Credit and firms' organization*

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Abstract

We investigate how credit availability affects the organization of firms' labor. We construct a firm-specific credit supply instrument derived from firm-bank credit linkages, and conduct an event study analyzing labor restructuring decisions within Portuguese firms. Our analysis uncovers a clear nexus between credit availability and labor adjustments. Specifically, firms that invest in machines and equipment are more sensitive to credit shortages. As a result, they tend to adjust their workforce by reducing the number of production and specialized workers closely associated with machine operations. These findings shed light on how credit dynamics shape labor decisions within firms, providing insights into aggregate responses to financial limitations.

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1 Introduction

Decision makers in a firm face many shocks and constraints, which affect the way production is organized (Antoni et al., 2022), as well as how inputs in production are combined (Caliendo and Rossi-Hansberg, 2012). Understanding how firms restructure their organization and change the combination of inputs in production provides insights on how shocks transmit to the real economy. This is important because the organization of the firm is directly linked to their productivity (Caliendo et al., 2020), as well as to within-firm inequality (Friedrich, 2022): firms reorganize to grow or to shrink, and each of these strategic decision has important implications for the workers.[1] The recent trade literature has extensively studied the effect of a trade shock on the workers in a local labor market (Autor et al. 2014, Hummels et al. 2014, Ebenstein et al. 2014, Kovak, 2013, Dvorkin et al., 2019), as well as on the organization of the firm (Guadalupe and Wulf, 2008, Brambilla et al., 2022). However, less is known on the relationship between firm organization and firm credit, which is of first order importance for firms' functioning (Bernanke and Gertler, 1990) and growth (Rajan and Zingales, 1998).

We are interested in understanding how credit interacts with the organization of labor in the firm. We use data on the universe of Portuguese firms and workers and the information on the task complexity of each occupation to precisely map workers to their role in the organization of the firm. We then link such a measure to the firm-bank credit registry, and to the amount of credit received by the firm from each of its lenders. In doing so, we focus on a setting allowing us to exploit exogenous variation in the data: the financial crisis in the aftermath of Lehman Brothers' collapse.

The financial crisis represents an ideal laboratory for our study for two reasons. First, the failure of Lehman Brothers was sudden and unexpected, and exogenous to the Portuguese economy. Second, the event led to a considerable dry-up of the inter-bank market, which Portuguese banks heavily relied upon to finance their corporate short-term credit. Since Portuguese firms are highly dependent on bank credit to cover their costs, the shock has a strong potential to generate sizable real effects. These two conditions allow us to (i) exploit the firm-bank credit network to construct a firm level instrument for the supply of credit to the firm that combines information on the firm's credit relationships with the bank's exposure to the foreign inter-bank market, and (ii) conduct an event study to evaluate the impact of a credit supply shortage on the organization of labor after the Lehman collapse.

Our findings highlight a novel heterogeneity in the degree of complementarity between credit and each of the occupational groups: a 10% drop in the supply of credit predicts a 1.76% drop in the ratio of skilled workers to production workers, driven by a 1.72% drop in the number of

[1] See for example Black and Lynch, 1997, Bloom et al., 2012, Garicano, 2000, Garicano and Rossi-Hansberg, 2004, Hubbard and Garicano, 2007, Ichniowski et al., 1997, Liberti, 2017.

skilled workers. In order to better qualify the significance of these results, we conduct a number of additional investigations. First, we show that one possible mechanism through which short term credit affects the organization of firms' labor is via the financing of machines and equipment. Firms with above the median investments in machines and equipment in the pre-period reduce their skilled and production workforce twice as much compared to our baseline. Splitting the firms along this dimension unveils an important additional finding: both production workers and skilled workers are complementary with credit via investments in machines and equipment. A shock to credit translates into a tightening of the capital constraint, which in turn affects skilled workers and production workers via their interaction with machines and equipment, while top managerial positions are unaffected.[2] This result points towards a strong complementarity between credit and both production and skilled workers. Second, we show that it is short-term credit and financing of shorter maturity assets to drive our results. While the link between credit shocks and firm investments with different maturities has been documented (see for example Garicano and Steinwender, 2016), our result further characterize the link between credit of different maturities and firms' investments, and their interaction with the organization of firm labor. Third, in order to better characterize the relevant dimension along which a firm reorganizes its labor force in response to a credit shock, we consider several complementary workers' characteristics: i) temporary versus permanent contracts, ii) age and tenure in the firm, and iii) education level. We show that firms do not reorganize by firing only temporary workers, confirming that the dualistic structure of the labor market is not driving our results. In line with our main findings, we also show that medium educated workers (high school diploma) are hit the most by the financial shock, and that the effects are mildly stronger for prime age workers with lower tenure compared to their older colleagues.

A recent strand of the literature has documented the transmission of a financial shock from banks to the real economy (Amiti and Weinstein, 2011; Jiménez et al., 2011; Iyer et al., 2014; Foley and Manova, 2015; Chor and Manova, 2012; Paravisini et al., 2015; Greenstone et al., 2020). However, less progress had so far been made on the impact of a credit supply shock on the reorganization of the workforce within the firm that can be more directly linked to specific attributes of the workers and ultimately allows a stronger causality claim. Some important contributions in this direction have been provided by Chodorow-Reich, 2014, Bentolila et al., 2017, Berton et al., 2018. We improve upon those studies by means of three key innovations. First, leveraging on the richness of the data, we zoom within the firm and look at workers and their roles in the firms' organization. This is possible thanks to the information on the tasks performed by each worker and their wages, which allows us to reconstruct the organization of the workforce for each firm in the country. Second, we dig deeper into the mechanism through which a tightening of the supply

[2] According to The Equipment Leasing and Financing Association (ELFA), 78% of U.S. businesses across all industries rely on financing equipment purchases through loans, leases and lines of credit. See the information provided by the US chamber.

of credit affects the labor organization of a firm: we explore whether investments in machines and equipment on the firm side or specific worker characteristics (age, tenure within the firm, wages, education, contract type) can explain the results. Third, we leverage on the combination of a dynamic event study and an instrumental variable approach to provide a more compelling evidence of the causal link between firm credit and the organization of the workforce within the firm.

An implication of the paper is that studying firms' organization is key to understand aggregate outcomes. This insight is particularly relevant for the recent literature on knowledge hierarchies that documents how firms adjust their organization to increase or decrease their efficiency and output (e.g. Caliendo and Rossi-Hansberg, 2012, Caliendo et al., 2015, Caliendo et al., 2020, Gumpert, 2018, Antoni et al., 2022, Brambilla et al., 2022).[3]

The rest of the paper is organized as follows. Section 2 describes the data used in the analysis, the mapping of workers to the organization of the firm and other firm level measures of organization. Section 3 presents the analysis and Section 4 shows some additional margins of adjustment. Section 5 concludes.

2 Data

To evaluate the nexus between the organization of firm labor and firm credit, we create a panel of Portuguese firms, workers, banks and firm-bank credit exposures for the 2005-2013 period combining data from four different sources: (i) a matched employer-employee panel dataset *Quadros de Pessoal* (QP) covering the entire universe of firms and their workforce in manufacturing and services in Portugal, (ii) a firm balance sheet dataset *Central do Balancos* (CB), covering the universe of firms, (iii) a bank-firm matched credit registry *Central de Responsabilidades de Crédito* (CRC), with data at the exposure level for the universe of loans, (iv) and a banks' balance sheet dataset *Balanco das institucoes monetarias and financeira* (BBS). The dataset covers manufacturing and services firms of continental Portugal for the years 2005-2013.

QP draws on a compulsory annual census of all firms in Portugal employing at least one worker and contains information on 350,000 firms and over 3 million employees per year.[4] For each firm, the dataset contains information on the firm's location, industry, total employment, and sales. The worker-level data cover information on all personnel working, their occupation,

[3] A related strand of literature uses an alternative modeling structure, the monitoring hierarchy framework, to have insights on similar predictions (e.g. Chen, 2017; Chen and Suen, 2019; Spanos, 2019). Mariscal, 2018 incorporates capital in a Caliendo and Rossi-Hansberg, 2012 model and shows how new information technology explains the decline of the US labor share using a knowledge hierarchy framework.

[4] The data set has been widely used in the labour literature (Card et al., 2017). See for example Blanchard and Portugal, 2001 which compares the US and Portuguese labour market looking at the unemployment duration and worker flows, Cabral and Mata, 2003 who study the evolution of the firm size distribution, Mion and Opromolla, 2014 who show that the export experience acquired by managers in previous firms leads their current firm towards higher export performance, and commands a sizable wage premium for the manager or Mion et al., 2022 who look at how the knowledge a manager acquires spills over the new firm.

qualification, earnings, and hours worked (normal and overtime). The information on earnings includes the base wage (gross pay for normal hours of work), seniority-indexed components of pay, other regularly paid components, overtime work, and irregularly paid components.

CB is a repository of yearly balance sheet data providing economic and financial information on non-financial corporations operating in Portugal. This dataset contains information on all the firms in the Portuguese economy from 2005 onwards. The data contains information on firm sales, balance sheet items, material assets, cost of materials and third party supplies and services.

A unique feature of the Portuguese data is the possibility of linking the workers' information to measures of credit exposure at the firm level using credit records. We construct the bank-firm matched credit dataset from the Bank of Portugal's credit registry CRC, which features the universe of bank-firm monthly exposures by Portuguese credit institutions. The dataset contains detailed information on the number of credit relationships, the corresponding amounts, broad maturity classes (with no maturity, maturity less than one year, less than five years or above five years) and the kind of exposure (regular as opposed as overdue, written-off or renegotiated).[5] In this paper we define as "short-term" credit any credit exposure which has maturity lower than one year, or credit lines which have no defined maturity, but are fungible credit instruments.

Finally, BBS is a repository of monthly balance sheet data for the universe of financial institutions in Portugal. For each bank or financial institution, the dataset reports information on the counterpart involved (i.e. the type of financial institution, central government, regional government, or other non-governmental body), the maturity of the item and the nationality of the counterpart.

