Banks, firms and jobs

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Abstract

We analyze the 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 contraction in credit supply explains one fourth of the reduction in employment. This result is concentrated in more levered and less productive firms. Also, the relatively less educated and less skilled workers with temporary contracts are the most affected. Our results are consistent with the cleansing role of financial shocks.

JEL Classification Numbers: G01; G21; J23; J63

Keywords: Bank lending channel; Job contracts; Employment; Financing constraints; Cleansing effect

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1 Introduction[1]

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 and on the skill content of occupations 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

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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 low-skill occupations, 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. Thus, skill upgrading strategies are heavily shaped by contract regulation. 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 that immigrant and young workers are hit disproportionately more by the credit shock, reflecting the prevalence of immigrants in low-skill occupations, and the lower tenure and the higher presence of younger workers in temporary jobs.

To shed light on the mechanisms linking the financial crisis to employment outcomes, 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. These results are consistent with the idea that firm balance sheets play a key role in the propagation of shocks, as highly levered firms find more costly to engage in labor hoarding when financially constrained (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. In particular, a reduction in the supply of credit translates in a reduction of employment in low-productive firms that is twice as large as the average, while there is no statistically significant effect in high-productive firms. This result, read together with the higher vulnerability of less educated workers and low-skilled occupations to the financial shock, is consistent with a productivity-enhancing reallocation and with recent evidence showing a cleansing effect of the Great Recession (Foster *et al.*, 2016).

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 (Chodorow-Reich, 2014; Benmelech *et al.*, 2015; Bentolila *et al.*, 2016; Berg, 2016; Caggese *et al.*, 2016; 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.* (2016) 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 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 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

[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).

[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.

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-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. Second, thanks to contract-firm-bank matched data, we can investigate heterogeneous responses to a financial shock across firms, workers, and job contracts. In particular, other than socio-demographic characteristics, we can exploit differences across contract types and look at the intersection between individual skills and job contracts, to assess which of the two dimensions matter more for firm's employment decisions.[4] 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.

[4]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.

2 Data

2.1 Veneto as a representative case study

Our analysis relies upon unparalleled loan-level information about the entire population of workers, firms and financial intermediaries operating in Veneto, a large Italian region with a population of 4.9 million individuals and a workforce of 2.2 million workers. 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 form the national social security administration and to the Italian credit register maintained by the Bank of Italy using firm-level unique identifiers, namely their VAT numbers. These feature of the data 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.

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 firms in each quarter. For each borrower, banks have to report to the Register, on a monthly basis, the amount of each loan—granted and used—for all loans exceeding a minimum threshold (75,000 euro until December 2008, 30,000 euro afterwards), plus all nonperforming loans. Given the low threshold, these data can be taken as a census.[5] Data also contain a breakdown by type of the loan (e.g. credit lines, credit receivables and fixed-term loans). From CR we essentially

[5]We do not (explicitly) include interest rates when examining the impact of credit conditions on firm employment for two main reasons: first, data on interest rates are collected only for a sub-sample of banks that exclude the majority of small and local banks and this would have entailed a severe reduction of observations and the dismissal of 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.

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).[6]

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

A further potential constraint of our data is the lack of firm balance-sheet information, which prevent us from 1) controlling for a number of possible drivers of employment decisions, 2) exploring additional sources of firm-level heterogeneity, and 3) assessing the effect of the credit crunch on capital accumulation. To overcome the first 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. To deal with the second and third concerns, in Section 5 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.[7]

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

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

[7] However, given the wealth of studies on the effect of financial shocks on firm investment, we keep the focus of our analysis on labor market outcomes.

null. Moreover, all firms with loan information are also present in ASIA, so extremely short-lived firms fall beyond the scope of the analysis. 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.[8]

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

[8] 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.

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 across the seven provinces of Veneto, with Padua (20 percent) and Verona (19 percent) being the two more populated provinces, while Venice (the regional capital) accounts for 16 percent of firms. Finally, our sample includes mostly firms that borrow from one bank, while only 29 percent of firms obtain credit from more than one bank. The job loss for the average firm is equal to 2.1 employees, while credit declined by 1.6 percent—see Table 1—consistent with the evidence of a significant credit crunch in Italy following the Lehman's collapse (Presbitero *et al.*, 2014; Cingano *et al.*, 2016).[9] 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

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

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, 2016). 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).[10] 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 4.2).

Second, bank lending is endogenous to firms' economic conditions and employment choices, so that standard OLS estimates are likely to be biased.[11] 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

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

[11] 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).

(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)[12]; 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 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.

[12] 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).

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).[13] 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,[14] 2) the share of rationed firms as reported by a survey on firms maintained by the Bank of Italy, and 3) a corporate credit rationing indicator developed by Burlon *et al.* (2016) using bank-firm matched data. The chart shows that the credit supply index follows closely the evolution of bank lending standards and the ones of firm financing constraints; the correlation of the CSI with the three measures of credit constraints varies between 0.5 and 0.6.

Second, our measure of credit supply shows the expected correlation with bank characteristics. We run a set of bank-level regressions on the cross section of banks, taking the average 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 (Table 2).

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-

[13] 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.

[14] 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.

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 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 3 on balancing properties, the exposure to credit shocks at the firm level in our sample period (obtained averaging CSI_{it} over the period 2008-2012) is not significantly correlated (both from a statistical and economic point of view) to firm size at the beginning-of-the-period.

As far as the second term is concerned, bank-time fixed effects $\hat{\delta}_{bt}$ 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. In both cases we should observe some correlation between credit supply and firm characteristics. However, summary statistics reported in Table 3 shows that there is no systematic correlation between the size of the exposure to the credit supply shocks and a set of firm characteristics, such as size, financial dependence, banking relationships, 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 the 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 Section 5).[15]

Our approach depart from Greenstone *et al.* (2014) along several dimensions that reinforce the exogeneity of the instrument.[16] 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.[17] 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 A1 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 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 from bank-specific demand shocks that may occur whenever banks specialize in lending to certain provinces and/or sectors and they both perform differently from others. 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.

[15] 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 3 and 14.

[16] 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 the fraction of firms who have multiple lending relationships varies a lot with firm size: in our data, for example, more than 90 percent of medium and large firms have multiple relationships in contrast to about 30 percent for micro-firms. Therefore the identification of bank fixed effects with a regression at the firm level is arguably less reliable with our sample that include a large number of micro and small firms.

[17] 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.

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

The top panel reports the first-stage estimates, which show that, as expected, the CSI is positively associated with the change in used loans and the coefficients is precisely estimated. The relevance of the instrument is further confirmed by the value of the first-stage F-statistic, which ranges between 156 and 180, well above the critical value of 10 suggested by Staiger and Stock (1997) 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.*, 2016), since the change in used loans has a significant and economically large effect on the variation in employment at the firm level. Comparing the four different specification shows that adding fixed effects reduces the employment effect of the credit crunch, as they are capturing time-varying borrower-specific demand and productivity shocks. In particular, the point estimate of the coefficient on $\Delta LOAN$ are broadly stable 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).

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.[18] In relative terms, one

[18] 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.

standard deviation of the predicted change of used loan explains 18% of the standard deviation of employment.

