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The Impact of Bank Shocks on Firm-Level Outcomes and Bank Risk-Taking

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The Impact of Bank Shocks on Firm-Level Outcomes and Bank Risk-Taking

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Abstract

We examine the impact of bank-loan supply shocks on firm outcomes and bank risk-taking employing bank-firm matched credit information from Belgium for the period 2002-2012. Towards this end, we develop and estimate cross-sectional measures of bank-loan supply shocks. We find that firms borrowing from banks with negative supply shocks exhibit slower growth, investment and employment. Banks faced with positive supply shocks show risk-taking behaviour at the extensive margin. Our estimated bank-loan shocks correlate positively with interbank liabilities growth and an alternative indicator of bank-loan supply, i.e. bank lending standards.

Keywords: bank-loan supply shocks, bank lending, growth, investment, employment, risk-taking
JEL codes: G21, G32

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1. Introduction

A nascent question is whether and how much bank-loan supply shocks impact credit availability, bank behaviour and ultimately the real economy. This topic is back on top of the research agenda since the recent global crisis, when a substantial part of the credit market was disrupted followed by the great recession. The bank lending channel stemming from bank-loan supply shocks, however, is not exclusive to crisis periods but may also occur in more tranquil periods. Changes in monetary policy, regulation and supervision or in the availability of wholesale and retail funding, for example, could translate into bank-loan supply shocks that are heterogeneous across banks. During the recent global crisis, for example, some banks and borrowers that were more exposed to the credit market disruption were also more heavily affected than others. This paper studies how bank-loan supply shocks in the period 2002-2012 impact firm-level outcomes and bank risk-taking by combining matched bank-firm lending data with information from firms' and banks' balance sheets and income statements. This period encompasses the global crisis but also more tranquil periods.

Bank-loan supply shocks translate into real effects if borrowers cannot easily substitute loans from shocked banks with alternative sources of financing. Banks facing shocks may alter their lending policies and accordingly adjust the riskiness and composition of their portfolio. Banks may take more credit risk in their lending when faced with positive supply shocks. The bank risk-taking channel, for example, posits that banks adopt lower lending standards in prolonged periods of loose monetary policy, in particular when banks are subject to severe agency problems (see, e.g., Jiménez et al., 2014; Ioannidou et al., 2015). Positive supply shocks may further reduce screening incentives, lead to a search-for-yield, and result in laxer lending standards (see, e.g., Ruckes, 2004).

Several approaches are taken to identify the bank lending channel and to study its effects. A first strand of literature relies on aggregate data and looks at correlations between variation in bank characteristics and changes in loans or real output. Bernanke (1983) for example studies the impact of bank failures during the Great Depression on aggregate production. Other papers investigate the impact of impairments of bank capital – which are seen as a negative supply shock – on economic activity. Papers in the tradition of macro-monetary economics use a (structural) autoregressive framework employing bank-level and economy-wide information to examine the macroeconomic relevance of bank supply shocks (e.g., Peersman, 2012). Demand and supply are disentangled using ordering and sign restrictions on the different variables considered. Others using aggregate data employ banking crisis events and rely on heterogeneity in external financial or bank dependence to come to identification of the impacts on lending and investment (see, e.g., Rajan and Zingales, 1998; Dell'Ariccia et al., 2008; Chava and Purnanandam, 2011).

A second strand of literature closer to ours uses bank-firm matched loan data to identify the bank lending channel and to assess its impacts.[1] Several scholars have indicated that credit register data, containing bank-firm level information, might be key to disentangle credit demand from credit supply (Gan, 2007; Khwaja and Mian, 2008; Jiménez et al., 2012b). However, two methodological choices may limit the generality of conclusions that can be made from this empirical approach. First, the vast majority of papers relies on exogenous events (e.g., the recent global crisis or the sovereign crisis in Europe) in order to analyse the impact of such very particular shocks on bank-loan supply. While these studies lead to interesting insights on the unravelling of the crisis, they remain silent on bank-loan supply shocks that may also occur in the (predominant) time periods when such disrupting events are absent.

Second, the use of bank-time fixed effects combined with a time-varying demand measure (firm-time fixed effects) enables the researcher to estimate the bank lending channel for multiple relationship firms. However, such effects help to disentangle demand and supply effects only in a setting that involves firms borrowing from more than one bank.[2] In many countries, such firms may represent the minority of borrowing firms (see, e.g., Ongena and Smith, 2001; Degryse et al., 2009), thus making the methodology only limitedly applicable.[3]

Using monthly-level credit register data from Belgium for the period 2002-2012 and combining them with annual balance sheet and income statement data on Belgian firms and on banks established in Belgium, this paper simultaneously addresses the two aforementioned challenges: (1) the development of a time-varying indicator of bank-loan supply across banks, (2) the inclusion of firms borrowing from just one bank into the calculation of the bank-loan supply indicator. In the estimation of the bank-loan supply measure, we use firm-level data to capture observable heterogeneity among firms.[4] We achieve this by providing an alternative demand control, which consequently also produces an alternative bank-loan supply indicator, encompassing the vast majority of firms: firm-time fixed

[1] See Jakovljević et al. (2015) for a review of other identification strategies and alternative data sources.
[2] See Gan (2007) and Khwaja and Mian (2008) for a further discussion.
[3] The dominance of single-bank firms may also be sample-driven, despite the fact that the banking system may be characterized by the prevalence of multiple-bank relationships; see Gobbi and Sette (2014) and Balduzzi et al. (2014) for such an example in the case of Italy.
[4] A recent cross-country analysis by Ongena et al. (2015), which also faced the issue of plentiful single-bank firms, adds that firm characteristics do equally well as solely firm fixed effects in controlling for credit demand.

effects are replaced by industry-location-size-time fixed effects. In this way, we use information on 97% of firms in our bank-firm sample instead of only 21% when employing multiple relationships, and show that the results from the standard setup used in the literature may not always be generalizable.

Our main results can be summarized as follows. First, heterogeneity in bank-loan supply shocks is relevant in the entire time window and not only during important crises. Second, bank supply shocks generate real effects, and these effects can be properly identified only with the use of appropriate estimates of bank supply shocks – those that have been constructed based on the sample of firm-bank relationships for which real effects are to be analysed, and those that account for the relevance of firm-bank relationships, i.e. using the weighting structure of Amiti and Weinstein (2016). Firms borrowing largely from banks faced with a negative supply shock experience lower growth, investment and employment over the following year than otherwise similar firms borrowing from unaffected banks. Moreover, smaller and more indebted firms are more strongly affected by such negative shocks in terms of their growth and investment. Third, banks faced with a positive supply shock exhibit risk-taking behaviour. The entry rate of new borrowers increases following the occurrence of a supply shock, while the exit rate of existing borrowers drops; both of these groups of borrowers are on average riskier (as measured by the Altman Z score) than the firms in the existing portfolio. Conversely, banks with a negative supply shock show risk-mitigating behaviour. Our analysis thus shows that our indicators of bank credit supply can be particularly useful for studying its impact on both firms' real-side policies and banks' risk-taking decisions. Finally, we show that our bank-loan supply shock measures meaningfully relate to bank characteristics and to survey responses of banks about their lending standards, which are typically used as supply shock proxies. Our supply shock measures correlate positively with interbank funding growth, and those banks reporting in the ECB Bank Lending Survey to have tightened their lending standards have a significantly lower bank-loan supply shock relative to banks with unchanged lending standards.

The remainder of the paper is structured as follows. Section 2 describes the data we use and explains our identification strategy. In Section 3, we use our bank-loan supply shocks to analyse their impact on firm growth/investment/employment and bank risk-taking behaviour. In Section 4 we test whether our estimates of bank-loan shocks meaningfully relate to bank funding conditions, as well as to banks' lending standards. The final section concludes.

2. Data and methodology

We use a comprehensive dataset on monthly bank-firm level authorized credit from the Central Corporate Credit Register (CCCR) in Belgium to measure bank-loan supply shocks over the period 2002-2012. As suggested by the recent empirical literature, 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 need to provide information to the credit register on all debtors to which they have an aggregate exposure exceeding 25,000 euro. 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[5], 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.

2.1. Disentangling the bank-lending and firm-borrowing channels: Existing methods for multiple-bank firms

With detailed credit register data, the bank-lending and firm-borrowing channels can be disentangled at each time period without the explicit need for a general exogenous event or the occurrence of a particular bank-specific shock. Such identification is easily obtained for the sample of firms borrowing from more than one bank 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, as shown in Equation 1:

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

where $\Delta L_{fbt} = \frac{L_{fbt} - L_{fbt-1}}{L_{fbt-1}}$ stands for the firm-bank annual growth rate of credit from bank b to firm f at time t. 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 loan demand for the same firm changes proportionally across the banks currently lending to the firm. In the existing literature, this equation has been estimated either directly (such

[5] We focus 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).

that the estimates of β_{bt} can be obtained, e.g., Greenstone et al., 2014) or indirectly, when the interest of the researchers was on estimating the effect of bank characteristics and monetary policy on credit availability, controlling for firm demand (e.g., Khwaja and Mian, 2008; Jiménez et al., 2012a). Put differently, researchers were using variables which are supposed to be correlated with the bank-fixed effects.

Two criticisms have emerged in the literature regarding this approach. First, Amiti and Weinstein (2016) have pointed to the inefficiency of using the fixed effects setup and were later followed by Amador and Nagengast (2015) and Flannery and Lin (2015). They argue that the predicted values of firm-bank loan growth stemming from Equation 1 hardly explain actual loan growth at the bank level. The reasoning for this is that the estimation of Equation 1 ignores adding-up constraints. These adding-up constraints entail the fact that a bank cannot lend more unless at least one of the firms is borrowing more, and a firm cannot borrow more unless at least one of the banks is lending more. Therefore, 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. Including these adding-up constraints should allow to explain the actual loan growth at the bank and economy-wide level. Their methodology yields the following system of equations at the bank and firm level, respectively:

$$D_{bt}^{B} = \beta_{bt} + \sum_{f} \phi_{fbt-1} \cdot \alpha_{ft} + \sum_{f} \phi_{fbt-1} \cdot \varepsilon_{fbt} \tag{2a}$$

$$D_{ft}^{F} = \alpha_{ft} + \sum_{b} \theta_{fbt-1} \cdot \beta_{bt} + \sum_{b} \theta_{fbt-1} \cdot \varepsilon_{fbt}, \tag{2b}$$

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 2a 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 2b, 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:

$$D_{bt}^{B} = \beta_{bt} + \sum\nolimits_{f} \phi_{fbt-1} \cdot \alpha_{ft} \tag{3a}$$

$$D_{ft}^{F} = \alpha_{ft} + \sum\nolimits_{b} \theta_{fbt-1} \cdot \beta_{bt} \tag{3b}$$

In the remainder of our paper we will refer to the weighting approach as the Amiti and Weinstein (2016) approach. The unweighted approach, using solely bank- and firm-time fixed effects, will be referred to as the Khwaja and Mian (2008) approach, after the authors who popularized the use of time-varying firm fixed effects in the empirical literature on credit supply.