We combine all four administrative datasets to obtain a complete picture of firms' and workers' conditions and their linkages to banks through credit. We restrict our attention to firms in mainland Portugal, and exclude the agricultural sector, the fishing sector, the energy sector (extraction, mining and distribution), the construction sector and the financial sector itself. The period covered in our analysis spans from 2005 to 2013. In our empirical exercise we refer to the years between 2006 and 2008 as the "pre-period", and to the years from 2009 to 2013 as the "post-period". To study firms' response to the shock, we consider firms with a credit relationship with any bank in 2005 (before the shock), conditional on their survival until the start of 2009 (after the shock). Moreover, we focus on firms with at least 9 employees, which is the threshold for the fourth quartile (75th percentile) in the distribution of firm size in the years before 2009, and covers more than 60 percent of the workforce in the QP in the pre-period. Finally, we exclude firms with gaps in employment data in QP for the entirety of the pre-period (from 2006 to 2008). [6]Table A.1 in Appendix A.1 reports descriptives for our sample of firms. The average firm has 30 employees, 6.6 million of turnover and 2.5 banking relationships.

[5]Before 2009 the dataset does not include information on collateral or more granular credit duration.

[6]We consolidate banks into banking groups and we use the term banks and banking groups interchangeably.

To construct the occupational structure at the firm level we exploit the information contained in QP. Each worker, in each year, is assigned to a category following a (compulsory) classification of workers defined by the Portuguese law. Classification is based on the task performed and skill requirements, and each category can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. On the basis of the hierarchical classification and taking into consideration the actual wage distribution, we assign "Top executives (top management)" to occupation category 3; "Intermediary executives (middle management)" and "Supervisors, team leaders" to occupation category 2; "Higher-skilled professionals" and "Skilled professionals" to occupation category 1, and the remaining employees, including "Semi-skilled professionals", "Non-skilled professionals", and "Apprenticeship" to occupation category 0. In the rest of the paper I will refer to occupation category 3 as "Top Managers", occupation category 2 as "Middle Managers and Team Leaders", occupation category 2 as "Skilled workers" and occupation category 0 as "Production workers". In the sample, firms with a more complex organizational structure employ more workers, pay higher salaries and use more external credit—both long and short term—to finance their activity.[7]

3 The empirical exercise

To quantify the importance of firms' credit for the organization of firms' labor, we restrict our analysis to the sample of firms that had a credit relationship at the beginning of our period in 2005, and that are still active after the shock – the failure of Lehman Brothers – in 2009. The baseline model we estimate is:

$$log(Y_{i,t}) = \gamma_i + \tau_t + \left(\beta S_i + \mathbf{\Gamma X_{i,pre}}\right) \cdot I\{t = Post\} + FE_{i,t} + \varepsilon_{i,t} \quad t \in \{Pre, Post\}. \tag{1}$$

where the dependent variable $log(Y_{i,t})$ is the number of workers in each occupational group, averaged for the years in the *Pre* and *Post* period. We also consider in some regressions two more dependent variables, namely the ratio of the number of workers in two adjacent occupational categories, commonly referred to as spans of control, and the wage bill of each occupational group.

Our main covariate of interest is S_i, a measure of credit variation for a firm i, that we measure as a symmetric growth rate:[8]

[7] More detail can be found in Appendix A.

[8] This measure ranges between -2 and 2 and it is particularly appealing in the literature (Chodorow-Reich, 2014) because it allows us to consider credit variation that ranges from the creation of a credit relationship (value 2) to its termination (value -2). Moreover, it limits the influence of outliers on empirical specifications. We still eliminate the outliers in the credit-growth data, dropping the 2.5 percent greatest positive variations before calculating the symmetric growth rate.

$$S_i = \frac{D_i^{post} - D_i^{pre}}{\frac{1}{2}\left(D_i^{post} + D_i^{pre}\right)} \tag{2}$$

We interact S_i with a dummy $I\{t = Post\}$ denoting years post Lehman shock, including the year 2009. The key parameter of interest of our difference-in-difference setting is the coefficient β. Controls in (1) include γ_i, a firm fixed effect, τ_t a time fixed effect, and $X_{i,pre}$, a vector of out-of-sample controls at the firm level in 2005, which we interact with a dummy equal to 1 for the post-period years (from 2009 to 2013) to allow differential trends over the post-period.[9] As pre-period effects are absorbed by the firm fixed effects γ_i, any further fixed effect $FE_{i,t}$ captures differential group-specific trends in the post period.[10]

To isolate the component of credit variation that is due to banks' supply decisions in equation (1), we use an instrumental variable approach. Building on Iyer et al., 2014 and Paravisini et al., 2015 we propose an instrument for credit supply S_i based on banks' exposures to the interbank market as a means of financing: the ratio of foreign interbank liabilities to total assets at the bank level in the year 2005, i.e. a year before the sample period of analysis. The choice of an out-of-period of analysis year for the measurement of the instrument allows us to mitigate the concern that firms and banks alter their matching in anticipation of the shock. Foreign interbank liabilities are measured as the sum of short-term deposits (up to 1 year) and repos where the counterparty is a foreign financial institution (excluding central banks). As this is defined at the bank level, we need to compute a measure of firm indirect exposure to the interbank market through its bank networks. We build a shift-share instrument at the firm level, in which the shift component is the bank's exposure to the foreign interbank market in 2005 and the shares are the shares of a firms' short-term credit with each bank in 2005. Formally, we define the foreign exposure of bank b as FD_b and firm i' s share of short-term credit with bank b in 2005 as $\omega_{i,b}$. The instrument Z_i is defined as:

$$Z_i = \sum_{b \epsilon B_i} \omega_{i,b} * FD_b \tag{3}$$

where B_i is firm's i set of banks with a credit relationship in 2005 and $\sum_{b \epsilon B_i} \omega_{i,b} = 1$.

We intuitively compare the change in employment and organization of two otherwise identical

[9] Controls include the log level of short-term credit, financial leverage, log of total assets, short- term credit growth between 2004 and 2005, debt towards suppliers over assets, number of loans, (weighted) length of banking relationships, cash over assets, share of temporary workers, trade credits over assets, log number of employees, asinh of the value added per employee, log of sales, firm age, share of short-term credit in regular credit, share of fixed tangible assets in total assets, share of exports in sales in 2006, ROA, ROS, log of the average wage, average workers' turnover rate between 2003 and 2005.

[10] Fixed effects include a 3-digit industrial sector, commuting zone, quintiles of firm age and size in 2005, and dummies for exporter status, firm with overdue loans in 2007, banking relationship with the banks failed before 2014, firm capable of issuing bonds, firm with a single banking relationship, all interacted with a post-dummy.

firms, depending on the exposure of the banks they have relationship with to the interbank market for financing. The causal identification for this exercise relies on the assumption that factors other than bank credit that may affect the organization of a firm's labor are not related to their bank portfolio; in other words, the organization of firm labor is affected by the composition of their pool of creditors only through credit supply after accounting for firm ex-ante heterogeneity in matching. In order to violate this assumption, one should think of firm specific shock changing the organization of firm labor that are correlated with firms' exposure to the bank shock but have nothing to do with credit supply.

Some considerations are in order. First, the assignment to banks' foreign interbank exposure must be as good as random conditional on observables. Relationship ties between banks and firms in Portugal are sticky, and the average duration of a relationship is around 9 years (Bonfim and Dai, 2017). Moreover, it is important to have an adequate set of observables and fixed effects. Appendix C.1 figures A.2a and A.2b report the balance checks for our sample: while the great majority of the covariates are not significant, we control explicitly for the trends related to the covariates that show mild significance in all our regressions. Besides including firm fixed effects and a large battery of covariates, to indirectly control for firm-bank matching dynamics we measure our instrument while referring to the bank-firm network in 2005, which is outside of our sample of analysis. Observing a strong first stage in the regressions would imply that endogenous firm-bank re-sorting in anticipation of the crisis is unlikely to be a relevant issue. We provide some more in-depth discussion about endogeneity in Appendix C.1. Second, banks did not differentially cut credit based on firms' observables, and the credit channel proxied by the interbank foreign funds' exposure is not influenced by the dynamics of the sovereign debt crisis. Appendix C.2 presents results of the exposure level analysis, where we check whether banks transmitted the credit shock differently across firms based on their observable characteristics within their own sector, and we also account for exposure to the sovereign debt crisis. Finally, the Portuguese corporate bond market is very limited in size and only very few firms (9% of the total in our period of analysis) issue bonds to finance their activity, while the great majority of firms rely on banks' loan.[11]

3.1 Results

Table 1 and table 2 present the results for our key covariates. In columns from 1 to 3 of table 1, we estimate a version of equation 1 where the dependent variable is a measure of span of control of two occupational groups, and respectively the change in the (log) ratio of skilled workers to production workers, middle managers and team leaders to skilled workers and managers to middle managers and team leaders. This specification serves the purpose of showing to what extent the organization of firm labor – in terms of spans of control – is related to firm credit. Firms shrink by reducing the ratio of skilled workers to production workers (column 1) while the other spans

[11] See the ECB Survey on the access to finance for enterprises.

of control are unaffected (columns 2 and 3). Quantitatively, a 10% drop in the supply of credit (column 1 of table 1) predicts a 1.76% drop in the ratio of skilled workers to production workers, hence an increase in the span of control of the former.

Table 1: Spans of control

	(1)	(2)	(3)
	Skilled workers / *Production workers*	*Managers & team leaders* / *Skilled workers*	*Top Managers* / *Managers & team leaders*
S_i	0.176*	-0.191	0.094
	(0.097)	(0.146)	(0.271)
Firms	10,409	7,576	4,669
Weak identif. statistic	39.67	28.81	12.73

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log levels of the averages before and after the shock (2009). The ratios are computed using the total number of workers in each occupation category. In column 1 the dependent variable is the log ratio of skilled workers to production workers, in column 2 is the log ratio of managers & team leaders to specialized workers, and in column 3 is the log ratio of top managers to managers & team leaders. The sample consists of only survivor firms. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. The weak identification test statistic is the 'Kleibergen-Paap rk Wald F statistic'. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

The increase in the span of control can be driven by an increase in the number of production workers, by a decrease in the number of skilled workers, or by a decrease of both, with the decrease in the number of skilled workers being more pronounced than the decrease in the number of production workers. We then estimate equation 1 on each occupational group separately, which allows us to further characterize the nexus between the organization of firm labor and firm credit. Table 2 presents the results for the (log) number of workers in each occupation group (panel A), and the average (log) wages (panel B). In panel A we observe a strong effect to the availability of credit on skilled workers' employment: a 10% drop in credit available to the firm implies a 1.72% decrease in the number of skilled workers. At the same time, the number of production workers, managers and team leaders (columns 1, 3 and 4 of panel A) does not appear to vary in response to a change in the credit supply. In panel B of table 2, we look at average (log) wages of each occupational group. We do not find any downward adjustment in the average wage within an occupational group, consistent with the presence of frictions – such as labor unions – that impede downward wage adjustment (see Addison et al., 2015 for evidence on unionization and wage rigidity in Portugal).