In order to have aggregate evidence of the impact, we calculate the share of the change of employment in our temporal window that can be attributed to the credit crunch, bearing in mind the caveat that there are general equilibrium effects that cannot be taken into account when extrapolating microeconomic estimate at the aggregate level (Chodorow-Reich, 2014). In our case, for example, results are obtained conditional on firms having bank debt, so that our estimates are silent on possible demand shift to firms non depending on bank credit. In our sample, the credit extended to firms diminishes by 1.6 percent while employment by 2.1 percent (see Table 1), both on a quarterly base. With simple algebra, it is easy to show that the credit drop attributable to the lending supply orientation over the period 2008-2012 explains about 28 percent of the employment loss.

Overall our results indicate a quite large effect of the credit crunch on employment. These findings are also roughly comparable, in magnitude, to those estimated by Bentolila *et al.* (2016) 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.[19]

4.2 Robustness

We test the robustness of our baseline results running a battery of additional tests. Results are showed in Table 5. First, to address the concerns that our set of borrower fixed effects might not fully absorb demand and productivity shock, we saturate our model with more demanding fixed effects. We start by interacting the quarter dummies with more restrictive borrower cells (industry$\times$size, industry$\times$province, and province$\times$size), allowing for time-varying demand to be the same not only across industries, class size and provinces, but also withing their two-way combinations (columns 1-3). Then, in the spirit of recent works that has to deal with a prevalence of single bank-firm relationships (Abuka *et al.*, 2015; Auer and Ongena, 2016; Degryse *et al.*, 2016), we fully saturate the model with firm cluster$\times$time—where the firm cluster is composed by all firms in the same industry, province, and class size—which are as close as we can get to quarterly firm fixed effects (column 4). Interestingly, the coefficient on $\Delta LOAN$ is not only precisely estimated, but it remains remarkably stable ranging between 0.34 and

[19] The average firm size is nearly 3,000 in Chodorow-Reich (2014) and about 25 in Bentolila *et al.* (2016), while in our case is around 6 as we are able to observe the universe of firms.

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. Hence, we will use the baseline set of fixed effects showed in Table 4 (column 4) throughout the rest of the analysis.

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

In column 6 we restrict the sample to firms which have a total debt above 75,000 euros throughout the entire sample period, to avoid potential biases arising from the change in the threshold in our sample period. We find that the coefficient on $\Delta LOAN$ slightly increases to 0.49, 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 A2 in the annex). In any case, to further avoid any confounding factor affecting our estimates, we add time-varying house prices at the municipality level and we find that the inclusion of house prices does not change the coefficients on the loan variable (column 7).

Finally, we do some robustness exercise on the $\Delta LOAN$ variable. Rather than taking the average change in used loans over two quarters, in columns 7 and 8 we consider exclusively the contemporaneous change (at time t) and the average changes over three quarters (t, $t-1$, and $t-2$), respectively.[20] 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.

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

4.3 Job contract heterogeneity

As a second step of our analysis we zoom in on the composition of the labor force adjustment, to assess in which way firms changed their workforce. Given that we cannot reconstruct the stock of workers by type of contracts and by worker characteristics 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.[21] Therefore, differently from the baseline model, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the job contracts/workers. Lacking that information in our sample, we use the aggregates shares at the regional level, as compiled by from the National Institute of Statistics ('Labour Force Survey'), in order to provide an economic interpretation of our findings, see Table 1.

At first, we consider open-ended and temporary contracts—which include fixed term direct hires, project workers, temporary agency workers, trainees and apprentices, and seasonal workers—to test whether firms react to more binding financing constraints by reducing the use of temporary contracts more than open-ended ones (Table 6, 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.[22] 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 also discussed by Bentolila *et al.* (2016) for Spain. Although temporary contracts account for only slightly more than one tenth of total contracts in the workforce (Table 1), they bear almost half of the effect of the change in credit supply ($0.191/0.363 = 0.53$, where 0.363 is the estimated coefficient of credit supply variation for the entire workforce—see Table 4, column 4).

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

[21]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).

[22]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).

though the effect on inflows is also marginally significant (Table 6, bottom-left panel). Then, within outflows, we differentiate across the possible reasons of the exit and we find evidence that outflows are exclusively due to non-renewal of expired contracts, while there is no evidence that the adjustment works through dismissal or quit (Table 6, top-right panel). Finally, we look at the transitions across job contracts, considering both contract type and time schedule. We find evidence that firms more exposed to negative credit shocks are are less likely to transform temporary contracts into open-ended ones, while it seems that financing constraints do not affect firm policies in terms of transition between part-time and full-time jobs (Table 6, bottom-right panel).

4.4 Worker heterogeneity

Looking at the workers' characteristics, we first differentiate across three levels of education—low (at most compulsory education), medium (at most upper secondary education), and high (tertiary education), based on the ISCED classification—and we observe that firms which have experienced a reduction in the supply of credit reacted reducing mostly the employment of low- and medium-educated workers, while the effect for the high-educated ones is smaller and only marginally significant (Table 7, top panel). In particular, using the relative shares reported in Table 1, the elasticity of employment to credit supply for low-educated workers is higher than the average and equal to 0.48 (= 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 $\Delta LOAN$ ($0.186/0.363 = 0.51$), even though low-educated workers account for less than 40 percent of the workforce.

Education may not perfectly overlap with the skill content of jobs; moreover, administrative data may record with errors self-reported information as the level of education. Therefore, we replicate the analysis by skill level directly looking at the skill content of each occupation (Table 7, bottom panel).[23] The results 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 ($0.156/0.363 = 0.43$). The differential effect across skills and education is consistent with the theory of skill upgrading, which indicates that, in a downturn, firms want to dismiss less skilled, less profitable workers first (Reder, 1955; Hershbein and

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

Kahn, 2016).

Then, we assess whether firms adjusted their labor force differentiating across workers, depending on their gender, age, and nationality. Our results—showed in Table 8—indicate that the employment effect in response to a reduction in the supply of credit is concentrated among women, foreign and younger workers. In particular, female workers represent around 40 percent of total employment, but they account for 61 percent of the total change in employment. Similarly, foreign workers are less the 10 percent of the labor force, but their employment dynamics explains more than 24 percent of the total change in employment.[24] There is also evidence that younger 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, even though they represent less than 20 percent of the workforce.

Finally, in Table 9 we take advantage of the several dimensions in which we can slice our data to measure the impact of the credit crunch on employment, conditional both on contract type and worker education. We find that indeed firms adjusted their labor force in response to a contraction in the supply of credit reducing temporary contracts and dismissing low- and medium-educated workers. By contrast, high-educated workers have been able to insulate themselves, even if hired with a temporary contracts. The effect on low-educated workers with a temporary contract account for 32 percent of the total employment effect, 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 are 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 and with the empirical evidence on Germany discussed by Hochfellner *et al.* (2016). Overall, the results of our analysis indicates that the combination of low-education and temporary contract identifies the profile of workers who has been hit by the credit crunch, while high education makes the difference between temporary and open-ended contracts almost irrelevant.

[24] 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).

4.5 Firm heterogeneity

As a fourth step, we explore possible heterogeneous effect across different firms.[25] 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 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 10, left panel). By contrast, the coefficient on $\Delta LOAN$ is not statistically significant in the sample of medium-large firms: the coefficient is positive but imprecisely estimated, and the first-stage F-statistic suggests that there are weak identification problems, possible due to the small sample size and to the capacity of large firms to negotiate 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 10, 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.[26]

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

[25] 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 (e.g. size and sector).

