Granular Borrowers*

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Preliminary version

Abstract

This paper uses a credit registry covering the quasi universe of firm-bank relationships in France for the period 1999-2016 to provide a detailed account of the role of very large borrowers ("granular borrowers") in shaping bank-level and aggregate credit variations. We document that the distribution of borrowers is fat-tailed, the top 100 borrowers representing 18% of aggregate long-term credit and 64% of total undrawn credit lines. We adapt the methodology of Amiti and Weinstein (2018) to identify the contributions of firm, bank, and aggregate shocks to credit variations at any level of aggregation. At the macroeconomic level, we show that aggregate properties of credit largely reflect granular borrowers' shocks. This finding highlights the limitations of using time series of aggregate credit to assess the magnitude of financial frictions in the economy. At the bank-level, we find that the concentration of the borrower bases of banks exposes them to considerable borrower idiosyncratic risk and leads liquidity flows to be more synchronized across banks.

JEL codes: E32, E51, G21.

Key words: granularity, bank concentration, cyclicality of credit, liquidity risk.

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1 Introduction

The "granular view" conceptualized by Gabaix (2011) has put the size distribution of firms (and in particular the recurrent presence of fat tails) at the forefront of empirical research in macroeconomics. As the law of large numbers does not apply in the presence of very large actors, idiosyncratic shocks do not average out and, instead, can be important drivers of aggregate fluctuations. According to this approach, the analysis of the microeconomic behavior of such actors can yield new answers to long-standing macroeconomic questions.[1] In finance, the prevalence of big banks throughout the world has therefore prompted researchers to explore the role of the distribution of bank size for the propagation of credit shocks to the real economy.[2]

By contrast, however, the presence of heavy tails in the distribution of borrowers has been so far largely overlooked. Using a data set covering the quasi universe of firm-bank relationships in France including both private and public companies between 1999-Q1 and 2016-Q4, we provide novel evidence of an extreme degree of concentration of credit on the borrower side. Our analysis reveals that the top 100 borrowing firms make up for 18% of the aggregate amount of long-term credit and 64% of total undrawn credit lines.

The presence in the economy of firms borrowing non-trivial fractions of aggregate credit ("granular borrowers") has two broad sets of implications. First, aggregate properties of credit are likely to be driven to a large extent by the characteristics and behaviour of granular borrowers. A "representative" agent model calibrated using moments of the aggregate credit time series, it follows, would effectively reproduce the economic behavior of a restricted sample of firms with extensive access to credit. Second, the ability of banks to diversify risk is limited as the set of borrowers is itself very concentrated. This statement challenges in particular the idea that banks are able to provide liquidity under the form of credit lines by smoothing fund withdrawals on a diversified portfolio of borrowers (Holmström and Tirole, 1998; Kashyap, Rajan and Stein, 2002). In a granular economy, granting credit lines could expose banks to a

[1] These include the origins of business cycles (Di Giovanni, Levchenko and Mejean, 2014; Carvalho and Grassi, 2019), of country comparative advantage (Gaubert and Itskhoki, 2018), or the presence of international business cycles comovements (Di Giovanni, Levchenko and Mejean, 2017, 2018).

[2] See Buch and Neugebauer (2011); Bremus and Buch (2017); Bremus et al. (2018) for cross-country analysis of granular banks and Amiti and Weinstein (2018); Alfaro, García-Santana and Moral-Benito (2019) for studies of the transmission of bank shocks through lending and input-output relationships.

non-diversifiable and potentially non-negligible amount of liquidity risk. This paper provides a careful assessment of the empirical validity of these two assertions.

The main empirical challenge that we face is to separately identify credit variations originating from individual borrowers ("firm components") from bank-level shocks affecting the different pools of borrowers ("bank components"). Building on Amiti and Weinstein (2018), we perform to that end a weighted linear regression of the credit growth rate at the firm-bank level on a full set of bank-time and firm-time fixed effects. The two sets of fixed effects respectively identify (up to a constant term) factors that simultaneously shift the evolution of credit in all the firm relationships of a bank and in all the bank relationships of a firm. We define individual components as the deviation of the estimated fixed effects from a common trend. In the end, credit variations can be expressed as the sum of two terms, respectively reflecting the aggregation of firm-specific and bank-specific shocks, and of a third term common to all lending relationships ("macro component").

We propose a simple modification of the procedure proposed by Amiti and Weinstein (2018). We show that using the mid-point growth rate defined by Davis, Haltiwanger and Schuh (1996) not only considerably simplifies the estimation but also allows to account for the entry and exit of firms and banks, a necessary feature when dealing with the universe of borrower-lender relationships. With this procedure, the loan-weighted averages of the estimated firm and bank components at time t exactly match the bank, firm, and aggregate credit growth for all the lending relationships active either at $t-1$ or t.

Armed with this decomposition, we first inspect the implications of the presence of granular borrowers for the properties of aggregate credit. We devote our attention to a moment of key interest in the macro-finance literature, namely the comovement of credit borrowed by non-financial corporations with the business cycle. The presence of a robust, positive relationship between the two is largely considered as reflecting to some extent the manifestation of financial frictions affecting firms.[3] Based on this insight, numerous studies have relied on the analysis

[3] The interpretation is that the ability of firms to borrow is linked to their net worth because of the presence of financial constraints, and net worth mechanically fluctuates with the business cycle. The cyclicality of aggregate credit is therefore largely considered as a manifestation of the "financial accelerator" (Bernanke, Gertler and Gilchrist, 1996; Kiyotaki and Moore, 1997), *i.e.* the magnifiying role of the financial sector in the propagation of negative shocks.

of the evolution of aggregate credit over the business cycle to infer the importance of financial frictions in determining macroeconomic outcomes.[4]

Our methodology allows to assess the respective contribution to the cyclicality of aggregate credit of individual variations originating from the borrower and the lender side. Should the loan size distribution of firms and banks not be fat-tailed, these contributions would be negligible and the large majority of the correlation between credit and GDP would be explained by the macro component.

On the contrary, we find that firm-specific shocks explain between 60% and 80% of the comovement of aggregate credit with the business cycle. Bank idiosyncratic variations, by contrast, do not seem to significantly contribute to the correlation with GDP fluctuations. The skewness of the credit distribution confers moreover a disproportionate importance to large borrowers compared to the loan volume they represent, with more than two thirds of the contribution of firm shocks originating from the top 100 borrowers. It follows that the properties of aggregate credit are to a large extent determined by the behavior of granular borrowers. All in all, we contribute to the granularity literature by quantitatively showing that shocks affecting individual agents or a very small fraction of them shape not only real macro variables, but also aggregate financial flows; and by showing that granularity on the borrower side is the essential driver of aggregate credit fluctuations, in sharp contrast with common wisdom.

Our findings imply that the analysis of the cyclicality of aggregate credit is unlikely to give useful insights on the intensity or the nature of financing frictions applying to the bulk of non-financial firms. Instead of tightening credit constraints, the decrease in aggregate bank lending during downturns could actually reflect the differential cyclicality of investment opportunities of granular borrowers or the presence of substitution patterns between credit and other types of financing.[5] In that respect, our paper strongly advocates for removing the largest borrowers when studying the determinants of firm financing over the business cycle.[6]

[4]For instance, see Chari, Kehoe and McGrattan (2007), Smets and Wouters (2007), Justiniano, Primiceri and Tambalotti (2010) or Jermann and Quadrini (2012).

[5]See Covas and Den Haan (2011) and Begenau and Salomao (2019) for evidence for large firms of substitution patterns between debt and equity over the business cycle.

[6]The fact that the disproportionate influence of large borrowers on aggregate financing flows occult the behaviour of smaller firms has been recognized by Covas and Den Haan (2011) and acknowledged in particular by Eisfeldt and Muir (2016) or Begenau and Salomao (2019). This paper, however, is the first to provide a quantitative assessment of the influence of large borrowers in shaping aggregate credit fluctuations.

We then turn to the bank-level implications of the presence of granular borrowers. When borrowers face idiosyncratic and diversifiable funding shocks, Holmström and Tirole (1998) shows that granting credit lines allows banks to optimally reallocate liquidity between liquidity-poor firms and firms with excess liquidity. In the presence of aggregate shocks, however, the reallocation process breaks down and there is a need for an external supply of liquidity.[7] Our paper documents a different yet complementary limit to the capacity of banks to act as "liquidity pools". When the distribution of borrowers is fat-tailed, banks may not be able to diversify idiosyncratic liquidity risk, even when the number of borrowers gets infinitely large. Holding liquid assets becomes therefore necessary not only to hedge against the possibility of runs on credit lines but also against negative idiosyncratic shocks affecting granular borrowers.

In line with the presence of under-diversification, we document a positive, strong relationship between the bank-level concentration of the portfolio of borrowers and the variance of total undrawn credit lines. Relying on our decomposition of credit variations, we estimate further that in the absence of borrower idiosyncratic shocks, the variance of credit lines would fall on average by 18% to 31%. The role of borrower shocks on bank-level credit line variations is therefore sizeable and comparable in magnitude to the effect of macro shocks, for instance.

In the aggregate, firm-specific shocks contribute substantially to credit lines fluctuations. The variance of the aggregate firm component amounts to 84% of the variance of aggregate credit line variations. There are two main channels that explain the importance of borrower shocks in aggregate fluctuation. As explained above, high borrower portfolio concentration first leads to high bank-level variance of credit lines. Since large borrowers have credit commitments in multiple banks, however, borrower idiosyncratic shocks may also increase aggregate variance by making banks more correlated with each other. We find that the variance of the aggregate firm component is driven by the linkages between banks which result from the presence of common borrowers. This result suggests that granular borrowers lead liquidity flows to be less diversifiable and more coordinated between banks.

The remainder of the paper is organized as follows. We present our data set and provide descriptive statistics on the credit distribution in section 2. Section 3 describes our estimation

[7] See Ivashina and Scharfstein (2010); Cornett et al. (2011); Bord and Santos (2014); Ippolito et al. (2016) for evidence of bank runs on credit lines during the 2008 financial crisis.

methodology. The results on the cyclicality of aggregate credit are presented and discussed in section 4. We analyze the role of granular borrowers for bank-level liquidity risk in section 5. Section 6 concludes.

Related literature

This paper draws on and contributes to three separate strands of research. The first body of research has been initiated by Covas and Den Haan (2011) and explores the cross-sectional heterogeneity of firms' financing over the business cycle to infer the distribution of financial frictions in the economy (Begenau and Salomao, 2019; Crouzet and Mehrotra, 2019).[8] While this literature zooms in on the differences in cyclicality of debt between firms, our focus is on assessing the contributions of large borrowers to the fluctuations of aggregate credit over the cycle. Overall, the heterogeneity in firm financing policies combined with the large influence of granular borrowers highlights the limitations of using aggregate credit data to assess the magnitude of financial frictions in the economy.

Our paper then adds to the literature on the role of banks as "liquidity providers" (Kashyap, Rajan and Stein, 2002). Acharya, Almeida and Campello (2013) show in particular that bank lines of credit to firms with greater aggregate risk (high beta) are more expensive as the liquidity risk they pose cannot be diversified away. We document another limit to diversification, namely the high degree of concentration of the credit lines portfolios. More broadly, this paper indicates that the composition of the portfolio of loan commitments is in itself a useful object of study to assess the liquidity risk faced by banks.[9]

The last stream of research aims at exploring the implications in macroeconomics and in finance of the existence of granular economic agents. Previous work has focused on the role of banks in the transmission of financial shocks to the real economy (Buch and Neugebauer, 2011; Amiti and Weinstein, 2018; Alfaro, García-Santana and Moral-Benito, 2019) and in the

[8]The use of firm size as a proxy for financial constraints to analyse the differential sensitivity of firms to macroeconomic shocks dates back at least to Gertler and Gilchrist (1994). Recently, Chodorow-Reich (2014) and Mian and Sufi (2014) relied on the size of firms to analyze the real effects of financial constraints during the Great Recession.

[9]Following Kashyap, Rajan and Stein (2002), the literature has mostly focused on the correlation between deposit outflows and credit line takedowns to assess banks' ability to provide liquidity on demand. See Gatev and Strahan (2006); Ivashina and Scharfstein (2010); Acharya and Mora (2015); Ippolito et al. (2016).

formation of sovereign bond yields (Gabaix and Koijen, 2019), on the effects of the presence of large institutional investors on stock and CDS prices (Greenwood and Thesmar, 2011; Ben-David et al., 2019; Siriwardane, 2019), and on the asset pricing consequences of a granular production network (Herskovic, 2018). This paper is to our knowledge the first to provide a detailed account of the importance of granular borrowers in shaping bank-level and aggregate credit variations.

2 Granular borrowers

2.1 Presentation of the data set

We use a comprehensive dataset on quarterly bank-firm level credit issued from the French credit registry covering the period 1999-Q1 to 2016-Q4. The credit registry contains information on loans granted by every national or foreign bank (credit institution or investment company) to every firm located in France. At the end of each month, all financial institutions which are subject to the 1984 Banking Act have to report the total loan amount extended to any borrowing firm located in France as soon as this amount exceeds a given reporting threshold.[10] The data set records for each bank-firm relationship the breakdown of credit by type of exposure.[11] We focus in the analysis on two main types of exposure. Long-term credit is defined as credit with a maturity of more than year at issuance. Credit lines are computed as the sum of all undrawn commitments (including documentary credits). The exposure of a bank to a firm is the sum of its individual loans as well as of the bank's share in syndicated loans.

[Insert figure 1 here]

On top of credit exposures, the data set gives basic information on the firm (location, size

[10] The threshold was set to €75,000 at the firm-bank level until January 2006. It has then been lowered to €25,000 at the firm-agency level and has stayed that way ever since. In order to ensure a constant coverage over the full period, we only consider loan-level data associated to borrowers for which banks have an aggregate exposure exceeding the pre-2006 reporting threshold.

[11] The different types of exposure are: current accounts, commercial debts, factoring, other short-term debt, property leasing, equipment leasing, credit with maturity of more than one year at issuance, export credit and securitized loans, undrawn commitments and available documentary credits. Undrawn commitments can have various maturities, ranging from less than a year (operating credit lines) to several years (investment credit lines). We do not include in the analysis the different types of short-term loans as their definitions in the data set have significantly evolved over time.

indicator, 5-digits sector). The registry also includes the credit score attributed by the Bank of France, which assesses the medium-term probability of default of the firm.[12] It is assigned by analysts based on hard information (tax returns, trade bills) as well as interviews conducted with managers. While all firms could in principle receive a credit score, only firms with sales exceeding €750,000 are in fact assessed by the Bank of France[13]. The credit score is communicated on demand to credit institutions.

To construct our sample, we consider only French non-financial firms and we exclude self-employed entrepreneurs. We also choose to remove public credit institutions from the analysis. Public supply of credit is large in France (about 30% of total long-term credit), but primarily directed towards specific entities and sectors (motorway companies, public housing sector, ...). It is therefore likely to be determined by different objectives from the private supply of credit which constitutes our main object of focus.

Whenever a bank disappears because of an absorption, all credit exposures are reallocated to the absorbing bank, leading to unwanted interruptions of banking relationships. The French Supervision and Prudential Authority (ACPR) keeps track of all the M&A operations involving banks located on the French territory. The date of the transaction as well as the identity of the acquiring and acquired bank are provided.[14] We checked the date of transaction by looking at when the acquired bank exits our data set and modified it where appropriate. We then neutralized the effects of M&As as following. Assume that bank B acquires bank A between quarters q and q+4. When comparing the evolution of credit over these two quarters we reprocess the data so that at quarter q and for each firm the amount of loan granted by B includes loans that were granted by A ($Credit^{*}_{f,B,q\text{-}4} = Credit_{f,A,q\text{-}4} + Credit_{f,B,q\text{-}4}$).[15]

[Insert tables 1, 2 and 3 here]

[12] The categories of the credit score are (in descending order): 3++, 3+, 3, 4+, 4, 5+, 5, 6, 7, 8, 9, P. Credit ratings below 7 indicate that at least one payment incident has been recently recorded for the firm. See Cahn, Girotti and Salvade (2018) for more information on the credit score.