In Appendix C.3, we provide a number of additional firm level results regarding wage bill,

Table 2: Occupation groups

Panel A: number of workers				
	(1)	*(2)*	*(3)*	*(4)*
$log(\#workers)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Top Managers*
S_i	*0.096*	*0.174***	*-0.073*	*0.189*
	(0.066)	*(0.071)*	*(0.105)*	*(0.139)*
Firms	*11,105*	*11,088*	*7,929*	*6,203*
Weak identif. statistic	*37.00*	*35.98*	*24.78*	*25.53*
Panel B: average wages				
	(1)	*(2)*	*(3)*	*(4)*
$log(avg.wage)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Top Managers*
S_i	*0.013*	*-0.006*	*0.044*	*-0.015*
	(0.018)	*(0.022)*	*(0.038)*	*(0.052)*
Firms	*12,942*	*12,880*	*9,208*	*7,114*
Weak identif. statistic	*37.00*	*35.98*	*24.78*	*25.53*

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log levels of the averages before and after the shock (2009). In panel A we look at the quantities, and the dependent variable is the (log) averages number of workers in each occupational group. In panel B we look at the prices, and the dependent variable is the (log) average wage in each managerial layer. The sample consists of only survivor firms. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. The weak identification test statistic is the 'Kleibergen-Paap rk Wald F statistic'. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

total number of employees and number of management layers, as well as a more general dynamic diff-in-diff and various robustness results. Table A.3 presents results for the total wage bill, the number of workers and the number of management layers in the firm, both for the complete sample as well as for the survivor firms only. Consistent with the previous literature on the aggregate effects of firm credit on firms' employment and wages (e.g. Chodorow-Reich, 2014, Bentolila et al., 2017, Berton et al., 2018), we find that firms shrink both in terms of total number of workers and total wage bill. Moreover, we find that firms do not systematically change the number of man-

agerial layers in response to the credit shock. This results provides new evidence on the pattern of firms reorganization, and more specifically to the literature on knowledge based hierarchies (e.g. Caliendo and Rossi-Hansberg, 2012, Caliendo et al., 2015, Gumpert, 2018, Caliendo et al., 2020, Antoni et al., 2022): firms change the number of layers to grow or to shrink, while they readjust the composition of the workforce within each occupational group when they face temporary shocks. Furthermore, the dynamic diff-in-diff in section C.5 reveals that the post-shock effect is negative, significant and persistent for the skilled workers, while no persistent effect is found for any other occupation group in all the years in the post period.

4 Digging deeper

In this Section, we further characterize the features of firms' labor force that might affect the reorganization observed in the data, and we provide evidence of a possible mechanism that links firm credit to the organization of firm labor.

Machines and Equipment

The results in section 3.1 highlight heterogeneous responses of each occupational group to a tightening of credit at the firm level. Firms reorganize their labor force by reducing the number of specialized workers, while managers are not affected. One possible explanation for the observed firm reorganization is in the link between firm credit and firm investments in machines and equipment.[12] The macro literature has documented complementarity between skilled workers and physical capital, like for instance machines or equipments (Griliches, 1969, Krusell et al., 2000 or Parro, 2013 among others). Indeed, while a number of tasks – and a share of the labor force – can be substituted away by machines, it is essential to have workers to operate and work with the machines for production to happen.

We test whether stronger investments in machines and equipment in the pre-period are correlated with layoffs of production workers, both specialized and non-specialized. We construct a measure of investment in machines and equipment in the pre-period–$Mach_i$–as a share of firm's sales, and we interact it with the instrumented measure of credit exposure S_i.[13] In Table 3 we report the results of equation 1 where we interact S_i with $Mach_i$, splitting the firms with above and below median investment in machines in 2005. We fully confirm the strong complementarity between skilled workers and credit. At the same time, firms with above median investment in

[12] According to The Equipment Leasing and Financing Association (ELFA), 78% of U.S. businesses across all industries rely on financing equipment purchases through loans, leases and lines of credit. Moreover, loans used to finance investments in machines and equipment are more flexible both in the duration and in the installments for repayment. See the US chamber.

[13] While extremely rich on the worker side, our firm level balance sheet data allows us to construct a measure of investments in machines and equipment only for the years before 2009.

machines and equipment in the pre-period reduce the number of *both* skilled workers and production workers, and the magnitudes of each reduction are double compared to our baseline results in table 2. This finding helps qualifying our results, and in particular points into the direction that the effect that we capture in Table 2 is related to the use of credit as a financing mean to acquire machines and equipment.

Table 3: Machines and equipments

Investments in machines and equipment				
	(1)	*(2)*	*(3)*	*(4)*
$log(\#workers)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Top Managers*
S_i*machines<median	-0.062	0.171**	-0.121	0.099
	(0.082)	(0.084)	(0.126)	(0.258)
S_i*machines>median	0.375**	0.352**	-0.073	0.258
	(0.168)	(0.157)	(-0.073)	(0.262)
Firms	12,942	12,880	9,208	7,114

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3 and interacted with investment in machines and equipment. The measure is constructed using pre-period variation. The dependent variables are log levels of the averages number of workers in each occupational group. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

Contract types

Our results are consistent with the hypothesis that credit is used to finance investment in machines and equipment, which in turn are complementary with production workers, both blue collars as well as skilled workers. However, an alternative explanation is that firms that are credit constrained reorganize their labor force based on the degree of contract flexibility of each worker category. In fact, one could argue that in a dual labor market – with permanent and fixed term contracts – firing costs can be a strong driver for the decision of whom to fire when facing a downturn or a shortage of credit.

In order to investigate this further, we use the information on the contract types observed in the data (QP) and construct a measure that characterizes the share of flexible contracts in a firm

using pre-sample variation.[14] In Table 3 panel B, we augment equation 1 with $flex_i$, the share of flexible contracts in the firm, and we interact it with the instrumented measure of credit exposure S_i and the post dummy. Results fully confirm the baseline findings of Table 2; Moreover, the share of flexible workers in the firm does not significantly affect the reorganization of firms' labor along the various occupational categories.[15]

Table 4: Flexible contracts

Contract types and duality of the labor market				
	(1)	*(2)*	*(3)*	*(4)*
$log(\#workers)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Top Managers*
S_i	*0.053*	*0.203***	*-0.067*	*0.118*
	(0.080)	*(0.090)*	*(0.113)*	*(0.167)*
S_i*flex*	*0.063*	*-0.082*	*-0.066*	*0.035*
	(0.123)	*(0.141)*	*(0.182)*	*(0.242)*
Firms	*12,942*	*12,880*	*9,208*	*7,114*

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3 and interacted with a measure of intensity in temporary contracts, defined as the share of flexible contracts in the firm. The measure is constructed using pre-period variation. The dependent variables are log levels of the averages number of workers in each occupational group. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

Long term credit

The third hypothesis we want to test is whether credit with longer maturities has any connection with the organization of firm labor. We construct a measure of credit growth as in equation 2 using credit with maturity above one year and estimate equation 1. Results in Table 5 indicate that long term credit does not have any effect in predicting the number of workers, the wage bill or the number of managerial layers in the firm. One possible explanation of the results in Table 5 is that credit with longer maturities is used to finance investments in production facilities and/or

[14]The dummy $flex_i$ is constructed using pre-sample variation in intensity in temporary contracts. For each firm in 2005 we measure the share of temporary contracts over the total of temporary and permanent contracts N and define the dummy $flex_i$ to be 1 if the firm share is above the sample mean.

[15]The share of flexible workers in occupational group is respectively 21% for production workers, 13% for team leaders, 8% for middle managers and 9% for top managers. This further highlights that firms' response is not driven by the contractual composition of the workers in each occupational group, but rather by an economic mechanism that drives these adjustments.

plant expansions, rather than investments in machines and equipment that seldom require a more flexible financing scheme. While we cannot directly link the use of credit to each investment item in the firms' balance sheet, this finding highlights the importance of credit maturity and firm reorganization, and more generally to the nexus between the supply of credit with different maturities and labor market outcomes.

Table 5: Long term credit

	(1)	(2)	(3)	(4)
$log(variable)_{i,t}$	*# of workers*	*Wage bill*	*Wage bill detrended*	*# of layers*
S_i	-0.137	-0.295	-0.301	-0.130
	(0.182)	(0.269)	(0.269)	(0.184)
Firms	10,108	10,108	10,108	10,108
Weak identif. statistic	2.50	2.50	2.50	2.50

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in long term credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log levels of the averages number of workers in each occupational group. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. The weak identification test statistic is the 'Kleibergen-Paap rk Wald F statistic'. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

5 Conclusion

We use data on Portuguese firms, workers, banks and firm-banks credit relationships to study the nexus between the organization of firm labor and firm credit. To do so, we first map workers to their role in the organization of the firm using information on the task complexity of each occupation. We then link firms to the the firm-bank credit registry and to the amount of credit recieved by the firm from each of its lenders. In doing so, we focus on a setting allowing us to exploit exogenous variation in the data: the financial crisis in the aftermath of Lehman Brothers' collapse.

Combining an instrumental variable approach with an event study desing, we find that a reduction to the supply of short term credit affects the size of the firm and the organization of the workforce. More specifically skilled workers exhibit a strong complementarity with short term credit. Our findings are consistent with the idea that a decrease in the availability of firm credit affects the organization of firm labor via the financing of machines and equipment: firms with above median investments in machines and equipment in the pre-period reduce their labor force more, especially skilled and less skilled production workers.