When estimating the firm-borrowing and bank-lending channel either through Equation 1 or through the system of Equations 3a and 3b, it is also important to take into account 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. Amiti and Weinstein (2016) resort to excluding α_{1t} (i.e., setting $\alpha_{1t} = 0$, which from an economic point of view means imposing that the credit demand component for firm 1 is zero). All firm-borrowing and bank-lending channel effects can then be estimated, but their size is still relative to the omitted firm. In order to eliminate the omitted firm effect, the obtained series of bank-month supply estimates can be adjusted by deducting the time-specific mean (or median) from the estimate:

$$\tilde{\beta}_{bt} = \hat{\beta}_{bt} - \bar{\beta}_{t} \tag{4}$$

Such a measure has been shown to be useful when constructing firm-level indicators of exposure to bank-loan supply shocks (e.g., Amador and Nagengast, 2015; Amiti and Weinstein, 2016; Greenstone et al., 2014). Importantly, this implies that bank-loan supply shocks can only be compared *within* a time period. This fact is of no concern in analyses at the bank-time level, since the inclusion of time fixed effects in bank-time regressions will remove the time-specific component from the bank shocks (thus implicitly removing the time-specific mean or median of these shocks).

A second point which is evident from Equation 1 is that the demand component α_{ft} is common across all banks. As Paravisini et al. (2014) emphasize, the implicit assumption behind using firm-time fixed effects as controls for demand is that each firm views its related banks as providers of a perfectly substitutable good, i.e. bank credit. This assumption can, however, be violated in case banks are specialized in market segments where demand shocks occur leading to firm-bank specific loan demand. Examples include export markets where some banks have more expertise than others. The offered good then might no longer be homogenous across banks. The correct identification of bank-loan supply shocks then becomes harder in the presence of such firm-bank specific demand shocks. Our data contain banks that are active in all industries and across the entire country, and mainly small firms. We expect therefore that such firm-bank specific demand is not an important source of concern in our analysis.

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

The methodology we employ in this paper points to a third potential drawback of the estimation of Equation 1 (with or without adding-up constraints), namely the reliance on multiple-bank firms only. Indeed, the loan supply shocks can only be estimated for firms that borrow from more than one bank as the identification of β_{bt} relies on estimating how different banks changed their lending towards the *same* firm. This implies thus that $\hat{\beta}_{bt}$ may not necessarily capture the representative bank-loan supply shocks of banks in an economy, but rather the bank-loan supply shocks to firms with multiple banking relationships in an economy. This implication might be especially relevant if single-bank firms represent a large share of the economy under investigation, and if they differ substantially from multiple-bank firms. Figure 1A considers the first issue raised: in our comprehensive sample of above 17 million bank-firm month observations on more than 230.000 firms, 87.4% of these firms borrow from only one bank at any given point in time, and such single-bank firms account for 46.3% of the total credit volume in the sample.

[FIGURE 1 HERE]

While the structure of our sample indicates that the single-bank firms make up a non-negligible fraction of it, the implicit assumption used by Khwaja and Mian (2008) still may hold. This is the assumption that "banks with better multiple-relationship firms also have better single-relationship firms". However, if this assumption is violated, then ignoring single-bank firms in the estimation of Equation 1 or in the system of Equations 3a and 3b might lead to biased estimates of bank-loan supply shocks compared to the actual bank shocks. For that reason, we compare the characteristics of multiple-bank and single-bank firms, focusing on firms that are either single-bank or multiple-bank borrowers throughout the period analysed. As is shown in Panel A of Table 1, we find that multiple-bank firms are on average older and larger (both in terms of total assets and the number of employees), which points in the direction of lower information opacity of such firms. They also have a lower investment ratio and borrow larger credit amounts. This result is suggestive of the non-negligible differences between multiple- and single-bank firms.

[TABLE 1 HERE]

For that reason, we expand our methodology to include firms beyond those only borrowing from multiple banks. In order to include as many single-bank firms as possible into our estimations, we replace firm-time fixed effects with industry-location-size-time (ILS-time) fixed effects as a time-varying demand control.[6] The industry bins are based on two-digit NACE classification codes of firms from the CCCR; location bins are based on two-digit postal codes from the CCCR; the size bins are based on deciles of total assets of firms from the CBSO. Consequently, Equation 1 in our case becomes:

$$\Delta L_{fbt} = \alpha_{ILSt} + \beta_{bt} + \varepsilon_{fbt} \tag{5}$$

The additional assumption that has to be made in order to progress from Equation 1 to Equation 5 is that the demand shocks of firms belonging to the same industry-location-size group in a given time period are identical: $\alpha_{1t} = \alpha_{2t} = \cdots = \alpha_{Ft},\ (1..F)\ \epsilon\ ILS$. The identifying assumption is now that firms in such an *ILS*-time group change their loan demand in the same way. This assumption is stronger than the one using firm-time fixed effects, but we are able to test within our set of multiple-bank firms whether such an identifying assumption is valid or not. Such grouping changes the estimation setup from a multiple-bank *firm* to a multiple-bank *ILS* setup. This allows us to keep the large majority of firms present in the credit register, i.e. all the multiple-bank firms and additional single-bank firms.[7] Panel B of Table 1 shows that the eligible sample of firm-bank relationships on which Equations 1 and 5 can be implemented includes a bit above 17 million observations;[8] our extension from a multiple-bank *firm* to a multiple-bank *ILS* setup allows us to keep 94% of observations on 97% of firms from this

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[6] A construction of industry-location-size bins similar to ours can be found in Edgerton (2012). However, balance sheet information on firms is not available to the author, so he resorts to using the size and purpose of equipment purchases as a measure of size and industry for firms in his sample. Our measure has more precision since it originates either from firm accounting data, or from the credit register.

[7] The multiple-bank *ILS* sample does not include 100% of the eligible sample as there are still *ILS*-time groups that are composed of firms borrowing from just one bank in a given time period.

[8] Equation 1 can only be implemented at the intensive margin, i.e. for firms for which growth rates of credit can be calculated. The issue of potential outliers is resolved by winsorizing credit growth rate observations at the 1% level. Additionally, 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. This is done by creating "temporary" banks made up of the acquiring and acquired bank one year prior to the M&A, in order to obtain correct credit growth rates for acquiring banks.

eligible sample. The appropriateness of this approach can also be seen from Figure 1B, which shows that only a negligible number of the *ILS* groups borrows from just one bank.

Another important consequence of extending the multiple-bank setup is that the multiple-bank *ILS* setting provides firm-bank credit growth rates which closely resemble the growth rates from the eligible sample. As can be seen from Figure 2, these credit growth rates almost entirely overlap, while the credit growth rates from the multiple-bank *firm* setup tend to overestimate the actual growth rates. This distinction may be especially relevant if one wants to make conclusions on the aggregate level, as is done by Amiti and Weinstein (2016) or Amador and Nagelgast (2015).

[FIGURE 2 HERE]

In order to address the possible inefficiency issue related to the direct estimation of Equation 5, we also consider the weighting structure suggested by Amiti and Weinstein (2016). Hence, when Equations 3a and 3b are adjusted to the multiple-bank *ILS* setup, we obtain the following system of equations:

$$D_{bt}^{B} = \beta_{bt} + \sum\nolimits_{f} \phi_{fbt-1} \cdot \alpha_{ILSt} \tag{6a}$$

$$D_{ft}^{F} = \alpha_{ILSt} + \sum\nolimits_{b} \theta_{fbt-1} \cdot \beta_{bt} \tag{6b}$$

Using *ILS*-time fixed effects as demand controls, we thus obtain two sets of bank shocks: the unweighted shocks that are obtained from directly estimating Equation 4 – referred to as using the Khwaja and Mian (2008) approach; and weighted shocks obtained from estimating the system of Equations 6a and 6b – referred to as using the Amiti and Weinstein (2016) approach.

