Banks, Firms, and Jobs*

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Abstract: Unemployment is one of the most visible effects of financial crises. We contribute to the empirical literature on the employment effects of a decline in bank credit, investigating individual heterogeneity across firms, workers and jobs in the response to a financial shock. We use a rich data set of over 1.5 million individual job contracts in an Italian region, that is matched with the universe of firms and their lending banks. To isolate the effect of the financial shock we construct a firm-specific time-varying measure of credit supply. Our findings indicate that a 10 percent supply-driven credit contraction reduces employment by 2.5 percent. The effect is mostly concentrated among the relatively less educated and less skilled workers with temporary contracts, and is consistent with the presence of a "dual" labor market and a skill upgrade strategy adopted by firms in response to the financial shock.

JEL Codes: G01; G21; J23; J63

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1 Introduction

In the aftermath of the global financial crisis, a severe credit crunch has had long lasting consequences on a number of advanced economies, where unemployment rates have increased markedly. These facts have triggered a renewed interest on the relationship between finance and employment (Pagano and Pica, 2012) and, specifically, on the effects of credit supply shocks have on firms' employment decisions (Chodorow-Reich, 2014; Duygan-Bump *et al.*, 2015).

While this literature provides original insights on the effects of financial crises on total employment at the firm or state level, it is generally silent about within-firm dynamics. For instance, little is knows about the impact of a decline in firm financing on different types of jobs. We contribute to this strand of literature by zooming in on the employment dynamics within the firm and by providing a series of novel findings on how firms adjust the level and composition of the labor force in response to credit shocks. We do so thanks to the availability of an original and extremely rich data set, that draws on an administrative archive that collects daily information on individual job contracts and labor market flows. The dataset covers the universe of firms, including micro-enterprises, in an Italian region, matched with their lending banks through the Italian Credit Register. We end up with a quarterly dataset of about 200,000 firms, spanning the period from 2008:Q1 to 2012:Q4 for which, thanks to the degree of granularity of the data, we can go beyond the standard job destruction/job creation dichotomy to investigate differential responses to a credit supply shocks across firms, workers, and job contracts.

We find that a 10 percent supply-driven credit contraction reduces employment by 2.5 percent. This effect is concentrated among individuals employed with temporary contracts and occurred mostly through more outflows rather than less inflows. This result is consistent with the existence of a "dual" labor market. The reduction of employment was concentrated among the relatively less educated individuals, who are employed in jobs with lower skill content. Immigrant and younger workers were also hit disproportionately more by the credit rationing, reflecting the prevalence of immigrants in low-skill occupations, and the lower tenure and the higher presence of younger workers in temporary jobs. The stronger impact on the less educated workers is consistent with the notion that during recessions firms adopt a skill upgrading strategy (Hershbein and Kahn, 2016). This strategy is pursued mostly by allowing temporary contracts to expire, and not renewing them, possibly because of the lower training and hiring costs (and therefore also firms' lower incentives for labor hoarding) for this segment of the population. By contrast, less educated workers with open-ended contracts are unaffected by firms' financing constraints. Therefore, skill upgrading strategies are heavily shaped by contracts regulation. To shed light on the mechanisms linking the financial crisis to employment outcomes, we find that firms that are more reliant on bank credit, that use more intensively granted credit, and that have weaker relationships with banks, experience a greater reduction in the availability of bank financing.

This paper contributes to the growing literature on the real effect of credit supply shocks (Amiti and Weinstein, 2011, 2016; Cingano *et al.*, 2016; Paravisini *et al.*, 2015) and is most closely related to the recent contributions that investigate the effects of a reduction in credit supply on employment outcomes at the firm level (Chodorow-Reich, 2014; Benmelech *et al.*, 2015; Bottero *et al.*, 2015; Bentolila *et al.*, 2015; Berg, 2016; Hochfellner *et al.*, 2016; Popov and Rocholl, 2016; Siemer, 2016).[1] Drawing on micro-level datasets, these studies consistently show that a tightening of the credit supply leads to a contraction of the labor force.

The analysis by Bentolila *et al.* (2015) has the unique feature of being based on loan level data from a credit register. Relying on the differences in bank health at the beginning of the financial crisis, the paper shows that firms exposed to *weak* banks contracted employment by 2.2 percentage points more than firms that were borrowing from healthier lenders, and results are able to explain about a fourth of the fall in aggregate employment in Spain between 2007 and 2010. Hochfellner *et al.* (2016) use employer-employee matched data for a sample of German firms to look at how individual characteristics affect labor outcomes. The identification strategy hinges on differences between firms that were affected or not by the credit shock, depending on their location in the seven federal states where the major bank was one of the five *Landesbanks* with significant exposure to the U.S. mortgage crisis. In addition to confirming the aggregate negative effect of credit contraction on employment, Hochfellner *et al.* (2016) show that workers in firms which have been exposed to a negative credit shock experience significant earning losses and an increase in the unemployment spell. They also find that unskilled, less educated and less experienced workers are the most affected by the credit shock. While both these studies limit their analysis to medium-sized and large firms, Siemer (2016) uses confidential firm-level employment data from the U.S. Bureau of Labor Statistics for the universe of U.S. firms, but relies on industry-level differences in external financial dependence to identify the effects of financial constraints on employment and firm dynamics. His results show that financing constraints reduce employment growth in small firms by 5 to 10 percentage points relative to large firms, but they are silent on within-firm heterogeneity.

[1]Using more aggregate data other papers provides additional support to the employment costs of the financial crisis, considering the US and Europe (Boeri *et al.*, 2013; Greenstone *et al.*, 2014; Haltenhof *et al.*, 2014; Duygan-Bump *et al.*, 2015).

Our analysis has the advantage of bringing together three key elements which in previous studies have been considered separately. First, thanks to contract-firm-bank matched data we can investigate heterogeneous responses to a financial shock across firms, workers, and job contracts. In particular, other than socio-demographic characteristics, we can exploit differences across contract types and look at the intersection between individual skills and job contracts, to assess which of the two dimensions matter more for firm's employment decisions.[2] Second, the availability of loan-level data (instead of aggregate credit data) makes it possible to control for credit demand and productivity shocks at a granular level, with a set of firm, time, and firm cluster$\times$time fixed effects, which absorb firm-specific time invariant demand shifters and time-varying demand shocks which are common to a narrowly defined cluster of borrowers. Third, our matched bank-firm data allow us to extend the identification strategy of Greenstone *et al.* (2014) and construct an exogenous firm-specific time-varying measure of bank credit supply, which gives us more precise estimates than the ones obtained with more aggregate data. We start by estimating time-varying nationwide bank's lending policies that are purged of local loan demand (and of any other province-industry-quarter level idiosyncratic shocks). Then, we build a credit supply variable at the firm level using banks' loan share to a given firm as weights and we show that this measure is strongly correlated with loan growth at the firm level. Finally, our analysis covers the universe of firms. While there is a wide consensus on the fact that smaller firms rely more on bank financing, the existing evidence rarely focuses on a representative sample of small firms. Our data, on the contrary, include the universe of individual and micro enterprises.

The rest of the paper is structured as follows: Section 2 describes the data and the variables; Section 3 presents the empirical strategy; Section 4 shows the results and Section 5 concludes.

2 Data

2.1 Veneto as a representative case study

Our analysis relies upon unparalleled loan-level information about the entire population of workers, firms and financial intermediaries operating in Veneto, a large Italian region with a population of 4.9 million individuals and a workforce of 2.2 million workers. Veneto accounts for roughly 9 percent of the Italian value added and of total employment.

Veneto shares with Italy a large prevalence of small firms (Figure 1, left panel): 94 percent of firms in the region have less than 10 employees (57 percent have at most one employee).

[2]In this way, our contribution also relates to and extends the evidence discussed by Caggese and Cuñat (2008), who show that financially constrained firms have a more volatile labor force and employ a larger proportion of temporary workers than financially unconstrained firms.

The productive structure is also fairly similar to the national one (Figure 1, right panel), and the service and industrial sectors accounts for 56 and 43 percent of total employment, respectively; with respect to the rest of Italy, the share of the industrial sector is slightly larger.

In terms of the banking system, in 2012 in Veneto there were about 120 banks, with small local banks accounting for nearly 20 percent of business loans. The degree of financial development, as measured with the number of branches per inhabitants, is higher with respect to the national average (Figure 2, left panel). Aggregate lending to non-financial corporations followed a similar dynamic in Veneto and Italy (Figure 2, right panel).

Veneto is hence very well representative of the Italian situation, which in turn represents an extremely interesting case studies for at least two reasons: first, Italian firms mostly rely on bank credit for their business activities, and more than other firms in the Euro area (Figure 3, left panel); second, small firms (less than 10 employees) are the most indebted, and the Italian productive structure is strongly biased towards small production units (Figure 3, right panel).

2.2 The contract-firm-bank matched data

Our dataset brings together an extremely rich set of information coming from different administrative sources. Daily labor market flows from the regional public employment service are indeed matched to stock information form the national social security administration and to the Italian credit register maintained by the Bank of Italy using firm-level unique identifiers, namely their VAT numbers. These feature of the data guarantee at the same time wide population coverage, high information reliability and a nearly total frequency of success in the matching procedure. In the following we provide an accurate description of our data sources.

The bulk of labor market information comes from PLANET, an administrative dataset of daily labor market *flows* maintained by the regional employment agency *Veneto Lavoro*.[3] PLANET builds upon the obligation for firms operating in Italy to notice the national and local employment agencies about all labor market transitions for which they are held responsible, including hires, firings and transformations of individual employment arrangements (e.g., from full-time to part-time, from temporary to permanent, and the like). Firm-level observables include geographical location and sector (5-digit NACE code), while workers' in turn cover gender, age, nationality, occupation (5-digit ISCO code), type of contract (44 different employment arrangement), educational attainment (13 categories), time schedule (full-time or vertical, horizontal or mixed part-time), and reasons for separation.

In order to overcome limitations in terms of labor market *stocks*, PLANET is complemented with information from ASIA, the archive of active firms maintained by the National Statistical

[3] Further information on PLANET (in Italian) is available here: www.venetolavoro.it/public-use-file

Institute (ISTAT) with register data from the Social Security Administration.[4] ASIA provides yearly data about firms whose economic activity spans for at least six months within a calendar year. To our purposes, ASIA adds information on firm size and on characteristics of those firms who are not interested by any job flows or transitions in our sample period. More specifically, we consider the stock in the first year in which we observe the firm and we reconstruct the stock forward using information on workers inflows and outflows. This exercise has been done to guarantee consistency between flows and stocks and, more importantly, to have quarterly stock data.