On a broader perspective, our analysis points at the importance of studying firms' organiza-

tion – and its interaction with firm credit – to understand aggregate outcomes. We believe more research in this direction is needed.

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Online Appendix

A Construction of the dataset

We bring together several data sources and construct an harmonized dataset on banks, credit relationships, firms and workers. In this appendix we describe in detail each dataset and the procedure to select the sample and construct the variables used in the analysis.

A.1 Credit registry

The *Central de Responsabilidades de Crédito* (henceforth CRC) is the credit registry of the Central bank of Portugal. The dataset has a monthly frequency and records all the loans to firms and individuals with value greater than 50 Euros from each bank in the Portuguese territory. It does not report credit given by foreign banks residing abroad to firms in the Portuguese territory, while it does record credit to foreign owned firms residing in Portugal. The dataset includes several informations on each loan which I use to select a my sample.

The dataset is used for supervisory purposes, and by the credit institutions themselves to obtain information on potential debtors. It contains detailed information on the number of credit relationships, the corresponding amounts and the kind of exposure: short- and long-term credit granted but still not materialized (potential), credit overdue, written-off or renegotiated. Given the time frequency in the other datasets we use, we average debt exposures at the yearly level. In our specifications we use *regular* credit as measure of credit, which corresponds to credit in good standing and in use by the firm. Credit is defined as short-term if (i) the maturity is below 1 year, (ii) it is a credit line with undefined maturity (post-2009 data) or (iii) is categorized as commercial, discount or other funding short-term pre-2009. We group together short-term loans, credit lines with defined short-term maturity and credit lines with undefined maturity because the latter category of credit lines comprehends all those exposures that, once withdrawn by the customer, should undergo renegotiation with the bank in order to be rolled-over. This feature makes them very liquid instruments that, similarly to short-term loans, is subject to short-term credit rates volatility and rollover risk. Credit lines always constitute above 3/4 of short-term credit as we define it. Long-term credit is thus obtained as the residual regular credit.

A.2 Bank balance sheet dataset

The *Balanço das Instituições Monetárias e Financeiras* (henceforth BBS) is the balance-sheet dataset for credit institutions. It is a proprietary dataset of the Bank of Portugal and contains the balance sheets of the universe of financial monetary institutions operating in the country. The dataset is utilized by the bank of Portugal to monitor the health of financial monetary institutions operating

in the country and the overall stability of the system. In the dataset, for each balance-sheet item (liability or asset) we observe the counterpart (i.e. the type of institution, government, private or non-governmental body, creditor or debtor), the maturity (time deposits, on demand deposits, interbank long-term or short-term exposures) and the nationality of the counterpart (extra-EU or each EU country separately). The data are reported at the monthly level.

We use this dataset to measure the interbank funding as the ratio of the average (yearly) short-term foreign interbank borrowing by the bank over total assets. Foreign short-term interbank borrowing is computed as the sum of short-term deposits with maturity up to 1 year and repos where the counterparty if a foreign financial institution (not a central bank).

In matching the BBS and the CRC, we also took care of harmonizing and making bank definitions consistent across datasets to account for mergers and acquisitions. Each M&A event between 2000 and 2013 (for institutions with at least 1 percent of total credit in a given month) was taken into consideration to make sure that credit flows across institutions were rightly accounted for, and definitions of bank codes across datasets and across time were consistent.

A.3 Matched employer-employee

The *Quadros de Pessoal* (henceforth QP) is a longitudinal matched employer-employee dataset, containing detailed data at the workers' and firms' level on employment composition for the firms and individual worker characteristics.[1] The data are collected and managed by the Ministry of Labour and Social Solidarity, and draws on a compulsory annual census of all the firms employing at least one worker at the end of October each year. It does not cover the public administration and non-market services, whereas it covers partially or fully state-owned firms, provided that they offer a market service. The dataset covers approximately 350,000 firms and 3 million employees per year. In 2010 the structure of the survey was reformed and the QP was incorporated into the Relatório Único, an integrated reporting system to enable employers to easily provide more extensive information on workers to the Ministry. As a consequence, some very small entrepreneurial firms were exempted from filing compulsorily the questionnaire, which is why after 2009 the coverage of QP is less complete than in previous years.[2]

The dataset is available at the Bank of Portugal from 1982 to 2013, and is hierarchically made up by a firm-level dataset, an establishment-level dataset and a worker-level dataset. The firm

[1] Quadros de Pessoal has been used by, amongst others, Cabral and Mata, 2003 to study the evolution of the firm size distribution; by Blanchard and Portugal, 2001 to compare the U.S. and Portuguese labour markets in terms of unemployment duration and worker flows; by Cardoso and Portugal, 2005 to study the determinants of both the contractual wage and the wage cushion (difference between contractual and actual wages); by Carneiro et al., 2012 who, in a related study, analyze how wages of newly hired workers and of existing employees react differently to the business cycle; by Martins, 2009 to study the effect of employment protection on worker flows and firm performance. See these papers also for a description of the peculiar features of the Portuguese labour market.

[2] Despite this inconvenience, we use the firms' balance sheet dataset, the Central de Balanços, which covers all non-financial corporations in Portugal, to correctly disentangle firms' failures.

level dataset contains information on the firm location (from regional to very narrowly defined parish level, which roughly corresponds to a neighborhood), industry of operation (CAE rev. 2.1 until 2006 and CAE rev. 3, based on NACE-Rev. 2 Statistical classification of economic activities in the European Community), total employment, total sales, ownership structure and legal incorporation. Analogous information is available on the establishment-level dataset.

The worker level dataset provides detailed information on worker characteristics and contracts. Information includes workers' gender, age, detailed occupational code, detailed educational level, qualification within the firm (managerial qualification, specialized workforce or generic workers, trainees).[3]At the contract level we observe the hiring date, the contract (various typologies that generally define the contract as fixed-term or open-ended), the hours arrangement (full-time versus part-time), the effective number of hours worked, and the compensation. More specifically, for each worker it is possible to obtain information on the base pay, any extra paid in overtimes or other extra-ordinary payments and other irregularly paid components. In contrast, there is no information on social security contributions. We winsorize the extreme 0.5% tails of the distribution of wages.[4]

The unique worker identifier is based on the workers' social security number, and given the extensive work of the Ministry to control and certify the quality of the data, the coverage and reliability is high.

A.4 Firm level financial statement data

The *Central de Balanços* (henceforth CB) is a firms level balance-sheet and income statements database, managed by the Bank of Portugal. It consists of a repository of yearly economic and financial information on the universe of non-financial corporations operating in Portugal from 2005 to 2013. It includes information on sales, balance- sheet items, profit and loss statements, and cash flow statements (after 2009) for all private firms in Portugal. The CB builds on the *Informaçào Empresarial Semplificada*, an administrative firms' balance-sheet dataset managed by the Ministry of Finance and Public Administration. The Bank of Portugal obtains the data from the Ministry and performs extensive consistency checks to guarantee that the data are reliable and consistent over the years. The dataset covers the universe of firms and it is based on information reported in the starts in 2006. [5]

[3]The occupational codes are based on the Classificação Nacional de Profissões (CNP94) up to 2009 and the Classificação Portuguesa das Profissões (CPP2010) from 2010 onward, which is based on ISCO08 International Occupational Classification Codes.

[4]As regards the qualification categories, the Portuguese Decree-Law 380/80 established that firms should indicate the qualification level as in the Collective Agreement. If this is not available, firms should select the qualification level of the worker. These categories are based on the degree of complexity of tasks that the worker performs within the firm (from more basic, routine tasks to more discretionary managerial ones). The categories are defined within a 9 levels hierarchy, that we simplify into four categories.

[5]Close to the entirety of firms already existing in 2005 provided balance sheet data for that year as well together with the 2006 filing. For this reason, we have a very high coverage of firms' balance sheets for 2005 as well.

After 2009, in order for the data to comply with international accounting standards, there has been a overhaul of the variables definitions in the dataset, from the *Plano Oficial de Contabilidade* (POC) to the *Sistema de Normalização Contabilística* (SNC). In all our computations, unless otherwise noted, we have gone through a variables' harmonization process, in collaboration with the statistics department managing the administrative datasets for researchers at the Bank of Portugal, BPLim, to guarantee comparability across periods.

The dataset contains information on firms' balance sheets and income statements. We use the dataset to obtain information on total assets, fixed assets, current assets total debt and interest expenditures, cash-flow and capital expenditures (after 2009), cash balances, exports and export status, trade credits, debt towards suppliers, inventories, return on equity, assets and sales, salaries, total employee related, revenues, costs and breakdowns (among which intermediate inputs, materials and services), profits, investments in machines and equipment (before 2009). We compute value added from this dataset by adding back employee related expenditures to the firm EBITDA.

A.5 Combined dataset and data processing

Central do balancos (BBS) and the credit registry (CRC) are merged by means of bank identifiers, while the matched employer-employee dataset is merged to CRC using the firm identifier. As in Cardoso and Portugal (2005), we account for sectoral and geographical specificities of Portugal by restricting the sample to include only firms based in continental Portugal while excluding agriculture, fishing, energy (extraction, mining and distribution), the construction sector and the financial sector itself. For the event study we only consider firms with a credit relationship with any bank in 2005, which must survive until 2009 to be present in the period of time after the credit shock. We focus on firms with at least 9 employees, which is approximately the threshold for the fourth quartile in the distribution of firms' sizes in the years before 2009, and covers more than 60 percent of the workforce in the QP matched to CRC in the pre-period. In order to reduce measurement noise, we consider only firms with no gaps in the data in the pre-period.

Concerning workers, we consider single-job, full-time workers between 16 and 65 years old, and working between 25 and 80 hours (base plus overtime) per week. Each worker in Quadros de Pessoal (QP) has a unique identifier based on her social security number. We drop from the sample a minority of workers with an invalid social security number and with multiple jobs. If a worker is employed in a particular year, we observe the corresponding firm identifier for that year.