2.3. Measuring the bank-lending channel: The effect of methodology and sample choices

We motivate the use of *ILS*-time fixed effects as controls for credit demand in two steps. We begin with the multiple-bank *firm* setup, and consider alternative time-varying firm demand controls. In the first stage, we consider five alternative credit demand indicators. We start from the least conservative setup (i.e., no firm demand controls), and progress by making our credit demand controls more sophisticated (i.e., adding firm-specific information) to end with the most conservative setup (i.e., the use of firm fixed effects). The first two intermediate specifications of credit demand consider location fixed effects (L) and industry-location fixed effects (IL). To the latter specification, several other firm characteristics are added: age (ILA effects), availability of internal resources measured by the ratio of current assets to total assets (ILC effects), risk measured similarly to Acharya et al. (2016) as the interest coverage ratio (ILR_1 effects), risk measured in terms of leverage (ILR_2 effects), risk measured using the Altman Z score (ILR_3 effects), and size in terms of total assets of firms (ILS effects). Each of these additional controls was incorporated using deciles of their annual distribution across firms. From each of these specifications we can then obtain estimates of bank credit supply. The equation of interest is the following:

$$\Delta L_{fbt} = \alpha_{it} + \beta_{bt}^{i} + \varepsilon_{fbt}, \;\; i = \cdot, L, IL, ILA, ILC, ILR_{1-3}, ILS, F \tag{7}$$

From these regressions we obtain ten sets of bank loan supply shocks ($\hat{\beta}_{bt}^{\cdot}, \hat{\beta}_{bt}^{L}, \hat{\beta}_{bt}^{IL}, \hat{\beta}_{bt}^{ILA}, \hat{\beta}_{bt}^{ILC}, \hat{\beta}_{bt}^{ILR_{1-3}}, \hat{\beta}_{bt}^{ILS} and\ \hat{\beta}_{bt}^{F}$) and use them in the second stage. Our rationale in the second stage is to investigate how similar the bank-loan shocks are when using alternative controls for credit demand, compared to using firm-time fixed effects. For every of the ten comparisons made, we are excluding groups of firms that are made up of only one (multiple-borrowing) firm. Panel A of Table 2 reports the relation between bank-loan shock estimates coming from the most conservative setup with a number of bank-loan shock estimates coming from regressions with alternative demand controls. More specifically, the panel reports $\hat{\delta}$ from the following regression:

$$\hat{\beta}_{bt}^{F} = \delta \cdot \hat{\beta}_{bt}^{i} + \mu_t + \varepsilon_{bt}, \;\; i = \cdot, L, IL, ILA, ILC, ILR_{1-3}, ILS \tag{8}$$

[TABLE 2 HERE]

The first result to note is that bank-loan shock estimates obtained using firm-time fixed effects as demand control are in strong positive co-movement with bank-loan shock estimates obtained using other less conservative demand controls. The coefficients range between 0.993 in Column 6 and 1.048 in Column 4, and are in almost all cases not significantly different from one. These qualitatively very similar results also reduce potential concerns about omitted variable bias related to unobserved time-varying firm characteristics that would not be captured by the different groupings of demand controls and would correlate with the bank-loan shocks. However, the main result in this exercise is that we are able to identify the demand control for which the obtained supply shocks are the closest (in terms of variation and ranking of banks) to the "standard" bank-loan shocks using firm-time fixed effects as the demand control. Looking at the adjusted R^2, the variation in bank-loan shock estimates obtained using firm-time fixed effects as demand controls is best captured with bank-loan shock estimates from the specification with industry-location-size-time fixed effects (Column 9, 0.791). 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 previously considered alternative ones is statistically significant. Furthermore, the Spearman rank correlation test shows that the ranking of the credit supply estimates approaches most closely the ranking from the "standard" specification when industry-location-size-time fixed effects are used as a demand control (Column 9, 0.813). Overall, these first results indicate that controlling for demand factors using *ILS*-time fixed effects can be a sensible alternative for using firm-time fixed effects. This is especially important when one wants to analyse lending behaviour in samples where the fraction of firms with multiple bank relations is limited, as using firm-time fixed effects then implies losing a large part of the sample. Additionally, Column 10 shows that the resemblance of these two series of bank-loan shocks is also present during the months that can be attributed to the banking crisis (September 2008 – December 2009), which will be relevant in our later analysis of the real effects of this crisis.

Our second step broadens the sample of bank-firm relationships from the multiple-bank *firm* setup to the multiple-bank *ILS* setup. Our starting point are thus the estimates of bank-loan shocks from the estimation of Equation 5:

$$\Delta L_{fbt} = \alpha_{jt} + \beta_{bt}^{j} + \varepsilon_{fbt}, \;\; j = \; ILS \tag{9}$$

Note here that the index j denotes the methodology used on the multiple-bank *ILS* sample, whereas index i (for Equations 7 and 8) referred to the multiple-bank *firm* sample. In the first stage we will look at the effect of changing the sample analysed. We will rely on the <u>industry-location-size-time fixed effects</u> as a credit demand measure, but implement it once to the <u>multiple-bank *firm* setup</u>, and then to the <u>multiple-bank ILS setup</u>. The obtained bank-loan shocks will be compared in the following way:

$$\hat{\beta}_{bt}^{j=ILS} = \delta \cdot \hat{\beta}_{bt}^{i=ILS} + \mu_t + \varepsilon_{bt} \tag{10a}$$

In the second stage we will additionally consider the effect of changing the methodology used. Therefore, the bank-loan shocks using <u>industry-location-size-time fixed effects</u> as a credit demand control on the <u>multiple-bank ILS sample</u> will be compared to the bank-loan shocks using <u>firm-time fixed effects</u> as a credit demand control on the <u>multiple-bank *firm* sample</u>:

$$\hat{\beta}_{bt}^{j=ILS} = \delta \cdot \hat{\beta}_{bt}^{i=F} + \mu_t + \varepsilon_{bt} \tag{10b}$$

The results in Panel B of Table 2 indicate that there is no one-to-one co-movement between the bank-loan shock estimates coming from the two different samples; the co-movement is additionally reduced as we also proceed to a different methodology (from 0.752 in Column 1 to 0.576 in Column 2). Also, the values of the adjusted R-squared and of the Spearman rank correlation test indicate significant differences in the obtained bank-loan shock estimates. These results show that the bank-loan supply estimates obtained using the most conservative identification strategy in the empirical literature in Equation 1 differ considerably from the bank-loan shock measures that are obtained using the identification strategy in Equation 5. This result highlights the importance of including single-bank firm relationships in order to properly estimate the bank lending channel.

2.4. Measuring the bank-lending channel: The inclusion of adding-up constraints

Finally, we address the issue brought up by Amiti and Weinstein (2016) on the inefficiency of credit supply estimates obtained using the Khwaja and Mian (2008) estimation methodology, i.e. without any consideration of adding-up constraints. For that reason, we compare the credit supply estimates obtained from Equation 1 with those from Equations 3a and 3b for the multiple-bank *firm* setup, as well as the bank-loan shock estimates obtained from Equation 5 with those from Equations 6a and 6b for the multiple-bank ILS setup:

$$\hat{\beta}_{bt}^{i=F,KM} = \delta \cdot \hat{\beta}_{bt}^{i=F,AW} + \mu_t + \varepsilon_{bt} \tag{11a}$$

$$\hat{\beta}_{bt}^{j=ILS,KM} = \delta \cdot \hat{\beta}_{bt}^{j=ILS,AW} + \mu_t + \varepsilon_{bt} \tag{11b}$$

Panel C of Table 2 shows the estimation results of the regressions above. There is a significant positive co-movement between the bank-loan shocks with adding-up constraints and those without adding-up constraints. While this co-movement and the value of the adjusted R-squared is higher as we encompass more firms in our measure of credit demand (Column 2 compared to Column 1), it is also evident that the two bank-loan shock measures can be considered to be reasonably similar to each other, as the adjusted R-squared goes up to 0.575 (Column 2). This result would suggest that the inefficiency issue emphasized by Amiti and Weinstein (2016) might not be so concerning, and we will address this question further by applying their approach. We thus compare actual bank-level credit growth rates to the ones obtained from the estimates of bank-firm credit growth using Equation 1 and weighted by the share of each firm in a bank's lending portfolio. When the authors regressed the actual bank growth rates (D_{bt}^{B}) on its weighted estimate obtained from Equation 1 ($\widehat{D}_{bt}^{B}$), they obtain an R^2 as low as 0.08, while Amador and Nagengast (2015) find an even lower R^2 of only 0.01. We analyse this issue both in the multiple-bank *firm* setup and the multiple-bank ILS setup; the results are qualitatively identical, so we keep our focus on the latter setup. As can be seen from Figure 3, the comparison of the two bank-level credit growth rates gives a high R^2 of close to 0.5.

[FIGURE 3 HERE]

We explain this result as follows: the differences between the weighted and the unweighted approach will be more significant in samples of firm-bank relationships where there is more asymmetric lending. In the unweighted – Khwaja and Mian (2008) – approach, the implicit weight assigned to each firm at a given bank is equal to $1/F$; if this weight is not very different from the explicit weight ϕ_{fbt-1} that is assigned with the Amiti and Weinstein (2016) approach, then the inefficiency of the Khwaja and Mian (2008) approach will not be as high. In the case of our multiple-bank *firm* and ILS samples, we find that the implicit and explicit weights are on average very close to one another, most likely due to the fact that we have a multitude of small and medium-sized enterprises in our sample, and suggesting that banks do not lend as asymmetrically to their borrowers as is probably the case in the samples of Amiti and Weinstein (2016) or Amador and Nagelgast (2015). With this result in mind, in the remainder of the paper we will use bank-loan supply shocks from both the unweighted approach of Khwaja and Mian (2008) and from the weighting approach suggested by Amiti and Weinstein (2016).

Finally, we discuss the added value of having a time dimension to our estimates of bank-loan shocks. As has been mentioned earlier, the estimation strategy employed in this paper (and in the related literature) only allows comparisons of bank-loan shocks *within* a given time period. Nevertheless, what can be analysed *across* time periods is the degree of variation of bank-loan shock estimates *within* time periods. Figure 4 displays the four-month moving average of the inter-quartile variation in bank-loan supply shocks across banks over the window 2002m1-2012m3, for both the Khwaja and Mian (2008) and the Amiti and Weinstein (2016) approach. Several facts are noteworthy. First, we observe substantial heterogeneity in bank-loan supply shocks over the entire window 2002-2012. The magnitudes are about 20 to 25 percentage points, which is slightly higher than what is reported by Amiti and Weinstein (2016). Second, the magnitudes are exhibiting a downward trend, in particular over the last years, which could reflect the more expansive ECB monetary policy. Third, both approaches show similar magnitudes but report some differences in certain periods. This could reflect differential effects on small versus large firms, as the Amiti and Weinstein (2016) approach gives more weight to large loans in its analysis.

[FIGURE 4 HERE]

As an overall conclusion of this section, we argue that applying the (widely used and almost standard) conservative approach in disentangling the firm-borrowing channel from the bank-lending channel in the credit market may not always be appropriate. We show that it is of great relevance to develop an estimation strategy which can control for credit demand with similar precision as the widely used firm-time fixed effects in settings with multiple-bank firms, but that can also be applied to broader samples which additionally include single-bank firms. Such a strategy might be especially important when single-bank firms represent a large part of the sample and when they have different characteristics than multiple-bank firms, as then the "standard" bank-loan shock estimates might be biased. We show that time-varying industry-location-size fixed effects perform very well as a credit demand control: within the multiple-bank *firm* setup, they yield bank-loan supply measures of similar ordering and magnitude as when firm-time fixed effects would be used as a credit demand control. At the same time, in the multiple-bank *ILS* setup, the bank-loan supply estimates obtained using our desired approach are of different ordering and magnitude than those using the most conservative approach from the multiple-bank *firm* setup. These results are thus suggestive of the importance of making an adequate methodological choice when constructing representative bank-loan supply indicators, which can be further used in analyses of firm and bank behaviour.