[13] Only 23.5% of firms on average do have a credit score each quarter in our data set.

[14] We moreover looked for every exiting bank whether there were any mention in the media of a M&A at that time. In some rare cases, the transaction was missing from the ACPR list. We added those cases to the list of transactions.

[15] We treat the cases where banks A and B merge to form a new bank C as the simultaneous acquisition of bank A and B by bank C. In some occurrences, a given bank is acquired several times in a short period of time (less than two years). We deal with this issue by assuming that the bank is acquired only once by the last acquiror.

The coverage of our data set is assessed in figure 1. This figure compares the time series of aggregate long-term credit to the non-financial sector obtained from the initial data set (blue curve), after imposing a constant reporting threshold (red curve) and after excluding public banks (green curve), with the time series recorded in the balance of payments ("Flow-of-funds" black line). Firm-bank loans higher than the 75k euros threshold account for 86.5% of total credit. Overall, aggregate long-term credit as reported in our final data set represents on average 65% of the value reported in the balance of payments. The two time series moreover exhibit very similar dynamics (correlation of 94%).

[Insert figures 2a and 2b here]

Tables 1, 2 and 3 present descriptive statistics at the firm-bank, bank, and aggregate level. There are 502 banks per quarter on average and 682 (211) thousands firms with positive long-term credit (credit lines) exposure. Aggregate long-term credit amounts to €307 billions and credit lines represents €146 billions. While most banks (79%) have positive long-term credit exposures, about one third of banks (38%) do not have any undrawn commitments to their creditors. Overall, the average bank lends long-term to 1573 firms and has opened 476 credit lines. The sectoral decomposition of total credit for 2007 Q1 is reported in Figure 2. Firms operating in the housing sector represent nearly 45% of aggregate long-term credit. By contrast, head offices and firms in other service activities concentrate most of the credit lines (respectively 32% and 23%). At a later stage our analysis will focus on multiple-bank firms. We find 77 thousands firms with positive long-term credit in at least two banks and 19 thousands with several opened credit lines.

2.2 Credit concentration: evidence at the bank and aggregate level

We use our data set to explore the empirical distribution of credit. Figure 3 shows that the distribution of banks is heavy-tailed as well: the top 10% of banks account in our sample for 63% of long-term credit in 2007Q1. Concentration appears to be higher for credit lines, with 78% of total undrawn commitments issued by the top decile of banks. These figures are line with the high degree of concentration observed in most large banking systems.

[Insert figure 3 here]

We then turn to the properties of the empirical distribution of borrowers which, by comparison, have not been subject to the same intense scrutiny. Figures 4a and 4b give a graphical representation of the distribution of long-term credit and credit lines. Firms are ordered by percentile according to the size of their credit exposure: a firm in the top 1% of borrowers will therefore belong to the [99,100] interval. Long-term credit exhibits a high degree of concentration: while firms in the bottom half of the distribution represent on average less than 10% of total credit, 47% of credit is attributed to firms in the top 1% of borrowers. This pattern is very stable over time though slightly more pronounced at the height of the financial crisis (2009-Q1). Strikingly, credit lines appear to be even more concentrated: firms in the bottom 99% represent a mere 17% of total exposure. By contrast, almost two thirds (64%) of the aggregate amount of credit lines can be traced down to a group of 100 top borrowers.

[Insert figures 4a and 4b here]

What does the presence of very large borrowers imply for banks? Faced with a concentrated distribution of borrowers, the ability of banks to diversify borrower risk is mechanically limited. Some banks will necessarily have, to a certain extent, to bear the risk associated with an under-diversification of their credit portfolio.

We formalize this idea by calculating for each bank b and each quarter q the Herfindahl-Hirschmann index of the loan portfolio. For each bank present in at least three consecutive years (12 quarters) in the data set, we then compare the average of its HHI index to the standard deviation of its total credit growth rate. Following Di Giovanni, Levchenko and Mejean (2014), we take the standard deviation and the square root of the HHI index in logs.

[Insert figures 5a and 5b here]

The corresponding scatter plots are displayed in figures 5a and 5b. There is a strong, positive relationship between the average degree of concentration of the bank and the volatility of its credit growth rate.[16] In the case of long-term credit, it shows that banks which display large

[16]The correlation between both variables is equal to 0.8 for long-term credit and 0.6 for undrawn credit lines.

lending volatility (and therefore potentially large comovements with the business cycle) are also those that are plausibly affected by borrowers idiosyncratic shocks. Indeed, firms credit shocks are less likely to cancel out when the HHI index of the loan portfolio is high. In the case of credit lines, this pattern suggests that banks with under-diversified borrower portfolios are subject to larger variations of undrawn commitments. This makes banks more vulnerable to off-balance sheet liquidity risk, which when materialized can have adverse consequences on their financial health and their ability to originate new loans (Ivashina and Scharfstein, 2010; Cornett et al., 2011; Acharya and Mora, 2015).

The graphical representation of the link between volatility and concentration is however not sufficient in itself to conclude that the individual shocks hitting granular borrowers drive credit fluctuations. Other bank-level variables (such as the business model of the bank or its reliance on certain types of funding) might simultaneously determine the variance of its credit exposure and the degree of diversification of the portfolio of borrowers. In order to explore further the role of granular borrowers, we need to be able to disentangle the contribution of firms and banks in the magnitude of credit fluctuations, a task we now turn to.

3 Estimating firm and bank shocks

3.1 Presentation of the methodology

Our ultimate goal is to assess the role of granular borrowers on credit fluctuations. We focus in the following on credit at the aggregate level, but the analysis is easily adaptable to other degrees of aggregation. Total credit $Credit_q$ is by definition given by $Credit_q = \sum_{f,b \in R_q} Credit_{fbq}$ where R_q is the set of banking relationships between firms f and bank b at time q. We then compute the evolution of aggregate credit between $q-4$ and q as

$$\Delta Credit_q = 2 * \frac{(Credit_q - Credit_{q-4})}{Credit_q + Credit_{q-4}}$$

This alternative specification of the growth rate has been put forward by Davis, Haltiwanger and Schuh (1996) and is referred to as the "mid-point growth rate" (or MPGR). Defining weights

w_{fbq} as $w_{fbq} = (Credit_{fbq\text{-}4} + Credit_{fbq})/(Credit_{q\text{-}4} + Credit_q)$, we get that

$$\Delta Credit_q = \sum_{f,b \in R_q \cup R_{q-4}} w_{fbq} \Delta Credit_{fbq} \tag{1}$$

where $\Delta Credit_{fbq}$ is the MPGR of credit at the firm-bank level. This decomposition simply states that aggregate credit fluctuations can be expressed as a weighted sum of individual variations.

Credit variations as such are not informative to assess the role of the loan distribution of borrowers as they reflect the outcome of a joint process between the lender and the borrower. Following Khwaja and Mian (2008), the introduction of firm-time fixed effects (and then bank-time fixed effects) has become a standard tool in the empirical banking literature to separate the role of firms and banks in the evolution of credit.[17] We decompose accordingly the growth rate of credit $\Delta Credit_{fbq}$ in a firm-specific, bank-specific, and match-specific component

$$\Delta Credit_{fbq} = \alpha_{fq} + \beta_{bq} + \epsilon_{fbq} \tag{2}$$

The firm-time α_{fq} and bank-time β_{fq} components capture factors that simultaneously shift the evolution of credit in all the banking relationships of a firm and all the borrower relationships of a bank.[18] It follows that equation 2 can only be estimated for firms with multiple banking relationships ("multiple-bank firms").[19] We explore the implications of this restriction in the next subsection.

By construction, the match-specific component measures the deviation of the actual variation of credit at the firm-bank level from the sum of the two trends. Whether most of the cross-sectional variance is captured by the bank and firm components or the match-specific residual will then depend on the degree of heterogeneity in firms' borrowing across banks and banks' lending between firms.[20]

[17] See Paravisini (2008); Chodorow-Reich (2014); Jiménez et al. (2014); Behn, Haselmann and Wachtel (2016); Jiménez et al. (2017); Carletti et al. (2019); Fraisse, Lé and Thesmar (forthcoming) for examples of causal analysis relying on firm-time fixed effects. See Paravisini, Rappoport and Schnabl (2017); Amiti and Weinstein (2018); Alfaro, García-Santana and Moral-Benito (2019) for examples of settings including both bank-time and firm-time fixed effects.

[18] Note that this specification encompasses any empirical model that would regress growth in lending on a set of variables measuring bank-level and firm-level characteristics.

[19] All the banks in our data set have more than two clients.

[20] If in particular banks are specialized in certain sectors of markets (Paravisini, Rappoport and Schnabl, 2017),

Our methodology aims at identifying firm and bank shocks so as to assess their role in the fluctuations of aggregate credit. Our research question, however, does not require us to take a strong stance on the structural interpretation of the different types of components. We therefore remain largely agnostic throughout the analysis about the economic origins of the shocks. The firm-time component may as well relate to demand (variations in input costs, productivity shocks) as to supply. In the event of a default on a trade bill, for instance, all banks might want to cut lending to the defaulting firm at the same time, leading to a low value of α_{fq}. Similarly, a low bank-specific component β_{bq} may either indicate that the bank is cutting back lending due to funding constraints or that borrowers are all reducing their credit exposure to this particular bank. This latter case is particularly relevant in the case of credit lines where the existence of "runs" (simultaneous drawdowns in periods of reduced access to liquidity) is well-known by the finance literature (*e.g.*, Ivashina and Scharfstein (2010); Ippolito et al. (2016)).

We need a method to estimate firm and bank components at the individual level that can be consistently used to decompose the evolution of credit at higher degrees of aggregation. Amiti and Weinstein (2018) recommends to that end to estimate equation 2 with weighted least squares (WLS). With this procedure, the loan-weighted average of the estimated firm and bank components will exactly match the bank, firm, and aggregate credit growth rates. Formally, $\hat{\alpha}_{fq}$ and $\hat{\beta}_{bq}$ verify the equations:

$$\Delta Credit_{fq} = \hat{\alpha}_{fq} + \sum_{b \in R_{fq}} w(f)_{bq} \hat{\beta}_{bq} \tag{3}$$

$$\Delta Credit_{bq} = \hat{\beta}_{bq} + \sum_{f \in R_{bq}} w(b)_{fq} \hat{\alpha}_{fq} \tag{4}$$

$$\Delta Credit_{q} = \sum_{b \in B_q} w_{bq} \hat{\beta}_{bq} + \sum_{f \in F_q} w_{fq} \hat{\alpha}_{fq} \tag{5}$$

where R_{fq} is the set of banks lending to firm f at time q or $q-4$, R_{bq} is the set of firms borrowing from bank b at time q or $q-4$, F_q and B_q are the set of banks with positive credit exposure at time q or $q-4$, $w(f)_{bq}$ is the weight of bank b in total borrowing of firm f and $w(b)_{fq}$ is the

firms will be unable to substitute between banks and the firm-specific component will explain a small share of the firm's credit variation. For that reason, we perform the analysis in a robustness check at the level of the banking group as groups are less likely to be specialized than bank units. We also try to focus on precisely defined categories of credit so as to maximize the degree of substitutability between bank relationships.

weight of firm f in total lending of bank b. Credit variations are expressed in mid-point growth rates; accordingly, the size of a credit exposure is computed as the average exposure between time $q-4$ and q.

We depart from the methodology of Amiti and Weinstein (2018) by replacing the standard growth rate (*i.e.*, $(Credit_{fbq} - Credit_{fbq\text{-}4})/Credit_{fbq\text{-}4}$) with the mid-point growth rate. This simple modification has important implications for the estimation process. First, the mid-point growth rate is by definition bounded between -2 and 2. As a result, the estimates of the bank and firm components are naturally less sensitive to large credit increases and therefore more robust to outliers.

Second, the MPGR is defined both for new loans ($Credit_{fbq\text{-}4} = 0$) and for terminated loans ($Credit_{fbq} = 0$) while the standard growth rate is only defined in the latter case. Amiti and Weinstein (2018) address this issue by modifying the WLS moment equations to account for the formation of new lending relationships. The resulting estimation procedure becomes however computationally demanding in the presence of a large number of firms.[21] By contrast, our approach can be readily estimated using the high-dimensional fixed-effects estimation routines that are now implemented on most econometric softwares. Third, while the Amiti-Weinstein procedure can account for new loans, it can not deal with the entry of firms or banks. Using the mid-point growth rate enables us to cover the whole distribution of multiple-bank borrowers, including new ones.[22]

3.2 Single- and multiple-bank borrowers

Our methodology relies on the presence of multiple-bank firms. This restriction may limit the validity of our analysis if aggregate credit fluctuations vary a lot whether single-bank firms are included or not. We show in this section that to a large extent, restricting the sample to multiple-bank firms preserves credit dynamics at various levels of aggregation.

[21] Amiti and Weinstein focus on listed Japanese firms. Their data set includes as a consequence less than 2,000 firms a year. By contrast, we estimate on average 75,000 firm shocks per quarter. This type of computational issues to estimate bank-time and firm-time fixed effects on large data sets has also been raised by Alfaro, García-Santana and Moral-Benito (2019) and Degryse et al. (forthcoming).

[22] A last advantage of using the midpoint growth rate is that it increases the set of multiple-bank firms. When variation in lending is measured by the standard growth rate, being a multiple-bank firms is equivalent to having multiple preexisting relationships. When it is measured using the midpoint growth rate, it is equivalent to having multiple preexisting *or* new relationships. This increases the number of firm-bank-time observations by 31%.

[Insert figures 6a, 6b, 6c and 6d here]

Firms with multiple bank relationships constitute a small subset of the universe of borrowers. Only 11% of firms borrow long-term in more than two banks, and 9% of firms have multiple credit lines (table 3). Yet, multiple-bank firms represent 50% of the aggregate long-term credit and 83% of the credit lines. Figure 6 compares the times series of aggregate credit including or excluding single-bank firms over the period 1999-Q1 to 2016-Q4. The level of the aggregate credit to multiple-bank firms mimics total credit quite well (Panel A). In growth rates, long-term credit borrowed by such firms appears to be a bit more volatile than total long-term credit.[23] Still, the two series co-moves closely together with a correlation of 94%. For credit lines, the correlation is almost perfect (97%).

[Insert figures 7a and 7b here]

Does the restriction to multiple-bank borrowers also preserve credit dynamics at the bank level? Figure 7 gives a graphical representation of the banks' mean credit growth rate including (x-axis) and excluding single-bank firms (y-axis). Each point represents a bank and the average growth rates are computed over the entire period of existence of the bank. Restricting the sample does not appear to alter the dynamics of the banks' credit portfolio, either for long-term credit (correlation of 92%) or credit lines (89%). The banks for which there are some apparent divergences are small banks which have few firms at each period. In this case, withdrawing the loans granted to multiple-bank clients results in zero total credit and in a mid-point growth rate equal to −200% or 200%. In the following, we further restrict the data set to banks having more than 100 multiple-bank borrowers in order to avoid this kind of issue. By simplicity, we refer to the resulting data set as the "connected set".