We also perform some consistency and sanity checks in selecting the relevant banks to be included in the analysis. More precisely, we exclude from the analysis the very small banks that disappear from the dataset before 2009. We also exclude from the set of banks for which foreign interbank funding is intra-banking-group funding from the foreign headquarter to the Portuguese subsidiary.

Table A.1: Firm-level descriptives

	Mean	*S.d*	*Min*	*Max*	*Firm-year*
Wage bill	*522,801*	*4066829*	*5615.441*	*2.93e+08*	*1,471,063*
# workers	*30.28*	*191.25*	*1*	*15359*	*1,471,063*
Tot. Sales	*6,648,312*	*6.20e+07*	*5011.533*	*1.05e+10*	*1,471,063*
# management layers	*1.24*	*1.07*	*0*	*3*	*1,471,063*
Tot. credits	*294,582*	*3,488,805*	*0*	*1.03e+09*	*1,471,063*
Short term Credit	*208,165*	*2,280,285*	*0*	*7.11e+08*	*1,471,063*
Bank x firm	*2.23*	*1.57*	*1*	*8*	*1,471,063*

Notes: This table reports descriptive statistics for all the variables used in the regressions. All the values in the table are an average over all the firms in the sample and all the years, from 2004 to 2013. The wage bill is calculated adding the monthly base and overtime wages plus regular benefits and multiplying by 14. We apply a trimming of the top and bottom 0.5 per cent within each year. A firm wage bill is the sum of the annual wages of all its workers. The number of workers is the sum total number of workers in the firm in the year. A firm reporting c occupational categories will be said to have L = c − 1 layers of management so that we have firms spanning from 0 to 3 layers of management (as in Caliendo et al., 2020). In terms of layers within a firm we do not keep track of the specific occupational categories but simply rank them. Hence a firm with occupational categories 2 and 0 will have 1 layer of management, and its organization will consist of a layer 0 corresponding to some skilled and non-skilled professionals, and a layer 1 corresponding to intermediary executives and supervisors. Short term credit computed summing all the bank credit with maturity up to 1 year for a firm in a given calendar year. Bank per firm is the number of bank relationships each firm has.

A.6 Definitions

Occupation groups. In the matched employer-employee data set, each worker, in each year, has to be assigned to a category following a (compulsory) classification of workers defined by the Portuguese law (see Mion and Opromolla, 2014, Mion et al., 2022). Classification is based on the tasks performed and skill requirements, and each category can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. On the basis of the hierarchical classification and taking into consideration the actual wage distribution, we partition the available categories into occupations. We assign "Top executives (top management)" to occupation 3; "Intermediary executives (middle management)" and "Supervisors, team leaders" to occupation 2; "Higher-skilled professionals" and some "Skilled professionals" to occupation 1; and the remaining employees, including "Skilled professionals", "Semi-skilled professionals", "Non-skilled

professionals", and "Apprenticeship" to occupation 0.

Number of layers of management. We use the Portuguese classification (Decreto Lei 121/78 of July 2nd 1978), which is not the ISCO. In addition, we follow Caliendo et al. (2015) in translating the different occupations in a firm into layers of management. A firm reporting c occupational categories will be said to have $L = c - 1$ layers of management: in the data we have firms spanning from 0 to 3 layers of management. In terms of layers within a firm we do not keep track of the specific occupational categories but simply rank them. We use this categorization of layers to calculate the number of layers in a firm, while the rest of the estimations are performed using the organizational structure defined grouping occupations as described in the paragraph above. According to the classification in layers, a firm with occupational categories 2 and 0 will have 1 layer of management, and its organization will consist of a layer 0 corresponding to some skilled and non-skilled professionals, and a layer 1 corresponding to intermediary executives and supervisors. A potential concern of this methodology is that firms can have layers with occupations that are not adjacent in the rank. In our sample however, 70% of the firms have adjacent layers and the share goes up to 85% if we use hours worked as a weighting factor. Our estimations in the paper use the categorization of occupation that define the managerial layers without filling non-adjacent occupations with the occupation above in the rank.

Reorganization. Firms can reorganize by changing the hierarchical structure or not. In fact, in line with the hierarchy model described in Caliendo and Rossi-Hansberg (2012), firms might decide to drop(add) a management layer if the shock to the production scale is sufficiently large to make the fixed cost of an additional management layer high(low) compared to the benefit of the reduction in marginal cost due to the increase in productivity that the new manager brings to the firm by making the production workers more productive. On the other hand, if the shock to the production scale is not big enough, firms might chose to change the internal organization without changing the hierarchical structure. In the latter case, the firm might decide to decrease the number of employees in a specific layer or in any layers or decrease the wages of the workers to decrease the total wage bill of the firm.

Wage bill. A worker annual wage is computed adding the monthly base and overtime wages plus regular benefits and multiplying by 14. We apply a trimming of the top and bottom 0.5 per cent within each year. A firm wage bill is the sum of the annual wages of all its workers that satisfy the criteria listed above.

A.7 Controls for empirical specifications

All empirical specification of differences-in-differences in the text, unless otherwise specified, include the following set of controls:

- Fixed effects: 3-digit industrial sector, commuting zone, quintiles of firm age and size in

2005, and dummies for exporter status, firm with overdue loans in 2007, banking relationship with the banks failed before 2014, firm capable of issuing bonds, firm with a single banking relationship.

- Additional controls: log level of short-term credit, financial leverage, log of total assets, short-term credit growth between 2004 and 2005, debt towards suppliers over assets, number of loans, (weighted) length of banking relationships, cash over assets, share of temporary workers, trade credits over assets, log number of employees, asinh of the value added per employee, log of sales, firm age, share of short-term credit in regular credit, share of fixed tangible assets in total assets, share of exports in sales in 2006, ROA, ROS, log of the average wage, average workers' turnover rate between 2003 and 2005.

When not differently specified, additional controls are measured as the 2005 values. All controls and fixed effects are interacted with a post-period dummy (or year dummies in dynamic specifications).

B The credit shock

Before the end of 2008 the Portuguese economy did not suffer from the global financial crisis directly, but rather through indirect channels, such as the collapse in global export demand Garin and Silverio, 2023. Moreover, unlike the United States or Spain, Portugal had in place regulations discouraging the set-up of off-balance-sheet vehicles for banks (Acharya and Schnabl, 2010) and did not experience the burst of a real estate bubble (Fradique Lourenço and Rodrigues, 2015).

The failure of Lehman Brothers in September 2008 led to a worldwide confidence crisis in the banking sector, and to a dramatic decrease in the liquidity available to the Portuguese financial sector. At that time, Portuguese banks relied heavily on very short-term interbank loans for financing and managing their day-to-day liquidity needs (Upper, 2006; Cocco et al., 2009; ECB, 2009). Liquidity suddenly dried up, as these financial instruments were often unsecured and the market for them was based on trust across financial institutions. These facts determined a collapse in the volume of funds exchanged. Figure 1a reports the aggregate volume of foreign interbank liabilities in the Portuguese banking system, measured as the sum of short-term deposits (up to 1 year) and repos where the counterparty is a foreign financial institution (excluding central banks). The volume of credit intermediated started shrinking in 2007, but the fall substantially accelerated after 2008, so that by 2013 the total volume was approximately 40 percent of its peak 2007 value.

Given the inability to obtain liquidity for their day-to-day operations in a period of global financial turmoil, banks around the world increased spreads and haircuts, and reduced the amount of credit supplied to the real economy and non-financial businesses, as shown for instance by the ECB "Bank Lending Surveys" at the time (BDP, 2009). Figure 1b shows the aggregate trends for

regular (neither over- due nor under renegotiation) short-term credit (with maturity less than one year, or liquid credit lines with no defined maturity). Credit supply was still increasing after the first signs of financial distress in 2007, and rapidly fell from 2009 onwards, primarily because of a strong decrease in the supply of short-term credit and credit lines. Overall, from the start of the financial crisis to the end of 2013 the total volume of credit shrank by 30 percent (regular credit, see Figure 1a) and 40 percent (short-term credit). In this way, the financial crisis that originated in the US spread to the Portuguese real economy.

The global financial crisis and the ensuing credit shock to the Portuguese banking system feature some peculiar characteristics, which make them particularly suitable to isolate the nexus between firm credit and the organization of firm labor. First, Portugal is a small open economy, and the credit shock originated outside of its economy. Thus, conditional on controlling for possible endogeneity or selection in banks' portfolios, our setting offers the best conditions to causally identify the real effects of an exogenous credit shock via banks. Second, the drop in bank credit is mostly driven by short-term credit. This is particularly interesting for the analysis of employment decisions as such shortages are likely to be unexpected to firms, and directly related to their day-to-day liquidity management. According to The Equipment Leasing and Financing Association (ELFA), 78% of U.S. businesses across all industries rely on financing equipment purchases through loans, leases and lines of credit. Moreover, loans used to finance investments in machines and equipment are more flexible both in the duration and in the installments for repayment. (See the US Chamber). All in all, these elements point at the importance of firm (short term) credit to finance investments in machines and equipment. Third, the Portuguese economy is characterized by medium- and small-sized firms, heavily reliant on bank credit. Portuguese firms are in general not able to access alternative means of financing, as very few of them can issue bonds and are likely to be involved in relationship lending with their banks, which makes it difficult for them to switch to different banks in case of shocks (Iyer et al., 2014; Bonfim and Dai, 2017). In appendix C.1 we discuss further how these characteristics make the set-up ideal for identification.