To be able to have a firm-specific measure of credit availability, we use information from the Credit Register (CR) database, managed by the Bank of Italy, on the credit extended to each firms in each quarter. For each borrower, banks have to report to the Register, on a monthly basis, the amount of each loan—granted and used—for all loans exceeding a minimum threshold (75,000 euro until December 2008, 30,000 euro afterwards), plus all nonperforming loans. Given the low threshold, these data can be taken as a census.[5] Data also contain a breakdown by type of the loan (e.g. credit lines, credit receivables and fixed-term loans). From CR we essentially draw two kind of information. First, borrower's outstanding loans (from all banks operating in Italy) at the end of each quarter; we consider the total amount instead of the different types of loans because banks and borrowers may endogenously change the composition of loans in reaction to shocks to the credit market. Second, the bank market share for each borrower at the beginning of the period, that will be used for the construction of the instrumental variable (see more on this below).[6]

One limitation of our data is the lack of information on wages, so that we can investigate only the quantity response to a financial shock, while we cannot say anything about price effects. However, very recent empirical evidence on Europe—and explicitly on Italy—shows that the prevailing labor cost reduction strategy that firms had adopted in response to the Global Recession has worked through the adjustment of quantities rather than prices (Fabiani *et al.*, 2015; Hochfellner *et al.*, 2016; Guriev *et al.*, 2016), consistently with the presence of downward wage rigidities in regulated labor markets (see Devicienti *et al.*, 2007, for a broader

[4] Further information on ASIA (in Italian) is available here: www.istat.it/it/archivio/106814

[5] We do not (explicitly) include interest rates when examining the impact of credit conditions on firm employment for two main reasons: first, data on interest rates are collected only for a sub-sample of banks that exclude the majority of small and local banks and this would have entailed a severe reduction of observations and the dismissal of the census analysis perspective. Second, one may reasonably argue that bank policies on prices are correlated with those on quantities and that utilized loans—which we use in our analysis—reflect both granted loans and (unobserved) price effects.

[6] To construct our measure of credit supply, we use data drawn from the Bank of Italy Supervisory Report (SR) database. Specifically, we use confidential data on outstanding loans extended by Italian banks to the firms in the local credit markets (i.e. provinces) to estimate time-varying bank lending policies.

discussion about Italy). Moreover, we observe the contract level bargained at the national level, which in Italy is a very good proxy of the wage level and allows for identification of promotions/demotions.

A further potential limitation of our data is the lack of firm balance-sheet information. While it would be possible to match a sub-sample of (medium and large) firms with balance-sheet and income statement data from the CADS database—a proprietary firm-level database owned by Cerved Group S.p.a.—this choice would come at the non-trivial cost of loosing one of the key feature of our analysis—the coverage of the universe of firms, including small and micro enterprises. Moreover, in the empirical analysis we saturate the model with a set of granular fixed effects which seem to capture most of the unobserved time-varying firm-level heterogeneity.

2.3 Sample selection and the final data set

All data sources are merged together using VAT numbers as univocal identifiers of firms. Genuine non-matches between PLANET and ASIA are possible, and are due to two reasons: very short-lived firms (less than a semester in a calendar year) are not recorded within ASIA, while firms with a very stable employed workforce (meaning no changes in both the intensive and the extensive margins, including the type of contract) do not appear in PLANET. None of the two entails any limitation to our purposes, as i) the stock of employed workforce for very short-lived firms can be easily induced from workers' flows, and ii) the worker flows in stable firms are by definition null. This grants that truly unsuccessful matches are infrequent and largely due to misreporting of VAT numbers by either the firms or the statistical offices maintaining the single sources, an occurrence that we can safely assume to be random and – due to the extremely large sample size – almost irrelevant from a statistical standpoint.

Sample selection is due to a number of reasons. First, although the available time series cover a longer period, we narrow our focus on the years from 2008 to 2012 (the last available year in most sources at the time of our analysis). The reason is that until 2007 the obligation for firms to notice hires and firings (from which PLANET originates) concerned dependent workers only and occurred largely through paper documents. The first limitation resulted in an incomplete coverage of labor market flows, inasmuch as independent contractors and disguised self-employees – widely spread in the Italian labor market and at high risk to represent a buffer stock of employment during downturns – were not observed in the data. The second limitation entailed in turn a non-negligible delay of data completion. Both have been overcome during 2007, when digital notice became compulsory for all workers, including independent ones.

Second, we focus on the private non-financial non-primary sectors. The reasons are self-evident. Employment in the public sector depends on different rationales that include macroeconomic stabilization, budget control and the supply of public services, and its funding relies to a great deal on out-of-market sources (taxes). The agriculture sector in turn is highly subsidized all over the EU and a credit crunch from the private sector may be overcome by financial resources that we cannot observe at the micro level. Finally, credit flows within the financial sector often respond to different factors than flows from banks to non-financial corporations.

Third, and last, we removed from our sample temp agencies, care givers and house cleaners. The reason for temp agencies is that we cannot distinguish between the internal staff and the workers leased to other firms, and since temp agency workers are also included within the employed workforce of the firms they are leased to, retaining temp agencies would results in a duplication of flow records. Care givers and house cleaners, instead, are excluded as in most cases they appear as self-employees if not individual firms. They would mistakenly increase the number of actual firms.

The final sample includes nearly 440,000 firms of which about 200,000 have bank relationships.

2.4 Some descriptive statistics

The firms included in the sample are predominantly micro and small enterprises, reflecting the structure of the Italian industry. This distribution is consistent with Census data both in terms of firms and employees (Figure 4). Over the sample period 2008-2012, the number of employees declines by nearly 90,000 units, and the number of firms records a significant drop too. These trends mimic the aggregate data from the National Institute of Statistics (Figure 5).

The average duration of temporary contracts in our sample is 9.4 months, and about two third of temporary contracts end within a quarter; by contrast, the average duration for open-ended contracts is longer than 4.5 years. Temporary contracts—which account for more than 10 percent of contracts (Table 1)—could act as a buffer for firms to adjust to a credit shock in the very short term.

Looking at the sub-sample of the indebted firms (i.e. those used in the empirical analysis), the average firm has 6.3 employees (the median is 2 employees); two third of the firms are in the service sector. In terms of the geographical distribution, firms are roughly equally distributed across the seven provinces of Veneto, with Padua (20 percent) and Verona (19 percent) being the two more populated provinces, while Venice (the regional capital) accounts for 16 percent of firms. Finally, our sample includes mostly firms that borrow from one bank, while only 29 percent of firms obtain credit from more than one bank. The job loss for the average firm is equal to 0.8 employees, while credit declined by 1.6 percent—see Table 1, consistent with the evidence of a significant credit crunch in Italy following the Lehman's collapse (Presbitero *et al.*, 2014; Cingano *et al.*, 2016).[7] However, the reduction in bank credit and employment was heterogeneous, as one fourth of firms experienced a negative change in employment and credit contracted for more than half of the firms in the sample.

3 Identification strategy

3.1 The empirical model

We test for the effect of credit supply on firm employment decisions estimating the following model:

$$\Delta EMPLOYMENT_{it} = \beta \Delta LOAN_{it} + \delta_i + (\gamma_{s(i)} \times \tau_t) + (\eta_{c(i)} \times \tau_t) + (\theta_{p(i)} \times \tau_t) + \epsilon_{it} \quad (1)$$

where the changes in total employment ($\Delta EMPLOYMENT_{it}$) and in loans used by the banking system $\Delta LOAN_{it}$ for firm i over the quarter t, are calculated as:

$$\Delta X_{it} = \frac{X_{it_1} - X_{it_0}}{0.5 \times X_{it_1} + 0.5 \times X_{it_0}} \quad (2)$$

where X_{t_0} and X_{t_1} are, respectively, the values of employment and bank lending at the beginning and the end of the quarter t. Variations calculated in this way are widely used (Moscarini and Postel-Vinay, 2012; Haltiwanger *et al.*, 2013; Siemer, 2016) because they have the advantage of being symmetric and bounded between -2 (exiters) and $+2$ (entrants) and they are equal to zero for firms that do not register any variation in employment or lending within the quarter. Since labor decisions are sticky and the real effects of a financial shock could be visible with some lag (Greenstone *et al.*, 2014; Popov and Rocholl, 2016), in the baseline specification we consider the average change in used loans over two quarters (formally, we calculate $\Delta LOAN_{it}$ and $\Delta LOAN_{it-1}$ and we take the average change).[8] Summary statistics for these variables—for different job contracts and workers—are reported in Table 1.

The estimate of β gives the magnitude of the bank lending channel on employment dynamics. To assess the effect of bank lending on firm employment we face two main challenges. First, the observed amount of bank credit is the equilibrium of demand for and supply of credit.

[7] We measure loan growth using utilized loans rather than granted loans because the former captures rationing in terms of both a reduction of granted loans (i.e. quantity side) and/or of an increase of interest rates (i.e. price effects). However, Section 4.2 we test the robustness of our results using granted loans to measure loan growth.

[8] In Section 4.2 we will show that our key results hold if we consider exclusively the contemporaneous change in loans, or the average change over three quarters.

To deal with possible demand and productivity shocks we first add firm and time (quarter) effects, which allow for firm-specific time invariant demand shifters and for common global shocks occurring at a quarterly frequency. Then, we saturate the model with more sophisticated industry $\times$ quarter ($\gamma_{s(i)} \times \tau_t$) and province $\times$ quarter ($\theta_{p(i)} \times \tau_t$) fixed effects, and with a set of dummies that vary across quarters and firm class size (micro, small and medium-large firms, $\eta_{c(i)} \times \tau_t$). The degree of granularity of these borrower fixed effects is such that our identification hinges on the assumptions that: 1) firm unobserved heterogeneity which drives labor demand (i.e. managerial risk appetite) is time invariant, and 2) all firms operating in the same 2-digit industry, in the same province, and in the same class size face the same demand or productivity shock in each quarter. Given that we consider the universe of firms in a relatively homogeneous region, we believe that such granular fixed effects should be sufficient to isolate time-varying unobserved demand shocks. That said, we run additional robustness test allowing for more demanding firm cluster$\times$time fixed effects to absorb time-varying borrower demand shocks, using sector-province-size-quarter fixed effects (see Section 4.2).

Second, bank lending is endogenous to firms' economic conditions and employment choices, so that standard OLS estimates are likely to be biased.[9] To isolate a credit supply shock from a lower demand for credit we build on an instrumental variable (IV) approach similar to the one proposed by Greenstone *et al.* (2014). We construct a time-varying firm-specific index of credit supply (CSI_{it}) – discussed in detail in the following section – and we use it as an instrument for $\Delta LOAN_{it}$. In this way, we can measure the firm-level 'aggregate' bank lending channel (Jiménez *et al.*, 2014), which takes into account general equilibrium effects (i.e. the possibility that firms substitute for credit across banks).