3. The effects of bank shocks on firm outcomes and bank risk-taking

We now examine the impact of bank-loan supply shocks on various firm outcomes and bank risk-taking behaviour. We expect that firms which are largely dependent on banks facing negative credit supply shocks will experience a deterioration of their growth, investment and possibly employment. The advantage of identifying cross-sectional variation in bank-loan shocks in all periods is that it allows us to study the relation between bank-loan supply shocks and outcome measures of interest not only during stress events but also during other periods. Our methodology thus enables us to examine the impact of bank-loan shocks through longer period of time (see also Amiti and Weinstein,2016; Amador and Nagengast, 2015). On the other hand, most other studies relied on specific events that act as exogenous shocks to loan supply (e.g., Chava and Purnanandam (2011) use the Russian default in 1998, Chodorow-Reich (2014) the Lehman collapse, or Acharya et al. (2016) the European sovereign debt crisis).

3.1. Bank-loan supply shocks and real sector outcomes

In this subsection, we study how bank-loan supply shocks impact firm growth, investment and employment. We measure firm asset, investment and employment growth by the annual growth rates of total assets, fixed assets and number of FTE employees[9], respectively. The growth rates calculated for a given year are then linked to loan supply shocks faced by the firm's lenders during that year. Given the annual nature of the firm balance sheet data, we adjust our bank-loan supply shock measure to reflect this frequency. In particular, we employ the annual average of the demeaned monthly bank-loan supply shocks faced by all lenders to a particular firm, weighted by the share of each bank in the firm's borrowing portfolio. Mathematically, the demeaned bank shock over year *t* is calculated as $\bar{\tilde{\beta}}_{ft}= \frac{1}{12}\sum_{i=1}^{12}\sum_b \tilde{\beta}_{bt+1-i}\,\theta_{fbt+1-i}$. We therefore run the following regressions:

$$\Delta Y_{ft}{}^{G} = \delta \cdot \bar{\tilde{\beta}}_{ft}^{(KM,AW)} + \mu_t + \gamma_{ft} + \varepsilon_{ft} \tag{12a}$$

$$\Delta Y_{ft}{}^{I} = \delta \cdot \bar{\tilde{\beta}}_{ft}^{(KM,AW)} + \mu_t + \gamma_{ft} + \varepsilon_{ft} \tag{12b}$$

$$\Delta Y_{ft}{}^{E} = \delta \cdot \bar{\tilde{\beta}}_{ft}^{(KM,AW)} + \mu_t + \gamma_{ft} + \varepsilon_{ft} \tag{12c}$$

where superscripts *G*, *I* and *E* denote growth in assets, investment and employment, respectively. Additional firm controls γ_{ft} include firm fixed effects, age, size and leverage of the firm. Regarding the bank supply shocks used in the analysis, we make comparisons between several approaches: (1) the Khwaja and Mian (2008) – KM approach without weighting versus the Amiti and Weinstein (2016) - AW approach that considers the weighting structure inherent to observed firm-bank relationships; (2) the methodology of estimating bank supply shocks (i.e. using firm-time or industry-location-size time effects as controls for demand; or FT methodology versus ILST methodology), and (3) to which sample these supply shock estimates are applied.

[TABLE 3 HERE]

[9] We exclude firms with zero employees in full-time equivalent.

The results in Table 3 point to several conclusions: in the sample of multiple-bank *ILS* groups, both the "standard" and our suggested bank supply shocks are found to have a significant effect on the performance of firms, although the results are somewhat weaker in terms of employment. We attribute the latter finding to a substantial degree of employment stickiness in Belgium, stemming from a quite restrictive employment protection legislation[10]. This also shows to be true in our further analyses of firm performance following the presence of loan supply shocks, hence our focus will only be placed on asset and investment growth. In terms of economic magnitudes and when the ILST methodology is applied, a one standard deviation decrease in the weighted bank loan supply estimate reduces asset growth for the average firm in the sample from 5.63 percentage points to 5.52 (KM approach) or 5.31 (AW approach) percentage points. This corresponds to a reduction in growth rates of about 1.9% and 5.6%, respectively. With the FT methodology, these reductions amount to 2.6% and 4.4%, respectively. For the equivalent one standard deviation decrease in the weighted bank loan supply estimate, investment growth for the average firm is reduced from 11.25 percentage points to 10.9 or 10.7 percentage points in the case of the KM and AW approach, respectively. This implies an investment decline by 2.8% and 5.1%, respectively. With the FT methodology, the decline amounts to 4.4% and 4.0%, respectively.

In the multiple-bank firm setup, no real effects of loan supply shocks would be identified unless the weighting structure of Amiti and Weinstein (2016) is applied. For the case of asset growth, this implies that the average firm experiences a drop in total assets growth from 5.47 percentage points to 5.1 (ILST methodology) or 5.3 (FT methodology) percentage points when faced with a one standard deviation negative loan supply shock, or equivalently by 7% and 3.6%. In the case of investment growth, such a negative shock results in a decrease of the average investment rate from 8.7 to 8.2 percentage points in the case of the ILST methodology, or roughly by 5.7%.

Combining these findings, it appears that appropriately accounting for the underlying weighting structure in firm-bank relationships is relevant, since in this case more weight is placed on the larger loans in the sample; the economic magnitudes of these effects differ depending on the sample of firms being analysed; in the multiple-bank *ILS* setup, the average effect can be identified with both the "standard" and our measure of bank supply shocks. We will explore the latter finding a step deeper when we examine how these supply measures perform in times of financial distress.

[10] The Belgian employment protection legislation requires that employers notify their employees before dismissal to enable them to find a new job. For a white collar worker with less than five years of service, the minimum notification period is 3 months. In case this worker had more than five years of service, this is 6 months; for more than 10 years of service this is 9 months.

We expand the analysis of the real effects of bank supply shocks by considering the effect of supply shocks in times of a banking crisis, when properly identifying these effects should in practice matter the most for policymakers. We also perform some additional analyses as robustness tests and provide more insight in the channels how the bank-loan supply shocks affect firm outcomes. We thus split our sample according to the size and leverage of firms – measured using quintiles of the distribution of firms in our sample – to test whether bank-loan supply shocks matter more for firms with low access to alternative sources of finance (small firms) or with high reliance on external financing (high leverage).

[TABLES 4 AND 5 HERE]

The results in Table 4 and Table 5 illustrate that firms borrowing from banks with negative loan supply shocks significantly reduce their asset growth and investments, but also that the impact of supply shocks becomes significantly stronger during periods of financial sector distress, which is an effect that can only be identified using the ILST methodology. Put differently, during periods of financial distress, loan supply shocks obtained from a limited number of borrowers (multiple-bank firms) could be a bad proxy for the supply shock faced by a broader set of firms (i.e. including single-bank firms).

In order for the above statement to be completely valid, we also have to be certain that the ILST methodology works as well in crisis times as in normal times, compared to the FT methodology. If not, the above result might as well be driven by a less reliable measure of the bank supply shocks. In order to verify that the ILST methodology is appropriate also in the crisis period of September 2008 – December 2009, we refer back to Table 2 (Panel A, Column 10). Looking at only the crisis months and comparing the supply shocks using firm-time and industry-location-size-time effects as demand controls, we again obtain a high adjusted R^2 (0.837 compared to 0.791 for the whole period) and a high Spearman's rank correlation (0.851 vs. 0.813 for the whole period). This finding confirms that it is highly unlikely that the ILST methodology might be yielding biased estimates of supply shocks in the 2008-2009 crisis period, and thus points to the importance of using appropriate sets of bank shock estimates to establish their real effects in times of financial distress.

We also investigate whether the impacts of bank-loan shocks are more strongly at work for small firms or firms with high indebtedness. These firms are more relying on banks and may have fewer alternatives available (e.g., Rajan and Zingales, 1998). Generally, our results show that the impact of a negative bank-loan supply shock is more pronounced among the smallest firms compared to the larger firms (bottom quintile compared to the bottom half of the distribution of total assets, Column 4-5). In the case of asset growth (Table 4), a one standard deviation decrease in the weighted bank-loan supply shock reduces asset growth of the smallest firms from the average of 7.3 percentage points by 4.0% or 4.5%, compared to a decrease from the average growth rate of 6 percentage points by 3.0% or 3.8% for larger firms. For investment growth (Table 5), the smallest firms' investment growth rate drops from an average of 15.5 percentage points by 6.1% or 6.0%, whereas for larger firms their investment rate is reduced from an average rate of 12.4 percentage points by 4.2% or 4.8%.

Highly indebted firms also suffer more from negative bank-loan supply shocks (top quintile compared to the top half of the distribution of leverage, Column 5-6). For these firms, a one standard deviation decrease in the weighted bank-loan supply shock leads to a reduction in average asset growth from 1.45 percentage points by as much as 21.2% or 24.5%, compared to a reduction from 3.9 percentage points by only 2.6% or 6.9% for the less indebted firm. In terms of investments, the reduction in their average growth rate of 3.8 percentage points for the more indebted firms amounts to 17.2%, while for the less indebted firms the average growth rate drops from 8.3 percentage points by only 4.2%.

Overall, our findings show that bank-loan supply shocks impact the real economy regardless of the aggregate state of the economy. The propagation of financial shocks is hence not limited to crisis periods, but the identification of the real effects of system-wide shocks will be affected by the choice of methodology to estimate these shocks. Hence, a "standard" approach of measuring supply shocks with the use of firm-time effects as demand controls will not be representative of the supply shocks faced by single-borrowing firms in times of widespread financial distress. Our results also indicate that smaller and more leveraged firms are more sensitive to bank-loan shocks. There are two potential explanations for this observation. First, smaller and more leveraged firms might be more bank-dependent and hence rely more on bank credit than other firms to fund their activities. In other words, firms which are typically considered as credit constrained also appear to be more sensitive to supply shocks (see, e.g., Dell'Ariccia, Detragiache and Rajan, 2008). Second, banks might decide to shield certain firms from credit supply shocks. De Jonghe et al. (2016), for example, show that banks that are hit by a funding shock tend to reallocate credit supply towards low-leverage firms, which could potentially explain our results for the firm leverage subsamples.

