Banks, Firms, and Jobs*

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Abstract: We analyze the heterogeneous employment effects of financial shocks using a rich data set of job contracts, matched with the universe of firms and their lending banks in one Italian region. To isolate the effect of the financial shock we construct a firm-specific time-varying measure of credit supply. The preferred estimate indicates that the average elasticity of employment to a credit supply shock is 0.36. The adjustment has effects both at the extensive and intensive margins and is concentrated among workers with temporary contracts. We also examine heterogeneous effects of the credit crunch by education, age, gender and nationality.

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. The labor market effects of the crisis have not been uniform, and young and less educated workers have been particularly hit by the crisis (Hoynes *et al.*, 2012). While these outcomes raise important distributional concerns, it has been argued that crises could also have a "cleansing" effect to the extent that the least productive jobs and firms are the ones relatively more affected by the financial shock (Caballero and Hammour, 1994; Petrosky-Nadeau, 2013). These developments 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; Buera *et al.*, 2015; Duygan-Bump *et al.*, 2015).

While this literature provides original insights on the effects of financial crises on aggregate employment at the firm or state level, it is generally silent about within-firm dynamics and labor reallocation. For instance, little is known about the impact of a decline in firm financing on different types of jobs, even though a differential impact of the crisis across demographic groups would have distributional implications. Moreover, the employment adjustment within firms—between workers and jobs characterized by a different skill content—can have an effect on aggregate productivity. 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. In particular, we focus on worker education to test whether the contraction in employment during the global financial crisis has been associated with a skill upgrading of the workforce, at the firm level. Understanding which jobs and workers are more exposed to the real effects of large financial shocks provides useful insights to better understand how firms re-organize themselves at times of crisis and can inform the debate on the distributional consequences and the possible cleansing effect of financial crises.

We run our analysis 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. This is an important feature of our data given that bank credit is very often the only source of external financing for micro and small enterprises. 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 3.6 percent. This effect is the result of adjustments at the intensive and extensive margins, is concentrated among workers with temporary contracts, and occurred mostly through increased outflows rather than decreased inflows. These results are in line with the existence of a "dual" labor market where temporary contracts absorb large part of the employment volatility. The reduction in employment is concentrated among relatively less educated individuals and happened mostly by allowing temporary contracts to expire. By contrast, less educated workers with open-ended contracts are almost unaffected by tighter firms' financing constraints, possibly because of higher firing costs and a rigid employment protection legislation (EPL). Even though skill upgrading strategies are heavily shaped by contract regulation, our results are not driven exclusively by high EPL: when focusing on a sub-sample of small firms for whom firing costs are lower, we still find that the adjustment is borne primarily by less educated workers with temporary contracts. These differential effects are mainly driven by the adjustment at the intensive margin, while the effects on employment due to firm exit are more homogeneous across contracts and workers. We also find evidence suggesting that women and foreign workers are hit disproportionately more by the credit shock, irrespective of the kind of job contract, while the stronger effect on young workers reflects their higher propensity to be hired with temporary contracts.[1]

From a more general perspective, it could still be the case that workers who are more likely to lose their job in our sample could be hired by non-banked firms. However, when we aggregate employment and loan outcomes for all firms in the region at the province-industry-quarter level, we still find a negative impact of the credit crunch (both from an economic and statistical point of view) on employment, suggesting that the contraction in employment has not been offset by firms without banking relationships.

This paper contributes to the growing literature on the real effect of credit supply shocks (Amiti and Weinstein, 2011, 2017; Cingano *et al.*, 2016; Paravisini *et al.*, 2015) and is closely related to the recent contributions that investigate the effects of financial shocks on employment outcomes at the firm level (Barbosa *et al.*, 2017; Benmelech *et al.*, 2015; Bentolila *et al.*, 2017; Berg, 2016; Caggese *et al.*, 2016; Chodorow-Reich, 2014; Ersahin and Irani, 2016; Giroud and Mueller, 2016; Hochfellner *et al.*, 2016; Popov and Rocholl, 2017; Siemer, 2016).[2] Drawing on micro-level datasets, these studies consistently show that a tightening of the credit supply leads to a contraction of the workforce.

The analysis by Bentolila *et al.* (2017) 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 2.8 percentage points more than firms that were borrowing from healthier lenders, and results

[1] In additional exercises we show that the effect of the shock is concentrated among firms that entered the crisis with a lower credit rating, a higher debt overhang, and that have weaker relationships with banks, consistent with the evidence that firm balance sheets play a key role in the propagation of shocks (Giroud and Mueller, 2016). We also find that the elasticity of employment to credit supply is especially relevant for micro and small firms, for younger firms, and for those with a lower *ex-ante* labor productivity (see Appendix A-III).

[2] 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).

are able to explain about a fourth of the fall in aggregate employment in Spain between 2007 and 2010. Also, their analysis uncovers that job losses have been mostly borne by temporary employees, while wages adjusted only marginally. 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 in firm location, distinguishing between firms that are located in one of the seven federal states where the major bank was one of the five *Landesbanks* with significant exposure to the U.S. mortgage crisis, and firms that are located elsewhere. 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.[3] 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.

Our analysis has the advantage of bringing together three key elements which in previous studies have been considered separately. First, the availability of loan-level data (instead of aggregate credit data) allows us to identify the bank lending channel at the firm-level. Moreover, those data make 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-

[3] In a related work, Caggese *et al.* (2016) show that financial constraints distort firm firing decisions. Financially constrained firms give more weight to current cash flows than to future ones and therefore decide on whom to fire on the basing of firing costs, rather than considering expected productivity. This hypothesis is confirmed using employer-employee matched data from Sweden, which show that financially constrained firms fire relatively more short-tenured workers, who are on average younger, with steeper productivity profiles and lower firing costs, than long-tenured ones.

specific time invariant demand shifters and time-varying demand shocks that are common to a narrowly defined cluster of borrowers. The matched bank-firm data also 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 lending policies that are purged of local loan demand (and of any other province-sector-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. We discuss different arguments to motivate the exogeneity of our instrument and we show that it is strongly correlated with loan growth at the firm level.[4] Second, thanks to contract-firm-bank matched data, we can investigate heterogeneous responses to a financial shock across workers, job contracts, and firms. In particular, we can exploit differences across contract types and look at the intersection between demographic characteristics (education, age, gender and nationality) and job contracts, to assess which dimensions matter more for firm's employment decisions.[5] 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 and this allows us to have a more precise (and larger) estimate of the employment effect of financial shocks.

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

[4] In one of the extensions, we show that results hold even if we build our measure of credit supply on the sub-sample of firms with multiple bank relationships, which allows to control for firm-specific time-varying credit demand.

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

a population of 4.9 million individuals and a workforce of 2.2 million workers. According to the National Institute of Statistics data, the region accounts for roughly 9 percent of the Italian value added and of total employment. A key feature for our analysis is that Veneto can be considered as a self-contained labor market. About 97 percent of the workers resident in the region have their workplace in a municipality within the region, and migration to other regions is a negligible phenomenon at the aggregate level (0.4 percent of the population per year); moreover, both figures are substantially stable in the temporal window considered in the analysis. As a result, it is unlikely that our results will be biased by dismissed workers finding jobs out of region.

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). 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 the share of the industrial sector being slightly larger than in the rest of Italy.

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 by 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. In the following we provide an overview of the construction and structure of dataset, while more detailed information are discussed in the annex A-I. Daily labor market flows from the regional public employment service are indeed matched to stock information from 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 guarantees at the same time wide population coverage, high information reliability and a nearly total frequency of success in the matching procedure.

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*. 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 worker information covers 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 from the firm.

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 Institute (ISTAT) with register data from the Social Security Administration. 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. The purpose of this exercise is to guarantee consistency between flows and stocks and, more importantly, to have quarterly stock data.[6]

To obtain 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 firm 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.[7] 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 we use to construct the instrumental variable (see Section 3.2).[8]

[6]One limitation of our data is the lack of information on wages. 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 Great Recession has worked through the adjustment of quantities rather than prices (Fabiani *et al.*, 2015; Bentolila *et al.*, 2017; Hochfellner *et al.*, 2016), consistently with the presence of downward wage rigidities in regulated labor markets. A further potential constraint of our data is the lack of firm balance-sheet information, which prevent us from controlling for a number of possible drivers of employment decisions. To overcome this limitation, in the empirical analysis we saturate the model with a set of granular fixed effects which capture most of the unobserved time-varying borrower-level heterogeneity. In addition, we match a sub-sample of relatively larger firms with balance-sheet and income statement data from the CADS database—a proprietary firm-level database owned by Cerved Group S.p.a.—to explore additional sources of firm-level heterogeneity, and assess the effect of the credit crunch on capital accumulation (see online Appendix A-III).

[7]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 our 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.

[8]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.

2.3 Sample selection and the final data set

All data sources are merged together using VAT numbers as univocal firm identifiers. 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 in 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. Moreover, all firms with loan information are also present in ASIA, so extremely short-lived firms fall beyond the scope of the analysis. Thus, we include all firms that are not in PLANET but are in the firm register, and we assume that inflows and outflows for those firms are zero. 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.

The selection of the sample is driven by two main 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, insofar 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.[9]

After a process of data cleansing, the final sample includes nearly 440,000 firms of which about 200,000 have bank relationships.

2.4 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).

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

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

[9]We also remove 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. In the latter case, they would mistakenly increase the number of actual firms. Moreover, when registered as employees, they are typically employed by households, rather than by firms.

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 about a third of firms were borrowing from more than one bank at the beginning of the period. The job loss for the average firm is equal to 2.1 percent, 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).[10] 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 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 (Moscarini and Postel-Vinay, 2012; Haltiwanger *et al.*, 2013; Siemer,

[10] 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).

2016).[11] 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, 2017), 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).[12] 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. 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 (2-digit) industry×quarter ($\gamma_{s(i)} \times \tau_t$) and province×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×time fixed effects to absorb time-varying borrower demand shocks, using industry-province-size-quarter fixed effects (see Section A-III.1).

Second, bank lending is endogenous to firms' economic conditions and employment choices,

[11]The dependent variable shows a high variability, with a large number of negative and positive changes, but it has a large share of zeros (corresponding to all firm-quarter observations in which the firm does not change its labor force), which could generate a bias in the estimate. In some circumstances, variations in the share of zeros across sub-samples, could explain part of the heterogeneity of our findings. We discuss extensively this issue in Section 6.3.

[12]In Section A-III.1 we will show that our key results hold if we consider exclusively the contemporaneous change in loans, or the average change over three quarters.

so that standard OLS estimates are likely to be biased.[13] 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, in the spirit of Greenstone *et al.* (2014). Specifically, we estimate the following equation that decomposes the contribution of demand and supply factors to bank lending growth at the national level:

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

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 excluding those located in Veneto) and main sectors of activity (agriculture, manufacturing, construction, and private non-financial services)[14]; 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 can be interpreted 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

[13] 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).

[14] 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).

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:

$$CSI_{it} = \sum_{b} w_{bit_0} \times \hat{\delta}_{bt} \tag{4}$$

where $\hat{\delta}_{bt}$ are the bank-time fixed effects estimated in equation 3 and 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 evolution of bank lending policies 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 ($\hat{\delta}_{bt}$) 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). Next, we can see that there is significant variability in credit supply across banks, with the large contraction in the supply of credit around 2009 being driven by banks with the lowest values of $\hat{\delta}_{bt}$ (Figure 6, panel c).[15] Finally, the time pattern of our credit supply indicator is also consistent with other aggregate 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,[16] 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 0.6 and 0.7.

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 of individual nationwide bank lending policies $\hat{\delta}_{bt}$ 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, consistent with the fact that those banks were likely more exposed to the liquidity drought in interbank markets and, more generally, to the financial turmoil (see Appendix Table A1).

The exogeneity of CSI_{it} relies on the two terms w_{bit_0} and $\hat{\delta}_{bt}$. As for 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 instance, one could think that bank business model may play a role. In that case, large banks could specialize in lending to large firms that are more exposed to the economic cycle (thus experiencing a decrease in

[15] Moreover, data show that the large drop in credit supply conditions from the beginning of the financial crisis on was mostly concentrated among large banks, consistent with the fact that those banks were more exposed to the liquidity drought in interbank markets.