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

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. We find that employment reacts relatively more to credit supply restrictions in firms that are more levered (Table 11, left panel). Second, we find that the elasticity of employment to credit is higher for firms that at the beginning of our sample period were using granted credit lines more intensively, as those firms are less able to cope with negative shocks using existing credit lines (Table 11, 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 11, right panel), 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).

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 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 sub-sample 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 12, 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.*, 2016). 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 4.4 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 13, 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 13, bottom panels).

5.2 Matching firm balance sheets

To have a better sense of which are the firms that reduce employment more in response to a financial shock, in this section 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.[27] 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 3. 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 14).

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 0.363 to 0.347 (compare Table 4, column 4, and Table 15, column 1). However, the coefficient is significantly smaller (and equal to 0.095) 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 15, 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 15 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 16 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, we can differentiate between low- and high-risk firms on the basis of the firm credit

[27] 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.

rating at December 2007. For each firm, the CADS database contains the Altman (1968) z-score, which indicates the likelihood of default within two years. This indicator is computed on the basis of multiple financial ratios and it is widely used by Italian banks to assess credit risk. The z-score takes integer values ranging from 1 (the safest firm) to 9 (the firm most likely to default) and we split the sample around the sample median. Our results show that ex-ante riskier firms are more sensitive to a credit crunch, with an estimated elasticity which is about three times larger than the one of low-risk firms.

Third, 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 in line with those of Bentolila *et al.* (2016) 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).

6 Conclusions

The recent literature on finance and labor has showed that firms reduce employment in response to a credit crunch. Our analysis takes advantage of a novel dataset on job contracts and labor market flows for the universe of firms in a large Italian region to look at the within-firm personnel dynamics and identify which kind of workers are more likely to be laid off, depending on firm, worker, and job contract characteristics. To identify the 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 and the point estimate indicates that the elasticity of employment to a credit supply shock is 0.36. This result is due to an adjustment at the intensive margin (the elasticity excluding firm closures is 0.25), but also to a higher probability of firm closure in response to a reduction in the supply of credit. The aggregate effect, based on our estimates, is economically meaningful since the contraction in bank lending is able to explain about one fourth of the reduction in employment. In addition, we show that the adjustment has been differentiated across firms, workers and job contracts. In particular, the credit crunch has mainly affected less educated and less skilled workers with temporary contracts, suggesting that firms have adjusted to the credit supply shock in a way which is consistent with a skill upgrading of the labor force, even though this strategy has been significantly affected by labor market regulation. Finally, we show that the employment effects of the credit crunch have been heterogeneous across firms: 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.

Our results inform the current debate on the real effects of financial shocks along different 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 findings confirm that firm balance sheet matters for the propagation of shocks to the real economy, with more levered firms reducing employment more when facing financing constraints. Finally, 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.

References

ABUKA, C., ALINDA, R. K., MINOIU, C., PRESBITERO, A. *et al.* (2015). *Monetary Policy in a Developing Country; Loan Applications and Real Effects*. IMF Working Paper 15/270, International Monetary Fund, Washington DC.

ACHARYA, V. V., EISERT, T., EUFINGER, C. and HIRSCH, C. (2016). Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans, mimeo, NYU.

ADELINO, M., SCHOAR, A. and SEVERINO, F. (2015). House prices, collateral, and self-employment. *Journal of Financial Economics*, **117** (2), 288–306.

ALTMAN, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, **23** (4), 589–609.

AMITI, M. and WEINSTEIN, D. E. (2011). Exports and Financial Shocks. *The Quarterly Journal of Economics*, **126** (4), 1841–1877.

— and — (2017). How Much do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Data. *Journal of Political Economy*, **Forthcoming**.

AUER, R. and ONGENA, S. (2016). The Countercyclical Capital Buffer and the Composition of Bank Lending, unpublished.

BECK, T., DEMIRGÜÇ-KUNT, A. and MAKSIMOVIC, V. (2008). Financing patterns around the world: Are small firms different? *Journal of Financial Economics*, **89** (3), 467 – 487.

BENMELECH, E., BERGMAN, N. K. and SERU, A. (2015). Financing labor, National Bureau of Economic Research.

BENTOLILA, S., JENSEN, M. and JIMENEZ, G. (2016). *When Credit Dries Up: Job Losses in the Great Recession*. Working Paper Series 4528, CESifo.

BERG, T. (2016). *Got rejected? Real effects of not getting a loan*. ECB Working Paper 1960, European Central Bank.

BOERI, T., GARIBALDI, P. and MOEN, E. R. (2013). Financial Shocks and Labor: Facts and Theories. *IMF Economic Review*, **61** (4), 631–663.

BOTTERO, M., LENZU, S. and MEZZANOTTI, F. (2016). *Sovereign debt exposure and the bank lending channel: impact on credit supply and the real economy*. Working Paper 1032, Bank of Italy.

BUERA, F., FATTAL-JAEF, R. and SHIN, Y. (2015). Anatomy of a Credit Crunch: From Capital to Labor Markets. *Review of Economic Dynamics*, **18** (1), 101–117.

BURLON, L., FANTINO, D., NOBILI, A. and SENE, G. (2016). *The quantity of corporate credit rationing with matched bank-firm data*. Working Papers 1058, Bank of Italy, Rome.

CABALLERO, R. J. and HAMMOUR, M. L. (1994). The Cleansing Effect of Recessions. *American Economic Review*, **84** (5), 1350–68.

CAGGESE, A. and CUÑAT, V. (2008). Financing constraints and fixed-term employment contracts. *Economic Journal*, **118** (533), 2013–2046.

—, CUÑAT, V. and METZGER, D. (2016). Firing the Wrong Workers: Financing Constraints and Labor Misallocation, mimeo, London School of Economics.

CHODOROW-REICH, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *Quarterly Journal of Economics*, **129** (1), 1–59.

CINGANO, F., MANARESI, F. and SETTE, E. (2016). Does Credit Crunch Investments Down?

New Evidence on the Real Effects of the Bank-Lending Channel. *Review of Financial Studies*, **29** (10), 2737–2773.

DEGRYSE, H., DE JONGHE, O., JAKOVLJEVIĆ, S., MULIER, K. and SCHEPENS, G. (2016). The Impact of Bank Shocks on Firm-level Outcomes and Bank Risk-Taking, Available at SSRN 2788512.

DEVICIENTI, F., MAIDA, A. and SESTITO, P. (2007). Downward Wage Rigidity in Italy: Micro-Based Measures and Implications. *Economic Journal*, **117** (524), F530–F552.

DUYGAN-BUMP, B., LEVKOV, A. and MONTORIOL-GARRIGA, J. (2015). Financing constraints and unemployment: Evidence from the Great Recession. *Journal of Monetary Economics*, **75**, 89–105.

ERSAHIN, N. and IRANI, R. (2016). Collateral Values and Corporate Employment, mimeo, University of Illinois at Urbana-Champaign.

FABIANI, S., LAMO, A., MESSINA, J. and ROOM, T. (2015). European Firm Adjustment During Times of Economic Crisis. *IZA Journal of Labor Policy*, **4** (1), 4–24.