3.2 Credit supply index

To isolate the exogenous component of credit supply we adopt a data-driven approach, borrowed from Greenstone *et al.* (2014). Specifically, we estimate the following equation that decomposes the contribution of demand and supply factors to bank lending growth:

$$\Delta L_{bpst} = \alpha + \delta_{bt} + \gamma_{pst} + \epsilon_{bpst} \tag{3}$$

where the outcome variable ΔL_{bpst} is the percentage change in outstanding business loans by bank b, in province p, in sector s at time t; specifically we observe outstanding loans for about 650 banks, 100 provinces (after having excluded those located in Veneto) and main sectors of

[9]On the one hand, low performing firms can be more likely to demand/receive less credit and to contract the labor force, inducing an upward bias in the OLS estimates. On the other hand, the OLS could be downward biased because of 'evergreening' practices, so that firms under stress would reduce their employment, but at the same time receive additional credit from their banks (Peek and Rosengren, 2005).

activity (agriculture, manufacturing, construction, and private non-financial services)[10]; γ_{pst} is a set of province-sector-quarter fixed effects that capture the variation in the change of lending due to province-sector cycles, which we can interpret as broadly measuring local demand; the bank-time fixed effects δ_{bt} represent our parameters of interest and capture (nationwide) bank lending policies. The identification of both γ_{pst} and δ_{bt} is guaranteed by the presence of multiple banks in each province-sector market (i.e. multiple banks exposed to the same demand) and the presence of each bank in multiple province-sector markets (i.e. multiple markets exposed to the same bank supply conditions).

We then construct a time-varying firm-specific index of credit supply, aggregating the bank-specific supply shocks estimated above with the beginning-of-the-period banks' shares at the firm level as weights. Specifically, the credit supply for the firm i at time t is:

$$CSI_{it} = \sum_{b} w_{bit_0} \times \overline{\delta_{bt}} \tag{4}$$

where $\overline{\delta_{bt}}$ are the bank-time fixed effects estimated in equation 1and w_{bit_0} is the bank b market share for firm i at the beginning of the sample period (end-2007).

By construction, CSI_{it} captures the time-varying credit supply at the firm level and its sources of variability are the substantial heterogeneity in changes in business lending across banks and the variation in bank market shares across firms. To further convince the reader that our measure of credit supply is actually correlated with the evolution of credit conditions in Italy and with bank characteristics we provide a set of stylized facts.

First, we show that, at the nationwide level, the credit supply index mimics quite well the growth rate of business loans; the correlation is stronger in the first part of the crisis and weaker in more recent years (Figure 6, panel a); the latter pattern might be due to the prevalence of demand factors in the second part of the crisis as main drivers of loan growth rate. More interestingly, from a microeconomic point of view, banks applying different conditions in terms of access to credit are characterized by significant differences in loans dynamics. Specifically, for each period we divide banks into two groups, depending on whether their estimated credit supply orientation was below or above the median, and we examine credit patterns for both groups: as expected, tight banks recorded more negative patterns than ease ones (Figure 6, panel b). Moreover, the large drop in credit supply conditions from the beginning of the financial crisis on, was mostly concentrated among large banks (Figure 6, panel c), consistent with the fact that those banks were more exposed to the liquidity drought in interbank markets. Finally, the time pattern of our credit supply indicator is also consistent with other aggregate

[10] Provinces correspond to NUTS 3 Eurostat classification (a geography entity similar to U.S. counties) and, according to the supervisory authority, they represent the "relevant" market in banking (see also Guiso *et al.*, 2004).

indicators measuring the credit supply orientation. Specifically, in panel d) of Figure 6 we plot the (inverse of) CSI together with: 1) the diffusion index from the ECB Bank Lending Survey on Italian banks,[11] 2) the share of rationed firms as reported by a survey on firms maintained by the Bank of Italy, and 3) a corporate credit rationing indicator developed by Burlon *et al.* (2016) using bank-firm matched data. The chart shows that the credit supply index follows closely the evolution of bank lending standards and the ones of firm financing constraints; the correlation of the CSI with the three measures of credit constraints varies between 0.5 and 0.6.

Second, our measure of credit supply shows the expected correlation with bank characteristics. We run a set of bank level regressions on the cross section of banks, taking the average CSI_{it} over the period 2008-2012 as the dependent variables and a set of bank characteristics measured at end-2007 as explanatory variables. The worsening in credit supply conditions was higher for larger banks and those with larger funding gap (measured with the deposit-to-loan ratio) and with lower capital, consistently with the fact that those banks were likely more exposed to the liquidity drought in interbank markets and, more generally, to the financial turmoil (Table 2).

The exogeneity of CSI_{it} relies on the two terms w_{bit_0} and $\overline{\delta_{bt}}$. As the first term, our assumption is that the bank market shares at the firm level, once we have controlled for firm-fixed effects, are not correlated with the employment *trend* at the firm level. Though this is a reasonable assumption, one may still have some concerns. For example, if main banks specialized in larger firms that were more exposed to the economic cycle (thus experiencing an employment decrease) and if those same banks also restricted credit supply more than other players, then a correlation between our credit supply indicator and firm employment growth would be spurious. In order to address this point we include in the specification sector-quarter and size-quarter fixed effects. If our parameter of interest is fairly stable we may argue that the argument discussed above is not an issue in our case. Moreover, as shown in Table 3 on balancing properties, the exposure to credit shocks at the firm level in our sample period (obtained averaging CSI_{it} over the period 2008-2012) is not significantly correlated (both from a statistical and economic point of view) to firm size at the beginning-of-the-period.

As far as the second term is concerned, bank-time fixed effects $\overline{\delta_{bt}}$ are exogenous by construction since they are purged of unobserved province-sector-quarter factors and it is rather implausible that unobserved effects at the firm level are able to affect nationwide banks' lending policies. Nevertheless, our identification assumption can be violated if banks with negative

[11] The "diffusion indexes" reflects subjective assessments of the lender on the relative importance of demand and supply factors in explaining the lending patterns. Technically, the diffusion index is the (weighted) difference between the share of banks reporting that credit standards have been tightened and the share of banks reporting that they have been eased.

supply shocks were more likely to grant credit to firm that were hit more by the crisis. This may occur if, for example, bank policies vary across bank characteristics (e.g. size) and the latter is correlated with firm characteristics (e.g. larger banks grant loans to larger firms). If this is true and if firm characteristics are correlated with firm employment outcomes—as plausible—then the instrument will not be orthogonal to the error term in equation 1. Also, one could argue that, even in the same province-sector cluster, some banks can specialize into lending to firms with a specific demand for credit, since they rely on different product markets (i.e. large exporters). In that case, the estimated bank-time fixed effects $\overline{\delta_{bt}}$ could capture a demand effect rather than a pure supply effect. However, summary statistics reported in Table 3 shows that there is no systematic correlation between the size of the exposure to the credit supply shocks and a set of firm characteristics, such as size, financial dependence, banking relationships, geographical location, and sector of activity.[12] The first five columns report summary statistics of firm beginning-of-the-period characteristics by quintile of CSI_{it}, averaged over the period 2008-2012 while the last column simplifies this information reporting the correlation between these pairs of variables. It turns out that firm characteristics are well balanced with respect to the average exposure to the credit shock during our temporal window.

Our approach depart from Greenstone *et al.* (2014) along several dimensions that, in our view, reinforce the exogeneity and reduce the bias of the indicator.[13] First, we translate bank-time fixed effects at the firm rather than at the county level. This approach reinforces the exogeneity of the instrument because while one may argue that unobservable shock in a county may affect (nationwide) lending policies of banks (especially when the local market is sufficiently large with respect to the national credit market of a certain bank), this is less plausible in case of unobservable shock at the firm level. Second, we strengthen the exogeneity also excluding the Veneto provinces from equation 1, so that we exclude the effects of demand and supply factors in this region from the calculation of bank-time fixed effects.[14] Third, our

[12] While the set of observable characteristics does not include some key variables (like the export orientation), it is difficult to think at firm characteristics which are correlated with the credit supply index while being orthogonal to the variables listed in Table 3.

[13] An alternative identification strategy is the one proposed by Amiti and Weinstein (2016), who identify the bank shocks (i.e. time varying bank fixed effects) through a regression on the dynamic of loans at the firm level, exploiting information from the sub-sample of firms who borrow from multiple banks. However we believe that their approach is less suitable for our case since the fraction of firms who have multiple lending relationships varies a lot with firm size: in our data, for example, more than 90 percent of medium and large firms have multiple relationships in contrast to about 30 percent for micro-firms. Therefore the identification of bank fixed effects with a regression at the firm level is arguably less reliable with our sample that include a large number of micro and small firms.

[14] The exclusion of Veneto provinces from the estimation of bank lending policies leads to the exclusion of only one bank (accounting for less than 0.1 percent of loans granted to all firms residing in Veneto), for which we were not able to estimate the national lending policy. Therefore, this strategy does not affect the representativeness of our sample, while it strongly reinforces the exogeneity of the instrument. It is also worth noting that Veneto represents about 8 percent of total loans granted by the median bank active in the region.

data allows us estimating time-varying bank fixed effects after having controlled for province-sector-time unobserved factors while Greenstone *et al.* (2014) control only for counties-time unobserved factors. This means that we are able to account from bank-specific demand shock that may occur whenever banks specialize in lending to certain industries and these industries perform differently from others. Fourth, in Italy government interventions in favor of the banking system has been very limited, contrarily to what happened in the U.S. and in other European countries. This implies that the lending policies of the banks were not affected by constraints imposed by the government as conditions to receive public support and, therefore, that our estimates are not affected by this potential source of bias.

4 Results

4.1 Main results

To help illustrate the impact of the credit supply, Figure 7 plots the employment patterns for firms classified in two groups, depending on whether they were exposed over the period 2008-2012 to tighter or easier lending policies (i.e. CSI below or above the median). More specifically, plotted values are the residuals (average of the two groups) of a regression of logarithm of employees on firm and quarter fixed effects, so that residuals are on average equal to zero and their time patterns shows the dynamics of employment for the two groups. The two lines suggest that less favorable lending conditions are associated with a decrease in employment and with a divergent dynamic with respect to firms who experienced a better access to credit. The following regression tables statistically substantiate this visual evidence.

Table 4 reports the 2SLS robust estimates of the baseline model for the whole sample of firms, including firm and quarter fixed effects (column 1), and time-varying industry, class size, and province fixed effects (columns 2 to 4).

The top panel reports the first stage estimates, which show that, as expected, the CSI is positively associated with the change in used loans and the coefficients is precisely estimated. The relevance of the instrument is further confirmed by the value of the first-stage F-statistic, which ranges between 156 and 180, well above the critical value of 10 suggested by Staiger and Stock (1997).

