 2008 and December 2009. *Multiple borrower* is a dummy equal to one for firms that borrow from more than one bank. Each regression includes firm-time level control variables (firm employment, age and leverage, all for year *t-1*) and bank, firm and industry-time fixed effects. Standard errors are clustered at the main bank level. The sample period is January 2003-April 2012.

Why do firms mainly adjust their balance sheet via fixed assets and not via receivables, inventories, or cash when faced with a reduction in financial debt? These findings are in line with the results and explanations of several other papers:

- For instance, Desai et al. (2008) show that differences in credit constraints explain firms' ability to increase assets, sales, and particularly investments in fixed assets in reaction to currency depreciations, which is consistent with our reported elasticities.
- One reason why firms could be inclined to cut back on their fixed assets rather than on their working capital when faced with a credit supply shock could be simply because postponing planned investments is easier than reducing working capital. For instance, reducing accounts receivable or increasing accounts payable (i.e., the most important part of our non-financial debt variable) implies renegotiating credit terms with customers and suppliers. The firm's ability to do this will strongly depend on its bargaining power with customers and suppliers (Klapper et al., 2012; Fabbri and Klapper, 2016). The majority of firms in our sample are single-bank firms, which are very small (on average 4 employees), making it quite unlikely that they will have the bargaining power to change their credit terms with their customers or suppliers.
- Reducing inventories might also not be desirable as lacking input goods might be very costly if the production process needs to be interrupted and as customers appreciate timely deliveries.
- Finally, the non-effect on cash and cash equivalent seems more puzzling at first sight, as the evolution of this balance sheet item is fully at the discretion of the firm itself. However, it appears that the average (non-)effect hides some heterogeneity in the reaction of firms in line with the recent findings of Berg (2018). We find some evidence that firms with above median cash buffers before the bank supply shock, reduced their cash holdings after the shock; while firms with below median cash buffers before the bank supply shock actually increased their cash holdings after the shock.

C. The Amiti-Weinstein estimator

Amiti and Weinstein (2018) have pointed out that the traditional approach to disentangle demand and supply shocks as portrayed in Equation 1 of the paper has the potential drawback that it does not account for general equilibrium constraints. The authors argue that the estimation of Equation 1 ignores the adding-up constraints that are implicitly assumed in Equation 1 They apply an approach that also considers the weight of each firm in the banks' lending portfolio, and the weight of each bank in the firms' borrowing portfolio. This weighting approach, which acknowledges the implicit adding-up constraints, is able to reproduce actual growth rates of credit at the bank level (at the intensive margin). Their methodology yields the following system of equations at the bank and firm level, respectively:

$$D_{bt}^{B} = \beta_{bt} + \sum_{f} \phi_{fbt-1} \cdot \alpha_{ft} + \sum_{f} \phi_{fbt-1} \cdot \varepsilon_{fbt} \tag{A1a}$$

$$D_{ft}^{F} = \alpha_{ft} + \sum_{b} \theta_{fbt-1} \cdot \beta_{bt} + \sum_{b} \theta_{fbt-1} \cdot \varepsilon_{fbt}, \tag{A1b}$$

where D_{bt}^{B} is the growth rate of total lending by bank *b* to all its client firms and D_{ft}^{F} is the growth rate of total borrowing by firm *f* from all its banks. As Equation A1a shows, a bank's growth in total lending in a given period depends on its loan supply shock and the sum of all the demand shocks from its clients weighted by their importance in the bank's portfolio the previous period (denoted by $\phi_{fbt-1} \equiv \frac{L_{fbt-1}}{\sum_f L_{fbt-1}}$). Similarly, as can be seen in Equation A1b, a firm's growth in total borrowing in a given period depends on its loan demand shock and the sum of all the loan supply shocks weighted by their importance in the firm's total borrowing in the previous period (denoted by $\theta_{fbt-1} \equiv \frac{L_{fbt-1}}{\sum_b L_{fbt-1}}$). Given that ϕ_{fbt-1} and θ_{fbt-1} are predetermined, the moment conditions that can be imposed are $\sum_f \phi_{fbt-1} \cdot E(\varepsilon_{fbt}) = 0$ and $\sum_b \theta_{fbt-1} \cdot E(\varepsilon_{fbt}) = 0$, respectively. With these moment conditions, the firm demand and bank supply shocks can be estimated from the following system of equations:

$$D_{bt}^{B} = \beta_{bt} + \sum_{f} \phi_{fbt-1} \cdot \alpha_{ft} \tag{A2a}$$

$$D_{ft}^{F} = \alpha_{ft} + \sum_{b} \theta_{fbt-1} \cdot \beta_{bt} \tag{A2b}$$

In practice, Tielens and Van Hove (2017) formally show that the proposed estimator for this series of equations in Amiti and Weinstein (2018) is equivalent to a weighted least square estimation of Equation 1. We thus estimate the Amiti-Weinstein supply shocks used in Section 5 of the paper by estimating a weighted least square version of Equation 3 (i.e. the version of Equation 1 that includes Industry-location-size-time fixed effects instead of firm-time fixed effects).

D. Alternative supply shock estimators: real effects

Table A.3 Real Effects of bank credit supply shocks: including the extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**Dependent variable = Financial debt (growth in %)**					
	ILST shock (IM+EM)			FT shock (IM+EM)		
Bank credit supply shock	0.206**	0.204**	0.258**	0.093	0.127	0.130
	(0.089)	(0.095)	(0.122)	(0.080)	(0.085)	(0.091)
Bank credit supply shock * crisis		0.009			-0.115	
		(0.103)			(0.108)	
Bank credit supply shock * multiple borrower			-0.340*			-0.233
			(0.175)			(0.172)
Panel B	**Dependent variable = Total assets (growth in %)**					
	ILST shock (IM+EM)			FT shock (IM+EM)		
Bank credit supply shock	0.048*	0.040	0.057**	0.013	0.011	0.013
	(0.025)	(0.027)	(0.028)	(0.025)	(0.028)	(0.029)
Bank credit supply shock * crisis		0.036			0.006	
		(0.032)			(0.045)	
Bank credit supply shock * multiple borrower			-0.059			-0.007
			(0.039)			(0.043)
Panel C	**Dependent variable = Fixed assets (growth in %)**					
	ILST shock (IM+EM)			FT shock (IM+EM)		
Bank credit supply shock	0.131	0.148*	0.166**	0.075	0.098	0.114*
	(0.079)	(0.087)	(0.078)	(0.069)	(0.076)	(0.066)
Bank credit supply shock * crisis		-0.071			-0.079	
		(0.060)			(0.063)	
Bank credit supply shock * multiple borrower			-0.223*			-0.248*
			(0.121)			(0.140)
Panel D	**Dependent variable = Operating margin (growth in %)**					
	ILST shock (IM+EM)			FT shock (IM+EM)		
Bank credit supply shock	0.105*	0.118**	0.142*	0.097**	0.099*	0.106*
	(0.060)	(0.057)	(0.072)	(0.046)	(0.052)	(0.058)
Bank credit supply shock * crisis		-0.052			-0.008	
		(0.111)			(0.091)	
Bank credit supply shock * multiple borrower			-0.231			-0.059
			(0.160)			(0.153)
Observations	1,026,426	1,026,426	1,026,426	1,026,426	1,026,426	1,026,426
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table relates bank credit supply estimates to firm financial debt growth (Panel A), total assets growth (Panel B), fixed assets growth (Panel C) and growth in operating margin (Panel D). We report results for ILST shocks (IM+EM) (Columns 1-3) and for FT shocks (IM+EM) (Columns 4-6). FT shocks (IM+EM) are bank credit supply shocks identified on the sample of multi-bank firms using firm-time fixed effects as demand control. ILST shocks (IM+EM) are bank credit supply shock identified on the sample of both single- and multi-bank firms using industry-location-size-time fixed effects as demand control. Most importantly, the bank credit supply shocks used in this table also include the extensive margin of credit supply. Regressions are on the firm-year level. For each firm, we calculate the average credit supply shock during year *t* and relate that to the dependent variable in year *t*. If a firm borrows from more than one bank, we calculate the weighted average credit supply shock, with weights depending on the relative size of the different loans. *Crisis* is a dummy equal to 1 for annual accounts filed between September 2008 and December 2009. *Multiple borrower* is a dummy equal to one for firms that borrow from more than one bank. Each regression includes firm-time level control variables (firm employment, age and leverage, all for year *t-1*) and bank, firm and industry-time fixed effects. Standard errors are clustered at the main bank level. The sample period is January 2003-April 2012.