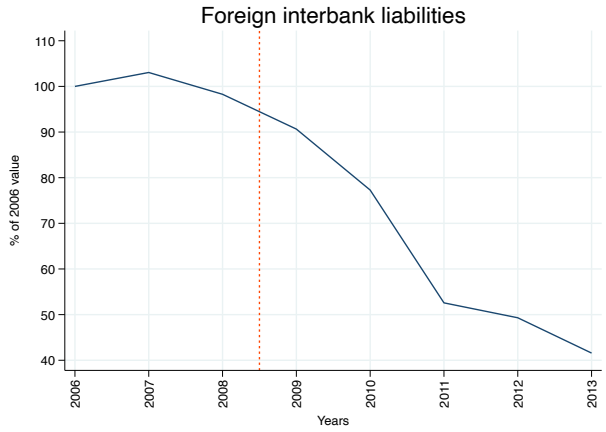
C Additional results

C.1 Instrument properties and identification

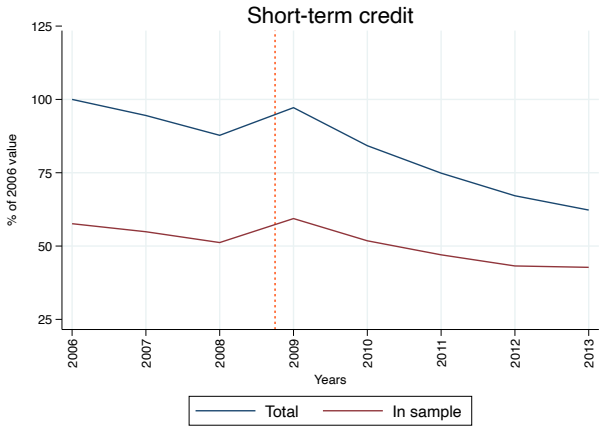
The identification of a causal effect of a variation in credit supply to a firm hinges on the possibility of setting apart banks' effective willingness to provide credit (supply) from firms' unobserved demand for it. As long as credit demand is correlated with a firms' investment decisions and idiosyncratic investment opportunities, the econometrician needs some way to isolate the component of credit variation that is only related to banks' supply decision. We thus use an instrument to identify banks' supply decisions: banks' foreign interbank market funds exposure as a share of total assets.

Figure A.1: Credit shock

(a) Foreign interbank liabilities



(b) Short-term credit



The Figures show the time series for the aggregate amount of short-term credit (panel A.1b) and foreign inter-bank liabilities (panel A.1a) for the firms and banks in the sample. Foreign interbank liabilities are the sum of short-term deposits (up to 1 year) and repos where the counterparty is a foreign financial institution (not central banks). Short-term credit is credit with a maturity of less than one year, or liquid credit lines with no defined maturity. The orange dotted line splits the sample into pre-period and post-period. Totals are expressed as a percentage of foreign interbank liabilities (panel A.1a) and short-term regular credit (panel A.1b) in 2006. Source: *Central de Responsabilidades de Crédito* merged with *Quadros de Pessoal* (left), Central de *Central de Responsabilidades de Crédito* merged with *Quadros de Pessoal* and banks' balance sheets (right), authors' calculations and sample selection.

In order for an instrument to be valid in disentangling the exogenous variation in credit supply, it must correlate to firms' real outcomes only through credit variation. Moreover, its assignment to firm-bank pairings must be as good as random conditional on observables. In the case of firms' real investment decisions, this implies that the econometrician should verify that there are parallel trends in firms' behavior absent the treatment, in our case the credit shock. It is also necessary to avoid bias in the estimates stemming from the possibly endogenous matching of banks and firms in the years leading to 2008. Relationship ties between banks and firms in Portugal are sticky, and the average duration of a relationship is around 9 years Bonfim and Dai, 2017. Nonetheless, it is possible that firms and banks re-sorted themselves in anticipation of the credit shock. To indirectly control for these dynamics, we measure our instrument while referring to the bank-firm network in 2005, which is outside of our sample of analysis. Observing a strong first stage in the regressions would imply that endogenous firm-bank re-sorting in anticipation of the crisis is unlikely to be a relevant issue.

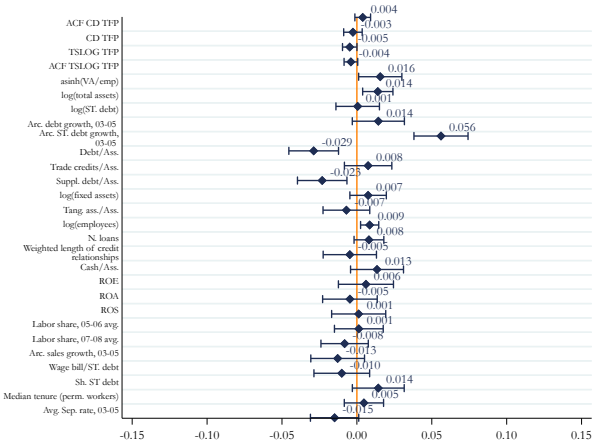
To further control for other sources of observed and unobserved heterogeneity that might affect our estimates, we saturate our empirical model with multiple fixed effects and firm level observables interacted with a time variable. This allows us to explicitly allow for differential trends in the outcome variables. As a consequence, our estimates compare variation across firms with

similar starting characteristics, and allow for differential trends depending on a firm's location, industry and many other observables. In this way, we can identify the effect onto firms as similar as possible to each other, but attached to banks with differential exposure to the credit shock.

In order for our instrument to disentangle a causal effect, we need to verify that it is quasi-randomly assigned, i.e. its distribution across firms is plausibly random conditional on the observables. Passing this test guarantees that the estimated effects are not the spurious by-product of other dynamics stemming from the non-random matching between a firm and a bank based on the bank's foreign funding exposure. Figure A.2a shows pairwise correlations of the instrument Z_i with firm-level observable characteristics, conditional on the set of fixed effects that we include in the main empirical difference-in-differences specification. In almost all cases coefficients are very small and close to 0. Still, given that some observables are correlated with the instrument, we control explicitly for trends related to these observables in our regressions, plus other observables that we include to improve precision and robustness.

Figure A.2: Balance checks

(a) Balance checks



(b) Balance checks (Borusyak et al., 2022)

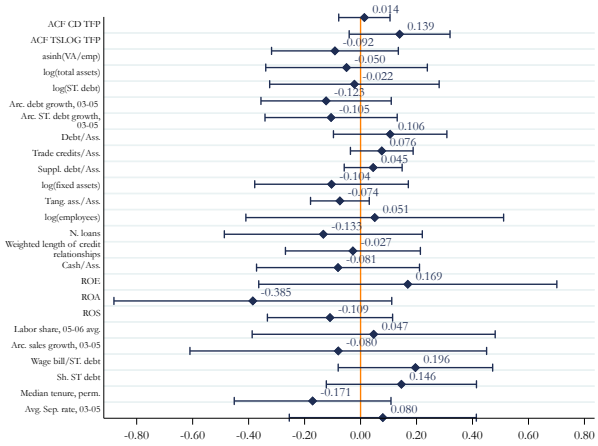


Figure A.2a reports the coefficients (with 95% confidence intervals) of pairwise regressions of the standardized value of each variable in 2005 (unless reported otherwise) on the instrument Z_i. All regressions include the same set of fixed effects of the main specification, which are 3-digit industrial sector, com- muting zone, quintiles of firm age and size in 2005, and dummies for: exporter, overdue loans in 2007, loans with banks failing up until 2014, bond issuance, exporter, single loans. Figure A.2b shows the coefficients (with 95% confidence intervals) of pairwise regressions of the standardized value of each variable in 2005 (unless reported otherwise) on the (standardized value of the) instrument Z_i. The regressions are run at the bank level, and all regressors are weighted bank exposures to firm characteristics, according to the method exposed in (Borusyak et al., 2022). Before weighting firm characteristics at the bank level, the variables are regressed on the fixed effects used throughout the analysis in the paper (see Section A for a list), and residuals are calculated and used in the analysis. In both graphs, standard errors robust to heteroskedasticity.

In a recent influential paper on the identification properties of shift-share instruments, Borusyak et al., 2022 highlight that the exogeneity of the instrument could stem from the quasi-randomness

of the underlying shifts with respect to firm characteristics, but does not per se stem from the overall shift-share structure. We show for completeness in Figure A.2b that the interbank exposures at bank level are not significantly correlated to weighted bank exposures to firm-level observables (where the weights are shares of bank-level short-term credit exposures with a firm). The absence of any significant correlation lends credibility to the assumption that our identification stems from shocks quasi-randomness.

C.2 Loan level analysis

The exposure-level analysis of the shock provides evidence that banks did not selectively cut credit to some firms in response to the liquidity shortfall. If that is true, we can be confident that our empirical analysis identifies average elasticities of firm outcomes to unexpected credit variation. We run the following specification:

$$S_{i,b} = \beta FD_b + \mu_i + \varepsilon_{i,b}, \tag{4}$$

where $S_{i,b}$ is the symmetric growth rate of credit variation for each credit exposure of firm i to bank b between 2006–2007 and 2009–2010 averages, calculated as the endogenous treatment in Equation 1 but at the firm-bank exposure level, and $f(FD_b)$ represents bank foreign exposure. The definition of the outcome variable allows us to simultaneously consider extensive and intensive margins of the treatment effect. In the baseline specification, we also add firm-level fixed effect μ_i so that we are effectively controlling for the within-firm variation in credit supply, i.e. the change in lending to the same firm by banks with different levels of exposure. This feature allows us to control for any firm-specific time-invariant heterogeneity, but restricts the sample of analysis to firms with multiple banking relationships when the firm fixed effect is included (Khwaja and Mian, 2008 and Paravisini et al., 2015).

Table A.2 shows the results of multiple specifications testing the robustness of the exposure-level relationship. We find significant negative (semi-)elasticities of firm short-term credit to our measure of a bank's exposure to the foreign interbank funds' market. In our preferred specification, in column 1, a 1 percentage point increase in a bank's exposure determines approximately a 2.1 percentage points decrease in the amount of short-term credit provided by that bank until 2010. Given that one might be concerned about the effects of omitted variable bias, which might imply that the estimated effects are biased by unobservable firm-level characteristics of effects specific to the matching between firms and banks, we perform several robustness checks to show that the estimated effect is very stable and precisely estimated. We use the results of the specification in column 1, which control for firm specific trends in short-term credit dynamics determined by unobservable characteristics through firm fixed effects as a benchmark, and compare them to the ones obtained with a regression on the same sample without controls (column 4).