The second-stage results—reported in the bottom panel—confirm the existing evidence about the negative effect of a credit supply shock on employment (Chodorow-Reich, 2014; Bentolila *et al.*, 2015), since the change in used loans has a significant and economically large effect on the variation in employment at the firm level. Comparing the four different specification shows that adding fixed effects reduces the employment effect of the credit crunch, as they are capturing time-varying borrower-specific demand and productivity shocks. In particular, the point estimate of the coefficient on $\Delta LOAN$ ranges from 0.36 in column 1 to 0.34 when adding time-varying industry and size fixed effects and finally to 0.25 when time-varying industry, size and province fixed effects are jointly added in the model (last column).

From now on, we will take the specification of column 4 as our baseline. The point estimate of the bank lending channel is 0.25, meaning that a 10 percent contraction in bank lending over two quarters translates into a 2.5 percent reduction in employment. In relative terms, one standard deviation of the predicted change of used loan explains 15% of the standard deviation of employment.

In order to have aggregate evidence of the impact, we calculate the share of the change of employment in our temporal window that can be attributed to the credit crunch, bearing in mind the caveat that there are general equilibrium effects that cannot be taken into account when extrapolating microeconomic estimate at the aggregate level (Chodorow-Reich, 2014). In our case, for example, results are obtained conditional on firms having bank debt, so that our estimates are silent on possible demand shift to firms non depending on bank credit. In our sample, the credit extended to firms diminishes by 1.6 percent while employment by 0.8 percent (see Table 1), both on a quarterly base. Since our preferred estimate of the elasticity of employment to credit is computed cumulating the effect over two quarters we can assume that the quarterly impact is roughly half. With simple algebra, it is easy to show that the credit drop attributable to the lending supply orientation over the period 2008-2012 explained about one fourth of the employment loss.

Overall our results indicate a quite large effect of the credit crunch on employment. These findings are also roughly comparable, in magnitude, to those estimated by Bentolila *et al.* (2015) for Spain and Chodorow-Reich (2014) for the U.S. However, compared to these exercises—which are generally focused on medium and large enterprises—our analysis is less subject to external validity concerns related to the representativeness of the data, since our sample include micro and small firms and covers almost the universe of private non-financial firms and employment of the region.[15]

4.2 Robustness

We test the robustness of our baseline results running a battery of additional tests. Results are showed in Table 5. First, to address the concerns that our set of borrower fixed effects might not fully absorb demand and productivity shock, we saturate our model with more demand-

[15]The average firm size is nearly 3,000 in Chodorow-Reich (2014) and about 25 in Bentolila *et al.* (2015), while in our case is around 6 as we are able to observe the universe of firms.

ing fixed effects. We start by interacting the quarter dummies with more restrictive borrower cells (industry $\times$ size, industry $\times$ province, and province $\times$ size), allowing for time-varying demand to be the same not only across industries, class size and provinces, but also withing their two-way combinations (columns 1-3). Then, in the spirit of recent works that has to deal with a prevalence of single bank-firm relationships (Abuka *et al.*, 2015; Auer and Ongena, 2016; Degryse *et al.*, 2016), we fully saturate the model with firm cluster$\times$time—where the firm cluster is composed by all firms in the same industry, province, and class size—which are as close as we can get to quarterly firm fixed effects (column 4). Interestingly, the coefficient on $\Delta LOAN$ is not only precisely estimated, but it remains remarkably stable at around 0.25 in columns 1-3. The inclusion of the four-way fixed effects only marginally attenuates the magnitudes of the estimated credit effect on employment, suggesting that there is no additional unobserved heterogeneity driving our estimates. Hence, we will use the baseline set of fixed effects showed in Table 4 (column 4) throughout the rest of the analysis.

In columns 5 we show that our results are robust to clustering the standard errors to allow for intra-group correlation in the error term at the province-industry-class size level: the standard error only marginally increases while the coefficient of interest remains highly significant. Similar results (available from the authors upon request) are obtained using different levels of clustering.

In column 6 we restrict the sample to firms which have a total debt above 75,000 euros throughout the entire sample period, to avoid potential biases arising from the change in the threshold in our sample period. We find that the coefficient on $\Delta LOAN$ slightly increases to 0.38, but it is still precisely estimated.

One could argue that employment dynamics could be affected also by the *housing net worth* channel, which can compress demand because of a direct wealth effect or tighter borrowing constraints, through a fall in collateral values. This channel has been responsible for a significant drop in employment in the U.S. during the financial crisis (Adelino *et al.*, 2015; Mian and Sufi, 2014) and it could also be important in our set-up, because of high home ownership rates in Italy (76 percent of households own their house in Veneto) and because, differently from most of the literature, we deal with entrepreneurs of micro firms, who are likely to post their house as a collateral for business loans. However, the housing boom-and-bust cycle in Italy has been quite limited, and even more so in Veneto (Figure A1 in the annex). In any case, to further avoid any confounding factor affecting our estimates, we add time-varying house prices at the municipality level and we find that the inclusion of house prices does not change the coefficients on the loan variable (column 7).

Finally, we do some robustness exercise on the $\Delta LOAN$ variable. Rather than taking the average change in used loans over two quarters, in columns 7 and 8 we consider exclusively the contemporaneous change (at time t) and the average changes over three quarters (t, $t-1$, and $t-2$), respectively.[16] We still find evidence that a contraction in the credit supply reduces employment and, as expected, the effect is smaller when looking at the contemporaneous effects and increasing allowing for more lags. In our final exercise we measure bank lending not in terms of used loans but as granted loans: the coefficient on lending is larger than the one on used loans, but it remains statistically significant.

4.3 Job contract heterogeneity

As a second step of our analysis we zoom in on the composition of the labor force adjustment, to assess in which way firms changed their workforce. Given that we cannot reconstruct the stock of workers by type of contracts and by worker characteristics, we estimate equation 1 taking as dependent variables the quarterly change of employment at the firm level for a given job or worker characteristic, scaled by the average stock of all firm's workers over the quarter.[17] Therefore, differently from the baseline model, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the job contracts/workers. Lacking that information in our sample, we use the aggregates shares at the regional level, as compiled by from the National Institute of Statistics ('Labour Force Survey'), in order to provide an economic interpretation of our findings, see Table 1.

At first, we consider open-ended and temporary contracts—which include fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers—to test whether firms reacted to more binding financing constraints reducing the use of temporary contracts more than open-ended ones (Table 6, top-left panel). We find that the employment adjustment happened primarily through the lay-off (or non-renewal) of temporary contracts. The coefficient on $\Delta LOAN$ is positive and statistically significant for both type of contracts, even though given that temporary contracts account for slightly more than one tenth of total contracts in the workforce (Table 1), the economic effect of the credit contraction is much stronger for temporary than open-ended contracts, since changes in employment due to the former account for 73 percent of the total effect ($0.185/0.252 = 0.73$).

This result is consistent with a growing body of literature pointing to endogenous selec-

[16]The construction of the instrument is modified accordingly.

[17]In other words, the dependent variable is calculated as the ratio between the job flows for a given category of contracts or workers—which we retrieve from PLANET—and the average stock of total workers ($0.5 \times X_{it_1} + 0.5 \times X_{it_0}$, as defined at the denominator of equation 2).

tion and lower human capital accumulation for temporary workers. In particular, temporary workers accumulate less skills—especially firm-specific skills—for both a mechanical reason (shorter seniority leading to less learning-by-doing) and a strategic decision by firms, which provide less on-the-job training. If wages display downward rigidities, firms are likely to reduce their temporary workforce first. Moreover, temporary workers suffer more than open-ended ones simply because they are easier to be dismissed. Indeed, recourse to temporary contracts is known to be more cyclical than the use of open-ended contracts (García Serrano, 1998; Goux *et al.*, 2001). Because firms do not have to pay dismissal costs upon termination of temporary contracts, they typically employ temporary workers as a buffer stock, to deal with expected or unexpected fluctuations in demand or in financial conditions.

To better understand the employment dynamics following the credit crunch, we differentiate between inflows and outflows and we find that our results are mostly driven by the dynamics of outflows, which are higher for firms more exposed to the credit supply shock (Table 6, bottom-left panel). Then, within outflows, we differentiate across the possible reasons of the exit and we find evidence that outflows are exclusively due to non-renewal of expired contracts, while there is no evidence that the adjustment works through dismissal or quit (Table 6, top-right panel). Finally, we look at the transitions across job contracts, considering both contract type and time schedule. We find evidence that firms more exposed to negative credit shocks are are less likely to transform temporary contracts into open-ended ones, while it seems that financing constraints do not affect firm policies in terms of transition between part-time and full-time jobs (Table 6, bottom-right panel).

4.4 Worker heterogeneity

Looking at the workers' characteristics, we first differentiate across three levels of education—low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education), based on the ISCED classification—and we observe that firms which have experienced a reduction in the supply of credit reacted reducing the employment of low- and medium-educated workers, while there is no effect for the highly educated ones (Table 7, top panel). In particular, using the relative shares reported in Table 1, the elasticity of employment to credit supply for low-educated workers is higher than the average and equal to 0.36 ($= 0.140/0.387$). In other words, changes in employment within low-educated workers account for 56 percent of the total effect of $\Delta LOAN$ ($0.140/0.252 = 0.56$), even though low-educated workers account for less than 40 percent of the workforce.

Education may not perfectly overlap with the skill content of jobs; moreover, administrative data may record with errors self-reported information as the level of education. Therefore we replicate the analysis by skill level directly looking at the skill content of each occupation (Table 7, bottom panel).[18] The results based on this different measure of skill level are very similar to those based on the education level. The differential effect across skills or education is consistent with the theory of skill upgrading, which indicates that, in a downturn, firms want to dismiss less skilled, less profitable workers first (Reder, 1955).

Then, we assess whether firms adjusted their labor force differentiating across workers, depending on their gender, age, and nationality. Our results—showed in Table 8—indicate that the employment effect in response to a reduction in the supply of credit is concentrated among women, foreign and younger workers. In particular, female workers represent around 40 percent of total employment, but they account for 70 percent of the total change in employment. Similarly, foreign workers are less the 10 percent of the labor force, but their employment dynamics explains more than 30 percent of the total change in employment.[19] There is also evidence that younger people are more likely to be hit by consequence of the credit crunch, consistent with recent evidence showing that young workers are the most affected during recessions (Forsythe, 2016). The under 30 contribute to more than a third of the overall employment effect, even though they represent less than 20 percent of the workforce.[20]

Finally, in Table 9 we take advantage of the several dimensions in which we can slice our data to measure the impact of the credit crunch on employment, conditional both on contract type and worker education. We find that indeed firms adjusted their labor force in response to a contraction in the supply of credit reducing temporary contracts and dismissing low and medium-educated workers. By contrast, highly-educated workers have been able to insulate themselves, even if hired with a temporary contracts. This result is consistent with the hypothesis that low-skilled individuals suffer most from recessions—possibly because of lower training and hiring costs compared to more educated workers—and with the empirical evidence on Germany discussed by Hochfellner *et al.* (2016). Overall, the results of our analysis indicates that the combination of low-education and temporary contract identifies the profile

[18]Specifically, we look at the ISCO classification of occupations and we consider low-skilled those employed in elementary occupations and services and sales workers; clerical support workers, craft and related trades workers and plant and machine operators, and assemblers have an intermediate level of skills; finally, managers, professionals and technicians are highly-skilled workers.