[16] 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.

employment) 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 issue we include in the specification industry×quarter and class size×quarter fixed effects. As our parameter of interest (β in equation 1) is fairly stable (see Section 4.1), we argue that the problem discussed above is not likely to be an issue in our case. Moreover, as shown in Table 2 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 $\hat{\delta}_{bt}$ 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. However, our identification assumption can be violated if banks with negative supply shocks were more likely to grant credit to firms that were hit more by the crisis. This may occur if, 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. more productive firms). In that case, the estimated bank-time fixed effects $\hat{\delta}_{bt}$ could capture a demand effect rather than a pure supply effect. Alternatively, it could be argued that there is an endogenous sorting between firms and banks, with weak banks lending to weak firms (Schivardi *et al.*, 2017). In both cases we should observe some correlation between credit supply and firm characteristics. However, summary statistics reported in Table 2 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, leverage, bad credit history, geographical location, and sector of activity. 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. Moreover, for a sub-sample of firms for which we have balance sheet information, we can extend this exercise and show that the instrument is not correlated with labor productivity, leverage and riskiness, which could be taken as different proxies for firm quality (see the online Table A12 and Appendix A-III).[17]

Our approach depart from Greenstone *et al.* (2014) along several dimensions that reinforce the exogeneity of the instrument.[18] First, one may argue that banks differentiate their policies over the territory and that local lending policies are influenced by local economic conditions. To address this concern, we estimate equation 1 dropping the Veneto provinces, so that we exclude the effects of demand and supply factors in this region from the calculation of bank-time fixed effects.[19] Moreover, it is worth noting that according to lending survey pursued by the Bank of Italy, there is no evidence that banks applied different lending policies across the four Italian macro-regions (see Figure A2 in the appendix). Second, we translate bank-time fixed effects at the firm rather than at the aggregate (i.e. county) level. This approach further reinforces the exogeneity of the instruments 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

[17]While, by definition, the set of observables cannot include all possible firm characteristics, we argue that it is difficult to think at firm characteristics which are correlated with the credit supply index while being orthogonal to the variables listed in Tables 2 and A12. Also, one could argue that the credit supply index is spatially autocorrelated—for instance, because some banks control large market shares in certain areas. This is indeed the case in our data, as shown by Figure A1 in the appendix and more formally by the Moran Index calculated on CSI. However, once we control for the standard set of fixed effects, the Moran Index does not show evidence of spatial autocorrelation in CSI and the residuals of our baseline regression are also not spatially autocorrelated.

[18]An alternative identification strategy is the one proposed by Amiti and Weinstein (2017), 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 only about a third of firms in our sample borrow from more than one bank at the beginning of the sample period. However, in Section 6.1 we discuss results obtained identifying the bank fixed effects δ_{bt} in a regression at the firm level with time-varying firm fixed effect, on a sub-sample of borrowers with multiple bank relationships.

[19]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.

is less plausible in case of unobservable shock at the firm level. Third, our data allows the estimation of 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 for bank-specific demand shocks that may occur whenever banks specialize, within the same provinces, in lending to different sectors that perform differently each other. Fourth, in Italy government interventions in favor of the banking system has been very limited, contrarily to what has happened in the U.S. and in other European countries. This implies that bank lending policies 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, the plotted values are the residuals (average of the two groups) of a regression of the logarithm of employees on firm and quarter fixed effects, so that the residuals are on average equal to zero and their time patterns show 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 3 reports the 2SLS 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). In line with most of the literature and to adopt a conservative approach, standard errors are clustered at that bank level.[20]

[20]More precisely, the bank corresponds to the firm's main bank. Results are robust to alternative levels of clus-

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 170 and 195, well above the critical value of 10 suggested by Staiger and Stock (1997) to avoid the weak instrument bias.

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.*, 2017), 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 specifications shows that adding fixed effects reduces the employment effect of the credit crunch, as fixed effects capture time-varying borrower-specific demand and productivity shocks. In particular, the point estimate of the coefficient on $\Delta LOAN$ are broadly stable around 0.44 in columns 1 to 3, when adding time-varying industry and class size fixed effects, but decreases to 0.36 when time-varying industry, size and province fixed effects are jointly added in the model (column 4). This result is robust to the inclusion of further controls to absorb demand and productivity shocks, and to alternative definitions of our key variables (see Appendix A-III for details).

From now on, we will take the specification of column 4 as our baseline. The point estimate of the bank lending channel is 0.36, meaning that a 10 percent contraction in bank lending over two quarters translates into a 3.6 percent reduction in employment.[21] In relative terms, one standard deviation of the predicted change of used loan explains 18% of the standard deviation of employment.

tering, which provide more conservative estimates compared to simple heteroskedasticity robust standard errors. In particular, since to construct the credit supply index we estimate bank lending policies with data at the bank-province-sector level, in annex Table A2 we show that clustering at that level leads to very similar standard errors.

[21] This elasticity is roughly twice as large as the one estimated by Cingano *et al.* (2016) on a sample of larger Italian firms, but over a different time span, confirming that focusing on the universe of firms helps providing a more precise estimate of the employment effect of a credit restriction.

4.2 Job contract heterogeneity

As a main contribution of our analysis, we look at within-firm dynamics and 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 for all firms, 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.[22] 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 aggregate 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 react to more binding financing constraints by reducing the use of temporary contracts more than open-ended ones (Table 4, top-left panel). We find that the employment adjustment happens primarily through variation of temporary contracts, consistent with the idea that firms use mostly fixed-term workers to absorb employment volatility (Caggese and Cuñat, 2008) and with lower termination costs for temporary contracts.[23] The coefficient on $\Delta LOAN$ is positive and statistically significant for both type of contracts, even though there is an over-representation of temporary workers among dismissed employees, as

[22] 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).

[23] Since 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. 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).

also discussed by Bentolila *et al.* (2017) for Spain. Although temporary contracts account for only slightly more than one tenth of total contracts in the workforce (Table 1), they bear more than half of the effect of the change in credit supply ($0.191/0.364 = 0.52$, where 0.364 is the estimated coefficient of credit supply variation for the entire workforce—see Table 3, column 4). By contrast, open-ended contracts account for 89 percent of the workforce, but contributed to less than half (48 percent) of the change in employment due to the credit crunch.[24]

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, even though the effect on inflows is also marginally significant (Table 4, 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 4, 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 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 4, bottom-right panel).

4.3 Worker heterogeneity

An alternative interpretation of the fact that the adjustment is mainly borne by temporary contracts could be related to the presence of a high EPL, which makes firing permanent workers for Italian firms very difficult. If terminating open-ended contracts is indeed difficult and costly, the concentration of the adjustment on temporary contracts does not come as a surprise.

[24] We also perform a test to confirm that the relative contribution of temporary and open-ended contracts to the estimated change in employment is statistically different from their share in the workforce, as listed in Table 1. The rationale for this test is that, if employment losses were random across contract type, each contract contribution to overall loss should mirror its share in the total workforce. The same reasoning also applies for other subgroups of workers; see the discussion below.

To mitigate this concern, in this section we take advantage of additional dimensions in which we can slice our data to measure the impact of the credit crunch on employment, conditional both on contract type and a number of workers' characteristics.[25]

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 mostly the employment of low- and medium-educated workers, while the effect for the high-educated ones is smaller and only marginally significant (Table 5, 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 0.48 ($= 0.186/0.387$). The corresponding elasticities are equal to 0.31 and 0.19 for medium- and high-educated workers, respectively. In other words, changes in employment within low-educated workers account for more than half of the total effect of $\Delta LOAN$ ($0.186/0.364 = 0.51$), even though low-educated workers account for less than 40 percent of the workforce.[26]

Then, we combine the effect of contract type with worker education. Results are reported in the middle and bottom panels of Table 5, and visualized in Figure 8, which shows in the blue bars the contribution of the overall estimated effect of credit supply on employment (0.364) due to the combination of contract type and education levels. For comparison, the white bars report the share in total employment by contract type and education. In all relevant cases discussed below, the difference between the two bars is statistically significant. We find that firms adjusted their labor force in response to a contraction in the supply of credit predominantly

[25]In Appendix A-III we discuss an additional set of results that exploit cross-firm heterogeneity. We find that smaller, younger and less productive firms, and those with higher debt overhang and weaker bank-firm relationships have been more vulnerable to the (negative) impact of the credit crunch on employment.

[26]The difference between the relative contribution of low-educated workers to the estimated change in employment (0.51) is statistically different from their share in the labor force (0.39). As education may not perfectly overlap with the skill content of jobs, we replicate the analysis by skill level directly looking at the skill content of each occupation. The findings based on this different measure of skill level are stronger than those based on the education level: the effect is predominantly concentrated on low-skill occupations, which represent about 15 percent of jobs, but account for about 43 percent of the total effect of the credit contraction. Results not shown but available upon request.

reducing temporary contracts of low- and medium-educated workers, even though they account for a relatively low share of total employment. By contrast, high-educated workers have been able to insulate themselves, even if hired with temporary contracts. The effect on low-educated workers with a temporary contract accounts for 32 percent of the total employment effect ($0.115/0.364 = 0.32$), even though they represent less than 4 percent of the workforce. This share declines to 19 percent moving to an open-ended contract (but they account for 33 percent of the workforce) and further down to 6 percent for a high-educated worker with an open-ended contract, which account for 11 percent of the workforce (the effect is not significant for high-educated workers with temporary contracts). These results are consistent with the hypothesis that low-skilled individuals suffer most from recessions, as firms follow a skill upgrading strategy (Reder, 1955; Hershbein and Kahn, 2016), and with the empirical evidence on Germany discussed by Hochfellner *et al.* (2016). Overall, our results indicate that the combination of low-education and temporary contract identifies the profile of workers who have been hit by the credit crunch, while high education makes the difference between temporary and open-ended contracts almost irrelevant.

Second, we assess whether firms adjusted their labor force differentiating across workers, depending on their gender, age, and nationality. As before, we first look at the whole sample (Table 6, top panel) and we then differentiate between contract type (middle and bottom panels). Our results 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 a significantly larger share—60 percent ($0.220/0.364$)—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 24 percent of the total change in employment.[27] There is also evidence that younger

[27] While this difference is statistically significant, 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).

people are more likely to feel the consequences 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 slightly less than a third of the overall employment effect, a value statistically larger than their share in the workforce, equal to 18 percent.

These findings could reflect a propensity of women, foreign and younger workers to have temporary contracts, so that they naturally end up being the most affected if firms primarily adjust cutting back on temporary rather than open-ended contracts. To address this concern we replicate what done in Table 5 and we consider separately temporary and open-ended contracts. Results indicate that both women and foreign workers are more likely to be affected by the credit crunch irrespective of the kind of contract, while the overall effect found for young workers is driven exclusively by those employed with temporary contracts.[28]

Overall, the fact that less educated workers, as well as women and foreign workers, are relatively more likely to lose their job, even within workers employed with temporary contracts, suggests that EPL is not the only driving force behind the adjustment in employment.[29] Moreover, the significant concentration of the employment adjustment on less educated workers and low-skill occupations is consistent with a productivity-enhancing reallocation and with recent evidence showing a cleansing effect of the Great Recession (Foster *et al.*, 2016).

5 Extensions

5.1 Adjustment at the extensive and intensive margins

So far our analysis has considered the effects of a financial shock at the extensive and intensive margins together. However, understanding if the aggregate employment effect is driven by a downsizing of the workforce in active firms or by firm closures has important implications

[28]When considering foreign workers, their relative contribution to the change in employment is significantly larger than their share in the labor force for both types of contracts, even though the coefficient for temporary contracts is imprecisely estimated.

[29]To further rule out the hypothesis that EPL is driving our findings, in a robustness exercises we exploit the fact that in Italy, during the observed period, the strength of EPL differs in a quite substantive way between firms across a threshold of 15 employees, with smaller firms facing weaker EPL and having more flexibility in adjusting their labor force. We replicate our key analysis on a sub-sample of firms with less than 15 employees and we still find that out results hold (see Appendix A-III, Table A15).

for the understanding the crisis and of the mechanisms of workforce management within the firm. To shed some light on the margins of adjustment we first re-estimate our model on a subsample that excludes the firms that close down in a given quarter. Specifically, in each quarter we consider all active firms that can adjust at the intensive margin and the ones that will close in future quarters, but that can still adjust their workforce in the quarters before closure. Then, to look at the extensive margin we estimate a linear probability model for the likelihood that a firm closes its activity in a given quarter.

Our results, reported in Table 7, indicate that the adjustment to a contraction in credit supply has happened both at the intensive and extensive margins, in line with the evidence on Spain (Bentolila *et al.*, 2017). When we drop from the sample firm closures, we still find a precisely identified elasticity, even though its magnitude is smaller, as a 10 percent contraction in credit translates into a 2.5 percent fall in employment. In addition, the adjustment at the intensive margin falls disproportionately on temporary workers, which account for about three quarters of the fall in employment (the effect is about 50 percent in the whole sample). Hence, part of the effect on open-ended contracts is due to firm exit, consistent with the presence of labor market rigidities and high dismissal costs for open-ended contracts. Finally, the last column shows that a shortfall in the supply of credit increases the likelihood of firm exit. This effect is economically meaningful: considering the average contraction of bank credit of 1.6 percent in the sample period, the estimated coefficient implies a 0.1 percent increase in the probability that a firm closes down, which accounts for about one seventh of the average exit rate (Table 1).