We show that the credit channel proxied by the interbank foreign funds exposure is not influenced by the dynamics of the sovereign debt crisis in columns 2 and 3, adding controls for the exposure of banks to sovereign debt by the Portuguese government. In column 2 (3) we control for the ratio of the average amount of sovereign debt on a bank's balance sheet over total assets in (the last quarter of) 2009. Even if these controls are highly significant in these specifications at the exposure level, our estimated coefficient for the effect of exposure to foreign interbank funds remain stable and not statistically distinguishable from the coefficient in column 1.[6]

Following Khwaja and Mian, 2008 and Chodorow-Reich, 2014 we perform further robustness tests in columns 4 to 7 of Table A.2. By removing the firm level fixed effect, the variation in the estimate should proxy the amount of bias implied by the not as-good-as-random matching between firms and banks, itself determined by firm-specific unobservable characteristics. In columns 4 and 5 we replicate the exposure-level regression with no controls, while in columns 6 and 7 we saturate the model with a series of fixed effects characterizing the firm operations, such as industry, location and other characteristics. In columns 5 and 7 we run the regressions on the full sample of firms that we use in the firm-level specifications in our sample of analysis, including firms with only a single bank relationship. The estimates are stable across specifications, with a range of variation for our preferred specifications (columns 1 and 6) of around 2–3 percent of the base estimate of column 1. All estimates are statistically indistinguishable at standard confidence levels.[7]

Finally, in column 8 we run a regression analogous to the specifications by Iyer et al., 2014, and analyze the impact on total credit of the banks' exposure to the interbank market as a whole (taking into account both domestic and foreign exposures). Our estimate with the 2005 exposure is on the same order of magnitude as theirs (-0.432 versus -0.556), despite the fact that they have estimates from a different set of firms, with a more recent measure of exposure, and a wider set of banks. Our estimates also show that the credit shock had an immediate and very strong impact on the volume of short-term credit, as the semi-elasticities imply that most of the variation in total credit determined by the Lehman shock comes from relatively fickle short-term exposures.

In conclusion, the average exposure results reported in this Appendix further lend credibility to the causal identification of our main effects. On the one hand, it strongly lend support to the argument that the matching of firms to banks in our natural experiment is plausibly orthogonal to the instrument. On the other hand, the stability of the estimated semi-elasticities of credit along multiple empirical specifications supports the thesis that banks did not selectively cut credit to firms based on the observables.

[6] In our dataset, the exposure of banks to sovereign-issued financial liabilities is one order of magnitude smaller than the exposure to foreign interbank exposure. Exposures rates are rarely above 4 percent, while interbank exposure typically ranges between 10 and 20 percent.

[7] Observing that the credit transmission of the shock is not affected by the observables, firm or match-specific characteristics lends credibility to the identification, given the validity assumptions in Goldsmith-Pinkham et al., 2019. If credit exposure or other characteristics were making the distribution of shares not-exogenous, one would expect semi-elasticites of credit with respect to interbank exposure to visibly vary, which is never the case.

Table A.2: Identification of the credit supply shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				$\Delta D_{st,pre-post}$				$\Delta D_{tot,pre-post}$
FD_{2005}	-2.104***	-2.151***	-2.186***	-2.145***	-2.192***	-2.159***	-2.237***	
	(0.229)	(0.221)	(0.218)	(0.251)	(0.251)	(0.248)	(0.247)	
$Sovs./Ass._{2009}$		-6.501***						
		(0.576)						
$Sovs./Ass._{2009,q4}$			-4.226***					
			(0.369)					
ID_{2005}								-0.432***
								(0.121)
Firms	9927	9927	9927	9927	13937	9927	13933	10413
Firm FE	Yes	Yes	Yes	No	No	No	No	Yes
Other FE	No	No	No	No	No	Yes	Yes	No
Sample	Multi-loans	Multi-loans	Multi-loans	Multi-loans	All firms	Multi-loans	All firms	Multi-loans

Notes: In columns 1-7 the dependent variables is the symmetric growth rate of average short term debt between 2006-2007 and 2009-2010. In column 10 the dependent variable is an analogous growth rate for total debt as in Iyer et al., 2014. The main regressor of interest *ID* in column 10, again as in Iyer et al., 2014, is the *overall* ratio of inter-bank funds' liabilities to assets in 2005 (domestic *and* foreign). In columns 1-5 and column 10 firm fixed effects control for unobservable firms' characteristics time-trends. In columns 6-7 there are no additional controls, whereas in columns 8-9 additional fixed effects for observables are added. Samples are either firms with loans with more than one bank (essential to identify the firm fixed effect) or the complete sample of firms (also firms with one loan only). In columns 4-5 we control for the ratio of sovereign debt on balance sheet over total assets, where the amount of government-issued debt is calculated as either the average of 2009 holdings, or the average of the last quarter of 2009 holdings. The logic of the control in the analysis follows Buera and Karmakar, 2017. Additional fixed effects include 3 digits industry, commuting zone, age and size quintiles, dummy for exporter in 2005, dummy for overdue loans in 2007, dummy for firm capable of issuing bonds, dummy indicating whether the firm has any loan with banks failing up until the year 2014. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level.

C.3 Firm level results

Table A.3 reports the results from estimating Equation (1) with the logarithm of (i) the number of employees (columns 1 and 2), (ii) the wage bill (columns 3 and 4), (iii) the wage bill detrended (columns 5 and 6) and (iv) the number of layers as an outcome variable. Given that we are averaging the outcome variable over a different number of observations in the post period due to firm exit or attrition from the QP, in column 2, 4, 6 and 8 we report the estimated coefficient over a sample of survivor firms. This last estimated coefficient more precisely characterizes the intensive margin of firm adjustment. The first stage F-statistic is always above 30 and not far from the 5-percent Nagar bias threshold (which is at 37.42 according to the methodology in Montiel Olea and Pflueger, 2013), showing that the instrument very strongly predicts the variation in credit. Overall, table A.3 confirms the main results found in the literature, namely that a drop in credit available to the firm predicts a decline in the overall labor force, as well as wage bill. Finally, the credit supply shock was not perceived as a permanent change, and firms did not re-organize by changing the number of managerial layers.

C.4 Margins of adjustment with fixed number of layers

One possible concern with the results in tables 1 and 2 is that firms could both reorganize their labor force and change the number of management layers at the same time. To strenghten our results and avoid this selection problem, we estimate equation 1 while holding the layer structure constant across the pre and post period. Tables A.4 and A.5 present the results. Both results of tables 1 and 2 are confirmed, and the estimated coefficients are statistically significant and larger in magnitude compared to the results obtained without conditioning to a fixed layer structure.

Table A.3: Firm level estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log	*# workers*		*wage bill*		*wage bill det.*		*# layers*	
S_i	0.071**	0.086**	0.091**	0.114**	0.093**	0.111**	0.040	0.046
	(0.034)	(0.035)	(0.038)	(0.041)	(0.038)	(0.040)	(0.029)	(0.031)
First stage	-1.702***	-1.765***	-1.702***	-1.765***	-1.702***	-1.765***	-1.702***	-1.765***
	(0.285)	(0.293)	(0.285)	(0.293)	(0.285)	(0.293)	(0.285)	(0.293)
Weak identif. statistic	35.63	36.32	35.63	36.32	35.63	36.32	35.63	36.32
Firms	13806	11802	13806	11802	13806	11802	13806	11802
Sample	Comp.	Surv.	Comp.	Surv.	Comp.	Surv.	Comp.	Surv.

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log changes of the averages before and after the shock (2009). The number of workers employed in the firm is the total amount of workers employed by the firm in the calendar year, the wage bill is the total amount of wages (base plus overtime) payed by the firm in each calendar year, the wage bill de-trended is the total amount of workers employed by the firm in the calendar year de-trended using a standard linear de-trending methodology to account for business cycle variation, while the number of layers is the number of management layers in the firm. A firm reporting c occupational categories will be said to have L = c − 1 layers of management: in our data we have firms spanning from 0 to 3 layers of management (as in Caliendo et al., 2020). All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. In the bottom part of the table, we report coefficients and standard errors of the first stage of our model as in equation 1. The dependent variable, S_i is the predicted change in credit as in equation 2. The independent variable is the instrument Z_i as in equation 3. The weak identification test statistic is the 'Kleibergen-Paap rk Wald F statistic'. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A.4: Spans of control keeping layer structure constant

	(1)	(2)	(3)
	Skilled workers / *Production workers*	*Managers & team leaders* / *Skilled workers*	*Top Managers* / *Managers & team leaders*
S_i	0.277**	-0.253	0.194
	(0.120)	(0.171)	(0.284)
Firms	7,429	5,738	3,688
Weak identif. statistic	27.61	18.21	8.61

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log levels of the averages before and after the shock (2009). The ratios are computed using the total number of workers in each occupation category. In column 1 the dependent variable is the log ratio of skilled workers to production workers, in column 2 is the log ratio of managers & team leaders to specialized workers, and in column 3 is the log ratio of top managers to managers & team leaders. The sample consists of only survivor firms. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. The weak identification test statistic is the 'Kleibergen-Paap rk Wald F statistic'. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

Table A.5: Occupation groups keeping layer structure constant

Panel A: number of workers				
	(1)	*(2)*	*(3)*	*(4)*
$log(\#workers)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Top Managers*
S_i	*0.068*	*0.189***	*-0.112*	*0.110*
	(0.080)	*(0.071)*	*(0.119)*	*(0.122)*
Firms	*7,789*	*7,925*	*5,962*	*4,653*
Weak identif. statistic	*26.95*	*27.07*	*18.11*	*16.92*
Panel B: average wages				
	(1)	*(2)*	*(3)*	*(4)*
$log(avg.wage)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Top Managers*
S_i	*0.006*	*-0.006*	*0.017*	*-0.039*
	(0.023)	*(0.028)*	*(0.028)*	*(0.062)*
Firms	*7,789*	*7,925*	*5,962*	*4,653*
Weak identif. statistic	*26.95*	*27.07*	*18.11*	*16.92*

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log levels of the averages before and after the shock (2009). In panel A we look at the quantities, and the dependent variable is the (log) averages number of workers in each occupational group. In panel B we look at the prices, and the dependent variable is the (log) average wage in each managerial layer. The sample consists of only survivor firms. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. The weak identification test statistic is the 'Kleibergen-Paap rk Wald F statistic'. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