[19]We cannot exclude that some of the penalty for foreign workers comes from sheer discrimination. For instance, it has been documented that economic downturns favor racial prejudice and lead to worse labor market outcomes for minorities (Johnston and Lordan, 2016).

[20]The recognition that unemployment has important distributional consequences goes back at least to Tobin (1972). In their comprehensive assessment of employment and unemployment patterns across U.S. business cycles, Hoynes *et al.* (2012) show that men, non-whites, youth, and less educated workers show higher sensitivity to economic conditions. These differences in cyclicality appear to be very stable over time, from the late 1970s to the Great Recession.

of workers who has been hit by the credit crunch, while high education makes irrelevant the difference between temporary and open-ended contracts.

4.5 Firm heterogeneity

Finally, we explore possible heterogeneous effect across different firms.[21] First, we are interested in assessing whether the employment response to a credit supply shock differ across firm size, given that SMEs are more likely to be financially constrained, have limited access to alternative sources of external finance, and depend more on bank credit than large firms, so that the real effects of credit shocks is likely to be larger (Beck *et al.*, 2008; Presbitero *et al.*, 2014; Cingano *et al.*, 2016). In our data the reliance on bank financing also differs across firm size (Figure 3). The estimation of equation 1 for the three sub-samples of micro (less then 10 employees), small (between 10 and 49 employees) and medium-large (50 or more employees) firms shows that our results hold only for micro and small firms, consistent with what found by Bottero *et al.* (2015) on a sample of Italian firms over a similar time period (Table 10, left panel). By contrast, the coefficient on $\Delta LOAN$ is not statistically significant in the sample of medium-large firms: the coefficient is positive but imprecisely estimated, and the first-stage F-statistic suggests that there are weak identification problems, possible due to the small sample size and to the capacity of large firms to negotiate with banks about credit terms, while small firms are more likely to be exposed to (nationwide) banks' credit policies.

When splitting our sample across sectors, we find that employment reacts to credit shocks only in services, while there is no evidence that industrial firms reduce employment in response to a credit crunch (Table 10, right panel). In our view, the negligible impact of financing constraints on employment patterns in the industrial sector may depend on the wider use of open-ended contracts and on the larger firm size (and, therefore, on the lower dependence on bank credit) of industrial firms compared to the one in the service sector.[22]

To shed light on the mechanisms through which financial shocks could affect employment

[21] We report all results using sub-samples, but we obtain similar findings estimating the equation 1 on the whole sample and interacting $\Delta LOAN$ by firm characteristics (size, sector and a dummy for multiple bank relationships).

[22] One may argue that the sources of heterogeneity discussed so far have a strong overlap, meaning that we are observing the same firm employment decision (the worker which has been dismissed) from different angles (a worker of small firm in the service sector, with a temporary contract and low education). To reassure the skeptical reader that job contracts and education really matters for employment outcomes during a credit crunch over and above the effect of firm characteristics, we run our model on different sub-samples according to sectors and firm size. Table A1—reported in the annex—shows that the effect of the credit crunch on temporary contracts holds even within firms in services, as well as within micro and small firms. The adjustment on open-ended contract, instead is generally not statistically significant and—when it is, like within micro firms—the size of the elasticity is rather small. Similarly, annex Table A2 confirms that the effect of the credit crunch on the occupation of less educated workers survives within micro and small firms and in the service sector. Similarly, it is worth noting that also differences across age, gender, and nationality are also valid within sectors and firm class size (results not shown but available upon request).

decisions we exploit a set of firms' financial characteristics available in our data. If banks play a crucial role in addressing firms' financing needs, then a sudden drop of credit supply should impact disproportionately more on firms relying more on bank credit, having less flexibility in the use of granted credit lines, and having weaker relationships with their lenders.

First, we examine whether firms that were more indebted at the beginning of our sample period suffered more from the tightening of credit conditions. We consider a firm as more (less) exposed to bank credit if its debt per employee is higher (lower) than the one of similar firms (i.e. we compare firms in the same industry and class size). This choice makes it possible to account for different production functions across industries and to avoid having results that overlap with those showed before. We find that employment reacts relatively more to credit supply restrictions in firms that are more dependent on bank credit (Table 11, left panel). Second, we find that the elasticity of employment to credit is higher for firms that at the beginning of our sample period were using granted credit lines more intensively (Table 11, middle panel). Finally, we explore the possibility that the extent of job disruption following a credit supply shock depends on the strength of the bank-firm relationship. We consider the number of bank relationships, differentiating between firms which borrow exclusively from one bank during the sample period and firms with multiple lending banks. We find positive and significant elasticities in the two sub-samples, even though the point estimate is larger for firms with multiple bank relationships (Table 11, right panel), suggesting that weaker lending relationships expose firms relatively more to the credit crunch. Thus, our results lend support to recent evidence showing that Italian firms that borrowed from fewer banks suffered a smaller contraction of bank credit and a lower increase in lending rates following the Lehman Brothers' bankruptcy (Gobbi and Sette, 2014; Gambacorta and Mistrulli, 2014).

5 Conclusions

The recent literature on finance and labor has showed that firms reduce employment in response to a credit crunch. Our analysis takes advantage of a novel dataset on job contracts and labor market flows for the universe of firms in a large Italian region to look at the within-firm personnel dynamics and identify which kind of workers is more likely to be laid off, depending on firm, individual, and job contract characteristics. To identify the employment effect of the credit crunch, our identification strategy relies of loan level data to build a firm-specific time-varying measure of credit supply restriction and to control for time-varying demand and productivity shocks using a granular set of borrower fixed effects.

Our baseline results confirm that financially constrained firms reduced employment and the point estimate indicate that the elasticity of employment to a credit supply shock is 0.25. The aggregate effect, based on our estimates, is economically meaningful since the contraction in bank lending is able to explain about one fourth of the reduction in employment. In addition, we also show that the adjustment has been differentiated across firms, workers and job contracts. In particular, the credit crunch has mainly affected less educated and less skilled workers with temporary contracts, suggesting that firms have adjusted to the credit supply shock in a way which is consistent with a skill upgrading of the labor force, even though this strategy has been significantly affected by labor market regulation. Finally, we show that high financial dependence and weak bank-firm relationships increase firms' vulnerability and exacerbate the (negative) impact of the credit crunch on employment.

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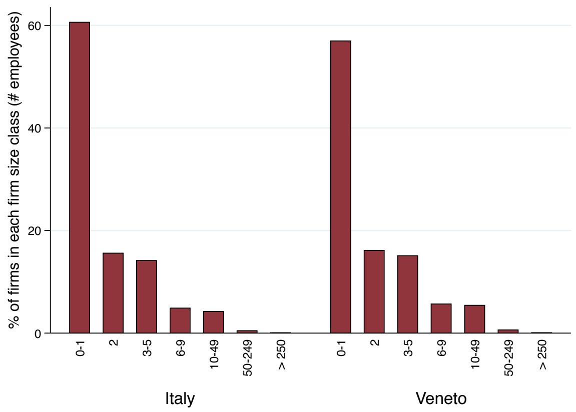
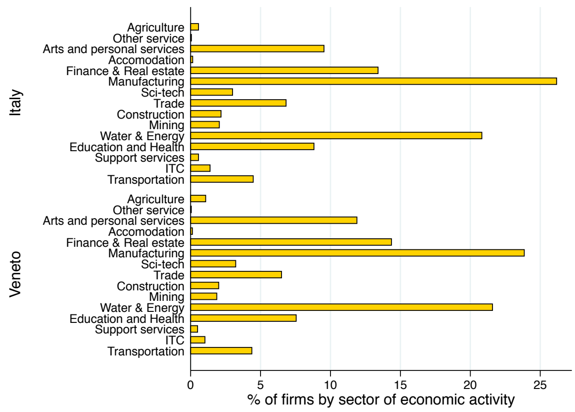
Figures

Figure 1: External validity: firm distribution across size and sectors in Veneto and Italy



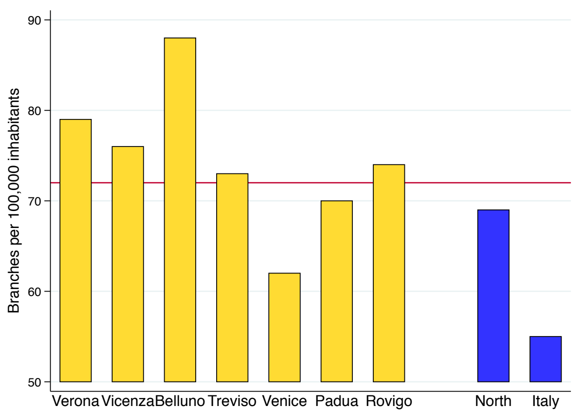
(a) Distribution of firms across size



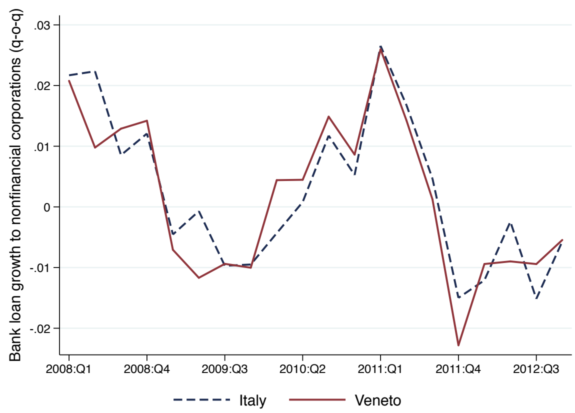
(b) Distribution of firms across sectors

Notes: elaborations on ISTAT data (census 2011).