FORSYTHE, E. (2016). Why Don't Firms Hire Young Workers During Recessions?, University of Illinois.

FOSTER, L., GRIM, C. and HALTIWANGER, J. (2016). Reallocation in the Great Recession: Cleansing or Not? *Journal of Labor Economics*, **34** (S1), S293 – S331.

GAMBACORTA, L. and MISTRULLI, P. E. (2014). Bank Heterogeneity and Interest Rate Setting: What Lessons Have We Learned since Lehman Brothers? *Journal of Money, Credit and Banking*, **46** (4), 753–778.

GARCÍA SERRANO, C. (1998). Worker turnover and job reallocation: the role of fixed-term contracts. *Oxford Economic Papers*, **50** (4), 709–725.

GERTLER, M. and GILCHRIST, S. (1994). Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms. *Quarterly Journal of Economics*, **109** (2), 309–340.

GIROUD, X. and MUELLER, H. M. (2016). Firm Leverage, Consumer Demand, and Unemployment during the Great Recession. *Quarterly Journal of Economics*, **Forthcoming**.

GOBBI, G. and SETTE, E. (2014). Do firms benefit from concentrating their borrowing? evidence from the great recession. *Review of Finance*, **18** (2), 527–560.

GOUX, D., MAURIN, E. and PAUCHET, M. (2001). Fixed-term contracts and the dynamics of labour demand. *European Economic Review*, **45** (3), 533–552.

GREENSTONE, M., MAS, A. and NGUYEN, H.-L. (2014). *Do Credit Market Shocks affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times*. NBER Working Papers 20704, National Bureau of Economic Research.

GUISO, L., SAPIENZA, P. and ZINGALES, L. (2004). Does Local Financial Development Matter? *Quarterly Journal of Economics*, **119** (3), 929–969.

GURIEV, S. M., SPECIALE, B. and TUCCIO, M. (2016). *How do regulated and unregulated labor markets respond to shocks? Evidence from immigrants during the Great Recession*. CEPR Discussion Paper 11403, Center for Economic Policy Research, London.

HALTENHOF, S., LEE, S. J. and STEBUNOVS, V. (2014). The credit crunch and fall in employment during the great recession. *Journal of Economic Dynamics and Control*, **43**, 31–57.

HALTIWANGER, J., JARMIN, R. S. and MIRANDA, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, **95** (2), 347–361.

HERSHBEIN, B. and KAHN, L. B. (2016). *Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings*. Working Paper 16-254, Upjohn Institute.

HOCHFELLNER, D., MONTES, J., SCHMALZ, M. and SOSYURA, D. (2016). Winners and Losers of Financial Crises: Evidence from Individuals and Firms, university of Michigan.

HOYNES, H., MILLER, D. L. and SCHALLER, J. (2012). Who Suffers During Recessions? *Journal of Economic Perspectives*, **26** (3), 27–48.

JIMÉNEZ, G., MIAN, A. R., PEYDRO, J.-L. and SAURINA, J. (2014). The Real Effects of the Bank Lending Channel, Available at SSRN: http://ssrn.com/abstract=1674828.

JOHNSTON, D. W. and LORDAN, G. (2016). Racial prejudice and labour market penalties during economic downturns. *European Economic Review*, **84**, 57–75.

KALEMLI-OZCAN, S., LAEVEN, L. and MORENO, D. (2015). Debt Overhang on Europe: Evidence from Firm-Bank-Sovereign Linkages, University of Maryland.

MIAN, A. and SUFI, A. (2014). What Explains the 2007–2009 Drop in Employment? *Econometrica*, **82** (6), 2197–2223.

MOSCARINI, G. and POSTEL-VINAY, F. (2012). The contribution of large and small employers to job creation in times of high and low unemployment. *American Economic Review*, **102** (6), 2509–2539.

PAGANO, M. and PICA, G. (2012). Finance and employment. *Economic Policy*, **27** (69), 5–55.

PARAVISINI, D., RAPPOPORT, V., SCHNABL, P. and WOLFENZON, D. (2015). Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data. *Review of Economic Studies*, **82** (1), 333–359.

PEEK, J. and ROSENGREN, E. S. (2005). Unnatural selection: perverse incentives and the misallocation of credit in Japan. *American Economic Review*, **95**, 1144–1166.

PETROSKY-NADEAU, N. (2013). TFP during a credit crunch. *Journal of Economic Theory*, **148** (3), 1150–1178.

POPOV, A. and ROCHOLL, J. (2017). Do Credit Shocks Affect Labor Demand? Evidence from Employment and Wages during the Financial Crisis. *Journal of Financial Intermediation*, **Forthcoming**.

PRESBITERO, A. F., UDELL, G. F. and ZAZZARO, A. (2014). The home bias and the credit crunch: A regional perspective. *Journal of Money, Credit, and Banking*, **46** (s1), 53–85.

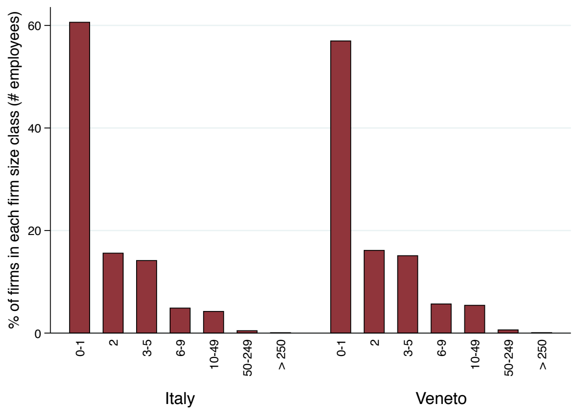
REDER, M. W. (1955). The theory of occupational wage differentials. *The American Economic Review*, **45** (5), 833–852.

SIEMER, M. (2016). Employment Effects of Financial Constraints During the Great Recession, Board of Governors of the Federal Reserve System.

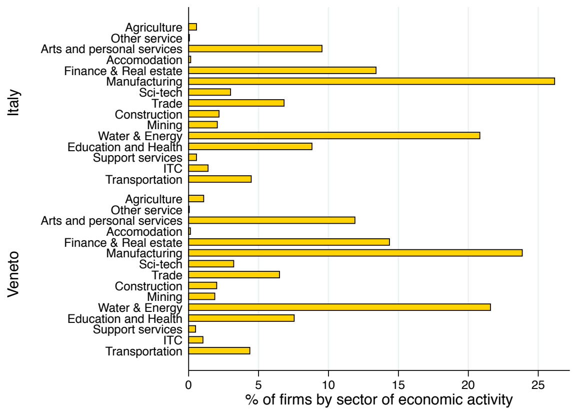
STAIGER, D. and STOCK, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, **65** (3), 557–586.