3.3 Aggregation and normalization of the shocks

At each time period the estimates $\hat{\alpha}_{fq}$ and $\hat{\beta}_{bq}$ are identified up to two normalizations. We choose to remove the cross-sectional medians of the firm and the bank components so as to make them directly interpretable as deviations from a common trend. The deviation to the median will

[23] Unless specified otherwise, credit variations are always computed in midpoint growth rates.

serve as our baseline definition for an idiosyncratic shock.[24] We use alternative definitions such as the deviation to the (simple) mean as well as others specifications in section 4.4. Denoting $\bar{\alpha}_q$ and $\bar{\beta}_q$ the medians of $\hat{\alpha}_{fq}$ and $\hat{\beta}_{bq}$, equation 5 can be rewritten as

$$\Delta Credit_q = \underbrace{\bar{\beta}_q + \bar{\alpha}_q}_{Macro_q} + \underbrace{\sum_{f \in F_q} w_{fq}(\hat{\alpha}_{fq} - \bar{\alpha}_q)}_{Firm_q} + \underbrace{\sum_{b \in B_q} w_{bq}(\hat{\beta}_{bq} - \bar{\beta}_q)}_{Bank_q} \tag{6}$$

This equation states that the variation of credit is the sum of three terms: $Macro_q$, $Firm_q$ and $Bank_q$. $Macro_q$ is a common term that shifts all firm-bank lending in the same direction. $Firm_q$ and $Bank_q$ are defined as the weighted sum of firm-specific and bank-specific shocks, and captures the effects of microeconomic shocks on the borrower and lender side on the evolution of aggregate credit over time.[25]

[Insert figures 8a, 8b, 8c and 8d here]

Figure 8 presents the different time series of the estimates of $Macro_q$, $Firm_q$ and $Bank_q$ for long-term credit.[26] The time series corresponding to the normalization by the median (solid red line) and by the mean (dotted green line) are displayed. As is apparent on the graph, the exact specification of the common trend does not impact much the decomposition of aggregate credit. Both $Firm_q$ and $Bank_q$ fall markedly around 2010-Q1, indicating that some big firms and banks experienced large negative idiosyncratic shocks at the time. On the lender side, one potential interpretation is that this sudden decrease may reflect the fact that banks were heterogeneously affected by the interbank market freeze (Iyer et al., 2013). By contrast, the $Macro_q$ component is essentially flat during that period. Taken together, this pattern suggests that the fall in aggregate credit following the financial crisis did not originate in an uniform decrease across all firm-bank relationships, but instead took its origins in individual negative shocks along the distribution of borrowers and lenders.

[24] Empirically, the normalization using the median proved to yield the most consistent results across specifications.

[25] When idiosyncratic shocks are defined as deviations to the mean, $Firm_q$ and $Bank_q$ represent according the decomposition of Olley and Pakes (1996) the cross-sectional covariances $Cov(w_{fq}, \hat{\alpha}_{fq})$ and $Cov(w_{fq}, \hat{\beta}_{bq})$.

[26] To save some space, the corresponding figures for the case of credit lines are relegated to the online appendix.

3.4 External validation of the firm components

The methodology estimates individual components that can be aggregated to match the evolution of credit at the firm, bank or economy level. Before using the resulting decomposition, it is interesting to assess whether the estimated components are able to effectively capture the presence of factors likely to affect microeconomic credit variations. While we do not need in general to characterize the economic origins of the idiosyncratic shocks, this exercise allows to externally validate the informativeness of our estimates.

[Insert figure 9 here]

A natural source of information on firm-level credit shocks is provided by the default status of firms made available in the credit registry. This status indicates whether the firm has recently defaulted on a trade bill or entered a procedure to safeguard or to liquidate the firm ("distressed firm"). Using an event study setting, a firm is said to be treated at $q = 0$ if its default status switches from "non-distressed" to "distressed" at that time.[27] The control group is defined as the set of firms in the same department, in the same risk category, in the same industry and of similar size as treated firms at $q = -1$ but that never become distressed.[28] When multiple control firms are found for a single treated firms, we select the one that minimize the absolute distance in terms of total long-term credit exposures at $q = -1$. At the end of the process, each treated firm is matched with zero (in which case it is dropped) or exactly one control firm. We impose that all treated and control firms are present in the database between $q = -4$ and $q = 0$.

This procedure leads us to retain 3516 control and treated firms. Figure 9 presents the evolution of the mean firm-specific shock $\tilde{\alpha}_{fq} = \hat{\alpha}_{fq} - \bar{\alpha}_q$ four quarters before and after the default event for treated firms and control firms. Before the treatment, firm components evolve similarly for control firms and treated firms. At $q = 0$, the idiosyncratic components of treated firms fall sharply on average. By comparison, the curve follows its pre-existing trend for control

[27] For the sake of readability, we make use in this subsection of the vocabulary of randomized controlled trials ("treated firms", "control firms"). This is admittedly not completely appropriate in our context as the "treatment" is probably not random. This is however not a problem for our econometric analysis as we do not attempt to obtain causal links.

[28] Firms are sorted in 16 industries, 4 size and risk categories as well as 101 departments.

firms. Table 9 validates this graphical illustration. The table displays the results of the regression

$$\tilde{\alpha}_{fq} = \mu_f + \gamma Post_q + \delta Post_q \times Treated_f + \epsilon_{fq}$$

$Post_q$ is a dummy variable equal to one (zero) when q is greater or equal (strictly inferior) to zero. $Treated_f$ is equal to one when f belongs to the treated group, zero otherwise. In line with the figure, we find that firm-level shocks fell relatively more after $q = 0$ for treated than for control firms ($\delta < 0$).

[Insert table 4 here]

After being declared in financial distress, treated firms may exit the credit registry as they go bankrupt or because their total credit exposure falls below the reporting threshold. This is reflected in the data by a credit growth rate equal to -200%, which leads by construction to a very low idiosyncratic component. The drop in individual shocks may therefore be entirely driven by credit adjustments at the extensive margin. Column 2 shows that we find a negative and significant coefficient even when imposing that firms stay in the credit registry during the two year period around $q = 0$ ("surviving firms"). This implies that firm components also capture idiosyncratic variations of the quantity of credit (intensive margin).

4 Granular borrowers and the cyclicality of aggregate credit

4.1 Granularity and cyclicality

This section explores the implications of the presence of granular borrowers for the cyclicality of aggregate long-term credit. The empirical importance of large firms for the properties of aggregate credit is *a priori* unclear. Indeed, a peculiar and interesting feature of credit is that both the distribution of borrowers and lenders feature heavy tails (see subsection 2.2). While the granularity literature suggests that the cyclicality of aggregate credit will be disproportionately determined by idiosyncratic shocks affecting large actors, it offers little guidance to determine whether firm or bank microeconomic variations will matter more in the aggregate.

Equation 6 provides a simple way to assess the respective contributions to the credit cycle of idiosyncratic shocks on the borrower and the lender side. In line with Covas and Den Haan (2011), we measure the cyclicality of aggregate credit as the comovement between the growth rate of aggregate credit and the growth rate of the non-financial sector real GDP.[29] Let $\Delta GDP_{q\text{-}k}$ be the growth rate of real GDP between $q-k-4$ and $q-k$ (k is an integer between 0 and 5). $\Delta GDP_{q\text{-}k}$ is normalized so that its standard deviation is equal to one. Using equation 6, we get that

$$\begin{aligned} \mathrm{Corr}(\Delta Credit_q, \Delta GDP_{q-k}) = & \pi^{Macro} \cdot \mathrm{Corr}(Macro_q, \Delta GDP_{q-k}) \\ & + \pi^{Bank} \cdot \mathrm{Corr}(Bank_q, \Delta GDP_{q-k}) \\ & + \pi^{Firm} \cdot \mathrm{Corr}(Firm_q, \Delta GDP_{q-k}) \end{aligned} \tag{7}$$

where, for instance, π^{Firm} is the ratio of the standard deviation of $Firm_q$ (σ^{Firm}) to the standard deviation of $\Delta Credit_q$ (σ^{Credit}). For clarity, we refer to $\pi^X \cdot \mathrm{Corr}(X_q, \Delta GDP_{q-k})$ as $Share(X_q, \Delta GDP_{q-k})$.

Before presenting the results of the decomposition implied by equation 7, it is useful as a benchmark to estimate an upper bar of the contribution of firm idiosyncratic shocks in a non-granular setting. Assume that firm shocks $\tilde{\alpha}_{fq}$ are independent random variables with identical variance σ. Following Gabaix (2011) we can show that the standard deviation of $Firm_q$ is proportional to the square root of the Herfindahl-Hirschmann index of the repartition of credit across borrowers:

$$\sigma_{Firm} = \sigma \sqrt{\sum_{f \in F_t} w_{ft}^2}$$

As long as the variance of the loan distribution of borrowers is finite (a condition that is generally not satisfied in the presence of fat tails), the law of large numbers ensures that when the number of firms N becomes infinitely large, the square root of the Herfindahl will at the limit be proportional to $1/\sqrt{N}$. Since the covariance between two random variables is bounded by the product of the standard deviations, the maximal contribution of firms idiosyncratic shocks to aggregate credit cyclicality will also decay at rate $1/\sqrt{N}$. To simplify the analysis, consider

[29] Data on GDP comes from the French National Statistics Institute (Insee).

the extreme example of an equal repartition of credit between firms (i.e. $w_{ft} = 1/N$). In this case, we would have

$$| \, Share(Firm_q, \Delta GDP_{q-k}) \, | \leq \frac{\sigma}{\sigma^{Credit}} \cdot \frac{1}{\sqrt{N}}$$

To get an estimate of σ, we calculate for each time period the cross-sectional standard deviation of the firm shocks and take the average over time. We find σ equal to 76%, set k equal to 4 quarters and take N equal to the average number of firms per quarter (approximately 75,000 firms). We obtain that if credit were equally distributed between borrowers, the contribution of idiosyncratic shocks on the firm side would not exceed 8% of the observed comovement between the evolution of credit and GDP growth.

4.2 Dissecting the cyclicality of aggregate credit

Figure 8d displays the time series of the growth rate of long-term credit (aggregated over all the bank-firm relationships in the connected set) and of the real GDP of the non-financial sector. We choose the value of k, the lag of the GDP growth rate, to be equal to one year (4 quarters) so as to maximize the observed correlation (49.4%) with the growth rate of credit.[30] The statistical relationship between the two series is clearly visible on the graph: one year after a decrease in real GDP, credit appears to fall in sizeable proportions.

[Insert table 5 here]

Table 5 gives the results of the decomposition of the cyclicality of aggregate credit given by equation 7. Following Di Giovanni, Levchenko and Mejean (2014), we compute standard errors using a block bootstrap procedure to account for the small sample size (68 observations) and the presence of serial correlation in the residuals.[31] The correlation between GDP and credit is only significant at 5% for k between 3 and 5 quarters and decreases in magnitude after $k = 4$. Strikingly, only firm individual shocks appear to be significantly related to the business cycle. About 80% of the total correlation with lag 4 of GDP is attributable to $Firm_q$, meaning that the

[30] Correlation with leads of GDP are either non-significantly different from zero or negative in some cases. We chose therefore to focus on lags of GDP for the sake of clarity.

[31] Our moving block bootstrap procedure (Kunsch, 1989) is based on 1000 replications and a block length of 4 observations.

importance of firm-specific variations is about 10 times higher than it would have been in the absence of borrower granularity.

By contrast, bank idiosyncratic shocks $Bank_q$ appear to play a limited role in the cyclicality of aggregate credit. This in itself should not be taken a sign that bank granular shocks do not affect real activity.[32] Our results suggest, however, that the credit cycle does not find its origins in shocks affecting homogeneously the lending relationships of large banks. The heterogeneity in loan size within the pool of borrowers is actually so large that most of the correlation between credit and GDP can be traced to shocks affecting individual borrowers.

We explore further the role of granular borrowers by breaking down the weighted sum of firm components $Firm_q$ by borrower loan size. Consider a partition of F_q, the set of firms present at time q, in S subsets F_{1q}, ..., F_{Sq}. For example, one simple partition would consist in dividing F_q in firms in the bottom 99% of the credit distribution and firms in the top 1%. The firm component can be in this line decomposed as

$$Firm_q = \sum_{s=1}^{S} \mu_{sq} \left(\sum_{f \in F_{sq}} \nu_{fsq}(\hat{\alpha}_{fq} - \bar{\alpha}_q) \right) = \sum_{s=1}^{S} \mu_{sq} Firm_q^s$$

where μ_{sq} denotes the share of subset s in aggregate credit at time q and ν_{fsq} the weight of firm f in subset s. This decomposition, however, is impractical for the decomposition of the correlation of credit with GDP as weights μ_{sq} also vary with time. We define to that end an alternative firm component, $Firm_q^*$ by replacing weights μ_{sq} with their average over time. As a result, we are able to further decompose the aggregate impact of firm-level shocks into the weighted sum of each subset's own contribution:

$$\text{Corr}(Firm_q^*, \Delta GDP_{q-k}) = \sum_{s=1}^{S} \bar{\mu}_s \rho_s \text{Corr}(Firm_q^s, \Delta GDP_{q-k}) \tag{8}$$

where ρ_s is the ratio of the standard deviation of $Firm_q^s$ to the standard deviation of $Firm_q^*$.

[Insert table 6 here]

Table 6 presents the results of the decomposition obtained with equation 8. Column 1 first

[32] Amiti and Weinstein (2018) and Alfaro, García-Santana and Moral-Benito (2019) show that bank shocks have a sizeable impact on firm-level and aggregate real variables such as investment or employment.

shows that replacing $Firm_q$ with $Firm_q^*$ does not alter much the correlations with the different lags of GDP. The weighted sum of idiosyncratic shocks to firms below the 95th percentile of the credit distribution $Firm_q^{0-95}$ appears to be significantly correlated to GDP for all values of k, although the coefficient is only significant at the 10% level for contemporaneous GDP. On the other hand, its contribution to the cyclicality of aggregate credit does not exceed 11% for the lag 4 of GDP, which is somewhat consistent with the benchmark given in section 4.1. By comparison, individual shocks to firms in the top 100 of borrowers represent 55% of the correlation.

Perhaps more importantly, we can see that the top 100 borrowers actually impose its structure of cyclicality to the aggregate time series. While $Firm_q^{0-95}$ comoves with contemporaneous GDP, the correlation becomes not significant once the rest of the distribution is included. The cyclicality of the firm component increases sharply when considering lagged values of GDP, this surge being largely driven by the top 100 borrowers. To a large extent, therefore, relying on aggregate data to analyze the evolution of credit over the business cycle amounts to focusing on the microeconomic behavior of a restricted set of large borrowers. As the latter are presumably financially unconstrained, inferring the intensity of financial frictions in the economy by matching aggregate credit fluctuations is likely to lead to biased conclusions.

[Insert figure 10 here]

Figure 10 gives a graphical illustration of the role of the loan distribution. We compare the contribution of each size bucket to total credit in volume (dark grey) and to the correlation of firm idiosyncratic shocks to GDP, Corr($Firm_q^*, \Delta GDP_{q-4}$) (light grey). Firms below the 95th percentile of the credit distribution, for instance, represent on average 31% of total credit and 14% of the correlation. Strikingly, the weight in total credit increases much faster than the contribution to cyclicality as we progressively add firms from the right tail of the distribution. This graph shows that granularity is not a pure size effect: the influence of shocks affecting the top 100 borrowers is disproportionate compared to their weight in total credit.

The weights $\bar{\mu}_s \rho_s$ present in equation 8 allows to rationalize the over-representation of granular borrowers. Imagine that we progressively zoom in on the right tail of distribution, by defining s as the top 10,000, then 1,000, and eventually 100 borrowers for instance. As we focus on a smaller sample, the variance of the weighted sum of idiosyncratic shocks will increase, hence a higher variance share ρ_s. In normal-tailed distributions, $\bar{\mu}_s$ should however become very small, leading in total to a negligible contribution of top borrowers. The slow convergence of $\bar{\mu}_s$ towards zero as s moves to the top of the credit distribution makes shocks to granular borrowers exert a disproportionate influence on aggregate credit.

4.3 Granular shocks and granular trends

Because the individual components we estimate are expressed as deviations from a common cross-sectional median or alternatively mean, we sometimes refer to these components as idiosyncratic shocks. On the other hand, these shocks are not necessarily independent from each other: the fact that to a large extent the cyclicality of aggregate credit can be traced back to the top 100 borrowers may reflect mechanisms that are specific to this type of firms. For example, large borrowers may be able to react relatively more to investment opportunities because they have easier access to alternative sources of external financing, or because they tend to be less financially constrained. Such mechanisms would induce positive pairwise correlation between the individual shocks of the granular borrowers, which in turn would contribute to increase the variance of the aggregate granular component $Firm_q^{top100}$ and the magnitude of its comovement with the business cycle.