Figure 2: External validity: bank penetration and lending in Veneto and Italy



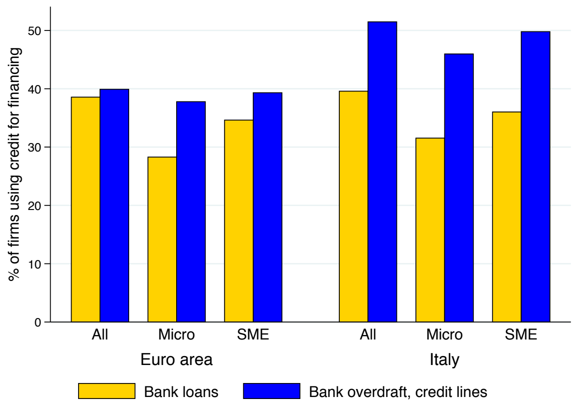
(a) Financial development



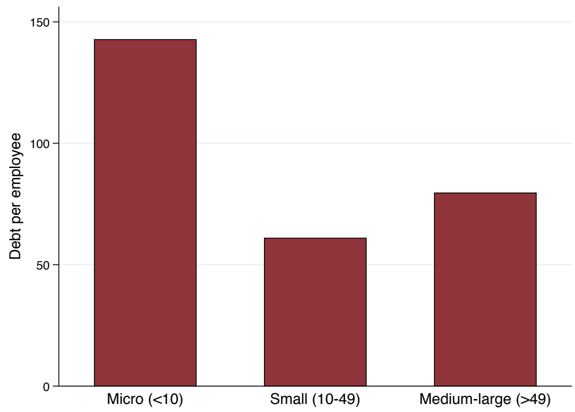
(b) Loans growth

Notes: elaborations on data from Bank of Italy.

Figure 3: Bank financing in Italy across firm size



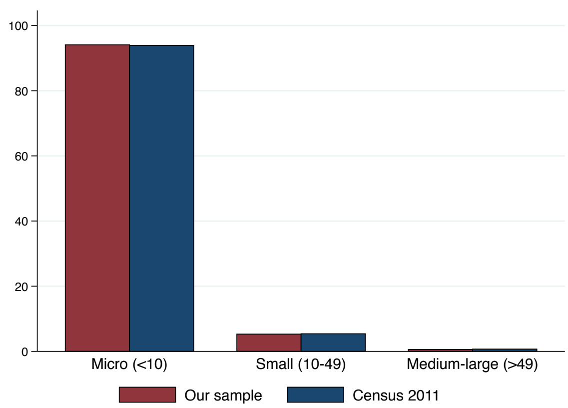
(a) Bank credit (Average 2009-2012, SAFE)



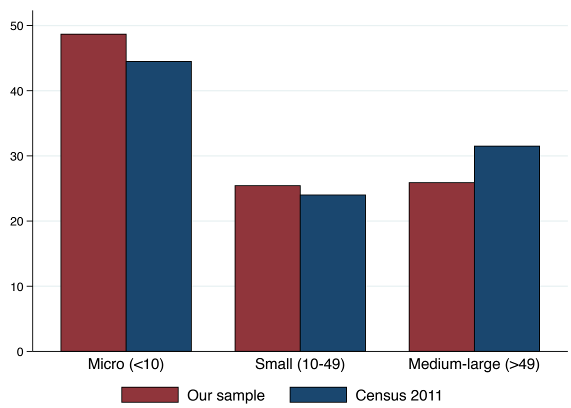
(b) Firms' indebtedness (our data)

Notes: elaborations on data from the Survey on the Access to Finance of Enterprises (SAFE, European Central Bank), Bank of Italy, PLANET, and ASIA. Debt per employee is measured in thousands of euro.

Figure 4: Sample representativeness, comparison with the Census



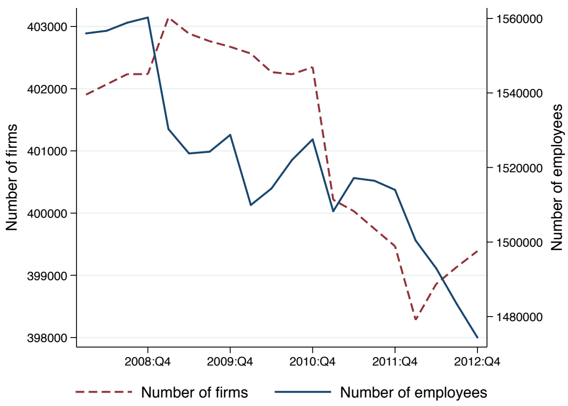
(a) Firms' distribution (%)



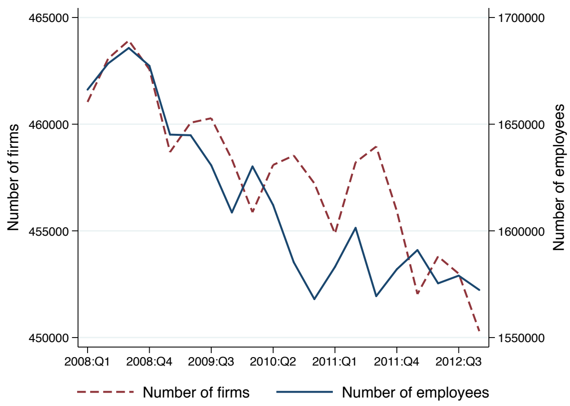
(b) Employees' distribution (%)

Notes: elaborations on data from ISTAT (2011 census), PLANET, and ASIA.

Figure 5: Sample representativeness, dynamics of firms and employment



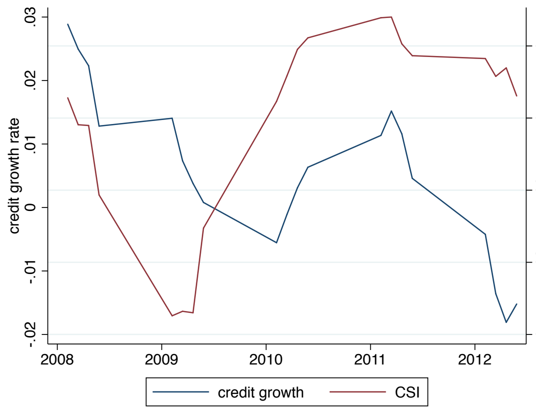
(a) Sample, non-financial private sector (deseasonalized data)



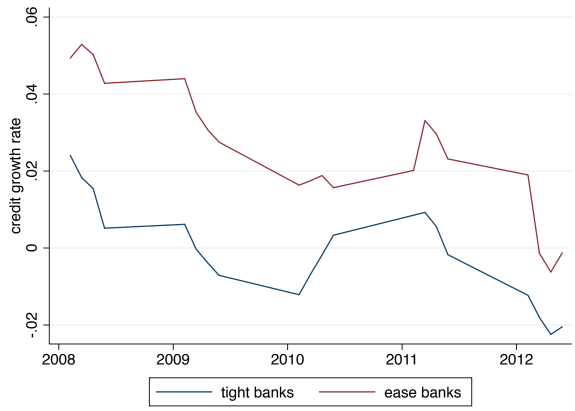
(b) Universe, total economy (Source: ISTAT, RFL)

Notes: elaborations on data from PLANET, ASIA and ISTAT ('Labour Force Survey').

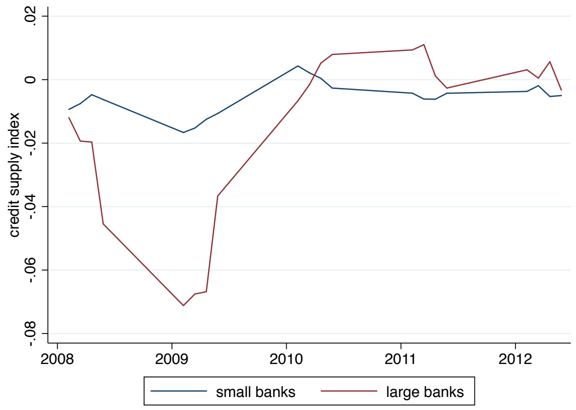
Figure 6: Credit supply index: descriptive statistics



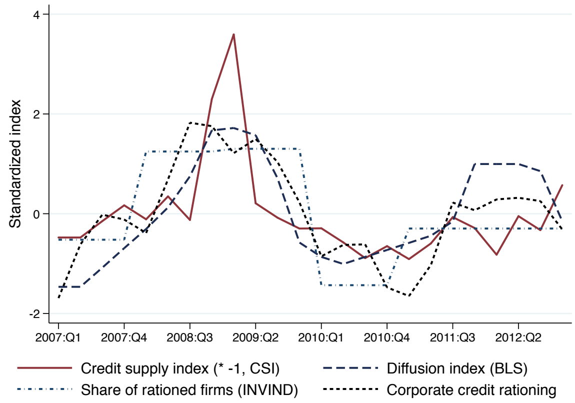
(a) Credit supply index & credit growth



(b) Credit growth across tight and ease banks



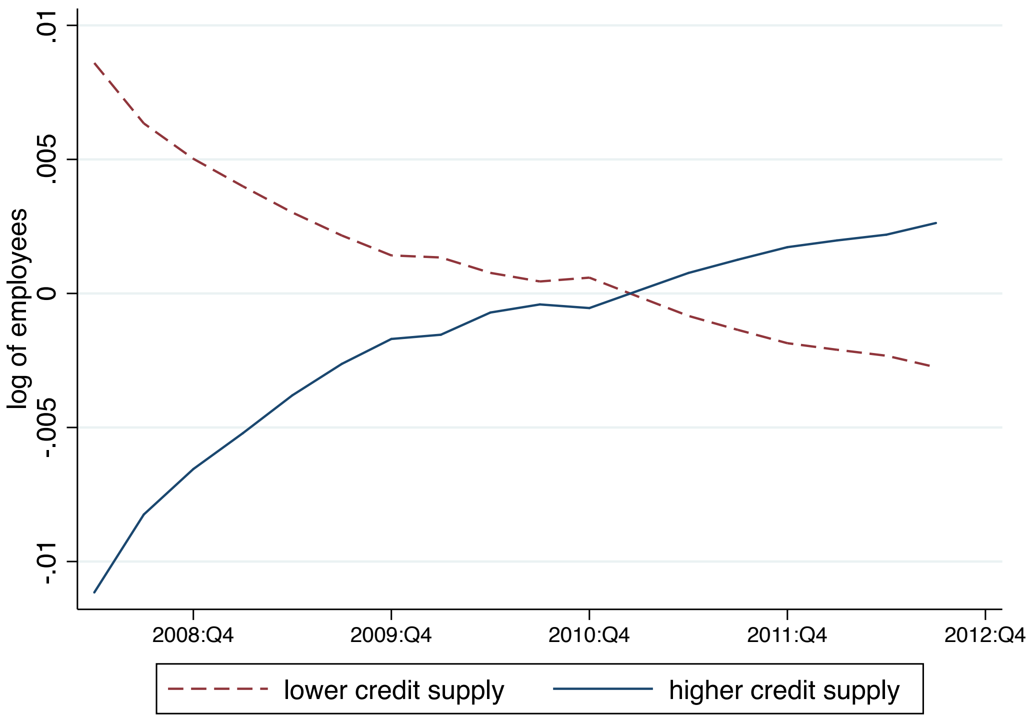
(c) Credit supply index across large and small banks



(d) Credit supply index, lending standards and credit rationing

Notes: The credit supply index (*CSI*) is obtained using the approach by Greenstone *et al.* (2014) and aggregating bank-quarterly fixed effects with banks' market share. In panel (b), tight (ease) banks are those that, in each quarter, have a credit supply index below (above) the median. In panel (c) small banks are mutual banks while large banks are the five largest banks. Panel (d) plots four indicators, all standardized to make the comparison easier: 1) the inverse of the *CSI*; 2) the Diffusion Index, calculated from answers to question 1 ("Over the past 3 months, how have your bank's credit standards as applied to the approval of loans or credit lines to enterprises changed?") of the ECB Bank Lending Survey on Italian Banks (the five possible answers to questions 1 and 6 are: (i) tighten considerably, (ii) tighten somewhat, (iii) remain basically unchanged, (iv) ease somewhat, and (v) ease considerably. The diffusion index varies between -1 and 1; it is computed as the weighted mean of answers (i)-(v), where the values attributed to each answer are 1, 0.5, 0, -0.5, and -1, and the weights are the observed frequencies. See www.ecb.int/stats/money/surveys/lend/html/index.en.html); 3) the share of rationed firms as reported by a survey on firms maintained by the Bank of Italy (INVIND): firms are considered as credit constrained if they asked banks or other financial intermediaries for more credit, and the request has been denied (even in part); 4) Burlon *et al.* (2016) identifies whether any bank-firm transaction is credit rationed or not through the estimation of supply and demand curves and under the assumption that the observed quantity of credit is the minimum between the demand and supplied quantities.
Source: elaboration on data drawn from the Bank of Italy SR, CR, BLS, and INVIND, European Central Bank, and Burlon *et al.* (2016).