Figures

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



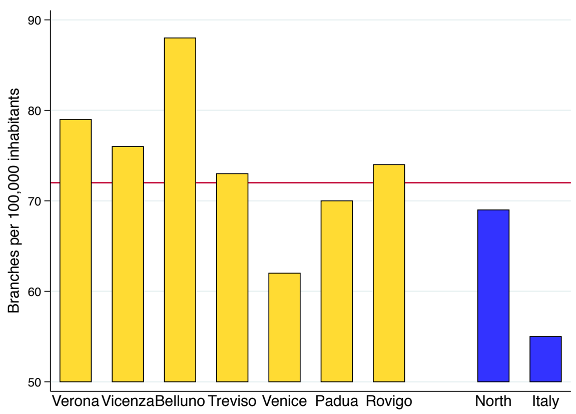
(a) Distribution of firms across size



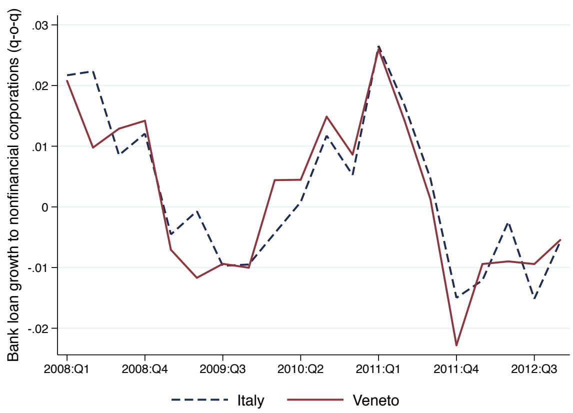
(b) Distribution of firms across sectors

Notes: elaborations on ISTAT data (census 2011).

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



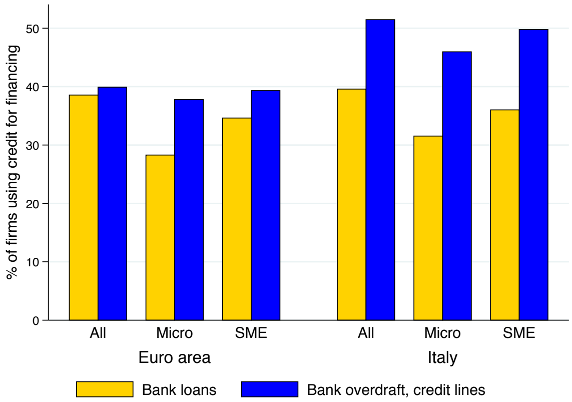
(a) Financial development



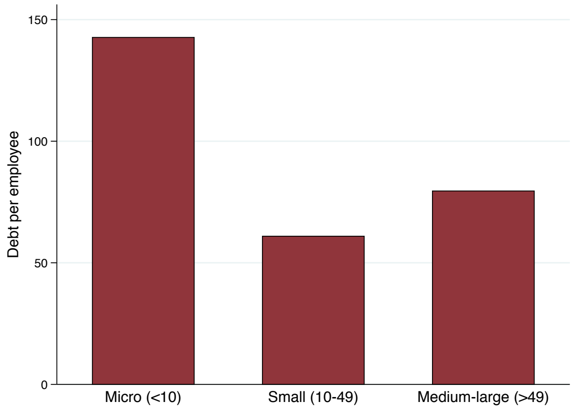
(b) Loans growth

Notes: elaborations on data from Bank of Italy.

Figure 3: Bank financing in Italy across firm size



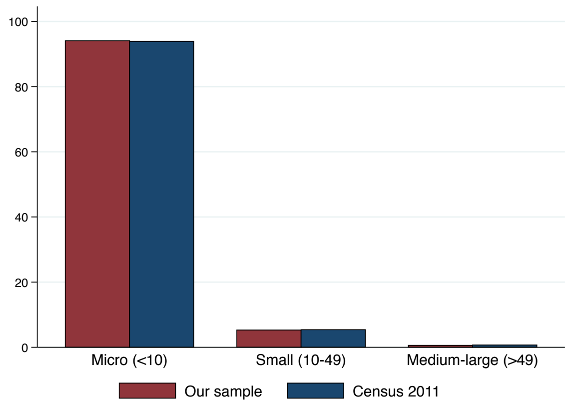
(a) Bank credit (Average 2009-2012, SAFE)



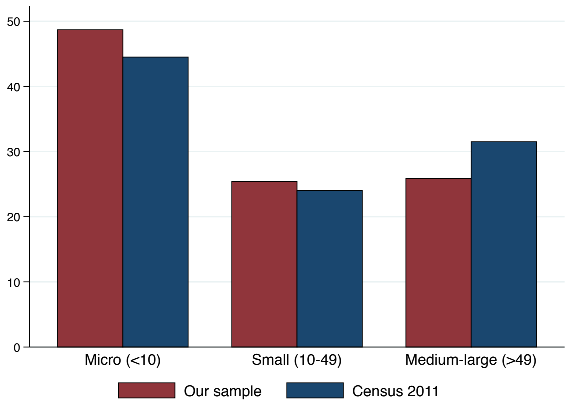
(b) Firms' indebtedness (our data)

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

Figure 4: Sample representativeness, comparison with the Census



(a) Firms' distribution (%)

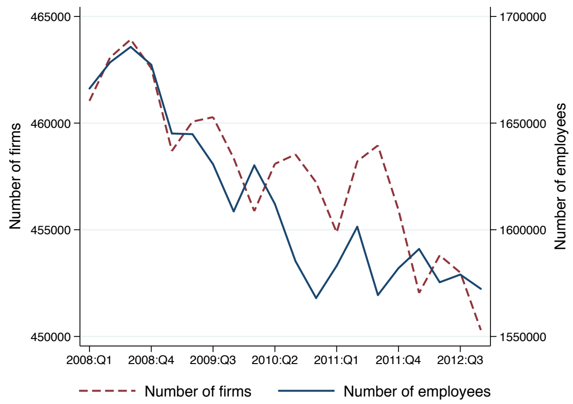


(b) Employees' distribution (%)

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

Figure 5: Sample representativeness, dynamics of firms and employment

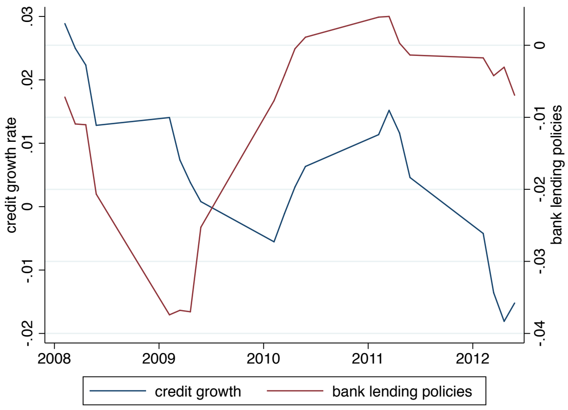
(a) Sample, non-financial private sector (deseasonalized data)



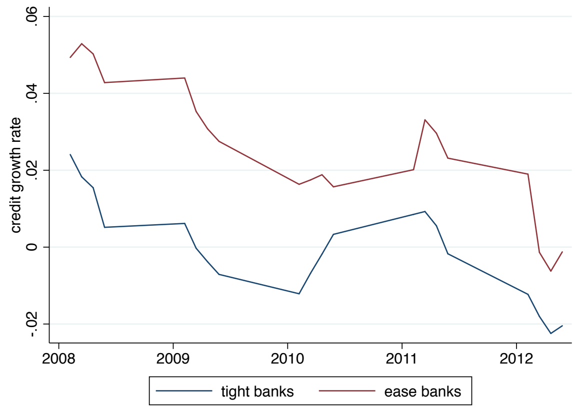
(b) Universe, total economy (Source: ISTAT, RFL)