To measure this pairwise correlation we first define for each granular borrower i the granular component that one would observe in the absence of this firm:

$$Firm_q^{top100-i} = \sum_{f \in F_{top100-i,q}} \frac{\nu_{fq}}{1 - \nu_{iq}} \tilde{\alpha}_{fq}$$

Then we regress $Firm_q^{top100-i}$ on $\tilde{\alpha}_{iq}$ and a set of firm fixed effects. The estimated coefficient is equal to 0.056 and significant at the 1% level.[33] Hence, the correlation between shocks is positive but small: one may be tempted to conclude that "at the firm level, most variation is idiosyncratic" (Gabaix, 2011).

[33]The fixed-effect regression implies that the estimated coefficient is a weighted sum of $Cov(Firm_q^{top100-i}, \tilde{\alpha}_{iq})/Var(\tilde{\alpha}_{iq})$. Under the assumption that standard deviations and pairwise correlations are constant across firms the coefficient we obtain is therefore an estimation of $Corr(\tilde{\alpha}_{iq}, \tilde{\alpha}_{jq})$. The standard errors are clustered at the firm level. We do not report the results of the regression in order to save some space.

However, it may be the case that even a small level of correlation between firms is enough to have a sizeable impact on aggregate fluctuations. To understand why, assume that individual standard deviations σ_g and pairwise correlations $corr_g$ are constant across granular borrowers. The variance of $Firm_q^{top100}$ writes

$$
\begin{aligned}
Var\left(Firm_q^{top100}\right) &= \sigma_g^2\left(h_g + corr_g - h_g \cdot corr_g\right) \\
&\approx \sigma_g^2\left(h_g + corr_g\right)
\end{aligned}
$$

where h_g denotes the Herfindhal of the repartition of credit *within* the set of granular borrowers. The first order approximation holds as long as both the pairwise correlation and the Herfindhal index are close to zero.[34] It implies that the relative contributions of concentration and correlation to the standard deviation of the aggregate component are directly related to their relative magnitudes. As a counterfactual exercise, we estimate the comovement of $Firm_q^*$ with the business cycle that one would obtain by setting $corr_g$ to zero.[35] We find that the contribution of $Firm_q^{top100}$ would decrease from 0.270 to 0.128, which in turn would lower by almost 40% the covariance between $Firm_q^*$ and one-year lag GDP, everything else equal. It suggests that mechanisms specific to granular borrowers and inducing a positive correlation between their individual shocks contribute to amplifying the cyclicality of the granular component. It is then the granular structure of the loan distribution, i.e the large share of the top 100 firms in total credit, which enables these mechanisms to impact aggregate cyclicality.

4.4 Robustness checks

We assess in this subsection the sensitivity of our findings to the specification of the methodology. In table 7, we report for each specification the decomposition of the correlation between the credit growth rate and the four-quarter lag of the GDP growth rate. The top panel displays the decomposition obtained with the baseline specification. Remember that the

[34] Gabaix (2011) reports that the median of the herfindhals generated by Monte Carlo simulations for a highly granular economy (Zipf distribution) with 10^6 firms is equal to $(0.12)^2 = 0.0144$, while he finds for the largest US firms that the correlation between the growth rates of sales is close to 0.07.

[35] To measure σ_g we calculate the cross sectional variance among the top 100 firms and take the square root of the time average. We measure h_g as the average over time of the Herfindhal index for the set of granular borrowers. The counterfactual standard deviation is then equal to $\sigma_g\sqrt{h_g}$.

baseline decomposition is obtained by (i) setting the median of the shocks at zero, (ii) keeping only firms with two banking relationships in a given quarter and (iii) keeping only banks with at least 100 relationships in a given quarter.

[Insert table 7 here]

Defining both bank-specific and firm-specific components as deviations to the mean (instead of the median) leads to slightly different results (see second panel of table 7). The contribution of $Firm_q$ to the cyclicality of aggregate credit (44%), in particular, is significantly reduced by comparison to the baseline case (80%). The correlations are however imprecisely estimated. Since the behavior of the different components does not appear moreover to be very affected by the choice of the normalization (see figure 8), we favor the results obtained with the deviation to the median in the analysis. Eventually we notice that in the mean normalization case the impact of borrowers individual shocks (although attenuated) remains large, close to the effect of the macro component, and way higher than both the non-granular benchmark and the contribution of bank shocks.

The third panel shows that imposing a minimum number of borrowers by bank of 10 firms do not change much our conclusions. The largest part of the correlation between the credit growth rate and the lagged GDP growth rate (0.553) is still explained by the correlation of the firm component with the GDP growth rate (0.381). Symmetrically, increasing the minimum required number of banking relationships for firms to 4 banks decreases the number of multiple-bank firms but may improve the precision of estimates of the firm components. As a matter of fact, our matched bank-firm loan dataset can be seen as a bipartite graph, in which interactions occur between two type of individuals but not within each type. Jochmans and Weidner (2019) suggest that the sparsity of the underlying network affects the accuracy with which the fixed effects can be estimated. They show that the second smallest eigenvalue of the network's normalized Laplacian matrix is a measure of global connectivity of the graph, and that the upper bounds on the variances of the estimated fixed effects are smaller when this measure is large. Restricting the dataset to firms borrowing from at least 4 banks strongly increases the corresponding eigenvalue, from 0.08 in our main specification to 0.15.[36] Still, the correlation of aggregate credit to the

[36]We compute these eigenvalues for the data corresponding to 2009-Q2. Because we perform a WLS estimation,

business cycle remains primarily explained by firm individual components, which suggests that the precision of the estimated fixed effects is unlikely to drive our results.

[Insert table 8 here]

Foreign banks might be less sensitive to the French business cycle, which may lower the cyclicality of aggregate credit. Panel 2 of table 8 shows that it is not the case: if anything, the correlation of aggregate credit to the business cycle is slightly lower when excluding foreign banks. Panel 3 then displays the results of the estimations obtained when excluding the housing sector. The housing sector represents a disproportionate part of long-term credit (see subsection 2.1). Since real estate firms financing decisions are determined by very specific mechanisms, it is interesting to assess how our results change after excluding them from the data set.[37] We find that the decomposition of the cyclicality of aggregate credit remains very similar to the baseline results. This suggests that the presence of the housing sector does not drive in itself our findings.

In an other robustness exercise, we consolidate banks at the group-level. An immediate drawback of this approach is that it mechanically reduces the number of multiple-bank firms. However, as banking groups are less likely to be specialized in some sector of activities or geographical markets (the French banking sector is dominated by so-called "universal" banks), firms might be more able to substitute credit between lenders. This may lead to a better identification of both bank and firm fixed effects in equation 2, which, in turn, could affect the decomposition of the cyclicality of aggregate credit. Panel 4 shows however that our results are not modified when banks are consolidated at a higher degree of aggregation.

A potential explanation of the fact that bank idiosyncratic components do not contribute much to the cyclicality of aggregate credit is that we do not allow for enough heterogeneity in the behavior of banks. Bank lending behavior might indeed vary between different groups of borrowers. Our specification may in that sense impose too much constraints in that it assumes an

the underlying network is a weighted graph, in which the weight of the edge connecting bank b to firm f is equal to the average exposure between $q-4$ and q. The global connectivity is even more improved when considering the (unweighted) graph associated to the OLS estimation, from 0.06 to 0.23.

[37] In particular, real estate firms are not scored by the Bank of France. A significant fraction of real estate firms are created to isolate and regroup the real estate assets of business groups and as such do not generate any cash-flows. Traditional financial analysis does not apply for this type of firms, hence the absence of credit score.

homogeneous bank component. In particular, if banking lending behavior depends on the loan size of the borrower, the firm aggregate component $Firm_q$ might erroneously capture some part of the variation of aggregate credit that should in theory be attributed to $Bank_q$. We use therefore a statistical rule to break down banks in sub-units. A borrower is classified as being small (large) if it borrows less (more) than the bank average. We then break each bank in a "retail" bank (which lends to small borrowers) and a "wholesale" bank (which lends to large ones) and rerun the estimations with twice as much bank components as in the baseline specification. We find that allowing heterogeneous bank idiosyncratic shocks does not significantly alter our results.

Measuring the change in lending by mid-point growth rates enables us to account for both the formation and the termination of firm-bank relationships. On the other hand, it implies that the distribution of our dependent variable displays mass points at 2 and -2, which might affect the econometric estimation. Therefore we restrict our initial dataset to ongoing relationships and discard both terminating and new loans. Under such specification our decomposition focuses on the intensive margin of credit growth. One may wonder to which extent the entries and exits of loan relationships impact the observed comovement between total credit and GDP. Panel 6 of table 8 shows that removing the extensive margin tends to lower the correlation of aggregate credit to the business cycle. Although the macro component now contributes negatively to our measure of cyclicality, we still find that bank shocks play a very limited role while the firm component drives to a large extent the correlation.

[Insert table 9 here]

In order to rule out sectoral or geographical variations from $Firm_q$, we use as alternative definition of idiosyncratic shocks the deviation to the *conditional* median. We successively take the median by industry, credit score category, size category, administrative division ("département") and by the category defined by the intersection of all the precedent variables ("cell"). Table 9 reports the contemporaneous and lagged correlations between the GDP growth rate and the different time series of $Firm_q$ obtained with these definitions. The correlations of the firm component with the one-year lag of the GDP growth rate are all positive and significant and represent 62% to 80% of the aggregate correlation.

[Insert table 10 here]

The estimation of equation 2 with weighted least squares gives by construction more importance to firms and banks with larger outstanding volumes of credit. One may therefore suspect that the importance of firm shocks in the aggregate fluctuations of credit mechanically derives from the estimation method. In table 10, we present the results obtained by estimating equation with ordinary least squares instead of WLS. A drawback of this specification is that the weighted sum of residuals does not cancel out in the aggregate: we add therefore a fourth term to the decomposition (match-specific component) that we name $Match_q$. The resulting decomposition is close to the one obtained with the baseline specification. The correlation between aggregate credit and GDP, when high and significant, is mainly driven by the firm component. The contribution of the match-specific component is large when focusing on contemporaneous GDP, but then slowly fades out as we consider lagged time series.

By construction, the decomposition of the cyclicality of aggregate credit excludes single-bank firms. In a last robustness exercise, we attempt to assess the relative contributions of the different components when including the entire population of borrowers. To that end, we first compute the mid-point growth rate $\Delta Credit_q^{agg}$ of aggregate long-term credit using the data set we obtained before restricting it to the connected set. This time series therefore includes credit borrowed by single-bank firms. We then regress $\Delta Credit_q^{agg}$ on the time series $Macro_q$, $Bank_q$ and $Firm_q$ obtained from equation 6. Table 11 displays the results obtained with the baseline specification and by defining idiosyncratic shocks as the deviation to the mean.[38]

[Insert table 11 here]

We use the estimated coefficients to compute the contribution of each of the three terms to the correlation of $\Delta Credit_q^{agg}$ with ΔGDP_{q-4}. The total correlation is given in the bottom of the table and is equal to 0.601. The respective contributions of each component are displayed below the standard errors of the coefficients. The decomposition now includes a fourth element,

[38] Note that if $\Delta Credit_q^{agg}$ was exactly equal to $\Delta Credit_q$, all the coefficients would be equal to one. Interestingly, we find for both specifications that the coefficients for $Macro_q$ and $Bank_q$ are not statistically different from one. The $Firm_q$ coefficient appears by contrast to be lower than one. Also notice that for both normalizations the R2 is high, respectively equal to 91.3 and 93.4%. Our aggregate time series estimated on the set of multi-bank firms are therefore able to capture the bulk of aggregate credit fluctuations, even when including single-bank firms.

corresponding to the comovement of the estimated error term with the business cycle and displayed in the "Residual" line. We find that in our baseline specification firm-specific shocks would remain a first order determinant of the cyclicality of aggregate credit (58% of the total correlation). In the specification with the mean, $Firm_q$ becomes the second contributing factor behind $Macro_q$ but still explains 29% of the link between credit and the business cycle.

5 Bank liquidity risk and borrower concentration

5.1 Can banks pool borrower idiosyncratic risk?

We turn in this section to the implications of the presence of granular borrowers on bank-level variations of undrawn credit lines. Banks' ability to provide liquidity on demand through credit lines or deposits will depend on the distribution of liquidity outflows (Holmström and Tirole, 1998; Kashyap, Rajan and Stein, 2002). In particular, if banks are unable to pool the idiosyncratic risk of their borrowers, they may have to hoard more liquid assets to hedge against negative shocks affecting individual borrowers.

We obtain with our decomposition the following equality for the evolution of undrawn credit lines at the bank-level:

$$\begin{aligned} \Delta Credit_{bq} &= Macro_q + \tilde{\beta}_{bq} + \sum w(b)_{fq}\tilde{\alpha}_{fq} \\ &= Macro_q + Bank_{bq} + Firm_{bq} \end{aligned} \tag{9}$$

It is easy to see following the logic of section 4.1 that a bank's exposure to borrower idiosyncratic risk will depend on whether the distribution of its borrower base $w(b)$ is fat-tailed or not. Given the extreme degree of concentration of credit lines (see section 2.2), there are reasons to believe that the ability of banks to pool idiosyncratic risk is actually limited.

[Insert table 12 here]

We have to slightly adjust our methodology to quantify the importance of idiosyncratic risk in banks' credit line portfolios. First, since the portfolio of borrowers is likely to be managed at the level of the group, we consolidate banks by banking group in the remainder of the analysis. Second, we focus our study on the six largest banking groups.[39] This choice allows first to keep only banks with very large borrower bases for which the law of large numbers should apply in the absence of granular borrowers. Moreover, the selected banks are present during the whole time period, which greatly simplifies the analysis in the following. Third, because of a change in the treatment of short-term loans in the credit registry, the analysis of credit lines at the firm-level is not reliable around 2006. We choose therefore to focus on the period starting from 2008-Q1 and ending in 2016-Q4.

We incorporate these changes into our estimation procedure to get the firm, bank and macro components of bank-level variations of credit lines. In order to quantify the role of borrower individual shocks, we compute for each bank the variance of the counterfactual time series of credit lines variations if $Firm_{bq}$ were constantly equal to zero. In a second step, we compute the average across banks of the resulting variances that we compare to the average variance of the original $\Delta Credit_{bq}$ time series.[40] We do the same counterfactual exercise by setting successively $Macro_q$, $Bank_{bq}$ and the weighted sum of firm components for the top 10 borrowers $Firm_{bq}^{Top\ 10}$ to zero in equation 9.[41] The estimated counterfactual variances are displayed in table 12.

From equation 9, it is apparent that muting borrower idiosyncratic shocks will have a large effect on bank-level credit lines variance if (i) firm-specific shocks are very volatile, (ii) borrower portfolios are not diversified, (iii) the weighted sum of borrower idiosyncratic shocks is positively correlated with the other components of the decomposition.

Our findings suggest that banks are substantially exposed to borrower idiosyncratic risk. Without borrower idiosyncratic shocks, bank-level variance of credit lines is reduced by 31%. The effect is larger than for the bank and macro components (respectively 29% and 9%). Muting the individual shocks of the ten largest borrowers reduces the variance even more (44%). This is expected as $Firm_{bq}^{Top\ 10}$ is likely to be more volatile than $Firm_{bq}$.

One may fear that the large role of borrower risk in our findings could be an artifact of our

[39]The six largest banking groups account in our sample for 84% of lending to firms.

[40]We build here on the methodology used by Kramarz, Martin and Mejean (2019) to estimate the level of under-diversification of French exporters.

[41]Note that this counterfactual exercises take the weights of firms in the bank credit lines portfolio as given. In practice, however, the weights are themselves a function of the past values of the different components. We chose to abstract from these indirect effects to keep the intuition simple.

definition of idiosyncratic shocks. Since we look at deviations from a common macro trend, our shocks could actually incorporate sectoral or geographical factors. We therefore proceed to the same exercise using the deviation to the median by cell as a more demanding definition of idiosyncratic shocks (a cell being the intersection of a sector, a credit risk category, a size category and a geographical zone; see section 4.4). As expected, muting borrower idiosyncratic shocks reduces less the variance of credit lines (19%). By contrast, the importance of macro shocks becomes larger (31%). Still, the role of borrower idiosyncratic risk on credit line variations appears to be far from negligible. Overall, our results strongly supports the idea that on average, banks are not fully able to diversify away the idiosyncratic risk of borrowers in their credit lines portfolio.