Figure 7: Credit supply and employment dynamics



Notes: the figure plots the averages of the residuals of a regression of the logarithm of employees on firm and quarter fixed effects. Averages are computed for the group of firms facing a more favorable (solid line) and less favorable (dashed line) credit supply conditions, defined considering the average *CSI* over 2008-2012 above or below the median, respectively.

Tables

Table 1: Summary statistics

The table reports the summary statistics for $\Delta EMPLOYMENT$ for all workers and for different characteristics of contracts and workers, for the average change in firm borrowing over two quarters ($\Delta LOAN$), and for the credit supply index (CSI). The sample is the one used in the empirical analysis, made by the universe of firms, conditional on having bank debt. The change in employment for temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. Education level are defined as low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education, based on the ISCED classification. The skill content of each occupation is defined as low (elementary occupations and services and sales workers), medium (clerical support workers, craft and related trades workers and plant and machine operators, and assemblers) and high (managers, professionals and technicians), based on the ISCO classification. The last column report the share of employment at the beginning of the period (end 2007) for different characteristics of contract and workers: these data are taken from the 'Labour Force Survey' of the National Institute of Statistics.

Variable	Mean	St. Dev.	Share in total employment (%)
$\Delta EMPLOYMENT$ - Total	-0.0079	0.2050	100.0
$\Delta EMPLOYMENT$ - Open-ended	-0.0055	0.1240	88.7
$\Delta EMPLOYMENT$ - Temporary	-0.0024	0.1657	11.3
$\Delta EMPLOYMENT$ - Under 30	-0.0001	0.1040	17.9
$\Delta EMPLOYMENT$ - Over 30	-0.0078	0.1620	82.1
$\Delta EMPLOYMENT$ - Male	-0.0047	0.1390	59.9
$\Delta EMPLOYMENT$ - Female	-0.0032	0.1330	40.1
$\Delta EMPLOYMENT$ - Italian	-0.0058	0.1720	91.4
$\Delta EMPLOYMENT$ - Foreign	-0.0021	0.0912	8.6
$\Delta EMPLOYMENT$ - Low-education	-0.0047	0.1340	38.7
$\Delta EMPLOYMENT$ - Medium-education	-0.0025	0.1190	48.0
$\Delta EMPLOYMENT$ - High-education	-0.0004	0.0528	13.3
$\Delta EMPLOYMENT$ - Low-skill	-0.0022	0.1370	15.2
$\Delta EMPLOYMENT$ - Medium-skill	-0.0048	0.1270	49.3
$\Delta EMPLOYMENT$ - High-skill	-0.0009	0.0664	35.5
$\Delta LOAN$	-0.0157	0.3130	.
CSI	-0.0085	0.0404	.

Table 2: Credit supply and bank heterogeneity

The table reports the results of a set of OLS regressions at the bank level (in cross section) in which the dependent variable is the average credit supply index (CSI) at the bank level over the sample period 2008-2012 and the explanatory bank-level variables are measured as of end-2007. For the definition of CSI see Section 3.2 and equation 4. Bank size is measured by the logarithm of total bank assets; the funding gap is measured by the loans-to-deposits ratio; Tier 1 capital ratio is defined as Tier 1 capital over risk-weighted assets; and the share of NPLs is the ratio of non-performing loans over total loan. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	CSI at the bank level (average 2008-2012)				
Bank size	-0.0047***				-0.0014**
	(0.0009)				(0.0007)
Funding gap		-0.0102***			-0.0085***
		(0.0018)			(0.0017)
Tier 1 capital ratio			0.0470***		0.0383***
			(0.0073)		(0.0074)
Share of NPLs				-0.0237	-0.0494
				(0.0388)	(0.0365)
Observations	536	536	536	536	536
R^2	0.084	0.113	0.148	0.001	0.240

Table 3: Orthogonality conditions

The table reports the average values of a set of variables (by row) for each quintile of the sample distribution of the credit supply index (CSI). The % industry (services) is the share of firms in the industry (services) sector; the % main province is the percentage of firms that is located in the main province (i.e. Verona); Utilized/granted credit is the ratio between the utilized credit and total granted credit lines; Multi-banks is a dummy equal to one if teh firm has multiple banking relationship and equal to zero for firms borrowing from only one bank. For the definition of CSI see Section 3.2 and equation 4. The last column reports the correlation between each of the row variables and the CSI in the whole sample

	Quintile of exposure to credit supply shock					Correlation with
	1	2	3	4	5	credit supply (CSI)
Credit supply index (CSI)	-0.040	-0.018	-0.007	0.000	0.022	1,000
% industry	0.324	0.328	0.341	0.277	0.298	-0.024
% services	0.676	0.672	0.659	0.723	0.702	0.024
# employees	4.706	7.646	9.325	4.826	3.935	-0.007
% main province	0.235	0.238	0.221	0.173	0.144	-0.055
Debt per employee	129,095	174,206	165,235	165,662	115,257	-0.003
Utilized/granted credit	0.870	0.855	0.823	0.987	0.884	0.003
Multi-banks	0.196	0.311	0.395	0.238	0.194	-0.017

Table 4: Baseline regressions – IV estimates

The table reports the regression results of the 2SLS estimation of equation 1. The top panel shows the first-stage results, while the bottom panel reports the second-stage results. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. Both variables are calculated as in equation 2, so that they are bounded between -2 and $+2$. CSI is the credit supply index, as defined in Section 3.2 and equation 4. All four regressions are based on the full sample and they differ because of the set of time and borrower fixed effects that are included, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

1^{st} stage	Dep var: $\Delta LOAN_{t,t-1}$			
$CSI_{t,t-1}$	0.0787***	0.0779***	0.0757***	0.0750***
	(0.00609)	(0.00609)	(0.00609)	(0.00622)
R^2	0.156	0.157	0.158	0.158
2^{nd} stage	Dep Var: $\Delta EMPLOYMENT_t$			
$\Delta LOAN_{t,t-1}$	0.359***	0.343***	0.342***	0.252***
	(0.0571)	(0.0568)	(0.0584)	(0.0572)
Observations	2,443,442	2,443,442	2,443,442	2,443,442
1^{st}-stage F-statistic	180.1	176.6	166.8	156.3
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	.	.	.
Industry × quarter FE	No	Yes	Yes	Yes
Size × quarter FE	No	No	Yes	Yes
Province × quarter FE	No	No	No	Yes

Table 5: Robustness exercises

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$; $\Delta LOAN_t$ is the change in used loans at the firm level in quarter t; $\Delta LOAN_{t,t-2}$ is the average change in used loans at the firm level in quarters t, $t-1$ and $t-2$. $\Delta GRANTED\ LOAN_{t,t-1}$ is the average change in granted loans at the firm level in quarters t and $t-1$. All these variables are calculated as in equation 2, so that they are bounded between -2 and $+2$. $HOUSE\ PRICE_t$ is .... In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4; the definition of the CSI follows the one of $\Delta LOAN$, so that it is calculated over two quarters (t and $t-1$) in all specifications but columns 8 and 9 where CSI is calculated on quarter t and on the three quarters t, $t-1$ and $t-2$, respectively. All four regressions are based on the full sample and they differ because of the set of time and borrower fixed effects that are included, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In column (5) standard errors are clustered at the province-industry-class size level.

Dep. Var.:	$\Delta EMPLOYMENT_t$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta LOAN_{t,t-1}$	0.259***	0.224***	0.250***	0.231***	0.252***	0.347***	0.252***			
	(0.0572)	(0.0558)	(0.0570)	(0.0563)	(0.0928)	(0.0841)	(0.0572)			
$HOUSE\ PRICE_t$							-0.0414***			
							(0.0135)			
$\Delta LOAN_t$								0.187***		
								(0.0424)		
$\Delta LOAN_{t,t-2}$									0.441***	
									(0.0792)	
$\Delta GRANTED\ LOAN_{t,t-1}$										0.645***
										(0.160)
Observations	2,443,442	2,443,442	2,443,442	2,443,442	2,443,442	1,852,098	2,443,442	2,443,451	2,443,442	2,338,048
1^{st}-stage F-statistic	157.1	156.2	156.9	154.6	169.7	116.5	156.3	113.3	143.0	65.7
Sample	All firms	All firms	All firms	All firms	All firms	Drop < 75k	All firms	All firms	All firms	All firms
Standard errors	Robust	Robust	Robust	Robust	Clustered s.e.	Robust	Robust	Robust	Robust	Robust
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	.	.	Yes	.	Yes	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	.	Yes	.	.	Yes	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	.	.	.	Yes	Yes	Yes	Yes	Yes	Yes
Industry × size × quarter FE	Yes	No	No	.	.	.	.	.	.	.
Industry × province × quarter FE	No	Yes	No	.	.	.	.	.	.	.
Province × size × quarter FE	No	No	Yes	.	.	.	.	.	.	.
Industry × province × size × quarter FE	No	No	No	Yes	.	.	.	.	.	.