Table A.4 Real effects of bank credit supply shocks using Amiti-Weinstein

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**Dependent variable = Financial debt (growth in %)**					
	ILST shock (AW)			FT shock (AW)		
Bank credit supply shock	0.097	0.104	0.133*	-0.008	0.008	0.008
	(0.073)	(0.083)	(0.071)	(0.068)	(0.084)	(0.062)
Bank credit supply shock * crisis		-0.042			-0.078	
		(0.139)			(0.133)	
Bank credit supply shock * multiple borrower			-0.204*			-0.089
			(0.104)			(0.087)
Panel B	**Dependent variable = Total assets (growth in %)**					
	ILST shock (AW)			FT shock (AW)		
Bank credit supply shock	0.046*	0.033	0.058**	0.016	0.008	0.017
	(0.023)	(0.022)	(0.024)	(0.017)	(0.017)	(0.018)
Bank credit supply shock * crisis		0.081**			0.038	
		(0.039)			(0.041)	
Bank credit supply shock * multiple borrower			-0.076*			0.002
			(0.038)			(0.035)
Panel C	**Dependent variable = Fixed assets (growth in %)**					
	ILST shock (AW)			FT shock (AW)		
Bank credit supply shock	0.070	0.070	0.097*	0.008	0.003	0.011
	(0.053)	(0.052)	(0.052)	(0.046)	(0.048)	(0.044)
Bank credit supply shock * crisis		0.004			0.023	
		(0.094)			(0.074)	
Bank credit supply shock * multiple borrower			-0.159			-0.010
			(0.105)			(0.073)
Panel D	**Dependent variable = Operating margin (growth in %)**					
	ILST shock (AW)			FT shock (AW)		
Bank credit supply shock	0.045	0.015	0.030	-0.008	-0.045*	-0.034
	(0.052)	(0.044)	(0.059)	(0.029)	(0.026)	(0.035)
Bank credit supply shock * crisis		0.186			0.181**	
		(0.117)			(0.089)	
Bank credit supply shock * multiple borrower			0.099			0.183*
			(0.109)			(0.099)
Observations	1,026,426	1,026,426	1,026,426	1,026,426	1,026,426	1,026,426
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table relates Amiti-Weinstein (2018) bank credit supply estimates to firm outcomes. We report results for ILST (AW) shocks (Columns 1-3) and for FT (AW) shocks (Columns 4-6). FT (AW) shocks are bank credit supply shocks identified on the sample of multi-bank firms using a weighted regression and firm-time fixed effects as demand control. ILST (AW) shocks are bank credit supply shock identified on the sample of both single- and multi-bank firms using a weighted regression and industry-location-size-time fixed effects as demand control. The bank credit supply shocks are subsequently related to financial debt growth (panel A), total assets growth (Panel B), fixed assets growth (Panel C) and operating margin growth (panel D). Regressions are on the firm-year level. For each firm, we calculate the average Amiti-Weinstein bank credit supply shock during year t and relate that to the dependent variable in year t. If a firm borrows from more than one bank, we calculate the weighted average credit supply shock, with weights depending on the relative size of the different loans. *Crisis* is a dummy indicator equal to 1 for annual accounts filed for the period between September 2008 (the month of the Lehman collapse) and December 2009. *Multiple borrower* is a dummy equal to 1 for firms that borrow from more than one bank. In each regression, we include firm-time level control variables (firm size, age and leverage) and bank, firm and industry-time fixed effects. Standard errors are clustered at the main bank level.

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