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

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

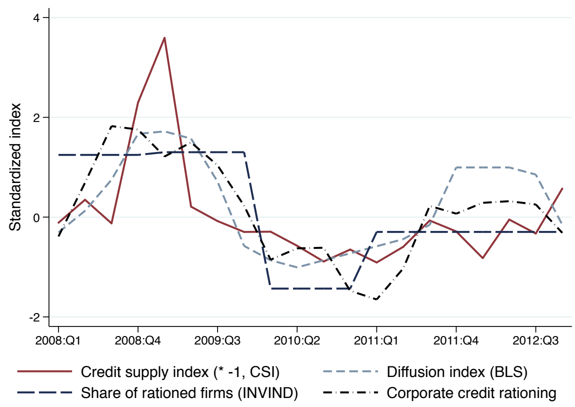


(a) Bank lending policies & credit growth



(b) Credit growth across tight and ease banks

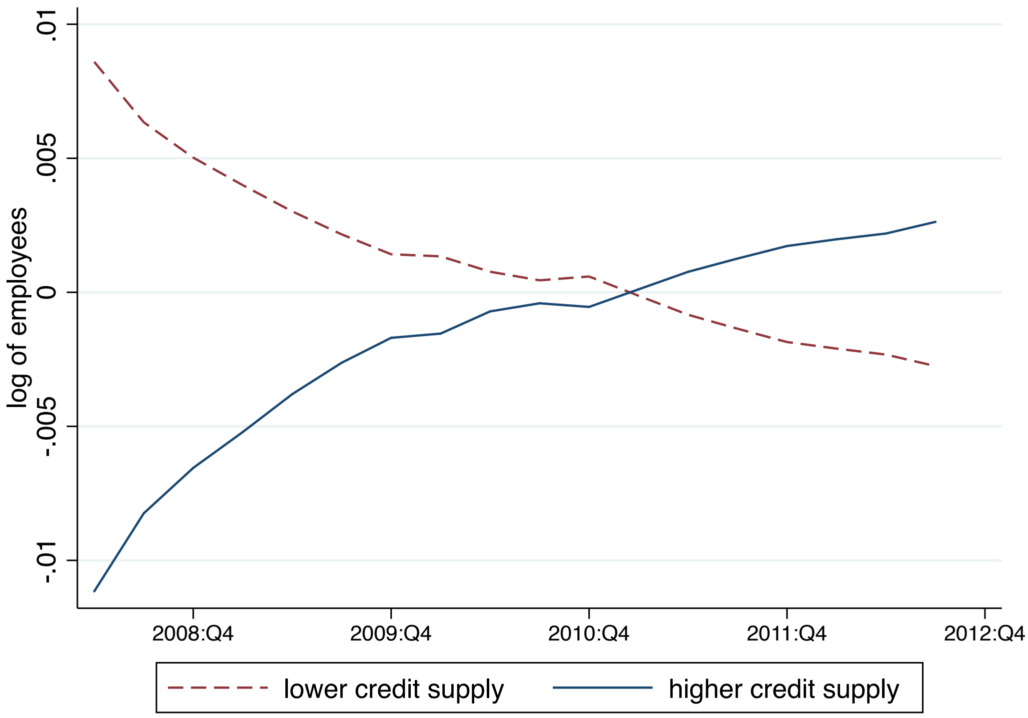
(c) Bank lending policies across banks



(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.

Tables

Table 1: Summary statistics

The table reports the summary statistics for $\Delta EMPLOYMENT$ for all workers and for different characteristics of contracts and workers, the average change in firm borrowing over two quarters ($\Delta LOAN$), the credit supply index (CSI), and 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 skill content of each occupation is defined as low (elementary occupations and services and sales workers), medium (clerical support workers, craft and related trades workers and plant and machine operators, and assemblers) and high (managers, professionals and technicians), based on the ISCO classification. The last column report the share of employment at the beginning of the period (end 2007) for different characteristics of contract and workers: these data are taken from the 'Labour Force Survey' of the National Institute of Statistics. For temporary and open-ended contracts the table reports also the decomposition across education levels.

Variable	Mean	St. Dev.	Share in total employment (%)
$\Delta EMPLOYMENT$ - Total	-0.0211	0.2610	100.0
$\Delta EMPLOYMENT$ - Open-ended	-0.0173	0.1890	88.7
low-education	-0.0080	0.1000	*3.9*
medium-education	-0.0075	0.1020	*5.4*
high-education	-0.0016	0.0355	*2.0*
$\Delta EMPLOYMENT$ - Temporary	-0.0039	0.1660	11.3
low-education	-0.0016	0.1060	*32.8*
medium-education	-0.0017	0.0993	*45.0*
high-education	-0.0006	0.0464	*11.0*
$\Delta EMPLOYMENT$ - Under 30	-0.0025	0.1080	17.9
$\Delta EMPLOYMENT$ - Over 30	-0.0186	0.2090	82.1
$\Delta EMPLOYMENT$ - Male	-0.0126	0.1690	59.9
$\Delta EMPLOYMENT$ - Female	-0.0085	0.1470	40.1
$\Delta EMPLOYMENT$ - Italian	-0.0179	0.2260	91.4
$\Delta EMPLOYMENT$ - Foreign	-0.0033	0.0919	8.6
$\Delta EMPLOYMENT$ - Low-education	-0.0098	0.1480	38.7
$\Delta EMPLOYMENT$ - Medium-education	-0.0088	0.1420	48.0
$\Delta EMPLOYMENT$ - High-education	-0.0022	0.0569	13.3
$\Delta EMPLOYMENT$ - Low-skill	-0.0042	0.1390	15.2
$\Delta EMPLOYMENT$ - Medium-skill	-0.0113	0.1500	49.3
$\Delta EMPLOYMENT$ - High-skill	-0.0056	0.0874	35.5
$\Delta LOAN$	-0.0163	0.3151	.
CSI	-0.0085	0.0404	.
$EXIT$	0.0066	0.0811	.

Table 2: Credit supply and bank heterogeneity

The table reports the results of a set of OLS regressions at the bank level (in cross section) in which the dependent variable is the average 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 3: 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 4: Baseline regressions – IV estimates

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

1^{st} stage	Dep var: $\Delta LOAN_{t,t-1}$			
$CSI_{t,t-1}$	0.0786***	0.0779***	0.0758***	0.0751***
	(0.00609)	(0.00609)	(0.00609)	(0.00622)
R^2	0.160	0.161	0.162	0.162
2^{nd} stage	Dep Var: $\Delta EMPLOYMENT_t$			
$\Delta LOAN_{t,t-1}$	0.437***	0.438***	0.445***	0.363***
	(0.0672)	(0.0676)	(0.0699)	(0.0689)
Observations	2,459,948	2,459,948	2,459,948	2,459,948
1^{st}-stage F-statistic	179.6	176.6	166.9	156.3
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	.	.	.
Industry × quarter FE	No	Yes	Yes	Yes
Size × quarter FE	No	No	Yes	Yes
Province × quarter FE	No	No	No	Yes