Given that the composition of the adjustment at the intensive margin looks different that the overall effect, we replicate the analysis discussed in Section 4.3 to look at the role of worker heterogeneity by education in the restricted sample that excludes firm closures. The results are qualitatively similar, but stronger than those obtained in the whole sample, suggesting that the reduction in employment due to firm exit has been relatively more homogeneous across contracts and workers than the one that involved active firms. In particular, firms which experienced a reduction in the supply of credit, but did not close, reduced employment mostly among low- and medium-educated workers (Table 8, top panel). Then, considering together contract type and education clearly reinforces one of our main findings. The intensive margin adjustment has exclusively affected less educated workers with temporary contracts, while high-educated temporary workers—which represent about a fifth of all temporary contracts—have not been hit by the financial shock (Table 8, middle and bottom panels).

5.2 General equilibrium effects

Overall, results indicate that the effect of the credit crunch on employment is economically relevant. Our findings are roughly comparable, in magnitude, to those estimated by Bentolila *et al.* (2017) 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.[30]

However, the contraction in employment estimated at the firm level could be offset by the behavior of firms that are not included in our analysis because they do not rely on bank credit (i.e. more formally, all firms which do not have a match in the credit register); for instance, temporary workers—which are more likely to lose their job in our sample—could be hired by non-banked firms. In that case, the welfare implications of our analysis could differ. In order to estimate the general equilibrium effects of the credit contraction, we run a set of regressions at the province-industry-quarter level, where we aggregate employment and loan outcomes considering all firms in the region—including the ones without a match in the credit register. The credit supply index is also computed aggregating bank-specific CSIs in each province-

[30]The average firm size is nearly 3,000 in Chodorow-Reich (2014) and about 25 in Bentolila *et al.* (2017), while in our case is around 6 as we are able to observe the universe of firms.

industry-quarter cluster. Results, reported in Table 9, show that the elasticity of aggregate employment to bank lending remains economically relevant, suggesting that any offsetting effect of the credit crunch due to firms without banking relationships, if present, has been relatively small. Moreover, considering separately temporary and open-ended contracts and workers with different education levels shows that the effect is again mostly driven by less educated workers and those with temporary contracts.

6 Robustness

6.1 Internal validity: credit supply index at the firm level

In Section 3.2 we have discussed the exogeneity of our measure of credit supply and provided some empirical evidence to support this assumption. In the end, the key identifying assumption is that firm-level loan demand is not bank-specific and, even though the orthogonality conditions show that the CSI is uncorrelated with a large number of observable characteristics, we cannot test the excluding restriction that changes in credit demand are not correlated with the credit supply index. Thus, to further strengthen the internal validity of our results, we construct the CSI based on a modified version of equation (3), which exploits the sub-sample of firms borrowing from multiple banks (Khwaja and Mian, 2008):

$$\Delta L_{bit} = \alpha + \delta_{bt} + \gamma_{it} + \epsilon_{bit} \tag{5}$$

where the outcome variable ΔL_{bit} is the percentage change in outstanding business loans by bank b to firm i at time t. In this case, the γ_{it} fixed effects absorb firm-specific time-varying credit demand, rather than assuming that all firms in the same province-sector cluster have the same demand. However, this choice comes at the cost of identifying the nationwide bank lending policies parameters δ_{bt} on the sub-sample of firms with multiple bank relationships. As those firms are likely to be different from those with only one bank under a number of characteristics (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), the identification of δ_{bt}

could be affected by the difference in the composition of the sample.

Results are shown in Table 10 and they are consistent with our baseline regressions. The average effect of the contraction in credit supply on employment is driven by temporary contracts and by less educated workers. However, the estimated elasticity is smaller than that estimated with the CSI constructed at the province-sector level. A possible explanation of the smaller magnitude of the coefficient on $\Delta LOAN$ could be due to the sample used to estimate the bank lending policies δ_{bt}: excluding firms with single bank relationships—which are over-represented among small firms borrowing from small banks—could imply a limited capacity to account for credit demand, leading to a weaker link between credit supply and bank lending policies.

6.2 External validity: the employment effect of the credit crunch in crises times

In Section 2 we have provided a broad set of statistics to support the fact that the Veneto region could be considered a representative case study. Another issue that may affect the external validity of our results is the specific time period under analysis, which covers the Lehman's bankruptcy and the European sovereign debt crisis.[31]

As job contracts data are not available before 2008, we are not able to do a standard comparison between a crisis and a tranquil period. However, to take into account the significant changes in economic and financial conditions over the four years of our sample, we split the analysis in 2 sub-samples: the first one covers the Lehman crisis and ends in 2011:Q2, while the second one excludes the Lehman shock and, starting in 2009:Q2, focuses instead on the European sovereign debt crisis. Separating the two episodes is of interest since the dynamics of the banking crisis in Italy has changed over time. The crisis been mostly concentrated among a few large banks at the beginning and became more widespread in coincidence with the sovereign debt crisis, when the tightening of credit conditions reflected the common shock

[31]The prevalence of micro enterprises could also undermine the generality of our findings to other setting where the presence of micro firms is lower. To deal with this issue, we run the analysis on a sub-sample composed by firms with at least 3 employees (see annex Table A3) and we find results in line with those on the whole sample, suggesting that micro firms are not those driving our findings.

of widening sovereign spreads, rather than idiosyncratic bank funding problems. However, notwithstanding these dynamics, results—reported in Table 11—show that the point estimates are relatively stable across periods, even when considering the effect across contract type and education level. In both cases, we find large significant effects on employment levels, mostly concentrated among less educated workers with temporary contracts, which represent almost 4 percent of total workforce but account for about 30 percent of total employment effect. The similarity of size of the effects over the two crises is consistent with the evidence showing large real effects of the Lehman and the Greek crises in Italy (for instance, see Bofondi *et al.*, 2017; Bottero *et al.*, 2016; Cingano *et al.*, 2016).[32]

6.3 Dealing with the large share of zero outcomes

Our dependent variable is characterized by a large share of zeros, corresponding to all firm-quarter observations in which the firm does not change its labor force (Table A4). This feature of the data could generate a bias in the estimates and, more important, as the share of zeros varies across sub-samples, variations in the extent of the bias could explain part of the heterogeneity of our findings.

To better understand the extent to which our results could be driven by differences in the share of zeros across sub-samples, we perform two robustness exercises. First, we collapse the data at a yearly frequency. Second, we restrict the sample to firms that have at least one worker with the characteristics (job contracts and demographics) that are the target of the analysis (e.g., the effect on workers with open-ended contracts is studied only on firms with at least one open-ended employee, and the like). Both exercises are aimed at reducing the share of zeros in the dependent variable, but they also imply some drawbacks along other dimensions. In the first case, the decrease in the fraction of zeros is also associated to a significant drop in their absolute number. As the number of firm fixed effects does not change, this entails a

[32]We also find that the differential effects across gender, nationality and age hold in the two sub-samples. Results are not shown but they are available upon request.

significant loss of variability in the data. In the second case, the estimation samples vary across specifications and, therefore, the coefficients are not perfectly comparable across different sub-samples.

In the first exercise, the share of zeros drops from 79 to 68 percent in the overall sample, and this trend is even stronger for sub-categories of workers. Even though the magnitude of some effects is weaker, and some heterogeneous effects across worker characteristics are not robust, our key findings are qualitatively similar to the baseline ones. Results, reported in Table 12, show that the relative contribution of temporary contracts ($0.082/0.348 = 0.23$) is less than half of that estimated with quarterly data ($0.19/0.36 = 0.52$), but it is still statistically significant and economically relevant, since it is twice as large as the share of temporary workers in the workforce (0.11). When interpreting these results it is worth considering that part of the reduced effect on temporary workers could be explained by the fact that moving to a yearly frequency washes out part of the variation in temporary jobs, which is infra-year.[33] By contrast, when we look at the heterogeneous effects across education, our baseline results are not confirmed, as low-educated workers account for 38.5 percent of the total estimated employment adjustment and for 38.7 percent of the workforce. However, the total employment effect for less educated temporary workers, while much smaller than that estimated with quarterly data, is still more than twice (9 percent) their share in the workforce.

The difference across age is relevant, but smaller than in Table 3, while the overall effect on women and foreign workers are not robust to the transition to yearly data. The fact that we do not find results across gender at the yearly frequency could again be due to the fact that women are more likely to be employed with temporary contracts. In fact, when considering the sub-sample of temporary workers, women are still dis-proportionally affected by the crunch, even if these effects are smaller than those estimated with quarterly data (see annex Table A5).

[33] In 2012, 46 percent of temporary contracts had a duration shorter than one month, 19.6 percent has a duration of 2-3 months, 30.9 percent of 4-12 months and only 3.6 percent of temporary contracts expired after more than one year.

In the second exercise we end up with sub-samples with a significant larger number of non-zero observations and, more important, the differences in the relative shares of zero outcomes across sub-groups are often mitigated. Our main results are replicated in Tables 13. As expected, coefficients are larger, but we still find a predominant contribution of temporary workers to the overall employment adjustment and, within these job contracts, workers with low and medium education are those affected by the credit crunch. We also confirm the relative larger adjustment borne by women and young workers (see the online Appendix A-III, Table A6). While this set of results is consistent with a minor role of the bias, we cannot rule out that it may also depend on sample selection, or be a simple mechanical consequence of the fact that we have eliminated from the sample those firms that could not reduce employment in some categories of workers due to the fact that were bound by null stocks.

Overall, these exercises show that the large share of zero outcomes and a certain heterogeneity in this dimension may play a role in explaining some of our findings. However, the key result that the employment adjustment following the credit crunch is dis-proportionally concentrated on workers with temporary contracts, as well as other differences across worker characteristics, even if weaker, are confirmed.

7 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 delve into the within-firm personnel dynamics and identify which kind of workers are more likely to be laid off, depending on worker and job contract characteristics. To identify the heterogeneous employment effects of the credit crunch, our identification strategy relies on 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: the point estimate indicates that the average elasticity of employment to a credit supply shock is 0.36. This result is due to an adjustment at the intensive margin, but also to a higher probability of firm closure in response to a reduction in the supply of credit. The adjustment has been strongly differentiated across firms, workers and job contracts. In particular, the credit crunch has mainly affected women, foreign, and less educated workers with temporary contracts. The effects across workers with temporary contract indicate that labor market regulation is not the only driving force behind the concentration of the employment adjustment on temporary workers. Moreover, these results suggest that firms have adjusted to the credit supply shock in a way which is consistent with a skill upgrading of the labor force.

Our findings inform the current debate on the real effects of financial shocks along two main dimensions. First, we show that large credit contractions have distributional effects, as some demographic groups have been more affected than others by the global financial crisis. Second, our analysis indicates that financial shocks could play a cleansing role and foster aggregate productivity gains, given that unskilled workers (and jobs in less productive firms) are more likely to be hit by the credit crunch. In this sense, while credit contractions can have short-run negative welfare effect, as employment (and investment) fall, in the medium term the labor re-allocation toward more educated workers and high-skill occupations could enhance productivity and growth.