3.2. Bank risk-taking

Bank-loan supply shocks may induce banks to adjust their behaviour, which ultimately may be reflected in the riskiness of their lending portfolio. In order to analyse how banks adjust the riskiness of their lending portfolio, we use the Altman Z score as a measure of risk at the firm level and construct average indicators of portfolio risk at the bank level, weighted by firms' credit size. These indicators are calculated separately for the following groups of borrowers: (i) those who remain in the portfolio of the bank at the time and following a supply shock (the intensive margin), (ii) borrowers that have a new relationship with a particular bank following the shock (entries), and (iii) borrowers with terminated lending relationships following the shock (exits). We investigate whether credit supply shocks impact the riskiness of a banks' portfolio in the following period relative to the riskiness of their portfolio at the time of the shock, by making adjustments at both segments of the extensive margin (entries and exits). It could well be that banks facing positive supply shocks exhibit risk-taking behaviour, while those facing negative supply shocks might act in a risk-mitigating manner. Additionally, the share of entries and exits in the lending portfolio might also vary according to the sign of the previously faced supply shock: banks with a negative supply shock might be attracting less new entrants, and firms might also be leaving them more intensely.

We consider both the riskiness of firm entries and exits and their lending share (winsorized at the 1% level) compared to the intensive margin, aggregated at the bank-month level. These indicators are then regressed on the previous month's supply shock of the bank:

$$\bar{Z}_{bt}^{\ entry} - \bar{Z}_{bt-1}^{\ int} = \delta \cdot \hat{\beta}_{bt-1}^{ILS(KM,AW)} + \mu_t + \omega_b + \varepsilon_{bt} \tag{13a}$$

$$\bar{Z}_{bt}^{\ exit} - \bar{Z}_{bt-1}^{\ int} = \delta \cdot \hat{\beta}_{bt-1}^{ILS(KM,AW)} + \mu_t + \omega_b + \varepsilon_{bt} \tag{13b}$$

$$\sum L_{bt}^{entry} / \sum L_{bt-1}^{int} = \delta \cdot \hat{\beta}_{bt-1}^{ILS(KM,AW)} + \mu_t + \omega_b + \varepsilon_{bt} \tag{13c}$$

$$\sum L_{bt}^{exit} / \sum L_{bt-1}^{int} = \delta \cdot \hat{\beta}_{bt-1}^{ILS(KM,AW)} + \mu_t + \omega_b + \varepsilon_{bt} \tag{13d}$$

[TABLE 6 HERE]

Results in Panel A of Table 6 suggest that banks facing a positive supply shock make less prudent decisions regarding the riskiness of the newly added firms following the shock. When focussing on the full period, the portfolio-weighted Altman Z score of this pool of newly added firms is lower compared to the risk of firms which remain in the portfolio in both periods, i.e. the newly added firms are more financially risky. Columns 1 and 4 in Panel A illustrate that a one standard deviation increase of the supply shock (equivalent to 12.7 percentage points for the KM and AW shock) increases the average gap in the Z-score between new and existing loans (equal to -0.048 points) by additional 0.018 points (KM shock) or 0.041 points (AW shock). This corresponds to an increase in the average gap by 38% and 85%, respectively. At the same time, the financially less healthy pool of borrowers is being dropped from banks facing a positive shock: a one standard deviation increase in the supply shock increases the average gap in the portfolio-weighted Altman Z score (equal to -0.039 points) by additional 0.036 points (KM shock) or 0.071 points (AW shock), corresponding to increases in the average gap by 92% and 182%.

Panels C and D of Table 6 show the impact of bank-loan supply shocks on the share of entries and exits. The results therein suggest that in case of positive supply shocks more firms are being added relative to the intensive margin, while fewer firms are being dropped. The impact of bank-loan supply shocks, however, is more pronounced for entries than for exits. In terms of economic significance, we find the following: a one standard deviation increase in the supply shock increases the average entry rate (equal to 20.3%) by additional 5.8 percentage points (KM shock) or 3.6 percentage points (AW shock), corresponding to an increase by 29% and 18%, respectively. Likewise, a one standard deviation increase in the supply shock reduces the average exit rate (equal to 24%) by additional 3.9 percentage points (KM shock) or 4.2 percentage points (AW shock), corresponding to a decrease by 16% and 18%, respectively.

Taken together, these results indicate that banks with positive supply shocks indeed take on more risk, while banks with negative supply shocks are more risk-mitigating. The overall effect of a one standard deviation increase in the supply shock on the entry side of the extensive margin varies between -0.008 points (KM shock) and -0.011 points (AW shock), while on the exit side of the extensive margin the effect is between 0.011 points (KM shock) and 0.023 points (AW shock). The net effect suggests a reduction in the Altman Z score at the intensive margin between -0.019 points and -0.034 points.

4. External validity of the bank-loan shock estimates

We now check whether the obtained bank-loan shock estimates 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, and at an alternative indicator of credit supply: bank lending standards from the ECB Bank Lending Survey (BLS).

4.1. Bank funding variables

We start our analysis by relating the estimated bank-loan 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 have an impact on their lending behaviour. For that purpose, we use information from balance sheets of banks, filed with the NBB at a monthly frequency. Table 7 reports the relation between our bank-loan shock estimates (with and without considering the adding-up constraints) and funding characteristics of banks (X_{bt}) on the sample of multiple-bank *ILS* groups:

$$\hat{\beta}_{bt}^{j=ILS} = \delta \cdot X_{bt} + \mu_t + \omega_b + \varepsilon_{bt} \tag{14}$$

The annual change in levels of each of these bank characteristics was scaled by previous year's total assets, and these growth rates are winsorized at the 1% level. The results are reported in Table 7 for the full sample period (2002m1-2012m3), the period prior to the Lehman collapse (2002m1-2008m9), and for the post-Lehman period (2008m10-2012m3).

[TABLE 7 HERE]

Independent of the bank-loan shock estimate used, we find a positive and significant relation between the bank-loan supply estimates and the growth in interbank funding. The effect is larger when the Amiti and Weinstein (2016) approach is applied. Depending on the approach used, the impact of a 10 percentage point increase in this funding variable leads to an average increase of the credit supply measure between 1.8 (Column 1) and 2.3 (Column 6) percentage points for the full period.

4.2. Bank lending standards

Another potential measure of credit supply that has been used in empirical research is the bank lending standards indicator from the ECB's Bank Lending Survey.[11] Research has suggested that the measures

[11] Examples include Lown and Morgan (2002, 2006) and van der Veer and Hoeberichts (2013).

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., Ciccarelli et al., 2014). The BLS survey is conducted at a quarterly level since 2003, and surveys European banks on lending conditions; in case of Belgium there are four respondent 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 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, on the multiple-bank *ILS* sample, are thus the following:

$$\hat{\beta}_{bt}^{j=ILS} = \delta^{T} \cdot BLS_{bt}^{T} + \delta^{E} \cdot BLS_{bt}^{E} + \mu_t + \omega_b + \varepsilon_{bt} \tag{15a}$$

$$\hat{\beta}_{bt}^{j=ILS} = \delta^{T} \cdot BLS_{bt}^{T} + \delta^{MT} \cdot M_t^{T} \cdot BLS_{bt}^{T} + \delta^{E} \cdot BLS_{bt}^{E} + \delta^{ME} \cdot M_t^{E} \cdot BLS_{bt}^{E} + \mu_t + \omega_b + \varepsilon_{bt} \tag{15b}$$

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]

We see from Table 8 that the credit supply indicators using the Khwaja and Mian (2008) approach contain more information on the tightening responses of banks: the credit supply estimates are on average 1.5 (Column 2, Panel A) percentage points lower in the case of lending standard tightening in the pre-crisis period. In Panel B we additionally consider the effects of multiple banks tightening their lending standards. As we have 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 2.6 (Column 2, Panel B) percentage points lower. It should be noted that in the entire observed period there have been no instances of multiple banks easing their lending standards, 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.

5. Conclusion

This paper investigates whether bank-loan shocks impact firm outcomes and bank-risk taking. We employ an alternative method of identifying bank-loan shocks, using highly disaggregated bank-firm level credit register data for Belgium for the period 2002-2012. Our methodology replaces firm-time fixed effects as controls for the firm-borrowing channel with industry-location-size-time fixed effects, which are especially useful when single-bank firms form the majority of the bank-firm relationships and when they are significantly different from the multiple-bank firms. Our analysis shows that the industry-location-size-time fixed effects perform very well as controls for the firm-borrowing channel: the bank-loan shocks obtained with such demand controls closely resemble the "standard" bank-loan shocks (in terms of ordering and magnitude) for the multiple-bank *firm* setup. Yet, in the multiple-bank ILS setup, their use points to noticeable differences when the corresponding bank-loan shocks are compared to the "standard" ones, and this especially holds for the real effects in times of distress in the banking sector. This points to the relevance of appropriately accounting for the structure of the credit register sample under analysis, and suggests that the "standard" approach to estimating the bank lending channel and the firm borrowing channel cannot be considered as a "one-size-fits-all" approach. Some concerns that have been emphasized so far in the empirical literature have also been addressed in our paper. More specifically, we consider the inclusion of adding-up constraints suggested by Amiti and Weinstein (2016), and find that the inefficiency issues of the “standard” approach might not be as relevant when the structure of lending relationships by banks is more symmetric.

When applying our bank-loan shock estimates to firm outcomes and bank risk-taking, our findings suggest that firms’ growth, investment and (to some extent) employment opportunities are negatively affected if their lenders face a negative supply shock, and additionally so in times of widespread financial distress. This spillover effect is more pronounced for bank-dependent borrowers with fewer alternative sources of finance available, i.e. smaller and/or highly-indebted firms. The results of our analysis also suggest that bank-loan supply shocks impact the riskiness of banks’ lending portfolio. Banks with more positive supply shocks add and remove firms of higher riskiness in their lending portfolio, but the inflow of new firms is higher than the outflow of firms. This suggests that banks having faced a more positive supply shock take on more risk, whereas banks with negative supply shocks mitigate risk. From a policy perspective, the latter result might be 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.