5.2 Borrower concentration as a source of synchronization

The previous subsection established that banks are exposed to borrower idiosyncratic risk. We turn now to the implications of this additional source of risk for aggregate liquidity flows. There are indeed several reasons to believe that borrower risk may be correlated across banks. Remember first that by construction, firms in our sample borrow from multiple banks. The presence of granular borrowers in several credit lines portfolios could therefore lead credit lines variations to be synchronized across banks. Second, input-output linkages can make idiosyncratic shocks propagate across the production network. A supplier hit by a natural disaster, for instance, is likely to draw on its credit line to make up for the decrease in production. In turn, the customers of the firm may themselves need to rely on their credit lines to handle the disruption of their supply chain.[42]

[Insert table 13 here]

We test this hypothesis by decomposing the variance of aggregate borrower risk. To simplify the analysis, we set bank weights w_b equal to their time average in the computation of the time

[42] For evidence of propagation of idiosyncratic shocks along the production network, see Barrot and Sauvagnat (2016).

series $Firm^*_q$. This allows us to write

$$
\begin{aligned}
Var(Firm^*_q) &= \sum_b w_b^2 Var(Firm^*_{bq}) + \sum_b \sum_{c \neq b} w_b w_c Cov(Firm^*_{bq}, Firm^*_{cq}) \\
&= Direct_q + Link_q
\end{aligned}
\tag{10}
$$

Equation 10 states that the aggregate variance of borrower idiosyncratic shocks is the sum of (i) $Direct_q$, the weighted sum of bank-level variances and (ii) $Link_q$, the weighted sum of the covariances of borrower idiosyncratic shocks between banks. The $Link_q$ component reflects the fact that different banks have common borrowers and are therefore subject to common shocks, but it may also be driven by pairwise correlations between the firms that constitute banks' borrower bases. To disentangle both mechanisms we measure the share of $Link_q$ which is driven by common shocks :

$$
Common_q = \sum_b \sum_{c \neq b} w_b w_c \left(\sum_{R_{bcq}} w(b)_{fq} w(c)_{fq} Var(\tilde{\alpha}_{fq}) \right)
$$

where R_{bcq} denotes the set of firms borrowing from both banks b and c at time q. Since the weights $w(b)_{fq}$ and $w(c)_{fq}$ differ over time, we report the values of $Common_q$ averaged across the sample time periods.

Table 13 presents the results of the decomposition obtained with our standard definition of idiosyncratic shocks and with the deviation to the median by cell. The variance of borrower idiosyncratic shocks is large (21% to 34%) compared to an overall variance of credit lines of 41%. As expected, the variance of idiosyncratic shocks is reduced when using the median by cell but still amounts to more than half of the variance of credit lines.

Importantly, we observe in both specifications that the contribution of bank linkages $Link_q$ far exceeds the sum of bank-level volatilies $Direct_q$, the latter representing less than 25% of $Var(Firm^*_q)$. The contribution of $Common_q$ is even larger and exceeds in both cases the variance of the aggregate firm component. This result highlights that the concentration of banks borrower bases is a source of synchronization for the banking system as it makes credit lines takedowns (i) less diversifiable and (ii) more correlated between banks.

6 Conclusion

Using a data set covering the quasi universe of firm-bank relationships in France for the period 1999-2016, we document that the distribution of borrowers is fat-tailed, a necessary condition for borrower idiosyncratic shocks to matter for aggregate fluctuations. We quantify the role of microeconomic shocks affecting firms by designing an exact, empirically tractable decomposition of credit variations into a lender, borrower and macro components at any level of aggregation.

Our findings indicate first that the comovement of aggregate credit with the business cycle, a key moment in macro-finance, is largely determined by the behavior of granular borrowers. It implies that any analysis of financial frictions relying on the cyclicality of aggregate credit is in effect based on the microeconomic behavior of firms that are likely to have extensive access to credit. It also suggests that at the macro level, changes in the financing policy of large firms, for instance to adapt to changes in investment opportunities, dominate shocks that are transmitted through bank-level lending variations or through credit frictions affecting small, constrained firms. Second, we find that the under-diversification of borrower bases makes credit line takedowns less diversifiable across borrowers and more correlated across banks. The resulting synchronization largely drives the volatility of aggregate liquidity flows.

While our paper documents the implications of the presence of granular borrowers, it is silent on the reasons leading to such high degrees of credit concentration. What are the costs of diversifying the base of borrowers? Does the funding structure of banks, and in particular their access to a stable base of deposits, play a role in determining the concentration of their loan portfolio? To which extent these granular borrowers rely on alternative sources of financing over the cycle? Answering those questions would help understanding the sources of the exposure of banks and ultimately of the aggregate credit market to borrower idiosyncratic risk.

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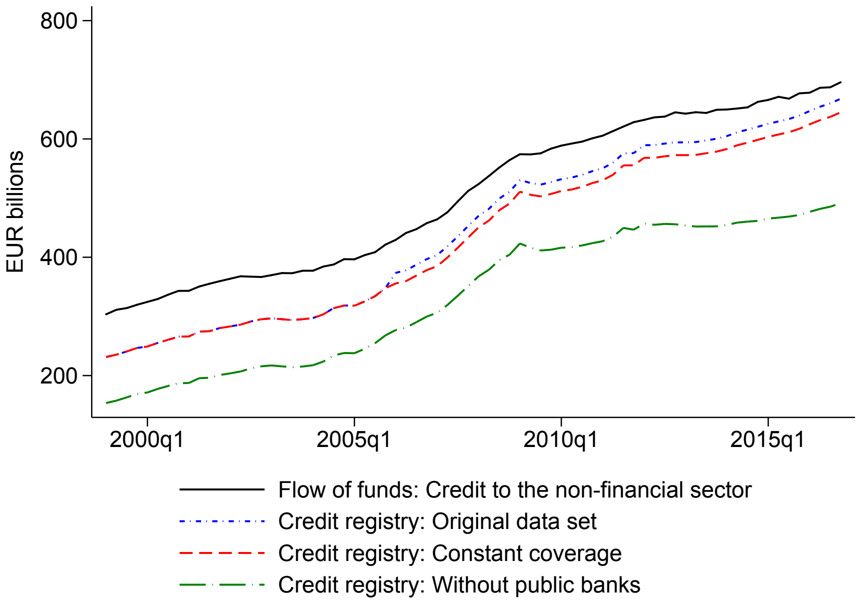
Appendix A Tables and figures

Figure 1: Coverage of the credit registry.



The graph compares the time series of aggregate long-term credit (defined as credit with a maturity of more than one year at issuance) obtained from the balance of payments (black line) and from the credit registry. The blue curve presents the time series obtained from the original credit registry. In the second curve, we impose the €75,000 reporting threshold to the entire period so that the coverage of the data set is constant over time. In the green curve, public banks are removed from the aggregation. The coverage of our data set corresponds to this last case.

Table 1: Descriptive statistics: firm-bank level.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
All firms : long-term credit							
Long term credit (EUR Mns)	0.39	4.00	0.00	0.08	0.14	0.26	3924.97
Long term credit (growth rate, %)	4.50	112.89	−200.00	−22.22	−7.33	15.63	200.00
# of banks per firm	1.04	0.66	0.00	1.00	1.00	1.00	57.00
Observations	59,286,238						
Multiple-bank firms: long-term credit							
Long term credit (EUR Mns)	0.82	6.43	0.00	0.08	0.16	0.39	2560.00
Long term credit (growth rate, %)	−0.99	117.73	−200.00	−36.02	−10.11	27.61	200.00
# of banks per firm	2.42	1.12	2.00	2.00	2.00	2.00	57.00
Observations	17,542,781						
All firms: credit lines							
Credit lines (EUR Mns)	0.61	10.95	0.00	0.00	0.02	0.08	4657.50
Credit lines (growth rate, %)	7.78	159.02	−200.00	−200.00	0.00	200.00	200.00
# of banks per firm	0.31	0.60	0.00	0.00	0.00	1.00	43.00
Observations	16,258,331						
Multiple-bank firms: credit lines							
Credit lines (EUR Mns)	2.58	24.20	0.00	0.01	0.07	0.29	4657.50
Credit lines (growth rate, %)	6.15	154.54	−200.00	−182.80	0.00	200.00	200.00
# of banks per firm	2.47	1.44	2.00	2.00	2.00	2.00	43.00
Observations	3,205,012						

Descriptive statistics are given at the level of a firm-bank relationship in a given quarter. The table is divided in four panels. In the first (third) panel, the coverage includes all firm-bank relationships with positive long-term credit (credit lines) exposure at q or $q-4$. In the second (fourth) panel, the coverage includes all firm-bank relationships with positive long-term credit (credit lines) exposure at q or $q-4$ for multiple-bank firms. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Table 2: Descriptive statistics: bank-level.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Long-term credit							
Long term credit (EUR Bns)	0.76	2.45	0.00	0.01	0.10	0.58	42.95
Long term credit (growth rate, %)	3.80	62.07	−200.00	−9.23	5.52	17.21	200.00
Observations	27,447						
Credit lines							
Credit lines (EUR Bns)	0.46	1.74	0.00	0.00	0.04	0.24	25.36
Credit lines (growth rate, %)	9.48	87.90	−200.00	−20.71	5.28	38.62	200.00
Observations	21,421						
Number of firms							
# of firms (long-term credit)	1573.92	4961.58	0.00	2.00	58.00	886.00	82195.00
# of firms (credit lines)	475.89	1448.02	0.00	0.00	8.00	173.00	26140.00
# of multiple-bank firms (long-term credit)	370.00	1149.49	0.00	1.00	24.00	250.00	20102.00
# of multiple-bank firms (credit lines)	93.81	278.49	0.00	0.00	2.00	45.00	4447.00
Observations	34,164						

Descriptive statistics are given at the bank-quarter level. The table is divided in three panels. In the first (second) panel, the coverage includes all bank-quarter observations with positive long-term credit (credit lines) exposure at q or $q-4$. In the third panel, the coverage includes all bank-quarter observations. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

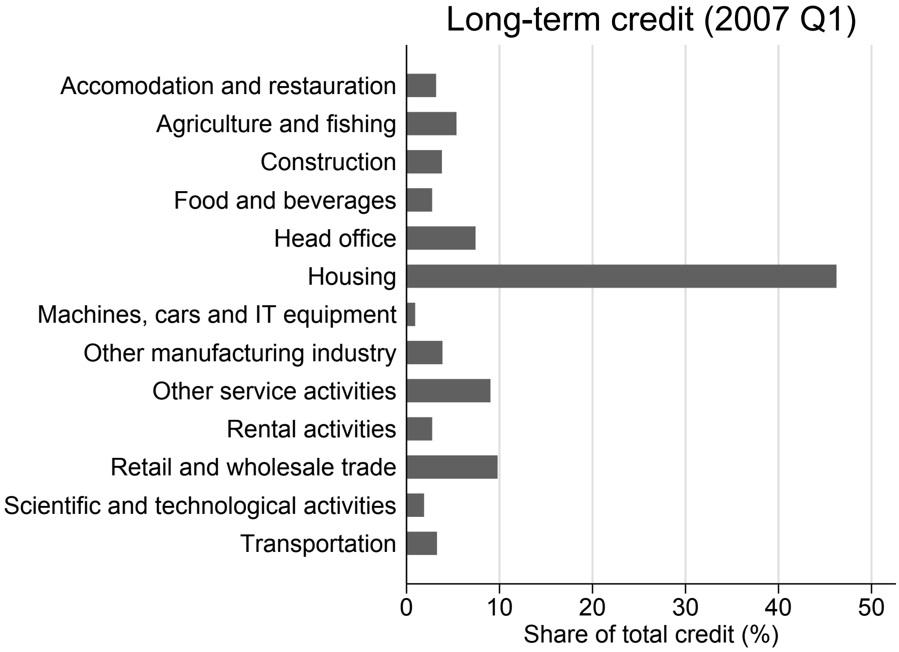
Table 3: Descriptive statistics: aggregate-level.

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Number of banks	502.40	88.77	365.00	421.50	494.00	579.00	666.00
Long-term credit (all firms)							
Long term credit (EUR Bns)	306.54	105.79	140.57	185.47	345.97	409.48	444.89
Long term credit (growth rate, %)	0.07	0.06	−0.02	0.02	0.06	0.11	0.20
Number of firms (in thousands)	681.69	196.06	346.20	493.95	740.58	869.14	937.46
Long-term credit (multiple-bank firms)							
Long term credit (EUR Bns)	152.56	46.78	80.99	100.70	174.92	195.00	209.52
Long term credit (growth rate, %)	0.05	0.08	−0.11	0.01	0.04	0.12	0.23
Number of firms (in thousands)	76.83	20.00	46.72	59.13	78.18	94.52	109.92
Lines of credit (all firms)							
Lines of credit (EUR Bns)	146.13	50.87	57.27	94.90	173.44	186.79	200.29
Lines of credit (growth rate, %)	0.07	0.10	−0.09	0.00	0.06	0.14	0.29
Number of firms (in thousands)	210.99	96.95	59.42	103.82	269.80	297.51	318.07
Lines of credit (multiple-bank firms)							
Lines of credit (EUR Bns)	121.89	40.77	49.04	82.48	141.75	154.48	162.95
Lines of credit (growth rate, %)	0.07	0.10	−0.08	−0.00	0.05	0.12	0.32
Number of firms (in thousands)	19.03	10.36	4.89	7.30	23.52	29.41	31.68
Observations	68						

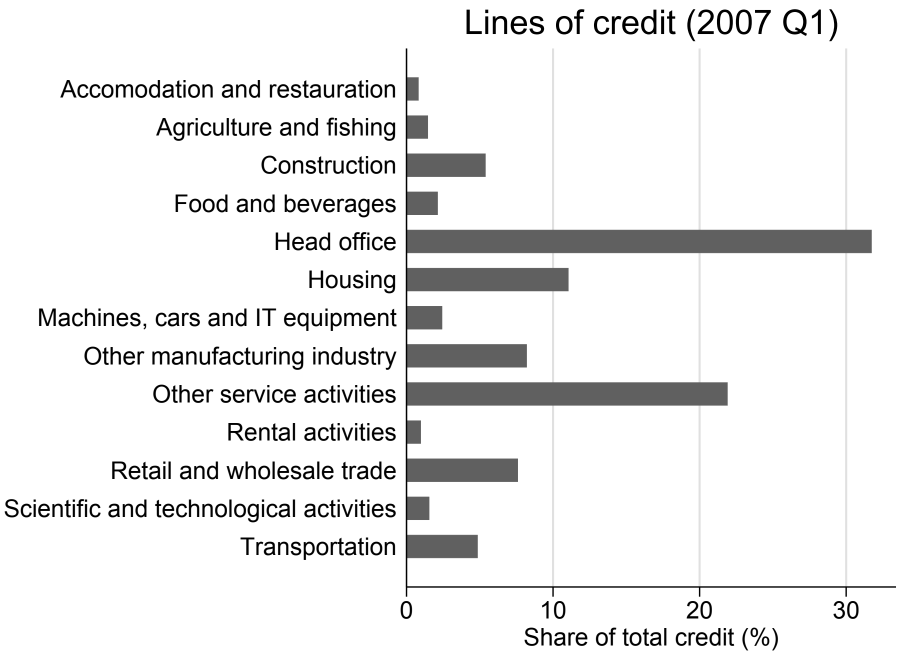
Descriptive statistics are given at the quarter level. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Figure 2: Sectoral repartition of credit (2007).