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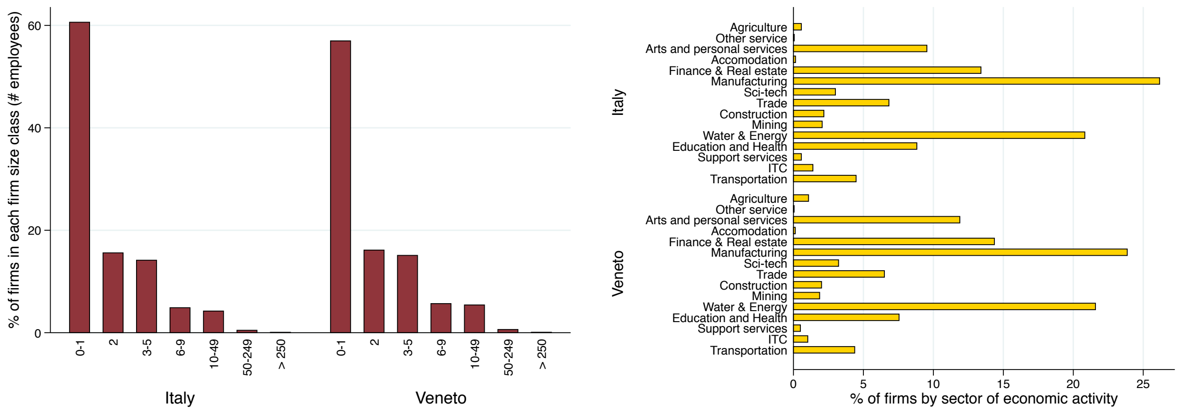
Figures

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

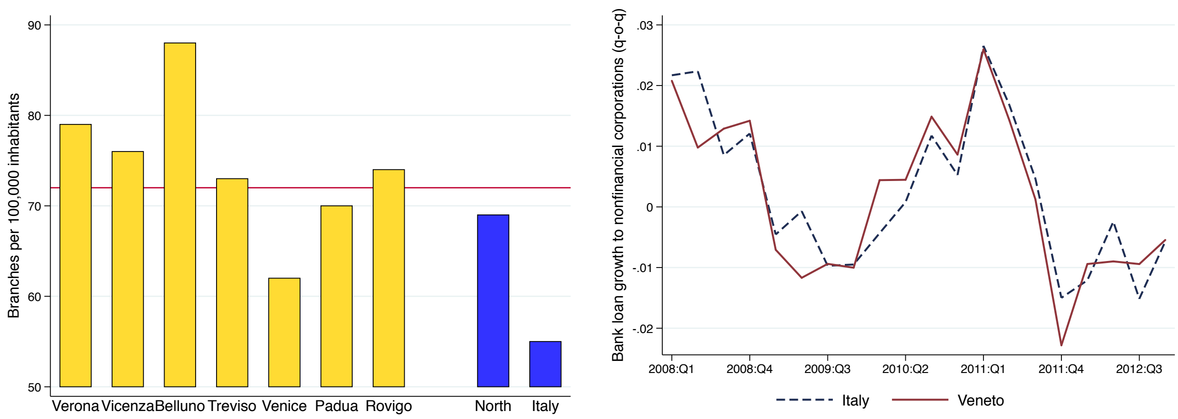


(a) Distribution of firms across size

(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

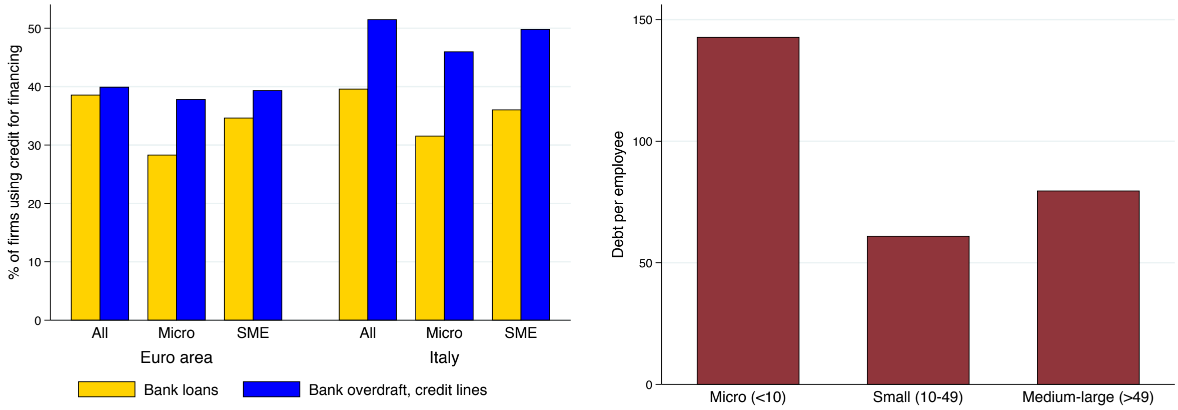


(a) Financial development

(b) Loans growth

Notes: elaborations on data from Bank of Italy.

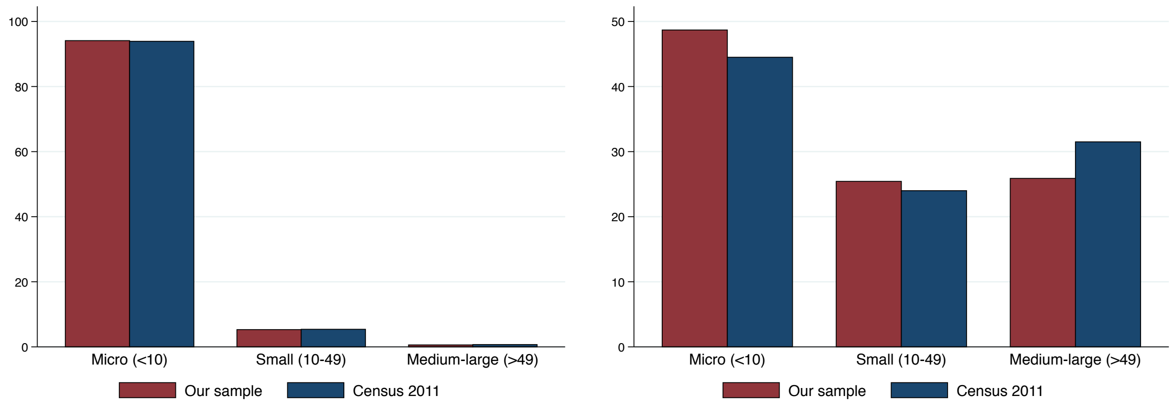
Figure 3: Bank financing in Italy across firm size



(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

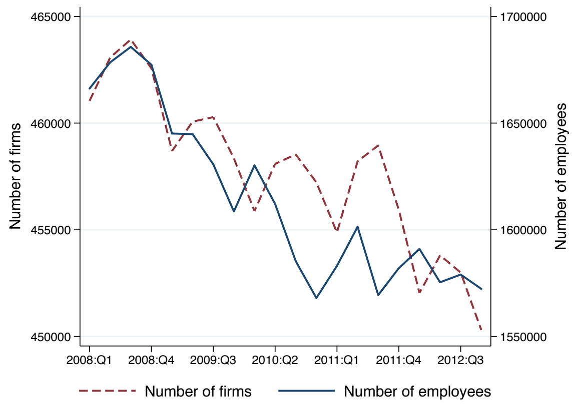


(a) Firms' distribution (%)   (b) Employees' distribution (%)

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

Figure 5: Sample representativeness, dynamics of firms and employment

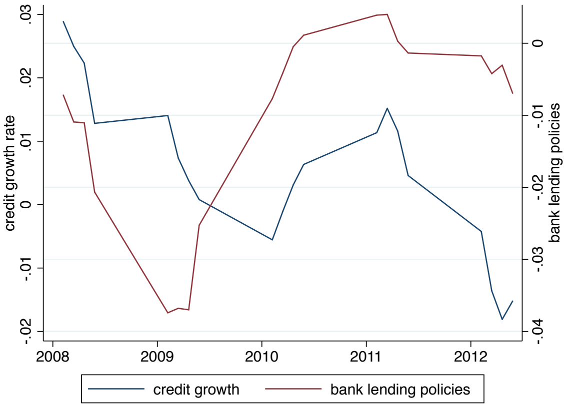
(a) Sample, non-financial private sector (deseasonalized data)



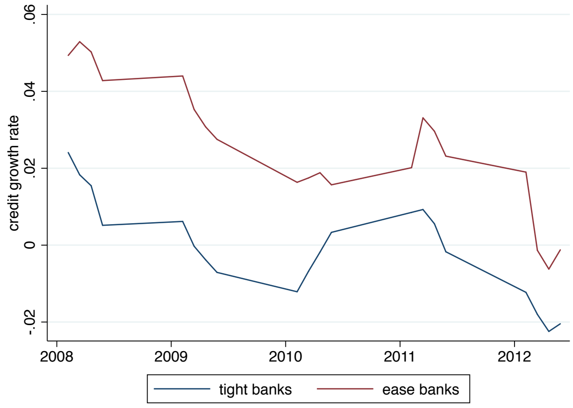
(b) Universe, total economy (Source: ISTAT, RFL)

Notes: elaborations on data from PLANET, ASIA and ISTAT ('Labour Force Survey'). Data on the total economy (panel b) are computed filtering the data along a sectoral composition as close as possible to that of the firms included in the sample: private non-financial non-primary sectors.

Figure 6: Bank lending policies and credit supply index: descriptive statistics

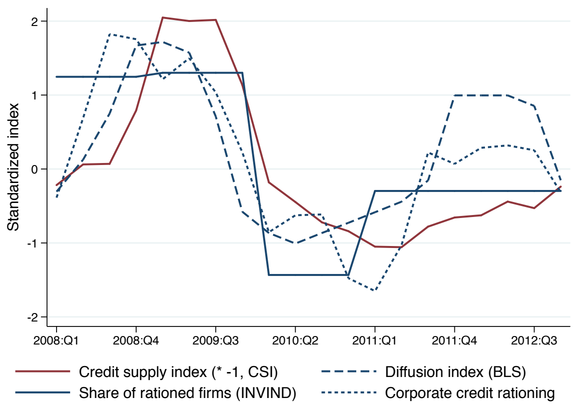


(a) Bank lending policies & credit growth



(b) Credit growth across tight and ease banks

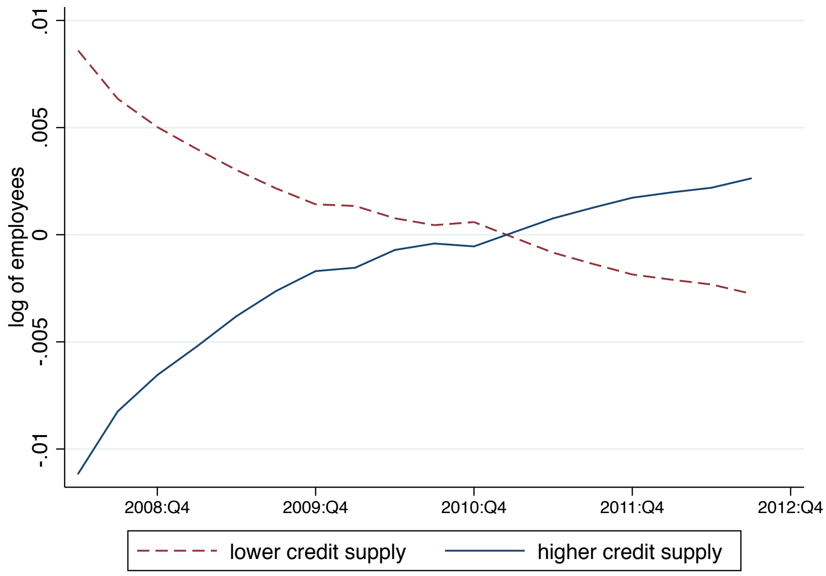
(c) Bank lending policies across banks



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

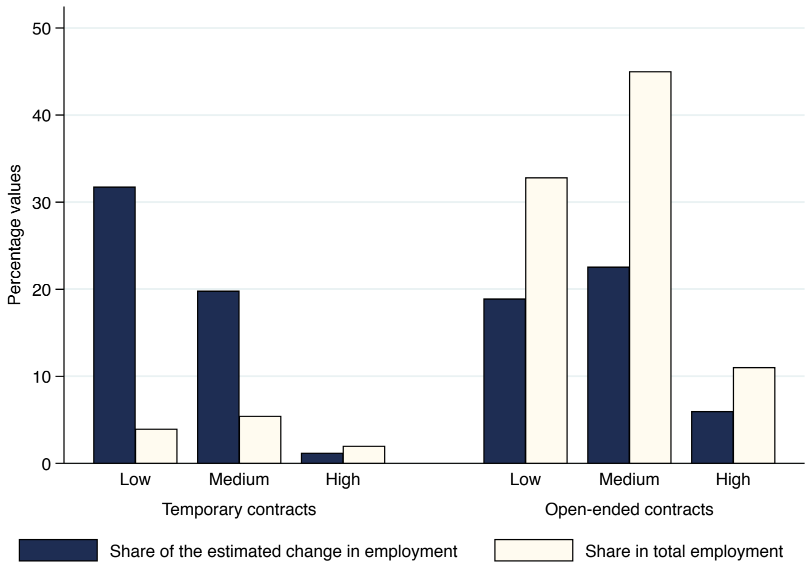
Notes: The time varying nationwide bank lending policies ($\hat{\delta}_{bt}$) at the bank level and the credit supply index (CSI_{it}) at the firm level are obtained following the approach by Greenstone *et al.* (2014), as discussed in Section 3.2 (see specifically equations 3 and 4, respectively). The credit supply index is constructed aggregating the bank-quarterly fixed effects ($\hat{\delta}_{bt}$) with initial banks' market share. All charts refer to Italy. Panel (a) reports the average bank lending policy obtained averaging the bank-level $\hat{\delta}_{bt}$ weighted by bank market share in terms of loans. In panel (b), tight (ease) banks are those that, in each quarter, have a bank lending policy ($\hat{\delta}_{bt}$) below (above) the median. In panel (c) we divide banks depending their lending policies ($\hat{\delta}_{bt}$) and we report the evolution of $\hat{\delta}_{bt}$ for banks at the 25^{th}, 50^{th} and 75^{th} percentile. 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) a measure of corporate credit rationing: 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.