Table 5: Robustness exercises

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

Dep. Var.:	$\Delta EMPLOYMENT_t$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta LOAN_{t,t-1}$	0.373***	0.337***	0.361***	0.345***	0.363***	0.491***	0.363***		
	(0.0691)	(0.0675)	(0.0687)	(0.0681)	(0.108)	(0.100)	(0.0689)		
$HOUSE\ PRICE_t$							-0.0341**		
							(0.0163)		
$\Delta LOAN_t$								0.229***	
								(0.0510)	
$\Delta LOAN_{t,t-2}$									0.620***
									(0.0976)
Observations	2,459,948	2,459,948	2,459,948	2,459,948	2,459,948	1,863,812	2,459,948	2,459,948	2,459,948
1^{st}-stage F-statistic	157.1	156.3	157.0	154.9	169.7	118.9	156.3	108.2	142.8
Sample	All firms	All firms	All firms	All firms	All firms	Drop < 75k	All firms	All firms	All firms
Standard errors	Robust	Robust	Robust	Robust	Clustered s.e.	Robust	Robust	Robust	Robust
Firm FE	Yes	Yes	Yes	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
Industry × size × quarter FE	Yes	No	No	.	.	.	.	.	.
Industry × province × quarter FE	No	Yes	No	.	.	.	.	.	.
Province × size × quarter FE	No	No	Yes	.	.	.	.	.	.
Industry × province × size × quarter FE	No	No	No	Yes	.	.	.	.	.

Table 6: Job contract heterogeneity

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

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Contracts		**Reason for exit**		
	Open-ended	Temporary	Dismissal	Expiry	Quit
$\Delta LOAN_{t,t-1}$	0.170***	0.191***	-0.0357	-0.158***	-0.0334
	(0.0449)	(0.0471)	(0.0222)	(0.0330)	(0.0283)
	Flows		**Transitions**		
	Inflows	Outflows	Fixed to open	Full to part-time	Part-time to full
$\Delta LOAN_{t,t-1}$	0.0834*	-0.277***	0.0219**	-0.00155	-0.00414
	(0.0447)	(0.0617)	(0.00864)	(0.00651)	(0.00590)
Observations	2,459,948	2,459,948	2,459,948	2,459,948	2,459,948
1^{st}-stage F-statistic	156.3	156.3	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

Table 7: Worker heterogeneity by education and skills

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

Dep. Var.:	$\Delta EMPLOYMENT_t$		
	Education level		
	Low	Medium	High
$\Delta LOAN_{t,t-1}$	0.186***	0.151***	0.0261*
	(0.0403)	(0.0371)	(0.0144)
	Skill level		
	Low	Medium	High
$\Delta LOAN_{t,t-1}$	0.156***	0.135***	0.0725***
	(0.0397)	(0.0375)	(0.0215)
Observations	2,459,948	2,459,948	2,459,948
1^{st}-stage F-statistic	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes

Table 8: Worker heterogeneity by personal characteristics

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

Dep. Var.:	$\Delta EMPLOYMENT_t$					
	Gender		**Age**		**Nationality**	
	Male	Female	Under 30	Over 30	Italian	Foreign
$\Delta LOAN_{t,t-1}$	0.144***	0.220***	0.105***	0.257***	0.274***	0.0885***
	(0.0421)	(0.0419)	(0.0295)	(0.0539)	(0.0586)	(0.0245)
Observations	2,459,948	2,459,948	2,459,948	2,459,948	2,459,948	2,459,948
1^{st}-stage F-statistic	156.3	156.3	156.3	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: The effect of contract type and education

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t, for the different types of contracts (open-ended and temporary) and workers (with low, middle, and high education), as labeled in each row and column, respectively. Those flows are divided by the average stock of all firm's workers over the quarter. Thus, the dependent variable is not a growth rate but a contribution to the aggregate (at the firm level) growth rate. This means that the estimated coefficients cannot be interpreted as elasticities, but they need to be scaled by the relative share of the workers in the workforce (see Table 1). $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. Results reported in the top panel refer to open-ended contracts, for different level of worker education. Results reported in the 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). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$		
Education:	Low	Medium	High
	Open-ended contract		
$\Delta LOAN_{t,t-1}$	0.0683***	0.0816***	0.0214***
	(0.0248)	(0.0247)	(0.00821)
	Temporary contract		
$\Delta LOAN_{t,t-1}$	0.115***	0.0716***	0.00420
	(0.0301)	(0.0275)	(0.0121)
Observations	2,459,948	2,459,948	2,459,948
1^{st}-stage F-statistic	156.3	156.3	156.3
Firm FE	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes

Table 10: Firm heterogeneity by size and sector

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

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Firm size			**Sector**	
	Micro	Small	Med-Large	Industry	Services
$\Delta LOAN_{t,t-1}$	0.327***	0.618***	3.737	0.167	0.427***
	(0.0719)	(0.226)	(7.980)	(0.135)	(0.0803)
Observations	2,086,193	333,629	40,126	818,609	1,641,339
1^{st}-stage F-statistic	133.5	25.13	0.320	34.76	122.6
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 11: Firm heterogeneity by financial characteristics

The table reports the (second-stage) regression results of the 2SLS estimation of equation 1. The dependent variable $\Delta EMPLOYMENT_t$ is defined as the change in employment at the firm level over the quarter t; $\Delta LOAN_{t,t-1}$ is the average change in used loans at the firm level in quarters t and $t-1$. In the first stage regressions, the excluded instrument is the credit supply index CSI, as defined in Section 3.2 and equation 4. The left panel reports the results for the sub-samples of firms with low and high debt per employee. 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). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. Var.:	$\Delta EMPLOYMENT_t$					
	Debt		**Credit lines use**		**Relationship lending**	
	Low	High	Low	High	Single-bank	Multi-banks
$\Delta LOAN_{t,t-1}$	0.269***	0.498***	0.276***	0.460***	0.369***	0.773***
	(0.0682)	(0.145)	(0.0760)	(0.129)	(0.114)	(0.260)
Observations	1,207,961	1,251,987	1,222,596	1,237,352	1,393,068	1,013,409
1^{st}-stage F-statistic	100.7	81.05	89.66	72.19	59.97	25.55
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: 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). Robust standard errors 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)
$\Delta LOAN_{t,t-1}$	0.363***	0.252***	0.0653**	0.185***	-0.0591***
	(0.0689)	(0.0572)	(0.0314)	(0.0472)	(0.0184)
Observations	2,459,948	2,443,651	2,443,651	2,443,651	2,459,948
1^{st}-stage F-statistic	156.3	156.0	156.0	156.0	156.3
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

Table 13: 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). Robust standard errors 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***	0.100***	0.0108
	(0.0373)	(0.0325)	(0.0136)
	Open-ended contract		
$\Delta LOAN_{t,t-1}$	0.0261	0.0307*	0.00897
	(0.0220)	(0.0186)	(0.00717)
	Temporary contract		
$\Delta LOAN_{t,t-1}$	0.114***	0.0694**	0.00181
	(0.0303)	(0.0276)	(0.0121)
Observations	2,443,651	2,443,651	2,443,651
1^{st}-stage F-statistic	156.0	156.0	156.0
Firm FE	Yes	Yes	Yes
Industry $\times$ quarter FE	Yes	Yes	Yes
Size $\times$ quarter FE	Yes	Yes	Yes
Province $\times$ quarter FE	Yes	Yes	Yes

Table 14: 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 15: 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). Robust standard errors 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)
$\Delta LOAN_{t,t-1}$	0.347***	0.0952**	1.210***
	(0.0504)	(0.0459)	(0.315)
Observations	715,920	169,881	169,881
1^{st}-stage F-statistic	421.8	71.26	71.26
Firm FE	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes
Size × year FE	Yes	Yes	Yes
Province × year FE	Yes	Yes	Yes

Table 16: 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). Firm riskiness is defined by the Altman (1968) z-score (see Section 5 for details) (columns 3 and 4). Leverage is measured by the ratio of financial debt over the sum of financial debt and equity (columns 5 and 6). Labor productivity is calculated as value added per worker (columns 7 and 8). Fixed effects are constructed based on 30 (2-digit) industries, 7 provinces and 3 class sizes (firms with less than 10 employees, between 10 and 49, and 50 or more). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In column (5) standard errors are clustered at the province-industry-class size level.