(a) Long-term credit

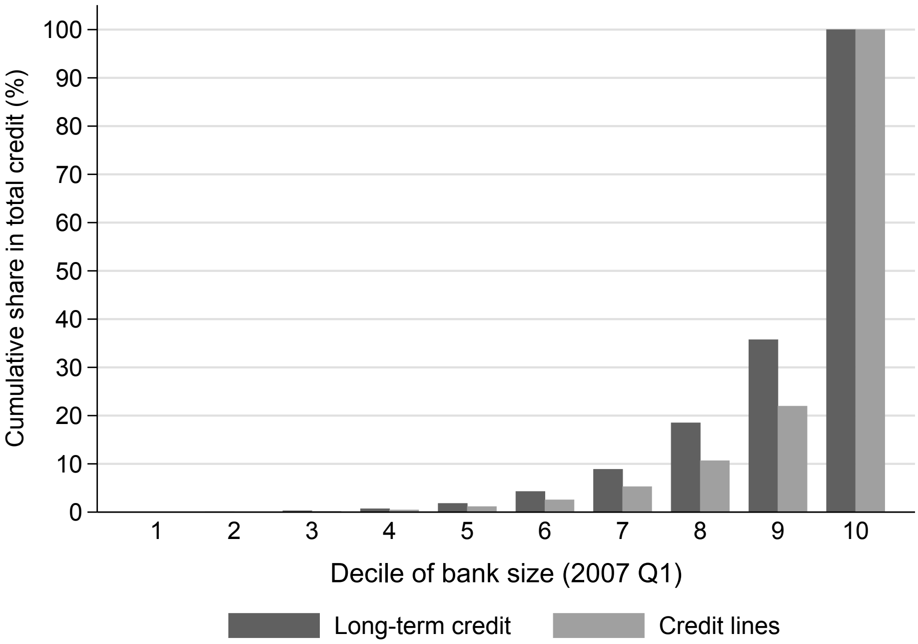


(b) Credit lines



The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

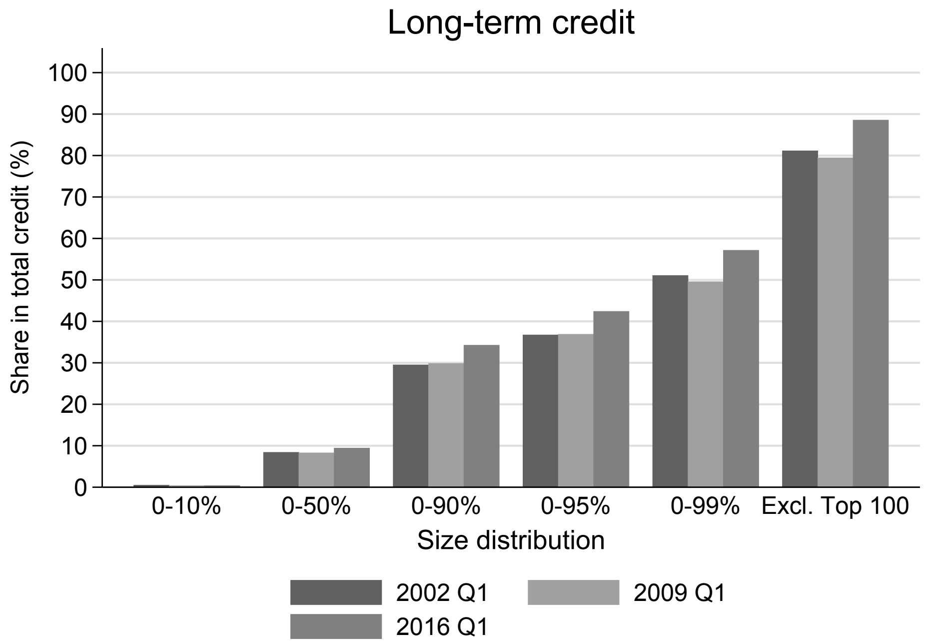
Figure 3: Distribution of credit (banks).



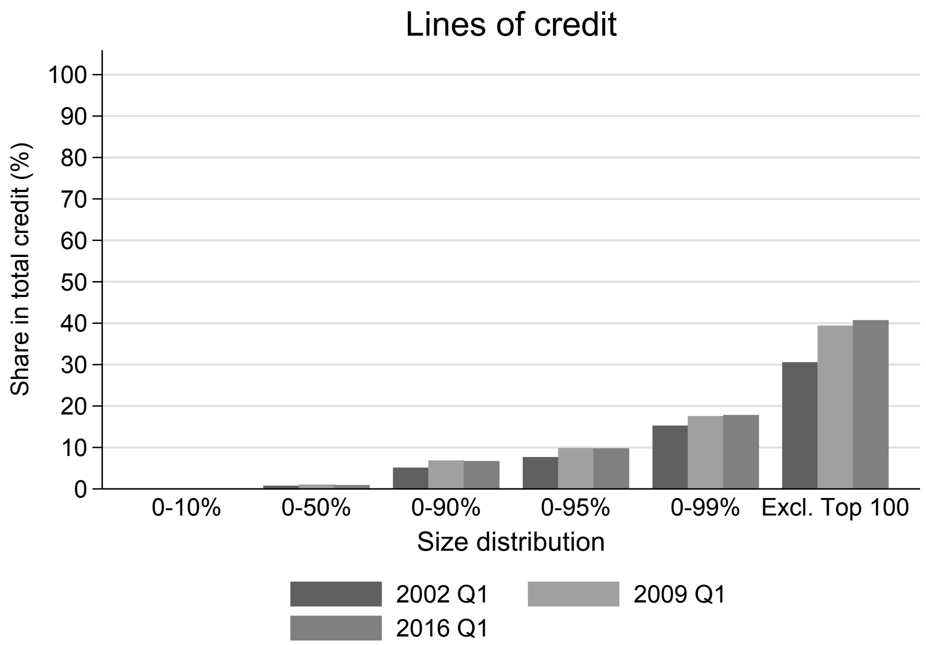
This graph gives the cumulative distribution of long-term credit and credit lines in 2007-Q1. Banks are sorted by deciles of credit exposure (long-term credit and credit lines). The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Figure 4: Distribution of credit (firms).

(a) Long-term credit



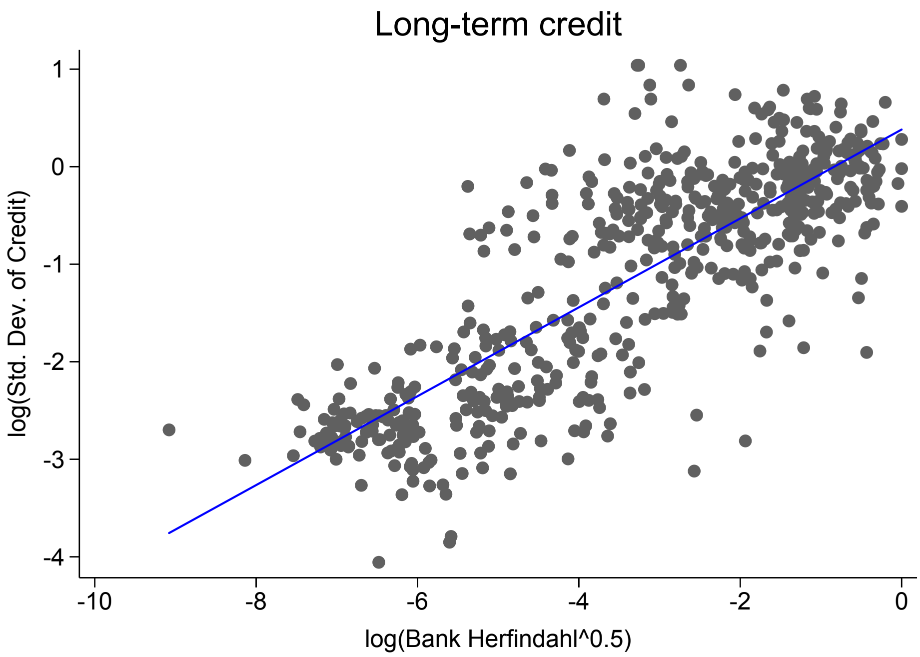
(b) Credit lines



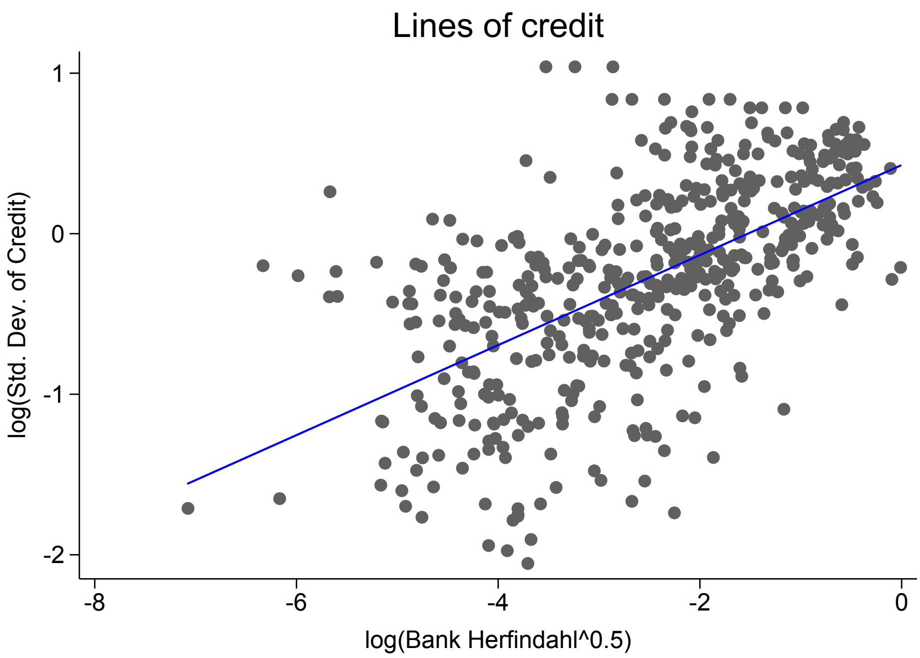
These graphs give the cumulative distribution of long-term credit and undrawn credit lines in 2002-Q1, 2009-Q1 and 2016-Q1. Firms are ranked by percentiles of credit exposure (long-term credit and credit lines). "Excl. Top 100" regroups all firms excluding the top 100 borrowers. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Figure 5: Concentration and volatility.

(a) Long-term credit



(b) Credit lines

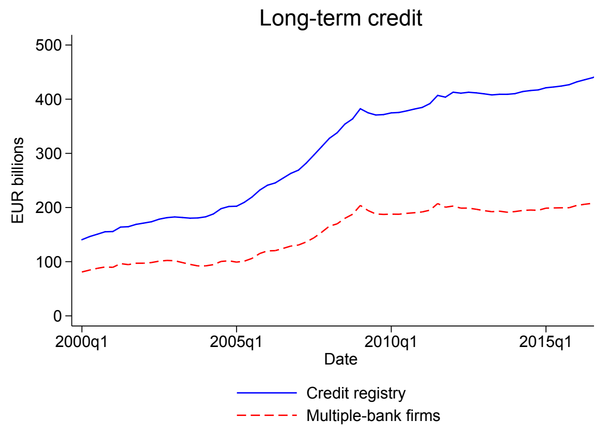


These graphs give a graphical representation of the relationship between banks' borrower portfolio concentration and credit volatility. We compute for each bank the average Herfindahl-Hirschmann index of its loan portfolio as well as the standard deviation of its credit growth. We only keep banks that are present in at least three consecutive years (12 quarters) in the data set. The volatility of credit and the square root of the HHI index are taken in logs. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

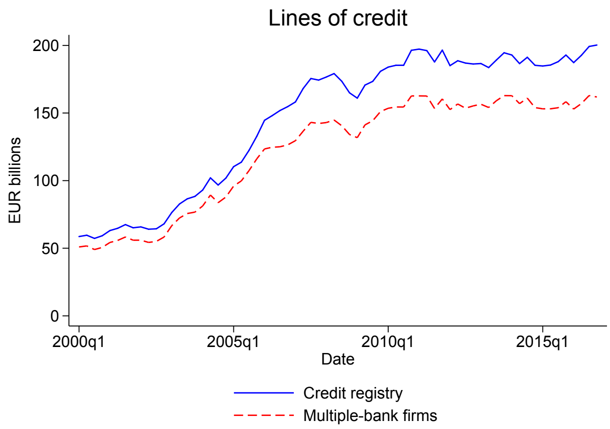
Figure 6: Single- and multiple-bank firms: aggregate variations.

Panel A: Credit level.

(a) Long-term credit

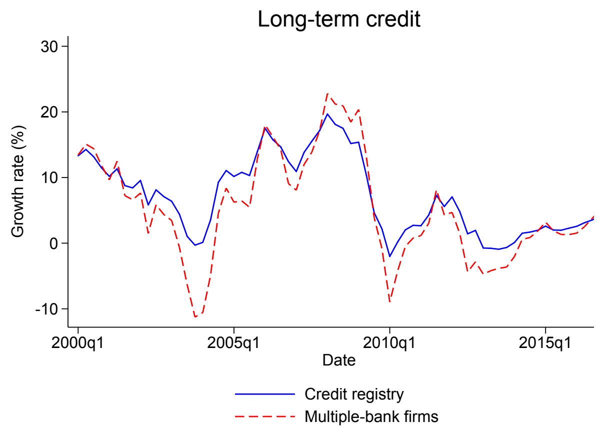


(b) Credit lines

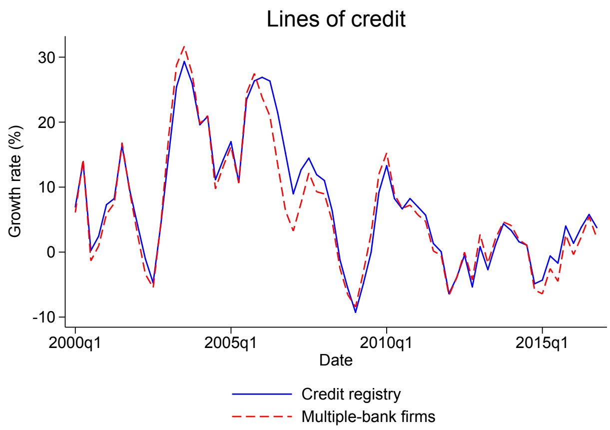


Panel B: Credit growth rates.