Figure 8: The effect of credit crunch by contract type and education



Notes: the figure plots with blue bars the contribution of the overall estimated effect of credit supply on employment (0.364) due to the combination of contract type (temporary contracts and open-ended contracts) and education levels (low, medium, and high). These relative shares are based on the estimates reported in Table 5. The white bars report the share in total employment by contract type and education, as reported in Table 1. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. Workers are divided across low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification.

Tables

Table 1: Summary statistics

The table reports the summary statistics for: 1) $\Delta EMPLOYMENT$ for different demographic characteristics, for all contracts and separately for open-ended and temporary contracts; 2) the average change in firm borrowing over two quarters ($\Delta LOAN$); 3) the credit supply index (CSI); and 4) a binary variable identifying firms that closed their activity in a given quarter t, but were active in $t-1$ ($EXIT$). 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 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	-0.0211	0.2610	100.0
low-education	-0.0098	0.1480	38.7
medium-education	-0.0088	0.1420	48.0
high-education	-0.0022	0.0569	13.3
under 30	-0.0025	0.1080	17.9
over 30	-0.0186	0.2090	82.1
male	-0.0126	0.1690	59.9
female	-0.0085	0.1470	40.1
Italian	-0.0179	0.2260	91.4
foreign	-0.0033	0.0919	8.6
$\Delta EMPLOYMENT$ - Open-ended	-0.0173	0.1890	88.7
low-education	-0.0080	0.1000	32.8
medium-education	-0.0075	0.1020	45.0
high-education	-0.0016	0.0335	11.0
under 30	-0.0015	0.0533	15.0
over 30	-0.0158	0.1620	73.8
male	-0.0102	0.1220	51.0
female	-0.0071	0.0984	37.7
Italian	-0.0148	0.1660	80.1
foreign	-0.0025	0.0596	8.6
$\Delta EMPLOYMENT$ - Temporary	-0.0039	0.1660	11.3
low-education	-0.0016	0.1060	3.9
medium-education	-0.0017	0.0993	5.4
high-education	-0.0006	0.0464	2.0
under 30	-0.0014	0.0972	5.4
over 30	-0.0025	0.1210	5.9
male	-0.0019	0.1080	4.9
female	-0.0019	0.1120	6.3
Italian	-0.0029	0.1410	9.8
foreign	-0.0009	0.0717	1.5
$\Delta LOAN$	-0.0163	0.3151	.
CSI	-0.0085	0.0404	.
$EXIT$	0.0066	0.0811	.

Table 2: Orthogonality conditions

The table reports the average values of a set of firm-specific 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 the firm has multiple banking relationship and equal to zero for firms borrowing from only one bank; NPLs is a dummy equal to one if the firm has non-performing loans at the beginning of the sample (December 2007). 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	0.323	0.329	0.342	0.278	0.298	-0.024
% services	0.677	0.671	0.658	0.722	0.702	0.024
# employees	4.578	7.728	9.308	4.825	3.919	-0.007
% main province	0.236	0.238	0.222	0.173	0.144	-0.055
Debt per employee	128,460	175,598	164,244	165,833	114,852	-0.003
Utilized/granted credit	0.194	0.311	0.396	0.237	0.194	0.003
Multi-banks	0.870	0.855	0.823	0.987	0.884	-0.017
NPLs	0.035	0.032	0.048	0.044	0.041	0.014

Table 3: 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

1^{st} stage	Dep var: $\Delta LOAN_{t,t-1}$			
$CSI_{t,t-1}$	0.0786***	0.0779***	0.0757***	0.0750***
	(0.0178)	(0.0167)	(0.0165)	(0.0171)
R^2	0.160	0.161	0.162	0.162
2^{nd} stage	Dep Var: $\Delta EMPLOYMENT_t$			
$\Delta LOAN_{t,t-1}$	0.438***	0.439***	0.446***	0.364***
	(0.142)	(0.140)	(0.136)	(0.111)
Observations	2,459,949	2,459,949	2,459,949	2,459,949
1^{st}-stage F-statistic	194.7	191.5	180.9	169.5
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 4: 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Contracts		**Reason for exit**		
	Open-ended	Temporary	Dismissal	Expiry	Quit
$\Delta LOAN_{t,t-1}$	0.170***	0.191**	-0.0357	-0.159**	-0.0334
	(0.0612)	(0.0873)	(0.0242)	(0.0765)	(0.0320)
	Flows		**Transitions**		
	Inflows	Outflows	Fixed to open	Full to part-time	Part-time to full
$\Delta LOAN_{t,t-1}$	0.0836	-0.277**	0.0219*	-0.00155	-0.00414
	(0.0542)	(0.111)	(0.0117)	(0.00631)	(0.00714)
Observations	2,459,949	2,459,949	2,459,949	2,459,949	2,459,949
1^{st}-stage F-statistic	169.5	169.5	169.5	169.5	169.5
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes
Size $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes
Province $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes

Table 5: Worker heterogeneity by education and contract type

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. The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.364***	0.186***	0.151***	0.0261*
	(0.111)	(0.0393)	(0.0366)	(0.0134)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.170***	0.0684**	0.0817***	0.0215**
	(0.0612)	(0.0299)	(0.0308)	(0.00862)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.191**	0.115**	0.0717**	0.00421
	(0.0873)	(0.0550)	(0.0363)	(0.0119)
Observations	2,459,949	2,459,949	2,459,949	2,459,949
1^{st}-stage F-statistic	169.5	169.5	169.5	169.5
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

Table 6: Worker heterogeneity by personal characteristics and contract type

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. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are 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
	All contracts					
$\Delta LOAN_{t,t-1}$	0.144**	0.220***	0.105***	0.258***	0.274***	0.0885**
	(0.0573)	(0.0686)	(0.0402)	(0.0807)	(0.0850)	(0.0353)
	Open-ended contracts					
$\Delta LOAN_{t,t-1}$	0.0785*	0.0941***	0.0355***	0.138***	0.130***	0.0423**
	(0.0411)	(0.0256)	(0.0130)	(0.0525)	(0.0501)	(0.0168)
	Temporary contracts					
$\Delta LOAN_{t,t-1}$	0.0610*	0.131**	0.0737*	0.116**	0.140**	0.0477
	(0.0350)	(0.0610)	(0.0396)	(0.0554)	(0.0613)	(0.0308)
Observations	2,459,949	2,459,949	2,459,949	2,459,949	2,459,949	2,459,949
1^{st}-stage F-statistic	169.5	169.5	169.5	169.5	169.5	169.5
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

Table 7: Adjustment at the intensive and extensive margins

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable is: $\Delta EMPLOYMENT_t$, defined as the change in employment at the firm level over the year t (columns 1 and 4); and $EXIT_t$, defined as a dichotomous variable equal to one if the firm closed in the quarter t but was still in operation in the previous quarter $t-1$, and zero elsewhere (column 5). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in the year $t-1$. $\Delta EMPLOYMENT_t$ and $\Delta LOAN_{t,t-1}$ are calculated as in equation 2, so that they are bounded between -2 and $+2$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. Results in columns 1 and 5 are based on the full sample, while all other results are based on the sub-sample that excludes firm closures (i.e. a firm that closes in a given quarter is still in the sample for the previous quarters, when it was active). Results for this sub-sample are reported both for all job contracts (column 2) and separated for the different types of contracts (open-ended and temporary, columns 3 and 4). Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. All linear 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$				$EXIT_t$
	Full sample	**Excluding firm closures**			**Full sample**
		All contracts	Open-ended	Temporary	
	(1)	(2)	(3)	(4)	(5)
$\Delta LOAN_{t,t-1}$	0.364***	0.253***	0.0653**	0.185**	-0.0591**
	(0.111)	(0.0914)	(0.0282)	(0.0886)	(0.0269)
Observations	2,459,949	2,443,652	2,443,652	2,443,652	2,459,949
1^{st}-stage F-statistic	169.5	169.1	169.1	169.1	169.5
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 8: The effect of contract type and education, intensive margin

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1 on a restricted sample that excludes firm closures (i.e. a firm that closes in a given quarter is still in the sample for the previous quarters, when it was active). 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 all job contracts, the ones reported in the middle panel to open-ended contracts, and the ones reported in the bottom 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$		
	Education level		
	Low	Medium	High
	All contract		
$\Delta LOAN_{t,t-1}$	0.141**	0.101***	0.0108
	(0.0604)	(0.0387)	(0.0121)
	Open-ended contract		
$\Delta LOAN_{t,t-1}$	0.0261	0.0307**	0.00897
	(0.0219)	(0.0152)	(0.00637)
	Temporary contract		
$\Delta LOAN_{t,t-1}$	0.114**	0.0695*	0.00181
	(0.0562)	(0.0370)	(0.0115)
Observations	2,443,652	2,443,652	2,443,652
1^{st}-stage F-statistic	169.1	169.1	169.1
Firm FE	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes

Table 9: General equilibrium effects

The table reports the regression results of the 2SLS estimation of the analogous of equation 1 on data aggregated at the province-industry-sector level, considering all firms in the region. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the province-industry-sector level over the quarter t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the province-industry-sector 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 and calculated aggregating bank-specific CSIs at the province-industry-sector level. The first column reports the results for the whole sample, the others report the results for two sub-samples of open-ended and temporary contracts, and the three sub-samples of workers with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers. All regressions include a set of time, industry and province fixed effects, as listed at the bottom of the Table. Fixed effects are constructed based on 30 (2-digit) industries and 7 provinces. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$					
	Whole sample	**Contracts** Open-ended	Temporary	**Education level** Low	Medium	High
$\Delta LOAN_{t,t-1}$	0.408**	0.140**	0.265*	0.140*	0.218**	0.0540
	(0.168)	(0.0618)	(0.135)	(0.0775)	(0.0911)	(0.0380)
Observations	3,780	3,780	3,780	3,780	3,780	3,780
1^{st}-stage F-statistic	14.52	14.52	14.52	14.52	14.52	14.52
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Credit supply index at the firm level

The table reports the regression results of the 2SLS estimation of equation 1 on the whole sample. 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 alternative credit supply index CSI, built from a nationwide bank lending regression that include firm×quarter fixed effects (see equation 5 and Section 6.1). The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.145**	0.0841**	0.0649**	-0.000487
	(0.0581)	(0.0335)	(0.0318)	(0.0133)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.0154	0.00716	0.00970	-4.61e-07
	(0.0405)	(0.0221)	(0.0219)	(0.00793)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.131***	0.0772***	0.0547**	-0.000517
	(0.0395)	(0.0251)	(0.0236)	(0.0109)
Observations	2,459,785	2,459,786	2,459,787	2,459,788
1^{st}-stage F-statistic	202.2	202.3	202.4	202.5
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

Table 11: Results by sub-periods

The table reports the regression results of the 2SLS estimation of equation 1 on two different samples that cover the periods 2008:Q1-2011:Q2 (top panel) and 2009:Q3 - 2012:Q4 (bottom panel). 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 alternative credit supply index CSI, built from a nationwide bank lending regression that include firm×quarter fixed effects (see equation 5 and Section 6.1). The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. For each of the two sub-periods, the table reports separate results for all contracts, open-ended contracts and temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
Time period:	**2008:Q1-2011:Q2**			
	All contracts			
$\Delta LOAN_{t,t-1}$	0.380***	0.183***	0.165***	0.0343
	(0.113)	(0.0627)	(0.0579)	(0.0209)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.180**	0.0534	0.106**	0.0230*
	(0.0760)	(0.0391)	(0.0415)	(0.0129)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.196***	0.126***	0.0611	0.0108
	(0.0713)	(0.0458)	(0.0379)	(0.0163)
Observations	1,627,847	1,627,847	1,627,847	1,627,847
1^{st}-stage F-statistic	77.29	77.29	77.29	77.29
Time period:	**2009:Q3 - 2012:Q4**			
	All contracts			
$\Delta LOAN_{t,t-1}$	0.302***	0.153***	0.124***	0.0203
	(0.0889)	(0.0529)	(0.0446)	(0.0158)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.167***	0.0629**	0.0754***	0.0252***
	(0.0513)	(0.0276)	(0.0275)	(0.00926)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.135**	0.0876**	0.0510	-0.00533
	(0.0688)	(0.0436)	(0.0354)	(0.0133)
Observations	1,955,341	1,955,341	1,955,341	1,955,341
1^{st}-stage F-statistic	140.5	140.5	140.5	140.5
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