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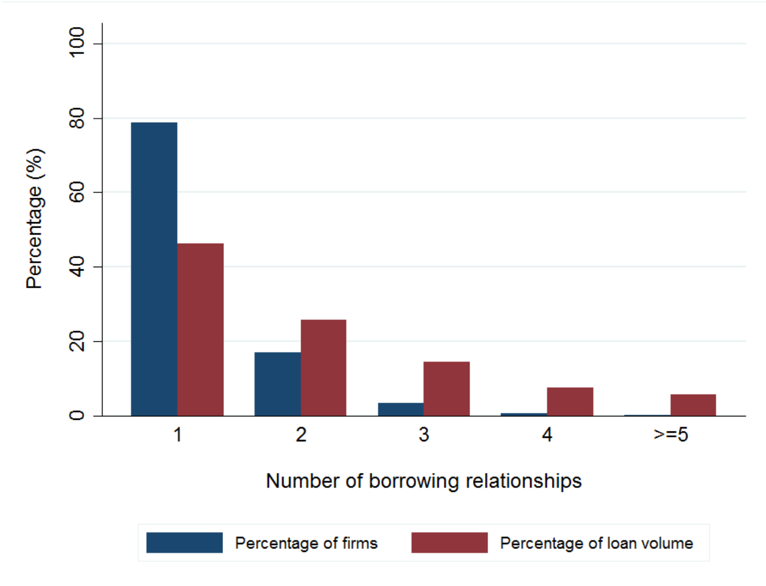
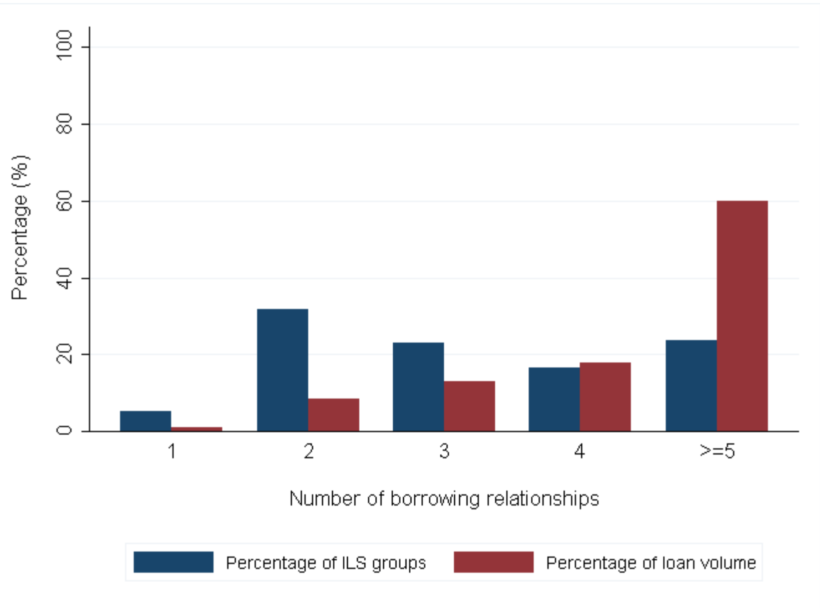
Figures and tables

Figure 1. The number of borrowing relationships
Panel A: Firms

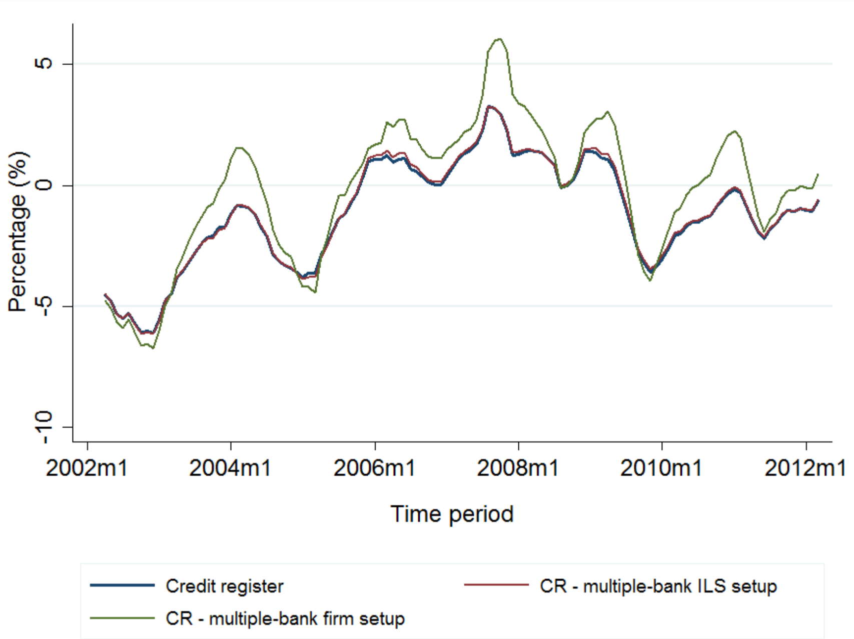


Panel B: *ILS* groups



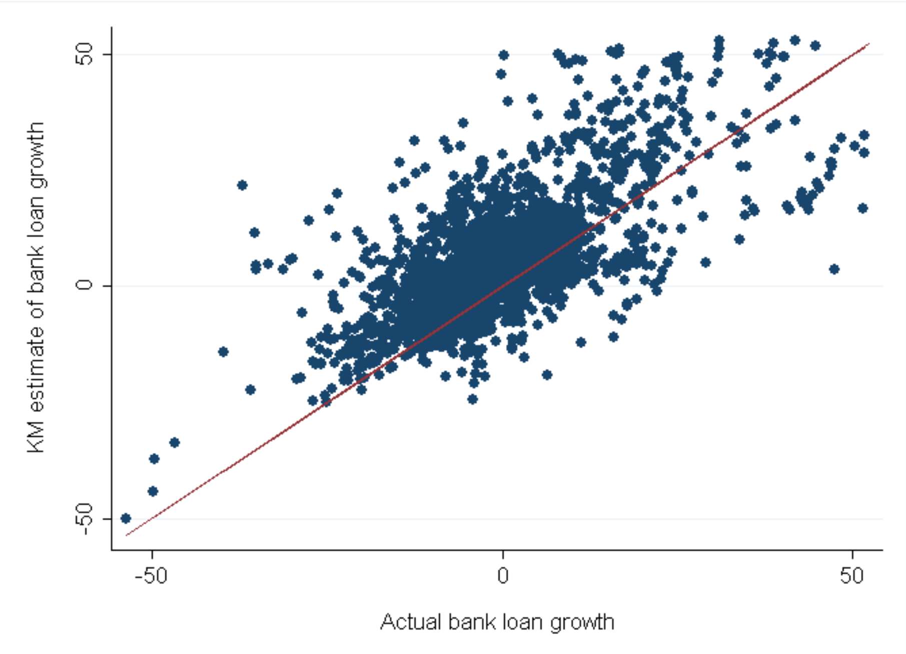
Note: Figure 1 shows the percentage of firms and the percentage of loan volume in the eligible sample dedicated towards firms with (1) one, (2) two, (3) three, and (4) four or more banking relationships.

Figure 2. The average credit growth rate



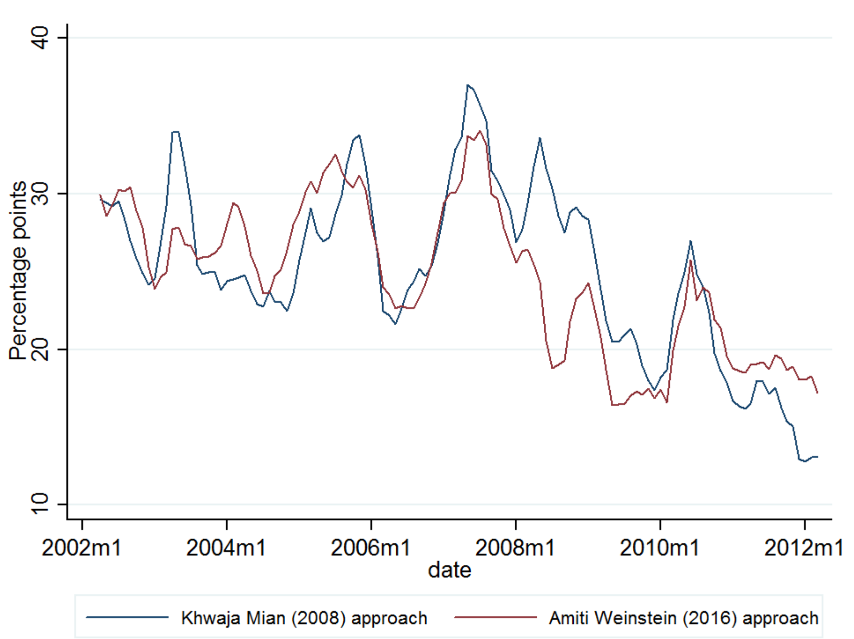
Note: Figure 2 shows the average credit growth rate from (1) the overall credit register sample, (2) the subsample of the multiple-bank *ILS* setup, and (3) the subsample of the multiple-bank *firm* setup.

Figure 3. The actual and predicted KM(2008) bank credit growth rates



Note: Figure 3 displays the bank-level credit growth rates, winsorized at the 1% level, that are obtained from the predicted values of the firm-bank credit growth rates estimated from Equation 5 (KM) and Equations 6a and 6b (AW).

Figure 4. Estimated bank-loan supply shocks



Note: Figure 4 displays the four-month moving average of the inter-quartile variation of the estimated bank-loan supply shocks for the period 2002m1-2012m3.