(c) Long-term credit



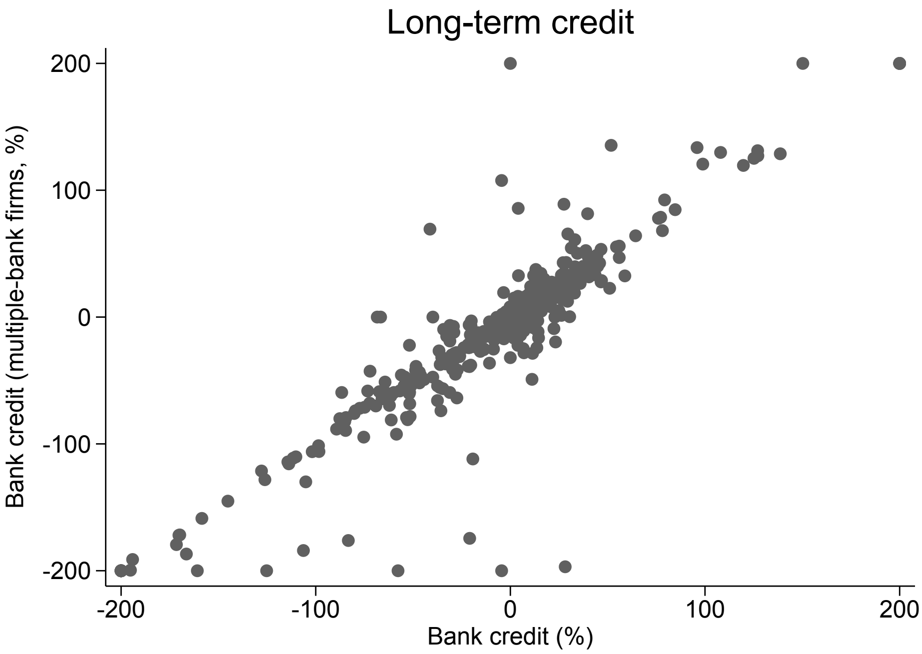
(d) Credit lines



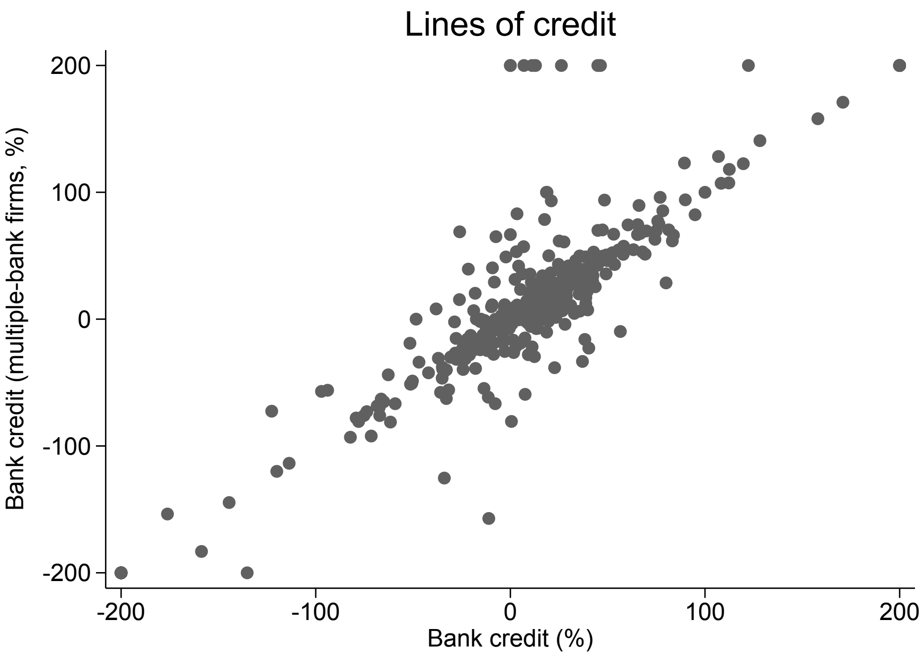
These graphs display the level and the variation of aggregate credit including and excluding single-bank firms. Panel A gives the time series of aggregate credit levels (long-term credit and credit lines) for the whole credit registry (red curve) and for multiple-bank firms (blue curve). Panel B gives the time series of the different credit growth rates. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Figure 7: Single- and multiple-bank firms: bank-level variations.

(a) Long-term credit



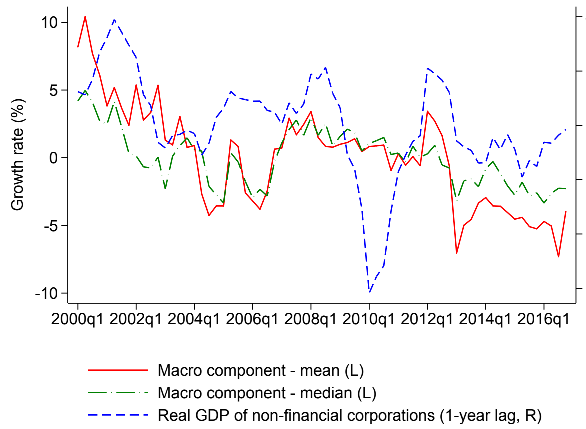
(b) Credit lines



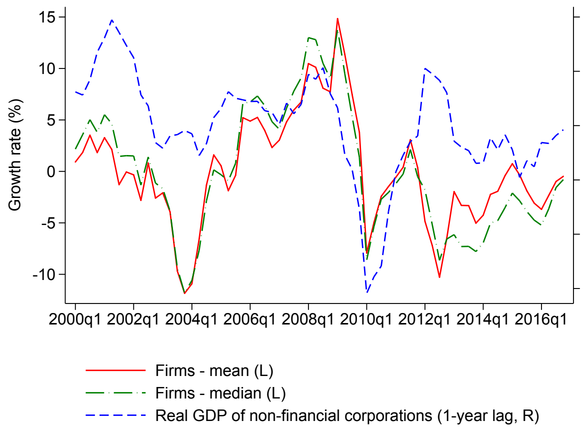
The figures give a graphical representation of the banks' mean credit growth rate including (x-axis) and excluding single-bank firms (y-axis). Credit growth rates are averaged for each bank over all the observations in which the bank is present. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Figure 8: Time series of $Macro_q$, $Firm_q$ and $Bank_q$.

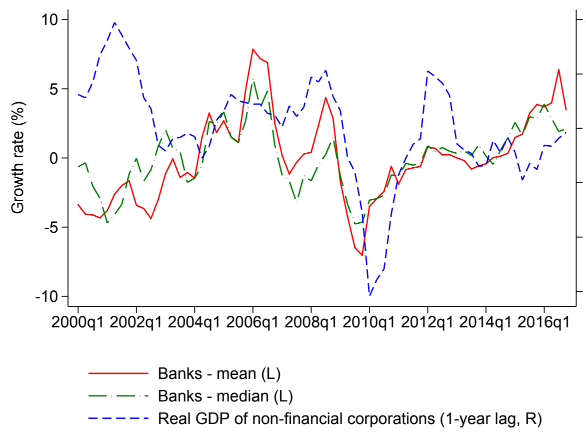
(a) $Macro_q$



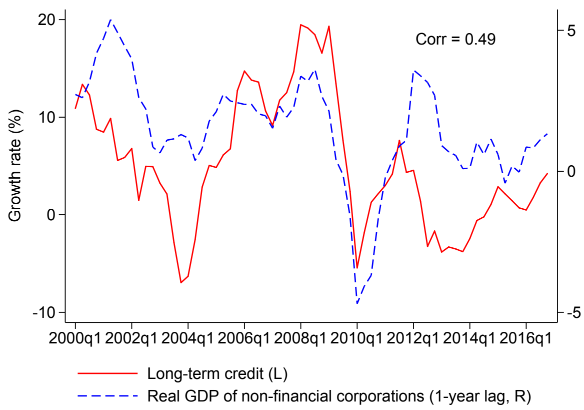
(b) $Firm_q$



(c) $Bank_q$

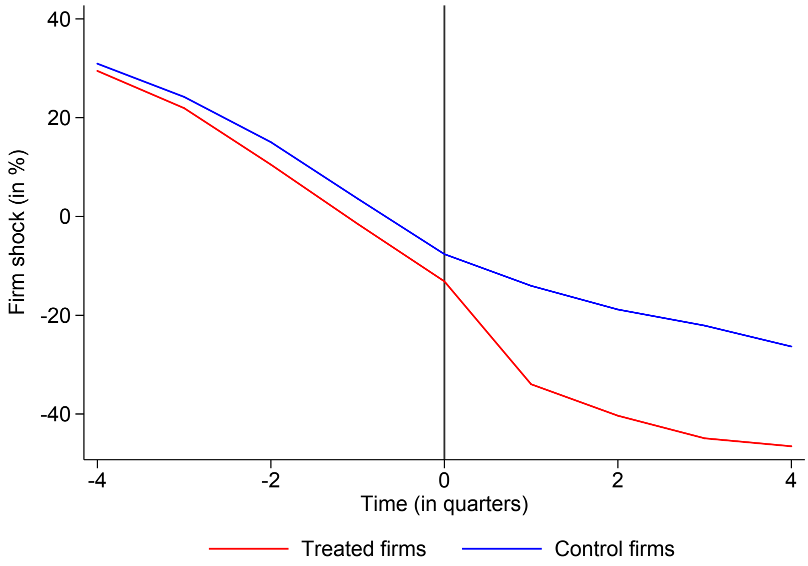


(d) $\Delta Credit_q$



These graphs display the time series of $Macro_q$, $Firm_q$, $Bank_q$ and $\Delta Credit_q$ (left axis) along with the growth rate of the non-financial sector real GDP lagged by one year (right axis). The different components verify the equality $\Delta Credit_q = Macro_q + Firm_q + Bank_q$ where $\Delta Credit_q$ is the growth rate of aggregate long-term credit. Long-term credit is defined as credit with a maturity of more than one year at issuance. Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. In order to use the decomposition displayed above, single-bank firms and banks lending to less than 100 multiple-bank firms are removed from the aggregation. Data on GDP comes from the French National Statistical Institute (Insee).

Figure 9: External validation of the firm components - graph.



This graph presents the evolution of the average firm-specific shock $\hat{\alpha}_{fq} - \bar{\alpha}_q$ four quarters before and after the default event for treated firms and control firms. $\hat{\alpha}_{fq}$ is obtained by performing a WLS regression of the growth rate of long-term credit at the firm-bank level on a firm-time and bank-time fixed effects. $\bar{\alpha}_q$ is the cross-sectional median of $\hat{\alpha}_{fq}$. At $t = 0$, treated firms default on at least one trade bills or enters a collective procedure. Control firms are defined as firms in the same department, in the same risk category, in the same industry and of similar size as treated firms but that never default or enter a collective procedure. When multiple control firms are found for a single treated firms, we select the one that minimizes the absolute distance in terms of total long-term credit exposures. The data set is an extraction of the French credit registry and covers the 1999 Q1-2016 Q4 time period. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance.

Table 4: External validation of the firm components - regression results.

	Dependent variable: $\tilde{\alpha}_{fq} = \hat{\alpha}_{fq} - \bar{\alpha}_q$	
	All firms	Surviving firms
Post_q	-0.345^{***}	-0.149^{***}
	(0.000)	(0.000)
$\text{Post}_q \times \text{Treated}_f$	-0.149^{***}	-0.070^{***}
	(0.000)	(0.003)
Observations	31644	15129
Firm FE	Yes	Yes
R2	0.424	0.376

This table presents the results of the regression

$$\tilde{\alpha}_{fq} = \mu_f + \gamma Post_q + \delta Post_q \times Treated_f + \epsilon_{fq}$$

where $\tilde{\alpha}_{fq} = \hat{\alpha}_{fq} - \bar{\alpha}_q$. $\hat{\alpha}_{fq}$ is obtained by performing a WLS regression of the growth rate of long-term credit at the firm-bank level on a firm-time and bank-time fixed effects. $\bar{\alpha}_q$ is the cross-sectional median of $\hat{\alpha}_{fq}$. At $t = 0$, treated firms default on at least one trade bills or enters a collective procedure. Control firms are defined as firms in the same department, in the same risk category, in the same industry and of similar size as treated firms but that never default or enter a collective procedure. When multiple control firms are found for a single treated firms, we select the one that minimizes the absolute distance in terms of total long-term credit exposures. $Post_q$ is a dummy variable equal to one (zero) when q is greater or equal (strictly inferior) to zero. $Treated_f$ is equal to one when f belongs to the treated group, zero otherwise. *Surviving firms* is the set of firms that don't exit the credit registry during the two years (8 quarters) period around $q = 0$ ($\Delta Credit_{fq} > -2$). The data set is an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. Long-term credit is defined as credit with a maturity of more than one year at issuance.

Table 5: Decomposition of the cyclicality of aggregate credit.

	$Corr(\Delta Credit_q, Z)$	$Share(Macro_q, Z)$	$Share(Banks_q, Z)$	$Share(Firms_q, Z)$
$Z = \Delta GDP_{q\text{-}5}$	0.440**	0.073	−0.002	0.370**
	(0.186)	(0.074)	(0.094)	(0.168)
$Z = \Delta GDP_{q\text{-}4}$	0.494***	0.080	0.016	0.398***
	(0.174)	(0.081)	(0.105)	(0.162)
$Z = \Delta GDP_{q\text{-}3}$	0.462***	0.079	0.033	0.350**
	(0.180)	(0.085)	(0.115)	(0.183)
$Z = \Delta GDP_{q\text{-}2}$	0.404*	0.082	0.039	0.283
	(0.225)	(0.094)	(0.119)	(0.233)
$Z = \Delta GDP_{q\text{-}1}$	0.256	0.069	0.040	0.147
	(0.278)	(0.096)	(0.114)	(0.279)
$Z = \Delta GDP_q$	0.071	0.054	0.027	−0.010
	(0.315)	(0.094)	(0.099)	(0.299)
Observations	68			

The table presents the results of the decomposition $\text{Corr}(\Delta Credit_q, \Delta GDP_{q-k}) = Share(Macro_q, \Delta GDP_{q-k}) + Share(Bank_q, \Delta GDP_{q-k}) + Share(Firm_q, \Delta GDP_{q-k})$ where $Share(X_q, \Delta GDP_{q-k}) = \pi^X \cdot \text{Corr}(X_q, \Delta GDP_{q-k})$ and π^X is the ratio of the standard deviation of X_q to the standard deviation of $\Delta Credit_q$. k is an integer between 0 and 5. $Macro_q$, $Firm_q$ and $Bank_q$ are the credit-weighted average of the macro, firm and bank components defined in subsection 3.3. ΔGDP_q is the growth rate of the real GDP of the non-financial sector. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. In order to use the decomposition displayed above, single-bank firms and banks with less than 100 multiple-bank firms are removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Table 6: Contribution of top borrowers.

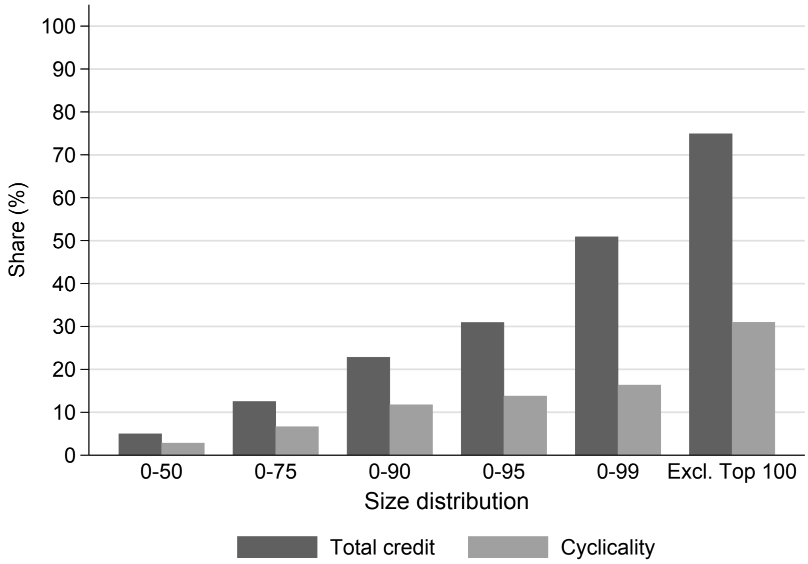
	$Share(Firm_q^*, Z)$	$\bar{\mu}_s \rho_s Share(X,Z)$ 0 – 95	95 – 99	99 – Top100	Top100
$Z = \Delta GDP_{q\text{-}5}$	0.343**	0.046**	0.014	0.055**	0.227**
	(0.028)	(0.020)	(0.309)	(0.033)	(0.030)
$Z = \Delta GDP_{q\text{-}4}$	0.369**	0.054***	0.010	0.034***	0.270***
	(0.014)	(0.009)	(0.448)	(0.010)	(0.004)
$Z = \Delta GDP_{q\text{-}3}$	0.327**	0.055***	0.005	0.003**	0.263***
	(0.041)	(0.006)	(0.742)	(0.033)	(0.010)
$Z = \Delta GDP_{q\text{-}2}$	0.268	0.052**	0.002	−0.023	0.236*
	(0.208)	(0.015)	(0.899)	(0.214)	(0.071)
$Z = \Delta GDP_{q\text{-}1}$	0.144	0.044**	0.000	−0.048	0.148
	(0.526)	(0.025)	(0.989)	(0.569)	(0.363)
$Z = \Delta GDP_q$	0.001	0.031*	0.001	−0.066	0.035
	(0.996)	(0.083)	(0.981)	(0.924)	(0.801)
Observations	68				

The table presents the results of the decomposition

$$Share(Firm_q^*, \Delta GDP_{q-k}) = \sum_{s=1}^{S} \bar{\mu}_s \rho_s Share(Firm_q^s, \Delta GDP_{q-k})$$

$Share(X_q, \Delta GDP_{q-k})$ is defined as $\pi^{Firm,*} \cdot \mathrm{Corr}(X_q, \Delta GDP_{q-k})$, $\pi^{Firm,*}$ is the ratio of the standard deviation of $Firm_q^*$ to the standard deviation of $\Delta Credit_t$, s is a size bucket of borrowers, $Firm_q^s$ is the credit-weighted sum of firm components for borrowers in size bucket s, $\bar{\mu}_s$ is the average weight of s in total credit and ρ_s is the ratio of the standard deviation of $Firm_q^s$ to the standard deviation of $Firm_q^*$. k is an integer between 0 and 5. ΔGDP_q is the growth rate of the real GDP of the non-financial sector. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. Single-bank firms and banks with less than 100 multiple-bank firms are also removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Figure 10: Illustration of the role of granularity.