Table 12: Variations at the yearly frequency

The table reports the regression results of the 2SLS estimation of equation 1 on the whole sample, but with data aggregated at the yearly frequency. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the year 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 year. 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 year t and $t-1$. In the first stage regressions, the excluded instrument is the alternative credit supply index CSI, built from a nationwide bank lending regression that include firm×year fixed effects (see equation 5 and Section 6.1). The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.348***	0.134***	0.162**	0.0532**
	(0.129)	(0.0470)	(0.0638)	(0.0209)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.265**	0.0971**	0.125**	0.0427***
	(0.106)	(0.0383)	(0.0552)	(0.0146)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.0816***	0.0303***	0.0433***	0.00942
	(0.0280)	(0.0113)	(0.0153)	(0.00780)
Observations	715,921	715,921	715,921	715,921
1^{st}-stage F-statistic	578.0	578.0	578.0	578.0
Firm FE	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes
Size × year FE	Yes	Yes	Yes	Yes
Province × year FE	Yes	Yes	Yes	Yes

Table 13: Only firms with at least one worker of that type

The table reports the regression results of the 2SLS estimation of equation 1 on sub-samples of firms with at least one worker of that type (e.g., the effect on workers with open-ended contracts is studied only on firms with at least one open-ended employee, and the like). 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 alternative credit supply index CSI, built from a nationwide bank lending regression that include firm×quarter fixed effects (see equation 5 and Section 6.1). The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.364***	0.406***	0.419***	0.100
	(0.111)	(0.146)	(0.145)	(0.0740)
Observations	2,459,949	1,212,081	1,230,238	609,171
1^{st}-stage F-statistic	169.5	76.13	48.55	29.60
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.382***	0.167**	0.268***	0.107**
	(0.121)	(0.0764)	(0.0932)	(0.0507)
Observations	1,339,077	1,118,185	1,123,290	571,684
1^{st}-stage F-statistic	67.00	62.45	40.74	23.51
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.426**	0.301**	0.196*	0.00855
	(0.207)	(0.152)	(0.117)	(0.0665)
Observations	1,272,214	1,068,597	1,109,633	587,797
1^{st}-stage F-statistic	64.37	61.74	47.48	29.70
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

Online Appendix

A-I Data: sources and construction of the final dataset

Our work relies on three main sources of data: (i) PLANET, an administrative dataset maintained by the regional public employment service Veneto Lavoro, which collects information on workers' flows in the Italian region of Veneto[34]; (ii) ASIA, the firm register maintained by the Italian Statistical Office (ISTAT), which provides information on the stock of employed workers[35]; and (iii) the Credit Register, managed by the Bank of Italy, which report information on the outstanding bank loans to Italian firms. In what follows we briefly describe each data source (Section A-I.1), the results of the merging process of the three archives and the additional filters that have been applied to clean the data (Section A-I.2), and the main choices behind the creation of crucial variables which are possibly missing in the data (Section A-I.3).

A-I.1 Data sources

A-I.1.1 PLANET

PLANET is an administrative dataset of daily labor market flows maintained by the regional employment agency *Veneto Lavoro*. According to the Italian law, firms have to notify the start, modification or end of a labor contract to the regional system of public employment services. The norm regards exclusively the work relationships regulated by a contract between the worker and the employer. Hence, the archive does not include self-employed and entrepreneurs, unless they hold a job contract. Moreover, given that PLANET collects only flow data, workers who never experienced a transition in the period of observation are not registered in the archive.

Since 2008 all the information have to be entered through online forms, leading to almost universal coverage. This massive amount of data is currently made available only for the Veneto region, thanks to the work of *Veneto Lavoro*, the regional public employment service.

Before entering the archive, each record filed to Veneto Lavoro undergoes a complex validation procedure, which includes, whenever necessary, a manual check of the information provided to the agency. All the validated records are compared to standardized ancillary tables in order to correctly interpret, from a semantic viewpoint, the reported information. This procedure is particularly relevant when free text is involved. Employers, for instance, may describe the same occupation in a variety of forms; ancillary tables allow to reconcile this variety with a rigid classification based on standardized codes and labels. Whenever the number of classes is particularly high, the procedure also includes some aggregation or simplification. The key variables that undergo this process are:

- the industry, based on the Ateco 2007 classification—a transformation of NACE rev. 2—and provided at three levels of aggregation;
- the job contracts, based on 44 different types and three aggregation levels defined jointly with the Labor Ministry in order to take into account the evolution of the relevant norms and laws;
- the skill content of each occupation, with five different levels of aggregation based on ISCO codes, starting from around 7,000 elementary descriptions originating from the National Statistical Office classification;
- the education of the worker, based on ISCED level-1 classification.

We can quantify what fraction of the stock of workers is covered in PLANET by computing the number of workers registered in PLANET who have an active spell of employment at any

[34]Further information on PLANET (in Italian) is available here: www.venetolavoro.it/public-use-file
[35]Further information on ASIA (in Italian) is available here: www.istat.it/it/archivio/106814

given moment in time, and comparing it with the official labor force statistics. For the sake of full comparability between the two data sources, we focus on employed workers in the non-financial private sector. The difference between the two sources is relatively small (less than 7 percent in 2012) and is due to employees that did not experience any labor market transition in the period 2008-2012.

A-I.1.2 ASIA

ASIA is the official register of active firms maintained by ISTAT, the Italian Statistical Office. The register covers firms in the private sector (agriculture is excluded) that have been active for more than 6 months in each calendar year, and include information on firms' geographical location, sector, number and location of plants, start and end date of activity, average workforce dimension.[36]

A-I.1.3 Credit Register

The Credit Register (CR) is an information system operated by the Bank of Italy that collects the data supplied by banks and financial companies on the credit they grant to their customers. Specifically, for each borrower, banks and financial companies have to report, on a monthly basis, the amount of each loan 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.

A-I.2 Merging the archives

The merge of the three archives uses the fiscal code as unique identifier of the firm. We consider only private non-financial non-primary firms and we also exclude temp agencies, care givers and house cleaners. The process of data cleansing involves the removal of: (i) firms that closed before January 1^{st} 2008, (ii) records with missing date for the event which originated the communication, (iii) records where the end of the contract is prior to the start of the contract, and (iv) records where the start of the contract is after the date of firm closure as reported in ASIA. After these filtering procedures, we are left with 436,311 firms, meaning that we loose about 10 percent of the firms from the original sample. Of these remaining firms, 204,301 can be matched with the credit register since they have credit relationship with the banking system.

A-I.3 Variable creation

We add two main variables to PLANET: a quarterly indicator whether a firm is alive, and a quarterly reconstruction of the stock of workers. For the first we take the start and end dates from ASIA, whenever possible. If the start date is missing, we place it:

- at the last quarter of the year before the firm is first observed in ASIA with positive size, or
- at the quarter before the first movement is observed in PLANET,

whatever comes first. If the end date is missing in ASIA, we place it:

- at the first quarter of the year after the firm is last observed in ASIA with positive size, or

[36] Hence, it is possible that some firms are not present in the archive even though their lifetime is longer than six months. For instance, a firm established in October 2009 and closed down in May 2010—hence spanning for more than six months overall—is not present in the archive. Moreover, a firm that has been established in October 2009 and remained active throughout 2010 is not recorded in the 2009 archive, but only in the 2010, which also reports the correct starting date of the firm. Similarly, a firm that was active throughout 2009 but closed down in May 2010 is not recorded in the 2010 archives; however, its closing date is not always reported back to the 2009 record.

- at the quarter of the last movement observed in PLANET, provided that the variation is negative and the cumulative employment variation is also negative,

whatever comes last. Firm-quarter observations where the firm is deemed inactive are dropped from the final sample, leaving us with an unbalanced panel.

To reconstruct quarterly employment stocks, we start from the last information available in ASIA and we complement it by adding the cumulative movements of workers not included in ASIA, as observed in PLANET. The two features of the data to confront with in this case are (i) ASIA registers firm size at the end of the year, but does not consider agency workers and independent contractors (who are not formally employed by the firm), (ii) PLANET does not contain information about the stocks, but provides data on daily flows concerning all workers working for the firm, irrespective of their contract type.

We hence proceed as follows.

1. For firms that are observed in PLANET at the beginning of the period (2008/I): we start from the ASIA initial (2007) stock, add an estimate of the initial stock of agency workers and independent contractors based on the information on contract termination, renewal of transformation available in PLANET, and then add quarter-specific employment variations directly observed in PLANET;[37]
2. For new firms that are first observed in PLANET after 2008/I: in this case, stocks can be retrieved by definition using flows; the first observed stock is given by the first flow augmented by one unit to include the entrepreneur, while the following stocks are retrieved simply by adding quarter-specific observed flows.
3. For firms observed only on ASIA: they do not have flows during the observed period, and hence their stocks are constantly equal to the initial stock observed in ASIA.

[37] As the average duration of temporary contracts in Italy is less than one year (by far in case of temp agency workers), the period of observation in PLANET (5 years) is long enough to see virtually all temporary contracts alive in 2007 coming to an end.

A-II Additional Tables

Table A1: 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 nationwide bank lending policies ($\hat{\delta}_b$) 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 $\hat{\delta}_b$ see Section 3.2 and equation 3. 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 A2: Alternative clustering, at the bank-province-industry level

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. The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the bank-province-industry level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.364***	0.186***	0.151***	0.0261*
	(0.105)	(0.0607)	(0.0465)	(0.0137)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.170***	0.0684***	0.0817***	0.0215**
	(0.0514)	(0.0264)	(0.0273)	(0.00838)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.191**	0.115**	0.0717*	0.00421
	(0.0863)	(0.0528)	(0.0375)	(0.0105)
Observations	2,459,949	2,459,949	2,459,949	2,459,949
1^{st}-stage F-statistic	169.5	169.5	169.5	169.5
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

Table A3: Only firms with at least 3 employees

The table reports the regression results of the 2SLS estimation of equation 1 on a restricted sample that includes only firms with at least 3 employees. 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. The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.668***	0.343**	0.287***	0.0383
	(0.236)	(0.134)	(0.104)	(0.0243)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.326***	0.140**	0.157***	0.0317*
	(0.115)	(0.0585)	(0.0608)	(0.0176)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.340*	0.197*	0.137*	0.00563
	(0.185)	(0.113)	(0.0768)	(0.0177)
Observations	1,179,278	1,179,278	1,179,278	1,179,278
1^{st}-stage F-statistic	49.25	49.25	49.25	49.25
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

Table A4: Share of non-zero outcomes in the dependent variable

The table reports the share of non-zero outcomes for $\Delta EMPLOYMENT$, as defined in equation 2, for different demographic characteristics, for all contracts and separately for open-ended and temporary contracts. 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 first two columns refer to data aggregated at a quarterly frequency, while the last column reports the share of non-zero outcomes for data aggregated at the yearly frequency. The second column reports the same share, but only for a sub-sample of firms that have at least one worker with the characteristics (job contracts and demographics) that are the target of the analysis. In this case, the Table does not report data on Italian vs foreign workers because data availability does not allow to reconstruct the stock of employees at the beginning of the period by nationality.

Variable	Whole sample	Only firms with a worker of that type	Yearly data
$\Delta EMPLOYMENT$ - Total	21.3	21.3	32.3
open-ended	12.5	22.9	26.3
temporary	18.1	34.9	29.1
low-education	13.5	27.5	23.7
medium-education	13.2	26.5	24.0
high-education	4.8	19.5	10.3
under 30	11.4	25.6	20.9
over 30	17.0	29.9	28.7
male	15.2	30.8	25.2
female	12.0	24.9	21.3
Italian	18.7	-	30.3
foreign	8.0	-	15.0
$\Delta EMPLOYMENT$ - Open-ended			
low-education	7.7	16.8	17.8
medium-education	6.8	14.9	16.6
high-education	2.4	10.3	6.5
under 30	4.3	10.7	11.4
over 30	10.6	20.2	23.2
male	8.8	19.3	19.4
female	6.2	14.1	15.3
Italian	10.6	-	23.5
foreign	4.1	-	10.2
$\Delta EMPLOYMENT$ - Temporary			
low-education	10.9	25.0	19.1
medium-education	11.3	25.1	20.9
high-education	4.2	17.6	9.0
under 30	10.8	25.3	20.2
over 30	13.0	27.0	22.3
male	12.6	29.0	21.8
female	10.2	24.0	18.4
Italian	15.7	-	26.5
foreign	6.8	-	12.6

Table A5: Yearly data: Worker heterogeneity by personal characteristics and contract type