Table 1. Descriptive statistics

Panel A: 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)					
Single-bank firms	12.70	9,705,534	973,368	183,885	166.36 (0.000)
Multiple-bank firms	24.01	1,367,672	48,419	5,752	
Total assets (in mil. EUR)					
Single-bank firms	1.74	9,705,534	973,368	183,885	10.98 (0.000)
Multiple-bank firms	29.44	1,367,672	48,419	5,752	
Number of employees, FTE					
Single-bank firms	4.17	9,705,534	973,368	183,885	18.30 (0.000)
Multiple-bank firms	57.67	1,367,672	48,419	5,752	
Fixed assets/total assets					
Single-bank firms	0.52	9,705,534	973,368	183,885	-132.69 (0.000)
Multiple-bank firms	0.36	1,367,672	48,419	5,752	
Loan size (in mil. EUR)					
Single-bank firms	0.30	9,705,534	973,368	183,885	32.77 (0.000)
Multiple-bank firms	1.33	1,367,672	48,419	5,752	

Panel B: Number of observations and firms in the sample

	Firm-bank-month observations	Firms
Sample of bank-firm relationships for the identification of credit supply and demand effects	17,089,149	234,392
of which: multiple-bank firms	4,971,851	50,507
of which: multiple-bank *ILS* groups	16,048,914	227,937

Note: Table 1 consists of two panels with descriptive statistics. Panel A provides summary statistics on various characteristics of firms for the subsamples of single-bank firms and multiple-bank firms: age, size, investment, credit amounts authorized. In the last column of panel A, we report the T-statistic and the associated p-value of the test of the difference in means of the two subgroups. Panel B presents information on the number of bank-firm-month observations and the number of firms for three samples. These are: (1) the full sample, (2) the sample of firms borrowing from multiple banks in a given month, and (3) the sample of *ILS* groups borrowing from multiple banks in a given month.

Table 2. Comparison of bank-loan shock estimates

Panel A: Multiple-bank firm sample: comparing credit demand controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Firm-time fixed effects									
Time fixed effects	1.001***									
	(0.0371)									
Location-time fixed effects		0.998***								
		(0.0350)								
Industry-location-time fixed effects			1.009***							
			(0.0201)							
Industry-location-age-time fixed effects				1.048***						
				(0.0260)						
Industry-location-CA-time fixed effects (resources)					1.023***					
					(0.0183)					
Industry-location-risk-time fixed effects (ICR)						0.993***				
						(0.0161)				
Industry-location-risk-time fixed effects (debt)							1.039***			
							(0.0223)			
Industry-location-risk-time fixed effects (Altman Z)								1.046***		
								(0.0264)		
Industry-location-size-time fixed effects									1.022***	
									(0.0140)	
Industry-location-size-time fixed effects 2008m9-2009m12										1.066***
										(0.0433)
Bank-month observations	4,480	4,480	4,480	4,480	4,480	4,480	4,480	4,480	4,480	531
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value coef.=1	0.983	0.951	0.671	0.0680	0.210	0.680	0.0828	0.0845	0.124	0.135
Adjusted R-squared	0.725	0.729	0.769	0.765	0.758	0.742	0.784	0.735	0.791	0.837
Difference with ILST adjusted R-squared	-0.0663	-0.0624	-0.0221	-0.0260	-0.0336	-0.0495	-0.00683	-0.0562		
T statistic for adjusted R-squared difference	-16.75	-16.08	-6.705	-7.817	-10.02	-15.20	-2.128	-15.79		
Spearman's rank correlation coef.	0.747	0.750	0.789	0.788	0.798	0.783	0.799	0.793	0.813	0.851

Panel B: Multiple-bank *firm* setup versus multiple-bank *ILS* setup

	(1)	(2)
	Industry-location-size-time fixed effects on ILS sample	
Industry-location-size-time fixed effects on firm sample	0.752***	
	(0.0323)	
Firm-time fixed effects on firm sample		0.576***
		(0.0585)
Bank-month observations	4,480	4,480
Time FE	Yes	Yes
p-value coef.=1	2.66e-10	1.34e-09
Adjusted R-squared	0.787	0.632
Spearman's rank correlation coef.	0.778	0.669

Panel C: Khwaja and Mian (2008) approach versus Amiti and Weinstein (2016) approach

	(1)	(2)
	Firm-time fixed effects on firm sample, KM	Industry-location-size-time fixed effects on ILS sample, KM
Firm-time fixed effects on firm sample, AW	0.590***	
	(0.0930)	
Industry-location-size-time fixed effects on ILS sample, AW		0.735***
		(0.106)
Bank-month observations	4,480	4,480
Time FE	Yes	Yes
Adjusted R-squared	0.503	0.575
p-value coef.=1	4.86e-05	0.0154

Note: Table 2 consists of three panels that document the relationships between credit supply estimates obtained (1) from the sample of multiple-bank firms, but with altering credit demand controls (panel A), (2) from the sample of multiple-bank firms and the sample of multiple-bank *ILS* groups (panel B), and (3) using the Khwaja and Mian (2008) approach and the Amiti and Weinstein (2016) approach for the samples of multiple-bank firms and multiple-bank *ILS* groups. All regressions include time fixed effects. Standard errors clustered at the bank level are reported in parentheses.

Table 3. Bank credit supply estimates and real effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Khwaja and Mian (2008) approach			Amiti and Weinstein (2016) approach		
	Growth	Investment	Employment	Growth	Investment	Employment
Multiple-bank ILS sample						
Weighted supply shock, ILST methodology	0.0327**	0.0941**	-0.0209	0.0973***	0.179***	0.0429*
	(0.0128)	(0.0395)	(0.0240)	(0.0132)	(0.0408)	(0.0245)
Weighted supply shock, FT methodology	0.0367***	0.122***	-0.0138	0.0456***	0.0820***	0.0357***
	(0.0101)	(0.0311)	(0.0187)	(0.00757)	(0.0234)	(0.0136)
Multiple-bank firm sample						
Weighted supply shock, ILST methodology	0.0287	0.0830	0.0139	0.105***	0.137**	0.103***
	(0.0240)	(0.0662)	(0.0348)	(0.0223)	(0.0614)	(0.0320)
Weighted supply shock, FT methodology	-0.00316	0.00983	0.0147	0.0434**	0.0420	0.0775***
	(0.0215)	(0.0592)	(0.0312)	(0.0171)	(0.0473)	(0.0243)

Note: Table 3 relates bank credit supply estimates to firm growth, investment and employment. Within the samples of multiple-bank *ILS* groups and multiple-bank firms, we compare the effect of weighted supply shocks obtained using industry-location-size-time fixed effects and firm-fixed effects as controls for loan demand, respectively. The comparison is made separately using the Khwaja and Mian (2008) approach and Amiti and Weinstein (2016) approach.

Table 4. Bank credit supply estimates and firm asset growth

Panel A: Khwaja and Mian (2008) approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50
Weighted supply shock (ILST)	0.0327**	0.0273**	0.0811**	0.0505**	0.0815**	0.0287*						
	(0.0128)	(0.0129)	(0.0406)	(0.0200)	(0.0330)	(0.0169)						
Weighted supply shock (ILST) * Crisis		0.112***	0.418***	0.133**	0.200**	0.129**						
		(0.0382)	(0.115)	(0.0580)	(0.0957)	(0.0506)						
Weighted supply shock (FT)							0.0367***	0.0383***	0.0684**	0.0323**	0.0739***	0.0359***
							(0.0101)	(0.0103)	(0.0319)	(0.0159)	(0.0258)	(0.0134)
Weighted supply shock (FT) * Crisis								-0.0233	0.0564	-0.0160	-0.0142	-0.0107
								(0.0295)	(0.0846)	(0.0439)	(0.0730)	(0.0389)
Constant	590.5***	590.5***	751.0***	641.2***	622.0***	608.6***	590.4***	590.4***	750.7***	641.1***	621.9***	608.4***
	(1.585)	(1.585)	(6.386)	(2.871)	(4.961)	(2.230)	(1.585)	(1.585)	(6.388)	(2.872)	(4.962)	(2.230)
Observations	848,497	848,497	150,678	407,916	163,795	515,556	848,497	848,497	150,678	407,916	163,795	515,556
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.231	0.231	0.301	0.277	0.225	0.228	0.231	0.231	0.301	0.277	0.225	0.228

Panel B: Amiti and Weinstein (2016) approach

	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50
Weighted supply shock (ILST)	0.0973***	0.0788***	0.0935**	0.0678***	0.0996***	0.0809***						
	(0.0132)	(0.0135)	(0.0438)	(0.0218)	(0.0348)	(0.0180)						
Weighted supply shock (ILST) * Crisis		0.263***	0.478***	0.243***	0.320***	0.266***						
		(0.0414)	(0.129)	(0.0654)	(0.107)	(0.0552)						
Weighted supply shock (FT)							0.0456***	0.0468***	0.0327	0.0225*	0.0708***	0.0560***
							(0.00757)	(0.00783)	(0.0258)	(0.0128)	(0.0205)	(0.0105)
Weighted supply shock (FT) * Crisis								-0.0143	0.00584	-0.0299	-0.0368	0.00799
								(0.0235)	(0.0716)	(0.0368)	(0.0623)	(0.0317)
Constant	590.6***	590.6***	751.0***	641.3***	622.2***	608.6***	590.7***	590.7***	751.1***	641.3***	622.2***	608.7***
	(1.583)	(1.583)	(6.384)	(2.870)	(4.959)	(2.228)	(1.584)	(1.584)	(6.384)	(2.870)	(4.959)	(2.228)
Observations	848,497	848,497	150,678	407,916	163,795	515,556	848,497	848,497	150,678	407,916	163,795	515,556
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.231	0.232	0.301	0.277	0.225	0.228	0.231	0.231	0.301	0.277	0.225	0.228

Note: Table 4 relates bank credit supply estimates to firm growth. In particular, we analyse whether firms that have borrowing relationships grow at a slower pace if the average shock faced by their lenders up to one year ago was negative. Moreover, we also analyse whether the relationship between firm growth and the bank's credit supply estimate depends on: (1) the crisis in the banking sector, by means of 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, (2) the size of the firm, by means of limiting the sample to firms below the 20th and 50th percentile, and (3) the extent of leverage, by means of limiting the sample to firms whose leverage ratio exceeds the 80th and 50th percentile. In each regression, we include firm and time fixed effects. We report results for bank credit supply estimates obtained on the multiple-bank *ILS* sample using both the Khwaja and Mian (2008) approach (Panel A) and the Amiti and Weinstein (2016) approach (Panel B).