Table 6: Job contract heterogeneity

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different types of job contracts, as labeled in each column, divided by the average stock of all firm's workers over the quarter. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the job contracts (see Table 1). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The top panel reports the results for two sub-samples of open-ended and temporary contracts, and the three sub-samples of contract termination (outflows) due to dismissal, expiration of the contract, or voluntary quit. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. The bottom panel reports the results for the sub-samples of changes in employment due to inflows or outflows, and the ones based on three different transitions: from temporary to open-ended contracts, from full-time to part-time jobs, and from part-time to full-time jobs. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Contracts		**Reason of exit**		
	Open-ended	Temporary	Dismissal	Expiry	Quit
$\Delta LOAN_{t,t-1}$	0.0652**	0.1850***	-0.0272	-0.124***	-0.0116
	(0.0314)	(0.0471)	(0.0222)	(0.0300)	(0.0275)
	Flows		**Transitions**		
	Inflows	Outflows	Fixed to open	Full to part-time	Part-time to full
$\Delta LOAN_{t,t-1}$	0.0690	-0.179***	0.0210**	-0.00263	-0.00429
	(0.0447)	(0.0508)	(0.00867)	(0.00654)	(0.00594)
Observations	2,443,442	2,443,442	2,443,442	2,443,442	2,443,442
1^{st}-stage F-statistic	156.3	156.3	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

Table 7: Worker heterogeneity by education and skills

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different types of workers, as labeled in each column, divided by the average stock of all firm's workers over the quarter. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the workers in the workforce (see Table 1). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The top panel reports the results for workers with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. The bottom panel reports the results for the sub-samples of workers, based on the skill content of each occupation, defined as low (elementary occupations and services and sales workers), medium (clerical support workers, craft and related trades workers and plant and machine operators, and assemblers) and high (managers, professionals and technicians)—based on the ISCO classification. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$		
	Education level		
	Low	Medium	High
$\Delta LOAN_{t,t-1}$	0.140***	0.100***	0.0108
	(0.0373)	(0.0325)	(0.0136)
	Skill level		
	Low	Medium	High
$\Delta LOAN_{t,t-1}$	0.142***	0.0772**	0.0334*
	(0.0393)	(0.0329)	(0.0170)
Observations	2,443,442	2,443,442	2,443,442
1^{st}-stage F-statistic	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Worker heterogeneity by personal characteristics

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different types of workers, as labeled in each column, divided by the average stock of all firm's workers over the quarter. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the workers in the workforce (see Table 1). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The left panel reports the results for the sub-samples of men and women. The middle panel reports the results for the sub-samples of workers whose age is below or above 30 years. The right panel show the results for the sub-sample of Italian and foreign workers. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$					
	Gender		**Age**		**Nationality**	
	Male	Female	under 30	Over 30	Italian	Foreign
$\Delta LOAN_{t,t-1}$	0.0741**	0.178***	0.0867***	0.164***	0.172***	0.0788***
	(0.0360)	(0.0386)	(0.0287)	(0.0441)	(0.0474)	(0.0243)
Observations	2,443,442	2,443,442	2,443,442	2,443,442	2,443,442	2,443,442
1^{st}-stage F-statistic	156.3	156.3	156.3	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: The effect of contract type and education

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different types of contracts (open-ended and temporary) and workers (with low, middle, and high education), as labeled in each row and column, respectively. Those flows are divided by the average stock of all firm's workers over the quarter. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the workers in the workforce (see Table 1). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. Results reported in the top panel refer to open-ended contracts, for different level of worker education. Results reported in the bottow panel refer to fixed-ended contracts, for different level of worker education. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. Education level are based on the ISCED classification: low means at most compulsory education, medium is at most upper secondary education, and high indicates tertiary education. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$		
Education:	Low	Medium	High
	Open-ended contract		
$\Delta LOAN_{t,t-1}$	0.0260	0.0307*	0.00895
	(0.0220)	(0.0185)	(0.00716)
	Temporary contract		
$\Delta LOAN_{t,t-1}$	0.114***	0.0693**	0.00184
	(0.0302)	(0.0275)	(0.0121)
Observations	2,443,442	2,443,442	2,443,442
1^{st}-stage F-statistic	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes

Table 10: Firm heterogeneity by size and sector

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The left panel reports the results for three sub-samples defined on the basis of firm size. Firm size bins identify micro (less than 10 employees), small (between 10 and 49 employees) and medium and large firms (50 or more employees). The right panel reports the results for the sub-sample of firms in the industry and service sectors. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Firm size			**Sector**	
	Micro	Small	Med-Large	Industry	Services
$\Delta LOAN_{t,t-1}$	0.246***	0.306**	3.449	0.0888	0.304***
	(0.0609)	(0.158)	(16.523)	(0.106)	(0.0680)
Observations	2,072,535	332,163	38,744	811,391	1,632,051
1^{st}-stage F-statistic	131.9	27.73	0.206	35.97	121.0
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

Table 11: Firm heterogeneity by financial characteristics

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The left panel reports the results for the sub-samples of firms with low and high debt per employee at the beginning of the period (the split is done around the median comparing firms in the same sector and size class). The middle panel reports the results for the sub-samples of firms which at the beginning of the period had a low and high utilization of granted credit lines (i.e. with the ratio of utilized loans over granted loans below or above the median). The right panel separates between firms which borrows from only one bank (Single-bank) and firms with multiple banking relationships (Multi-banks). All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$					
	Debt		**Credit lines use**		**Relationship lending**	
	Low	High	Low	High	Single-bank	Multi-banks
$\Delta LOAN_{t,t-1}$	0.183***	0.358***	0.206***	0.315***	0.303***	0.397***
	(0.056)	(0.123)	(0.064)	(0.107)	(0.098)	(0.201)
Observations	1,199,222	1,244,220	1,214,350	1,229,092	1,384,664	1,006,591
1^{st}-stage F-statistic	101.8	79.3	89.3	72.5	60.7	23.5
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

A-I Additional Tables

Table A1: The effect of contract type within firm sector and size

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different types of job contracts—open-ended in the top panel and temporary contract in the bottom panel—divided by the average stock of all firm's workers over the quarter. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the job contracts (see Table 1). Results are reported for different sub-samples across sectors (industry and services) and firm size. Firm size bins identify micro (less than 10 employees), small (between 10 and 49 employees) and medium and large firms (50 or more employees). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Over sectors		**Over firm size**		
	Open-ended contract				
$\Delta LOAN_{t,t-1}$	0.0550	0.0660**	0.0573*	0.109	0.817
	(0.0756)	(0.0327)	(0.0333)	(0.0907)	(2.276)
	Temporary contract				
$\Delta LOAN_{t,t-1}$	0.0356	0.235***	0.186***	0.192	1.462
	(0.0757)	(0.0585)	(0.0507)	(0.122)	(3.975)
Observations	811,391	1,632,051	2,072,535	330,973	39,934
1^{st}-stage F-statistic	35.97	121.0	131.9	27.73	0.206
Sector	**Industry**	**Services**	All firms	All firms	All firms
Firm size	All firms	All firms	**Micro**	**Small**	**Medium-large**
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

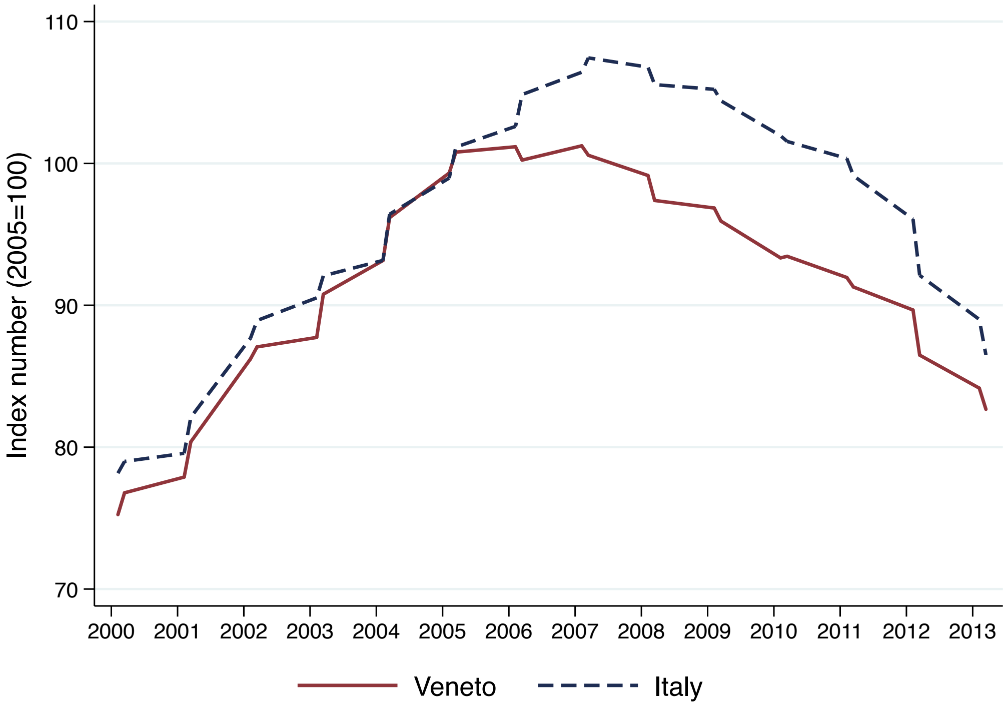
Table A2: The effect of education within firm sector and size

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different levels of education—low, medium and high—divided by the average stock of all firm's workers over the quarter. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. Education level are based on the ISCED classification: low means at most compulsory education, medium is at most upper secondary education, and high indicates tertiary education. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the job contracts (see Table 1). Results are reported for different sub-samples across sectors (industry and services) and firm size. Firm size bins identify micro (less than 10 employees), small (between 10 and 49 employees) and medium and large firms (50 or more employees). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. All regressions are based on the full sample and include the same set of time and borrower fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Over sectors		**Over firm size**		
	Low education				
$\Delta LOAN_{t,t-1}$	0.0671	0.165***	0.131***	0.199*	1.755
	(0.0805)	(0.0415)	(0.0397)	(0.105)	(4.685)
	Medium education				
$\Delta LOAN_{t,t-1}$	0.0192	0.127***	0.103***	0.0885	0.390
	(0.0545)	(0.0398)	(0.0355)	(0.0718)	(1.156)
	High education				
$\Delta LOAN_{t,t-1}$	-0.00179	0.0142	0.0115	0.0112	0.0595
	(0.0190)	(0.0173)	(0.0149)	(0.0288)	(0.306)
Observations	811,391	1,632,051	2,072,535	330,973	39,934
1^{st}-stage F-statistic	35.97	121.0	131.9	27.73	0.206
Sector	**Industry**	**Services**	All firms	All firms	All firms
Firm size	All firms	All firms	**Micro**	**Small**	**Medium-large**
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

A-II Additional Figures

Figure A1: Housing prices in Veneto and Italy, 2000–2013



Notes: elaborations on data from Bank of Italy and Osservatorio sul Mercato Immobiliare.