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 year t, for the different types of workers, as labeled in each column, divided by the average stock of all firm's workers over the year. 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 year 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. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are 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
	All contracts					
$\Delta LOAN_{t,t-1}$	0.186**	0.162***	0.0851***	0.262**	0.316***	0.0314**
	(0.0747)	(0.0553)	(0.0238)	(0.107)	(0.118)	(0.0138)
	Open-ended contracts					
$\Delta LOAN_{t,t-1}$	0.145**	0.124***	0.0489***	0.220**	0.238**	0.0306**
	(0.0602)	(0.0474)	(0.0171)	(0.0902)	(0.0963)	(0.0130)
	Temporary contracts					
$\Delta LOAN_{t,t-1}$	0.0303**	0.0503***	0.0438***	0.0355*	0.0734***	0.00550
	(0.0136)	(0.0169)	(0.0124)	(0.0194)	(0.0246)	(0.00783)
Observations	715,921	715,921	715,921	715,921	715,921	715,921
1^{st}-stage F-statistic	578.0	578.0	578.0	578.0	578.0	578.0
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Only firms with at least one worker of that type: Worker heterogeneity by personal characteristics and contract type

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 right panel reports the results for the sub-samples of workers whose age is below or above 30 years. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Gender		**Age**	
	Male	Female	Under 30	Over 30
	All contracts			
$\Delta LOAN_{t,t-1}$	0.321**	0.555***	0.274**	0.515***
	(0.132)	(0.180)	(0.113)	(0.153)
Observations	1,213,984	1,181,733	1,090,026	1,401,825
1^{st}-stage F-statistic	64.73	60.76	52.23	79.61
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.198**	0.294***	0.105**	0.317***
	(0.0959)	(0.0845)	(0.0450)	(0.106)
Observations	1,116,375	1,076,371	983,094	1,291,788
1^{st}-stage F-statistic	60.40	45.79	42.16	65.95
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.149	0.357**	0.207*	0.277*
	(0.0955)	(0.180)	(0.121)	(0.143)
Observations	1,070,404	1,041,496	1,047,823	1,184,350
1^{st}-stage F-statistic	55.10	55.60	48.26	61.32
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

A-III Additional Results

A-III.1 Robustness: Controlling for credit demand and alternative lag structure

We test the robustness of our baseline results (Table 3) running a battery of additional tests. Results are showed in Table A7. 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 demanding fixed effects. We start by interacting the quarter dummies with more restrictive borrower cells (industry×size, industry×province, and province×size), allowing for time-varying demand to be the same not only across industries, class size and provinces, but also within 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.*, 2017; Auer and Ongena, 2016; Degryse *et al.*, 2016), we fully saturate the model with firm cluster×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 ranging between 0.34 and 0.37 in columns 1-3. The inclusion of the four-way fixed effects does not significantly alter the magnitude of the estimated credit effect on employment, suggesting that there is no additional unobserved heterogeneity driving our estimates.

In column 5 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 0.49, 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 A3 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 6).

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.[38] 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 increases allowing for more lags.

A-III.2 Firm heterogeneity

As an extension of our main analysis, we explore possible heterogeneous effect across different firms.[39] 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 (see Figure 3), so that the real effects of credit shocks is likely to

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

[39] 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.

be larger (Gertler and Gilchrist, 1994; Beck *et al.*, 2008; Buera *et al.*, 2015; Duygan-Bump *et al.*, 2015; Cingano *et al.*, 2016). 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 (Table A8, 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 their credit terms with the banks, 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 A8, right panel). This result may be explained by 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.[40]

To shed light on the mechanisms through which financial shocks could affect employment decisions we exploit a set of firm financial characteristics available in our data. If banks play a crucial role in addressing firm 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, province 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.[41] We find that employment reacts relatively more to credit supply restrictions in firms that are more levered (Table A11, 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 credit lines more intensively, as those firms are less able to cope with negative shocks using existing credit lines (Table A11, middle panel). These results are consistent with the idea that firms with less financial slack find it more costly to engage in labor hoarding when exposed to a financial shock and therefore react to the shock adjusting the labor force (Giroud and Mueller, 2016).

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 for firms with multiple bank relationships is twice as large as that for firms with one bank (Table A11, right panel),

[40]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 A9 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 is also concentrated in services and in small firms, but the size of the elasticity is rather small. Similarly, Table A10 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 persist within sectors and firm class size (results not shown but available upon request).

[41]We acknowledge that this is an imperfect measure of leverage and it could pick up other factors, as differences in productivity. Results should be interpreted with caution, and read together with those reported in the next sub-section A-III.3, where the match with firm balance sheet for a sub-sample of firms allows for a more precise definition of leverage.

suggesting that stronger lending relationships contribute to mitigate the effect of the credit crunch on employment outcomes. 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).

A-III.3 Matching firm balance sheets

To have a better sense of which are the firms that reduce employment more in response to a financial shock, we show a set of additional results estimated on a sub-sample of larger firms for which it is possible to obtain and match balance-sheet information from the CADS database.[42] While the availability of balance-sheet information allows for a better understanding of the mechanisms through which a financial shock propagates to the real economy, the match with the CADS data comes at the non-trivial costs of loosing one of the key feature of our analysis—the coverage of the universe of firms, including small and micro enterprises—and moving from a quarterly to a yearly frequency in the empirical analysis. In particular, in this (smaller) sample the average (median) firm size is 16.4 (4.8) employees, nearly three times the respective values in the whole sample. Nonetheless, thanks to balance sheet information, we can extend the analysis of the exogeneity of the instrument looking at its balancing properties, in the same vein of what done in Table 2. Additional results reinforce our identification strategy, given that the credit supply index is not systematically correlated with labor productivity, capital intensity, age, leverage and riskiness (see Table A12).

Moving from a quarterly to a yearly frequency does not significantly alter our baseline results: the coefficient on $\Delta LOAN$ on the whole sample goes from 0.364 to 0.348 (compare Table 3, column 4, and Table A13, column 1). However, the coefficient is significantly smaller (and equal to 0.096) when considering the restricted sample of firms with balance sheet information. The large drop in the elasticity of employment to credit supply further confirms the importance of focusing on the universe of firms to have a precise estimate of the employment effect of a financial shock (Table A13, columns 1 and 2). By contrast, if the analysis is limited to a sample of relatively large firms—as in most of the empirical literature so far—the employment effect is likely to be under-estimated. To put our analysis in the context of the extant literature, Table A13 reports also the effect on capital accumulation. Consistently with recent evidence on the real effects of large credit contractions (Acharya *et al.*, 2016; Amiti and Weinstein, 2017; Bottero *et al.*, 2016; Cingano *et al.*, 2016; Degryse *et al.*, 2016), we find a negative impact of credit supply on investment, which—as expected—is stronger than the one on labor.

Having being assured that the restricted sample provides results that are consistent with the ones on the universe of (indebted) firms and with the recent evidence on European firms, in Table A14 we look at what firms reacted more to the financial shock. First, we separate young from old firms splitting the sample around the median age within each industry, province and class size cluster. We find that the effects on employment are limited to relatively young firms, in line with the hypothesis that these firms have higher borrowing needs and therefore are more exposed to a financial shock (Buera *et al.*, 2015; Siemer, 2016).

Second, to better understand how firm balance sheet can propagate the effect of financial shocks, we delve into the role of corporate leverage, defined as the ratio of financial debt over financial debt and equity. Again, we split the sample at the median of each variable at December 2007. We find that the role of leverage is much stronger in this sub-sample larger firms than in the whole sample. Specifically, the elasticity of employment to the supply of credit is almost four times higher in high-indebted than in low-indebted firms. Overall, our results are

[42] The Company Accounts Data Service (CADS, "Centrale dei Bilanci" in Italian) is a proprietary database, managed by the Cerved Group, that includes annual balance sheets and income statements for almost all of the Italian limited companies. Specifically, from CADS we draw information on value added, tangible and intangible assets, the z-score (a measure of credit risk), the financial situation, the number of employees and age.

in line with those of Bentolila *et al.* (2017) for Spanish firms, and complement what recently found by Kalemli-Ozcan *et al.* (2015), who show that Southern European firms that entered the sovereign debt crisis with higher debt overhang have contracted investment relatively more than others.

Finally, to substantiate the hypothesis that the global financial crisis had a cleansing effect through firms' workforce management, we look at whether *ex-ante* less productive firms are more likely to reduce employment. By measuring labor productivity as value added per employee as of December 2007, we find that a 10 percent reduction in the supply of credit translated in a reduction of employment of 1.8 percent in low-productive firms—twice the effect estimated for the average firms—while there is no statistically significant effect in high-productive firms. This result is consistent with recent evidence on the U.S. showing that less productive establishments are more likely to exit during the Great Recession (Foster *et al.*, 2016).

A-III.4 Employment protection legislation

In Section 4.3 we have discussed the possibility that our results could be related to the presence of a high EPL, which makes firing permanent workers for Italian firms very difficult. Here we exploit the fact that in Italy the strength of EPL differs in a quite substantive way between firms across a threshold of 15 employees to further rule out this interpretation. In particular, the law indicates that an employer is legitimated to dismiss a worker if a just cause exists (damage of equipment, fight or violence towards other colleagues) or in case of a justified reason, that can be either subjective (major breaches of contract obligations) or objective, when the organization of the production process would make impossible the continuation of the employment relationship. The consequences of unlawful dismissals depend then upon the firm size. In firms employing more than 15 workers, an illegitimate layoff is deprived of any legal effect, gives the dismissed worker the option to be reinstated to her former position, and leads to the compensation of all foregone salaries and social security contributions since the layoff date. In the those with employing less than 15 workers, the employer is obliged to choose between starting a new employment relationship with the dismissed worker, or to compensate her with a sum ranging from 2.5 to 14 monthly salaries, depending on firm size and worker seniority.[43] Thus, we take into account of the difference in EPL strength across firm size and replicate our results on the sample of firms with 15 or less employees, which face the same law regulations and have more flexibility in adjusting their labor force, irrespective of the contract type. Our results again show that the adjustment is concentrated among less educated workers with temporary contracts (see Table A15), suggesting that our main findings are not a mechanical implication of high EPL.

[43]The regulations on individual layoffs was substantially changed on July 2012. However, these changes apply only to a short period of our analysis and our results are robust to the exclusion of 2012 from the sample, see Table 11.

Table A7: 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 $t-2$. All these variables are calculated as in equation 2, so that they are bounded between -2 and $+2$. $HOUSE\ PRICE_t$ is the average real housing price at the municipality level in quarter t. 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 7 and 8 where CSI is calculated on quarter t and on the three quarters t, $t-1$ and $t-2$, respectively. In all columns (except column 5), 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. In column 5 the sample is limited to firms with a total debt above 75,000 euros throughout the entire sample period. 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta LOAN_{t,t-1}$	0.373***	0.337***	0.362***	0.345***	0.492***	0.364***		
	(0.112)	(0.105)	(0.112)	(0.107)	(0.147)	(0.111)		
$HOUSE\ PRICE_t$						-0.0341**		
						(0.0159)		
$\Delta LOAN_t$							0.229***	
							(0.0837)	
$\Delta LOAN_{t,t-2}$								0.620***
								(0.187)
Observations	2,459,949	2,459,949	2,459,949	2,459,949	1,863,813	2,459,949	2,459,949	2,459,949
1^{st}-stage F-statistic	170.3	169.5	170.2	167.9	128.6	169.5	117.5	154.9
Sample	All firms	All firms	All firms	All firms	Drop < 75k	All firms	All firms	All firms
Firm FE	Yes	Yes	Yes	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
Industry × size × quarter FE	Yes	No	No	.	No	No	No	No
Industry × province × quarter FE	No	Yes	No	.	No	No	No	No
Province × size × quarter FE	No	No	Yes	.	No	No	No	No
Industry × province × size × quarter FE	No	No	No	Yes	No	No	No	No

Table A8: 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). Standard errors, clustered at the main bank level, are 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
$\Delta LOAN_{t,t-1}$	0.327***	0.618**	3.737	0.167	0.427***
	(0.118)	(0.244)	(8.971)	(0.175)	(0.122)
Observations	2,086,194	333,629	40,126	818,609	1,641,340
1^{st}-stage F-statistic	145.1	26.88	0.340	37.58	133.1
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 A9: 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				
$\Delta LOAN_{t,t-1}$	0.124	0.185***	0.136***	0.394**	2.346
	(0.106)	(0.0478)	(0.0467)	(0.153)	(5.046)
	Temporary contract				
$\Delta LOAN_{t,t-1}$	0.0444	0.239***	0.189***	0.225*	1.392
	(0.0769)	(0.0581)	(0.0504)	(0.130)	(3.036)
Observations	818,609	1,641,339	2,086,193	333,629	40,126
1^{st}-stage F-statistic	34.76	122.6	133.5	25.13	0.320
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 $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes
Size $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes
Province $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes

Table A10: 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				
$\Delta LOAN_{t,t-1}$	0.106	0.213***	0.166***	0.323**	2.091
	(0.0874)	(0.0448)	(0.0423)	(0.127)	(4.458)
	Medium education				
$\Delta LOAN_{t,t-1}$	0.0490	0.184***	0.138***	0.237**	1.255
	(0.0679)	(0.0445)	(0.0398)	(0.101)	(2.710)
	High education				
$\Delta LOAN_{t,t-1}$	0.00843	0.0313*	0.0229	0.0514	0.334
	(0.0222)	(0.0180)	(0.0156)	(0.0349)	(0.743)
Observations	818,609	1,641,339	2,086,193	333,629	40,126
1^{st}-stage F-statistic	34.76	122.6	133.5	25.13	0.320
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 A11: 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. 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 different sample splits (low and high) are calculated along the median value within each industry-province-size cluster, measured at end-2007. 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). Standard errors, clustered at the main bank level, are 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
$\Delta LOAN_{t,t-1}$	0.277***	0.474**	0.277***	0.460**	0.370**	0.773*
	(0.0964)	(0.217)	(0.0872)	(0.219)	(0.165)	(0.403)
Observations	1,193,744	1,266,205	1,222,597	1,237,352	1,393,069	1,013,409
1^{st}-stage F-statistic	108.8	89.65	97.21	78.30	67.02	28.04
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

Table A12: Orthogonality conditions, balance sheet characteristics

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). Labor productivity is calculated as value added per worker; Capital per worker is defined as the ratio between the stock of (tangible and intangible) assets and total employment; Age is measured by the number of years in operation; Riskiness is defined by the Altman (1968) z-score (see Section 5 for details); Leverage is measured by the ratio of financial debt over the sum of financial debt and equity. 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)	-0.037	-0.017	-0.008	-0.001	0.018	
Labor productivity	51.4	55.0	53.7	46.4	49.3	-0.007
Capital per worker	303.1	284.7	386.3	352.4	287.6	0.000
Age	10.300	12.300	12.500	10.400	9.350	-0.036
Riskiness	5.407	5.253	5.260	5.176	5.319	-0.026
Leverage	0.669	0.661	0.663	0.632	0.640	-0.034

Table A13: The effects of financial shocks on employment and capital accumulation

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable is: $\Delta EMPLOYMENT_t$, defined as the change in employment at the firm level over the year t (columns 1 and 2); and $\Delta CAPITAL_t$, defined as the change in the stock of (tangible and intangible) assets at the firm level over the year t (column 3). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in the year $t-1$. $\Delta EMPLOYMENT_t$ and $\Delta LOAN_{t,t-1}$ are calculated as in equation 2, so that they are bounded between -2 and $+2$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. Results in column 1 are based on the full sample, while all other results are based on the sub-sample obtained matching the whole sample with the data from the CADS database. 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). Standard errors, clustered at the bank-province-industry level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$		$\Delta CAPITAL_t$
Sample:	All firms	CADS	CADS
	(1)	(2)	(3)
$\Delta LOAN_{t,t-1}$	0.348***	0.0960*	1.226***
	(0.0770)	(0.0569)	(0.358)
Observations	715,920	169,882	169,882
1^{st}-stage F-statistic	421.8	70.49	70.49
Firm FE	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes
Size × year FE	Yes	Yes	Yes
Province × year FE	Yes	Yes	Yes

Table A14: Adding balance sheet characteristics

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1, based on the sub-sample obtained matching the whole sample with the balance-sheet data from the CADS database. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the year t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in the year $t-1$. Both variables are calculated as in equation 2, so that they are bounded between -2 and $+2$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The different sample splits (low and high) are calculated along the median value of the each variable within each industry-province-size cluster, measured at December 2007. Firm age is measured by the number of years in operation (columns 1 and 2). Leverage is measured by the ratio of financial debt over the sum of financial debt and equity (columns 3 and 4). Labor productivity is calculated as value added per worker (columns 5 and 6). 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). Standard errors, clustered at the bank-province-industry level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$					
	Age		**Leverage**		**Labor productivity**	
	Young	Old	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta LOAN_{t,t-1}$	0.251*	-0.00888	0.0300	0.195*	0.177**	-0.0158
	(0.133)	(0.0554)	(0.0580)	(0.108)	(0.0830)	(0.0798)
Observations	84,240	85,642	84,937	84,945	84,937	84,945
1^{st}-stage F-statistic	20.23	49.23	37.08	38.44	34.05	32.37
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

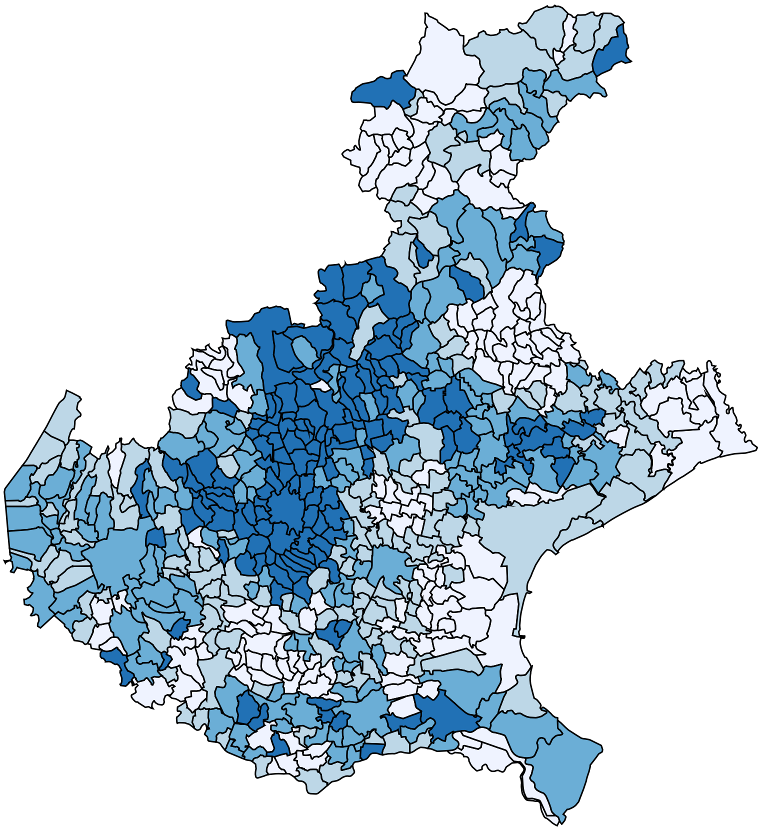
Table A15: Only firms with no more than 15 employees

The table reports the regression results of the 2SLS estimation of equation 1 on a restricted sample that includes only firms with no more than 15 employees. 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. The table reports the results for all workers, irrespective of their education level (first column), and for those with low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education) education—based on the ISCED classification. Results reported in the top panel refer all contracts, while those in the middle panel to open-ended contracts, and the ones in the bottom panel refer to temporary contracts. Temporary contracts includes fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal 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). Standard errors, clustered at the main bank level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$			
	Education level			
	All	Low	Medium	High
	All contracts			
$\Delta LOAN_{t,t-1}$	0.309**	0.190***	0.113**	0.00911
	(0.149)	(0.0495)	(0.0452)	(0.0170)
	Open-ended contracts			
$\Delta LOAN_{t,t-1}$	0.102	0.0382	0.0569*	0.0138
	(0.0928)	(0.0327)	(0.0331)	(0.0106)
	Temporary contracts			
$\Delta LOAN_{t,t-1}$	0.206**	0.150***	0.0577*	-0.00493
	(0.102)	(0.0356)	(0.0312)	(0.0138)
Observations	2,063,013	2,063,013	2,063,013	2,063,013
1^{st}-stage F-statistic	127.5	127.5	127.5	127.5
Firm FE	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes

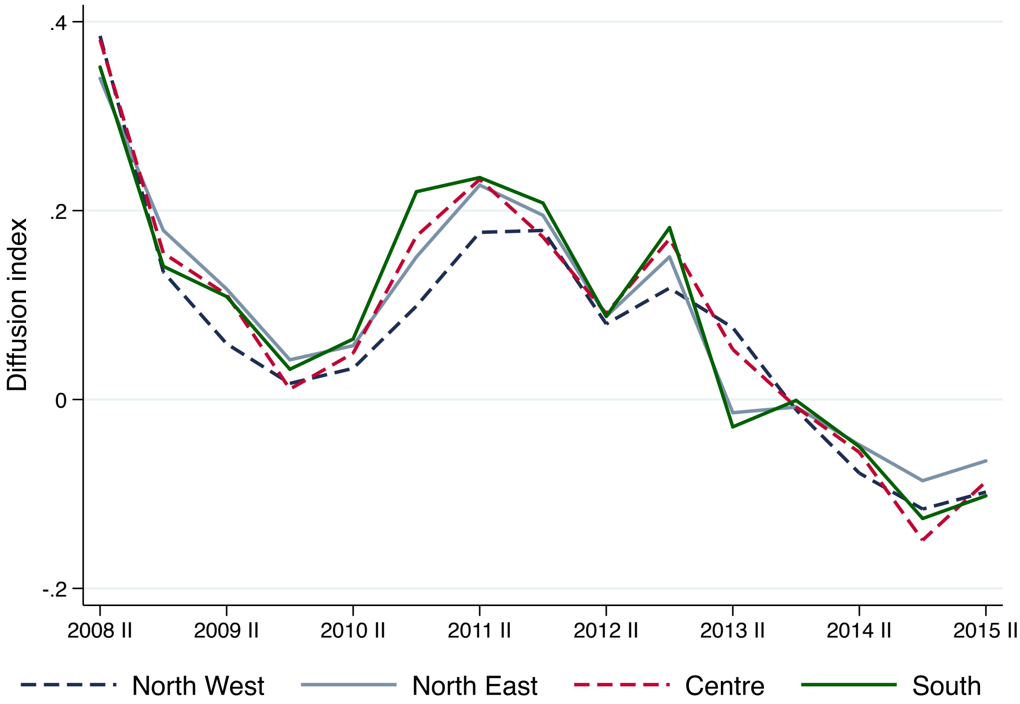
A-IV Additional Figures

Figure A1: Spatial distribution of the credit supply index across municipalities



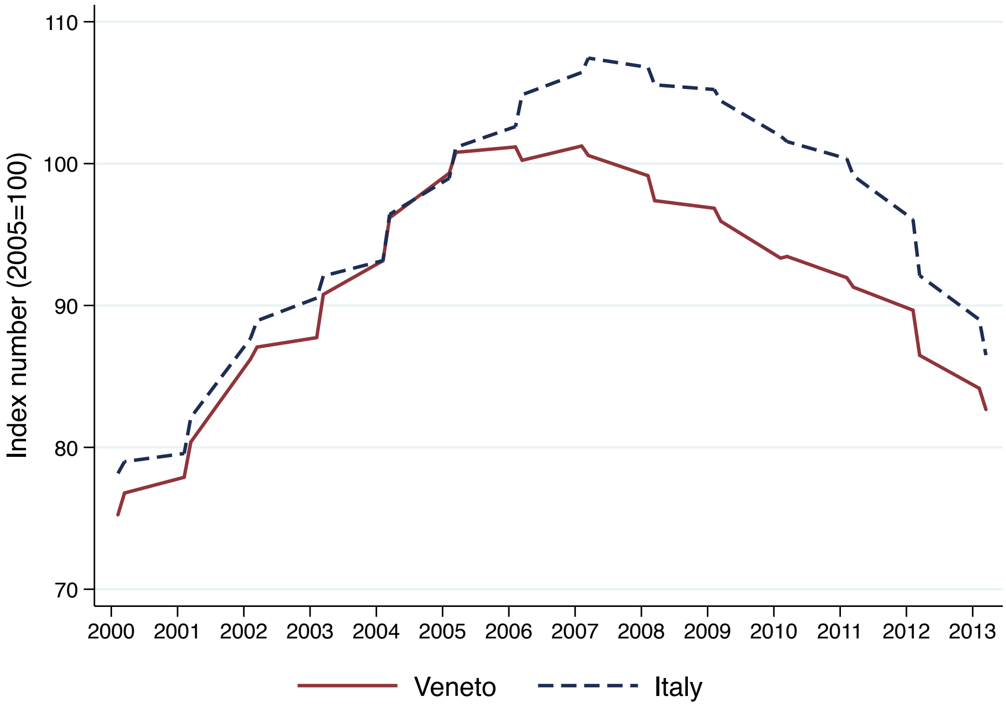
Notes: the chart reports the average values of the credit supply index (CSI) over the period 2008-2012, calculated at the municipality level, aggregating the bank-specific CSI with the shares of bank lending in the municipality. Darker areas indicate higher values of the CSI (i.e. more credit supply).

Figure A2: Regional bank lending policies



Notes: elaborations on data from Bank of Italy (Regional Bank Lending Survey). The chart plots the Diffusion Index, calculated from answers to question 1 (“Over the past 6 months, how have your bank’s credit standards as applied to the approval of loans or credit lines to enterprises changed?”) of the Regional 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.

Figure A3: Housing prices in Veneto and Italy, 2000–2013



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