Table 5. Bank credit supply estimates and firm investment growth

Panel A: Khwaja and Mian (2008) approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50
Weighted supply shock (ILST)	0.0941**	0.0862**	0.260**	0.147**	0.122	0.0338						
	(0.0395)	(0.0399)	(0.125)	(0.0620)	(0.0864)	(0.0476)						
Weighted supply shock (ILST) * Crisis		0.165	0.595*	0.235	0.676***	0.482***						
		(0.118)	(0.353)	(0.180)	(0.252)	(0.143)						
Weighted supply shock (FT)							0.122***	0.129***	0.297***	0.148***	0.166**	0.0761**
							(0.0311)	(0.0318)	(0.0982)	(0.0493)	(0.0675)	(0.0378)
Weighted supply shock (FT) * Crisis								-0.0932	0.0618	-0.0410	0.270	0.0849
								(0.0910)	(0.260)	(0.136)	(0.192)	(0.110)
Constant	859.8***	859.8***	1,132***	985.1***	806.2***	817.8***	859.4***	859.3***	1,131***	984.7***	805.7***	817.4***
	(4.950)	(4.950)	(20.00)	(9.000)	(13.28)	(6.341)	(4.951)	(4.952)	(20.00)	(9.003)	(13.28)	(6.342)
Observations	842,050	842,050	148,305	404,179	161,022	511,118	842,050	842,050	148,305	404,179	161,022	511,118
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.060	0.060	0.141	0.109	0.060	0.062	0.060	0.060	0.141	0.109	0.060	0.062

Panel B: Amiti and Weinstein (2016) approach

	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50	Full period		TA<p20	TA<p50	LEV>p80	LEV>p50
Weighted supply shock (ILST)	0.179***	0.147***	0.261*	0.174**	0.180**	0.104**						
	(0.0408)	(0.0418)	(0.135)	(0.0676)	(0.0912)	(0.0506)						
Weighted supply shock (ILST) * Crisis		0.459***	1.366***	0.702***	0.848***	0.445***						
		(0.128)	(0.400)	(0.203)	(0.283)	(0.156)						
Weighted supply shock (FT)							0.0820***	0.0853***	0.120	0.0565	0.130**	0.0861***
							(0.0234)	(0.0242)	(0.0797)	(0.0398)	(0.0537)	(0.0295)
Weighted supply shock (FT) * Crisis								-0.0395	0.0516	-0.0714	0.125	0.0362
								(0.0725)	(0.221)	(0.114)	(0.164)	(0.0894)
Constant	860.2***	860.2***	1,133***	985.6***	806.4***	817.8***	860.3***	860.3***	1,133***	985.6***	806.5***	817.9***
	(4.946)	(4.946)	(19.99)	(8.996)	(13.27)	(6.337)	(4.946)	(4.946)	(19.99)	(8.996)	(13.27)	(6.337)
Observations	842,050	842,050	148,305	404,179	161,022	511,118	842,050	842,050	148,305	404,179	161,022	511,118
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-time control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.060	0.060	0.141	0.109	0.060	0.062	0.060	0.060	0.141	0.109	0.060	0.062

Note: Table 5 relates bank credit supply estimates to firm investment. In particular, we analyse whether firms that have borrowing relationships invest at a slower pace if the average shock faced by their lenders up to one year ago was negative. Moreover, we also analyse whether the relationship between firm investment and the bank's credit supply estimate depends on: (1) the crisis in the banking sector, by means of 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, (2) the size of the firm, by means of limiting the sample to firms below the 20th and 50th percentile, and (3) the extent of leverage, by means of limiting the sample to firms whose leverage ratio exceeds the 80th and 50th percentile. In each regression, we include firm and time fixed effects. We report results for bank credit supply estimates obtained on the multiple-bank *ILS* sample using both the Khwaja and Mian (2008) approach (Panel A) and the Amiti and Weinstein (2016) approach (Panel B).

Table 6. Bank credit supply estimates and bank risk-taking

Panel A: Altman Z score of entries

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in portfolio-weighted average Altman Z: entries					
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Industry-location-size-time fixed effects on full sample (KM)	-0.00140**	-0.00109*	-0.00394**			
	(0.000614)	(0.000659)	(0.00155)			
Industry-location-size-time fixed effects on full sample (AW)				-0.00323***	-0.00291***	-0.00340*
				(0.000775)	(0.000797)	(0.00186)
Bank-month observations	4,123	2,969	1,154	4,123	2,969	1,154
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.119	0.141	0.278	0.124	0.146	0.278

Panel B: Altman Z score of exits

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in portfolio-weighted average Altman Z: exits					
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Industry-location-size-time fixed effects on full sample (KM)	-0.00287***	-0.00298***	-0.00278**			
	(0.000855)	(0.000953)	(0.00136)			
Industry-location-size-time fixed effects on full sample (AW)				-0.00560***	-0.00622***	-0.000419
				(0.00128)	(0.00143)	(0.00161)
Bank-month observations	3,816	2,966	850	3,816	2,966	850
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.112	0.0923	0.424	0.124	0.107	0.421

Panel C: Share of entries

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of entries					
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Industry-location-size-time fixed effects on full sample (KM)	0.456***	0.514***	0.0903**			
	(0.0571)	(0.0662)	(0.0414)			
Industry-location-size-time fixed effects on full sample (AW)				0.281***	0.320***	0.0137
				(0.0370)	(0.0420)	(0.0317)
Bank-month observations	4,123	2,969	1,154	4,123	2,969	1,154
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.624	0.626	0.823	0.610	0.610	0.822

Panel D: Share of exits

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of exits					
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Industry-location-size-time fixed effects on full sample (KM)	-0.308***	-0.133***	-1.656***			
	(0.0596)	(0.0391)	(0.535)			
Industry-location-size-time fixed effects on full sample (AW)				-0.334***	-0.194***	-1.327***
				(0.0574)	(0.0490)	(0.401)
Bank-month observations	3,816	2,966	850	3,816	2,966	850
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.268	0.177	0.514	0.269	0.179	0.509

Note: Table 6 contains information on how banks change the riskiness (measured by the Altman Z score) and share of entries and exits in response to a bank credit supply shock. Using regression analysis, we analyse whether and how a credit supply shock in the previous period affects (1) the weighted average riskiness of the current period's new borrowers of the bank (panel A), (2) the weighted average riskiness of the current period's dropped firms by the bank (panel B), (3) the share of firm entries (panel C), and (4) the share of firm exits (panel D). We express each of the measures at the extensive margin in the period following the shock compared to the portfolio of banks' borrowers that were present both in the period of the shock and following the shock. In each panel, we report results for bank credit supply estimates obtained on the multiple-bank *ILS* sample using both the Khwaja and Mian (2008) approach and the Amiti and Weinstein (2016) approach. For each credit supply measure, 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.

Table 7. Bank-loan shock estimates and bank sources of funding

	(1)	(2)	(3)	(4)	(5)	(6)
	Industry-location-size-time fixed effects on ILS sample - KM			Industry-location-size-time fixed effects on ILS sample - AW		
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Deposit growth	0.0139	-0.00894	0.0621	0.0538	0.0571	0.125
	(0.0400)	(0.0536)	(0.0551)	(0.0382)	(0.0568)	(0.0801)
Equity growth	0.121	0.271	-0.464	-0.361	-0.542	-0.506
	(0.325)	(0.408)	(0.439)	(0.272)	(0.453)	(0.446)
Interbank liabilities growth	0.179***	0.225***	0.0923	0.225***	0.238***	0.252***
	(0.0472)	(0.0700)	(0.0582)	(0.0493)	(0.0685)	(0.0740)
Bank-month observations	4,480	3,208	1,272	4,480	3,208	1,272
Number of banks	57	55	38	57	55	38
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.321	0.310	0.551	0.182	0.178	0.333

Note: Table 7 shows regression results of specifications in which we relate two bank credit supply measures – multiple-bank *ILS* sample; Khwaja and Mian (2008) approach versus Amiti and Weinstein (2016) approach – to three observable sources of bank funding growth: growth in deposits, growth in equity and growth in interbank funding. For each credit supply measure, 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 clustered at the bank level are reported in parentheses.

Table 8. Bank-loan shock estimates and BLS supply indicators

Panel A: BLS lending standards

	(1)	(2)	(3)	(4)	(5)	(6)
	Industry-location-size-time fixed effects on ILS sample - KM			Industry-location-size-time fixed effects on ILS sample - AW		
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Supply tightening	-0.722	-1.552***	0.961	0.539	0.523	-1.667
	(0.505)	(0.497)	(1.216)	(0.676)	(0.734)	(2.382)
Supply easing	-0.818	-0.985		-0.814	-1.060	
	(1.546)	(1.436)		(1.774)	(1.975)	
Bank-month observations	152	96	56	152	96	56
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.869	0.878	0.952	0.120	0.054	0.496

Panel B: BLS lending standards, multiple tightening/easing

	(1)	(2)	(3)	(4)	(5)	(6)
	Industry-location-size-time fixed effects on ILS sample - KM			Industry-location-size-time fixed effects on ILS sample - AW		
	Full period	2002m1-2008m9	2008m10-2012m3	Full period	2002m1-2008m9	2008m10-2012m3
Supply tightening	-2.032***	-2.618***	0.961	-0.349	-0.741	-1.667
	(0.734)	(0.488)	(1.216)	(0.993)	(1.116)	(2.382)
Tightening * Multiple banks tightening	2.042**	1.837**		1.384	2.180*	
	(0.898)	(0.768)		(1.263)	(1.200)	
Supply easing	-0.898	-1.045		-0.868	-1.131	
	(1.554)	(1.446)		(1.792)	(1.997)	
Observations	152	96	56	152	96	56
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank M&A controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital injection controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.870	0.879	0.952	0.113	0.044	0.496

Note: Table 8 shows regression results of specifications in which we relate two bank credit supply measures – multiple-bank *ILS* sample; Khwaja and Mian (2008) approach versus Amiti and Weinstein (2016) approach – 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) – Panels A and B. To 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 provide an identical answer in that time period – Panels C and D. Monthly data on credit supply estimates refer to end-of-quarter months. For each credit supply measure, 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.