The figure compares the contribution in total credit and in the cyclicality of credit of different size buckets of borrowers. The x-axis corresponds to size buckets of borrowers. "0-95", for instance, regroups all firms below the 95th percentile of the credit distribution. Dark grey bars give the ratio (in percentage) of total credit for a given size bucket to total credit (averaged over the time period). Light grey bars then give the ratio of $Share(Firm_q^s, \Delta GDP_{q-4})$ to $Share(Firm_q^*, \Delta GDP_{q-4})$. Firms in the "0-95" size bucket, therefore, represent on average 31% of total credit and 14% of the correlation between $Firm_q^*$ and ΔGDP_{q-4}. $Share(X_q, \Delta GDP_{q-4})$ is defined as $\pi^{Firm,*} \cdot \mathrm{Corr}(X_q, \Delta GDP_{q-4})$ where $\pi^{Firm,*}$ is the ratio of the standard deviation of $Firm_q^*$ to the standard deviation of $\Delta Credit_q$. It can be decomposed as

$$Share(Firm_q^*, \Delta GDP_{q-4}) = \sum_{s=1}^{S} \bar{\mu}_s \rho_s Share(Firm_q^s, \Delta GDP_{q-4})$$

where s is a size bucket of borrowers, $Firm_{sq}$ is the credit-weighted sum of firm components for borrowers in size bucket s, $\bar{\mu}_s$ is the average weight of s in total credit and ρ_s is the ratio of the standard deviation of $Firm_q^s$ to the standard deviation of $Firm_q^*$. ΔGDP_{q-4} is the growth rate of the real GDP of the non-financial sector lagged by one year. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. Single-bank firms and banks with less than 100 multiple-bank firms are also removed from the aggregation.

Table 7: Robustness checks I - Normalization, firm-bank relationships.

	$Corr(\Delta Credit_q, Z)$	$Share(Macro_q, Z)$	$Share(Banks_q, Z)$	$Share(Firms_q, Z)$
	Median, 2 banks, 100 firms (baseline)			
$Z = \Delta GDP_{q\text{-}4}$	0.494***	0.080	0.016	0.398***
	(0.174)	(0.081)	(0.105)	(0.162)
	Mean, 2 banks, 100 firms			
$Z = \Delta GDP_{q\text{-}4}$	0.494***	0.223	0.051	0.220*
	(0.174)	(0.142)	(0.115)	(0.128)
	Median, 2 banks, 10 firms			
$Z = \Delta GDP_{q\text{-}4}$	0.553***	0.105**	0.066	0.381***
	(0.160)	(0.049)	(0.059)	(0.156)
	Median, 4 banks, 100 firms			
$Z = \Delta GDP_{q\text{-}4}$	0.439***	−0.012	0.073**	0.377***
	(0.170)	(0.068)	(0.033)	(0.124)
Observations	68			

This table reports for each specification the decomposition of the correlation between the credit growth rate and the four-quarter lag of the GDP growth rate. The top panel displays the decomposition obtained with the baseline specification. The baseline decomposition is obtained by (i) setting the median of the shocks at zero, (ii) keeping only firms with two banking relationships in a given quarter and (iii) keeping only banks with at least 100 relationships in a given quarter. In the second panel, both bank and firm idiosyncratic components are defined as deviations to the mean. The third panel shows the results of the decomposition when imposing a minimum number of borrowers by bank of 10 firms. In the fourth panel, the minimum required level of banking relationships for firms is set to 4 banks. ΔGDP_q is the growth rate of the real GDP of the non-financial sector. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. Single-bank firms are also removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Table 8: Robustness checks II - Coverage, unit of observation.

	$Corr(\Delta Credit_q, Z)$	$Share(Macro_q, Z)$	$Share(Banks_q, Z)$	$Share(Firms_q, Z)$
		Baseline		
$Z = \Delta GDP_{q\text{-}4}$	0.494^{***}	0.080	0.016	0.398^{***}
	(0.174)	(0.081)	(0.105)	(0.162)
		Only French banks		
$Z = \Delta GDP_{q\text{-}4}$	0.469^{***}	0.113	−0.050	0.406^{***}
	(0.179)	(0.077)	(0.106)	(0.166)
		Without housing sector		
$Z = \Delta GDP_{q\text{-}4}$	0.512^{***}	0.068	0.057	0.387^{***}
	(0.171)	(0.079)	(0.091)	(0.139)
		Banking group		
$Z = \Delta GDP_{q\text{-}4}$	0.511^{***}	0.128	−0.033	0.415^{***}
	(0.173)	(0.089)	(0.073)	(0.158)
		Wholesale banks and retail banks		
$Z = \Delta GDP_{q\text{-}4}$	0.483^{***}	0.103^{*}	0.060	0.321^{*}
	(0.187)	(0.056)	(0.091)	(0.170)
		Only ongoing relationships		
$Z = \Delta GDP_{q\text{-}4}$	0.372^{*}	-0.137^{***}	0.020	0.489^{***}
	(0.205)	(0.047)	(0.052)	(0.170)
Observations	68			

This table reports for each specification the decomposition of the correlation between the credit growth rate and the four-quarter lag of the GDP growth rate. The top panel displays the decomposition obtained with the baseline specification. In the second and third panels, we respectively remove foreign banks and borrowers belonging to the housing sector from the data set. In the fourth panel, banks are consolidated at the level of the banking group. In the fifth panel, each bank is divided in a retail bank (which lends to small borrowers) and in a wholesale bank (which lends to large ones). A borrower is classified as being small (large) if it borrows less (more) than the bank-level average. In the sixth panel, we remove from the initial dataset both terminating and new loans. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. Single-bank firms are also removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Table 9: Robustness checks III - Definition of firm individual shocks.

	Baseline	Industry	Risk	Sales	Location	Cell
			$Share(Firm_q, Z)$			
$Z = \Delta GDP_{q\text{-}5}$	0.370**	0.320**	0.319**	0.264**	0.363**	0.284**
	(0.024)	(0.038)	(0.042)	(0.028)	(0.023)	(0.011)
$Z = \Delta GDP_{q\text{-}4}$	0.398***	0.349**	0.331**	0.315***	0.393***	0.307***
	(0.009)	(0.013)	(0.028)	(0.009)	(0.006)	(0.006)
$Z = \Delta GDP_{q\text{-}3}$	0.350**	0.314**	0.271*	0.322**	0.343**	0.271**
	(0.033)	(0.035)	(0.088)	(0.011)	(0.026)	(0.011)
$Z = \Delta GDP_{q\text{-}2}$	0.283	0.260	0.203	0.312**	0.278	0.223*
	(0.216)	(0.195)	(0.332)	(0.021)	(0.197)	(0.097)
$Z = \Delta GDP_{q\text{-}1}$	0.147	0.138	0.074	0.239	0.139	0.117
	(0.550)	(0.512)	(0.732)	(0.143)	(0.553)	(0.469)
$Z = \Delta GDP_q$	−0.010	−0.006	−0.068	0.137	−0.019	−0.005
	(0.970)	(0.981)	(0.737)	(0.382)	(0.938)	(0.977)
Observations	68					

This table reports the correlations between ΔGDP_{q-k} and the different time series of $Firm_q$ obtained with alternative definitions of firm-level shocks. The first column gives the results with the baseline definition (deviation to the unconditional median). In the following columns, we use as alternative definition of individual shocks the deviation to the conditional median. We successively take the median by industry, credit score category, size category, administrative division ("département") and by the category defined by the intersection of all the precedent variables ("cell"). k is an integer between 0 and 5. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. Single-bank firms are also removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Table 10: Robustness checks IV - OLS regression.

	$Corr(\Delta Credit_q, Z)$	$Share(Macro_q, Z)$	$Share(Banks_q, Z)$	$Share(Firms_q, Z)$	$Share(Match_q, Z)$
$Z = \Delta GDP_{q\text{-}5}$	0.440**	0.079	0.000	0.377*	−0.015
	(0.186)	(0.080)	(0.123)	(0.240)	(0.103)
$Z = \Delta GDP_{q\text{-}4}$	0.494***	0.083	0.023	0.343*	0.045
	(0.174)	(0.082)	(0.115)	(0.220)	(0.102)
$Z = \Delta GDP_{q\text{-}3}$	0.462***	0.089	0.036	0.221	0.116
	(0.180)	(0.081)	(0.115)	(0.256)	(0.107)
$Z = \Delta GDP_{q\text{-}2}$	0.404*	0.097	0.037	0.098	0.171
	(0.225)	(0.078)	(0.116)	(0.329)	(0.110)
$Z = \Delta GDP_{q\text{-}1}$	0.256	0.102	0.024	−0.076	0.207*
	(0.278)	(0.075)	(0.117)	(0.394)	(0.113)
$Z = \Delta GDP_q$	0.071	0.096	0.007	−0.240	0.208*
	(0.315)	(0.070)	(0.115)	(0.419)	(0.113)
Observations	68				

The table presents the results of the decomposition Corr$(\Delta Credit_q, \Delta GDP_{q-k}) = Share(Macro_q, \Delta GDP_{q-k}) + Share(Bank_q, \Delta GDP_{q-k}) + Share(Firm_q, \Delta GDP_{q-k}) + Share(Match_q, \Delta GDP_{q-k})$ where $Share(X_q, \Delta GDP_{q-k}) = \pi^X \cdot$ Corr$(X_q, \Delta GDP_{q-k})$ and π^X is the ratio of the standard deviation of X_q to the standard deviation of $\Delta Credit_t$. k is an integer between 0 and 5. $Macro_q$, $Firm_q$ and $Bank_q$ are the credit-weighted average of the macro, firm and bank components obtained from the OLS estimation of

$$\Delta Credit_{fbq} = \alpha_{fq} + \beta_{bq} + \epsilon_{fbq}$$

$Match_q$ is the credit-weighted average of the residual ϵ_{fbq}. ΔGDP_{q-k} is the growth rate of the real GDP of the non-financial sector, lagged by k quarters. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. In order to use the decomposition displayed above, single-bank firms and banks with less than 100 multiple-bank firms are removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Table 11: Including single-bank firms : out-of-sample test.

	Dependent variable: $\Delta Credit_q^{agg}$	
	Median	Mean
$Macro_q$	1.296***	1.153***
	(0.248)	(0.095)
	0.118	0.293
$Bank_q$	1.276***	1.190***
	(0.226)	(0.099)
	0.024	0.069
$Firm_q$	0.771***	0.699***
	(0.064)	(0.049)
	0.350	0.176
Residual	.11	.063
Total	.601	.601
Observations	68	68
R2	0.913	0.934

This table presents the decomposition of the cyclicality of aggregate credit when including the entire population of borrowers. In a first step, we compute the mid-point growth rate $\Delta Credit_q^{agg}$ of aggregate long-term credit obtained before restricting our observations to the connected set (this time series therefore include single-bank firms). We then regress $\Delta Credit_q^{agg}$ on the time series $Macro_q$, $Bank_q$ and $Firm_q$ obtained from equation 6. The table presents the estimated coefficients and standard errors obtained with the baseline specification and by defining individual shocks as the deviation to the mean. In a second step, we use the estimated coefficients to compute the contribution of each of the three terms to the correlation of $\Delta Credit_q^{agg}$ with ΔGDP_{q-4}. The total correlation is given in the bottom of the table. The respective contributions of each component are displayed below the standard errors of the coefficients. There is a fourth term in the decomposition which reflects the comovement of the estimated error term with the business cycle (displayed in the "Residual" line). ΔGDP_{q-k} is the growth rate of the real GDP of the non-financial sector, lagged by k quarters. Data on GDP comes from the French National Statistical Institute (Insee). Credit data comes from an extraction of the French credit registry and covers the period from 1999-Q1 to 2016-Q4. Public banks, financial firms and self-employed entrepreneurs are excluded. In order to use the decomposition displayed above, single-bank firms and banks with less than 100 multiple-bank firms are removed from the aggregation. Standard errors are obtained by applying block-bootstrap with 1000 replications and a block length of 4 observations.

Table 12: Bank exposure to borrower liquidity shocks.

Normalization:	Median		Median by cell	
	Variance	S.E.	Variance	S.E.
No $Macro_{bq}$	0.678	(0.093)	0.515	(0.090)
No $Bank_{bq}$	0.532	(0.045)	0.532	(0.045)
No $Firm_{bq}$	0.513	(0.128)	0.608	(0.188)
No $Firm_{bq}^{Top\ 10}$	0.421	(0.097)	0.585	(0.162)
$\Delta Credit_{bq}$	0.746	(0.113)	0.746	(0.113)

The table presents the results of the decomposition of bank-level variations of credit lines:

$$\Delta Credit_{bq} = Macro_q + \tilde{\beta}_{bq} + \sum w(b)_{fq}\tilde{\alpha}_{fq} = Macro_q + Bank_{bq} + Firm_{bq}$$

We compute for each bank the variance of the counterfactual time series of credit lines variations if $Firm_{bq}$ was constantly equal to zero. In a second step, we compute the average across banks of the resulting variances (No $Firm_{bq}$) that we compare to the average variance of the original $\Delta Credit_{bq}$ time series ($\Delta Credit_{bq}$). We do the same counterfactual exercise by setting successively $Macro_q$, $Bank_{bq}$ and the weighted sum of firm components for the top 10 borrowers $Firm_{bq}^{Top\ 10}$ to zero. Standard errors are reported between parentheses. The first column presents the results using the baseline definition of idiosyncratic shocks (deviation to the median). In the second column, idiosyncratic shocks are defined as deviations to the median by cell. A cell is defined as the intersection of an industry, a credit score category, a size category, and an administrative division ("département"). Credit data comes from an extraction of the French credit registry and covers the period from 2008-Q1 to 2016-Q4. Banks are consolidated at the level of the banking group. Only the six largest banking groups are retained. Financial firms and self-employed entrepreneurs are excluded. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).

Table 13: Synchronization and borrower shocks.

	Variance	
Normalization:	Median	Median by cell
$Firm^*_q$	0.346	0.213
$Direct_q$	0.080	0.053
$Link_q$	0.266	0.160
$Common_q$	0.870	0.694
$\Delta Credit_q$	0.410	0.410

The table presents the results of the decomposition of the aggregate variance of credit lines:

$$\begin{aligned} Var(Firm^*_q) &= \sum_b w_b^2 Var(Firm^*_{bq}) + \sum_b \sum_{c \neq b} w_b w_c Cov(Firm^*_{bq}, Firm^*_{cq}) \\ &= Direct_q + Link_q \end{aligned}$$

$Common_q$ represents the part of $Link_q$ which is directly attributable to common borrower shocks:

$$Common_q = \sum_b \sum_{c \neq b} w_b w_c \left(\sum_{R_{bcq}} w(b)_{fq} w(c)_{fq} Var(\tilde{\alpha}_{fq}) \right)$$

The first column presents the results of the decomposition using the baseline definition of idiosyncratic shocks (deviation to the median). In the second column, idiosyncratic shocks are defined as deviations to the median by cell. A cell is defined as the intersection of an industry, a credit score category, a size category, and an administrative division ("département"). Both columns also display the variance of aggregate credit lines. We report the values of $Common_q$ averaged over time. Credit data comes from an extraction of the French credit registry and covers the period from 2008-Q1 to 2016-Q4. Banks are consolidated at the level of the banking group. Only the six largest banking groups are retained. Financial firms and self-employed entrepreneurs are excluded. Credit lines are defined as the sum of all undrawn commitments (including documentary credit).