Dep. Var.:	$\Delta EMPLOYMENT_t$							
	Age		**Riskiness**		**Leverage**		**Labor productivity**	
	Young	Old	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta LOAN_{t,t-1}$	0.247**	-0.00888	0.0445	0.179*	0.0293	0.195**	0.177**	-0.0162
	(0.110)	(0.0464)	(0.0462)	(0.101)	(0.0487)	(0.0897)	(0.0690)	(0.0681)
Observations	84,239	85,642	84,899	84,982	84,936	84,945	84,937	84,944
1^{st}-stage F-statistic	20.80	49.23	44.81	26.96	37.72	38.44	34.05	33.16
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	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[28]; (ii) ASIA, the firm register maintained by the Italian Statistical Office (ISTAT), which provides information on the stock of employed workers[29]; 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

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

[29] 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.[30]

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 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

[30] 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;[31]
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.

[31] 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: 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 × quarter FE	Yes	Yes	Yes	Yes	Yes
Size × quarter FE	Yes	Yes	Yes	Yes	Yes
Province × quarter FE	Yes	Yes	Yes	Yes	Yes

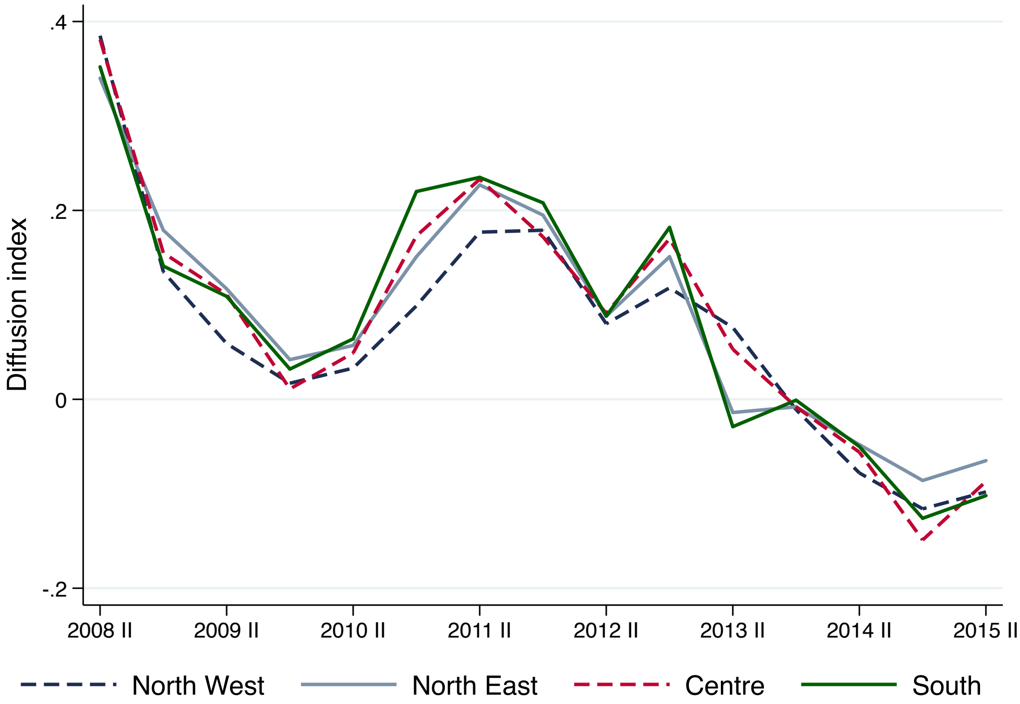
Table A2: The effect of education within firm sector and size

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

Dep. Var.:	$\Delta EMPLOYMENT_t$				
	Over sectors		**Over firm size**		
	Low education				
$\Delta LOAN_{t,t-1}$	0.106	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

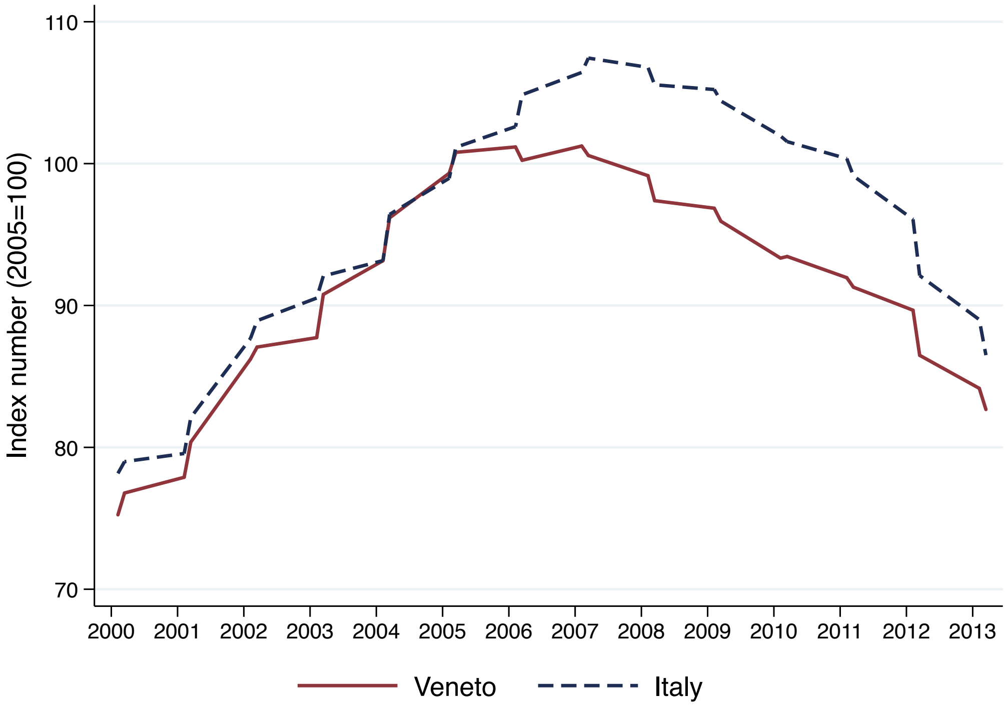
A-III Additional Figures

Figure A1: 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 A2: Housing prices in Veneto and Italy, 2000–2013



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