C.5 Dynamic difference in difference

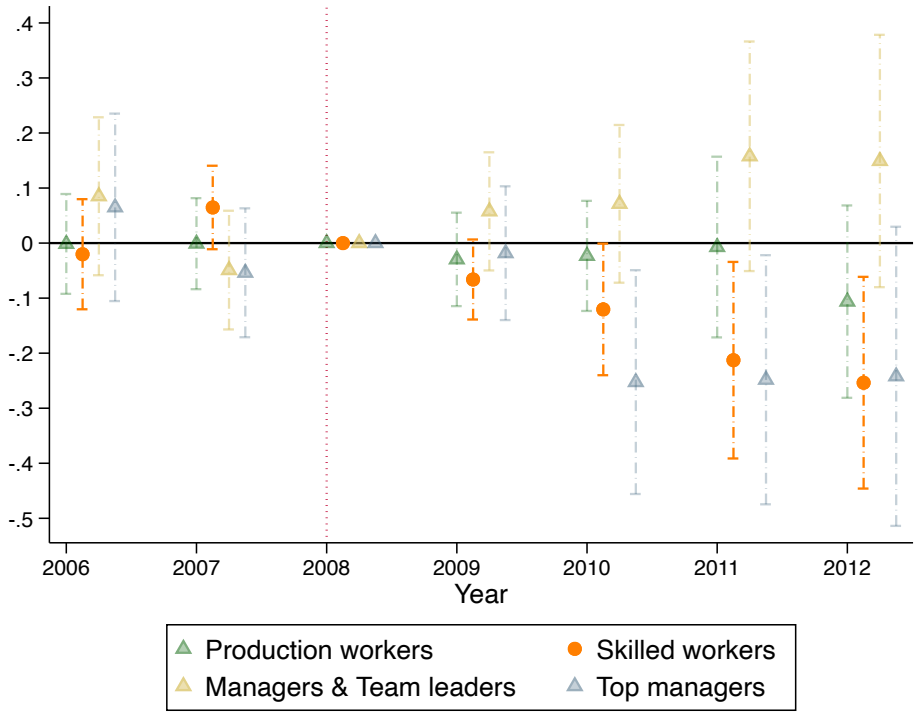
The dynamic counterpart of equation 1 is:

$$log(Y_{i,t}) = \gamma_i + \tau_t + \sum_{k \neq 2008} \left(\beta S_i + \mathbf{\Gamma X_{i,pre}}\right) \cdot I\{t = k\} + FE_{i,t} + \varepsilon_{i,t} \tag{5}$$

where we estimate a different treatment coefficient for each year k. We normalize treatment to be 0 in 2008, so that all other treatment coefficients in the regression can be interpreted as variation

in the outcome with respect to its level in 2008. In all dynamic specifications as in equation 5, the outcome variables are always expressed as ratios of the level of the outcome over its average in the pre-period. Moreover, all regressors and fixed effects are interacted with a year dummy. Figure A.3 presents the results for the dynamic specification, where we look at the (log) number of workers in each occupation group and each year post 2008. The dynamic specification in figure A.3 confirms the findings in table 2.

Figure A.3: Dynamic specification



The dependent variables in these regressions are the logs of the number of employees in each occupational category as defined in the text, interacted with year dummies. In the specifications the coefficient for the year 2008 are normalized to 0, so that all the other coefficients have to be interpreted as the effect on the percentage variation of employment with respect to the 2008 level. See section A.7 for the list of controls and fixed effects in the regressions. All regressors and fixed effects are interacted with a year dummy. Survivors sample. 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

C.6 Age and education of the workers

An additional element to understand the findings in Table 2 relates to the age and the education of the workers employed by a firm. While the age and educational composition of the workforce within the firm do not represent a threat to our identification strategy – firm fixed effects account for potential heterogeneity along this dimension, while allowing for differential group specific

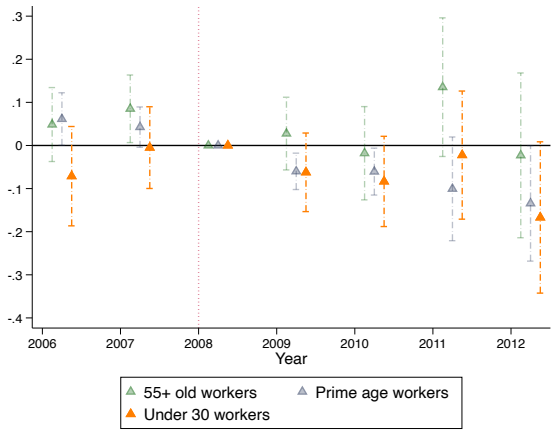
trends in the post-period – we are interested in understanding if firms reorganize the labor force by anticipating retirement of old workers, whether prime age workers are affected the most by the reorganization of the workforce or whether reorganization along the education dimension aligns with the reorganization observed across occupation groups.

We leverage on the information on the age and education of the workers and split the workforce into 3 age groups, prime age, below 30 and 54 or above as well as in 3 education groups, low, medium and high educated. We then look at each age or education group in a dynamic specification as defined in equation 5.

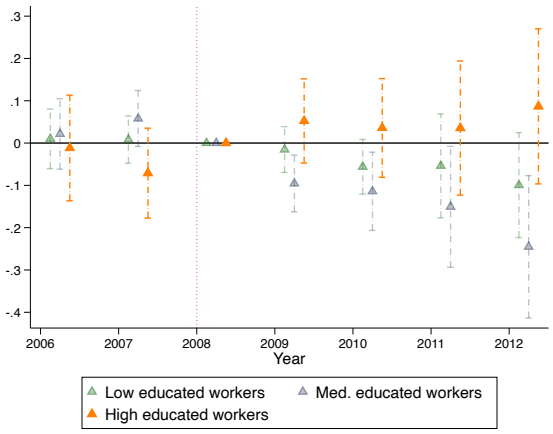
Figure A.4a presents results of the estimation for age groups, while figure A.4b present results for education. Early retirement is not a major factor in determining the separation observed in the data while we observe a moderate effect for prime age workers only for the first two years post-2008, suggesting that younger cohorts suffered a stronger effect of the drop in credit availability to the firms in the economy. Moreover, in line with the results in Table 2, figure A.4b shows that the effects are stronger for medium educated workers, the category that broadly maps to skilled workers.

Figure A.4: Age and education of the workers

(a) Age of the workers



(b) Education of the workers



The dependent variables in these regressions are the logs number of employees by age (panel A.4a) or education (panel A.4b), interacted with year dummies. In the specifications the coefficient for the year 2008 are normalized to 0, so that all the other coefficients have to be interpreted as the effect on the percentage variation of employment with respect to the 2008 level. See section A.7 for the list of controls and fixed effects in the regressions. All regressors and fixed effects are interacted with a year dummy. Survivors sample. 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

C.7 Constraining the sample to manufacturing

In this section we perform the analysis as in section 3.1 constraining the sample to the manufacturing sector. In table A.6 we report the estimates of equation 1 for the (i) number of workers in each occupation group (panel A), (ii) average wages in each occupation group (panel B) and (iii) the interaction of the instrument with the investments in machines and equipment in the pre-period (panel C).

Panels A and C confirm the results in sections 3.1 and 4: firms reorganize their labor force when facing a credit shortage by reducing the number of production workers and skilled workers (columns 1 and 2). Perhaps unsurprisingly, the nexus between firm credit and the organization of firm labor is stronger for manufacturing firms, with bolder adjustments both in the number of workers employed as well as in the average wages for each occupation group. This further lends credibility to the mechanism described in section 4: the complementary between production workers, skilled workers and machines is confirmed in Panel B, although the results can only descriptively point towards this correlation due to the lower first stages.

D Interpretation of the results

To structure the interpretation of the results this section presents two different conceptual framework that allow to link the organization of firm labor and firm credit.

D.1 Models of knowledge-based hierarchies

Models of firm organization — both knowledge-based hierarchies or incentive-based hierarchies — suggest that the optimal number of hierarchy layers increases with production scale. These models interpret managers as fixed costs that reduce marginal costs by making workers more productive; additional managers will decrease average costs if production scale is sufficiently large (as, for instance in Caliendo and Rossi-Hansberg, 2012 or Garicano, 2000).

More formally, production can be seen as a problem-solving process based on labor, knowledge and capital.[8] The number of layers satisfies $1 \leq L \leq 3$ and workers in the firm are either production workers (at the bottom of the hierarchy) or higher skilled workers, which we call managers when at the top of the hierarchical structure. Workers are combined with capital at each layer and the input bundle is $y_l \equiv \left(k_l^{\beta_l} + n_l^{\beta_l}\right)^{\frac{1}{\beta_l}}$. Assume that production at the bottom of the hierarchy takes place using 3 different inputs: labor from home n_{1h}, labor from abroad n_{1f} (outsourcing) and machines k_1 or a combination of them, $y_1 \equiv \left(k_1^{\beta_1} + \left((\rho n_{1h} + (1-\rho) n_{1f}\right)^{\beta_1}\right)^{\frac{1}{\beta_1}}$. Assume also that the firm first decides on the share ρ of each labor input n depending on the relative price

[8] Mariscal, 2018 formalizes a model of firm hierarchies and focuses on the impact of ICT adoption (and drop in costs) has on the organization of firm's hierarchy.

Table A.6: Occupation groups, manufacturing only

Panel A: number of workers				
	(1)	*(2)*	*(3)*	*(4)*
$log(\#workers)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Managers*
S_i	*0.131**	*0.363****	*-0.238**	*0.169*
	(0.068)	*(0.115)*	*(0.125)*	*(0.180)*
Panel B: Machines and Equipment				
$log(\#workers)_{i,t}$	*Production workers*	*Skilled workers*	*Managers & team leaders*	*Managers*
S_i*machines<median	*-0.037*	*0.290***	*-0.328**	*0.220*
	(0.081)	*(0.128)*	*(0.170)*	*(0.210)*
S_i*machines>median	*0.305****	*0.432****	*-0.081*	*-0.046*
	(0.113)	*(0.161)*	*(0.122)*	*(0.232)*
Firms	*11,596*	*10,770*	*8,200*	*6,024*

Notes: The table reports IV coefficients and standard errors of the main covariates of interest of our model as in equation 1, for the sample of manufacturing firms. The independent variable, S_i is the predicted change in credit to firm i instrumented by Z_i as in equation 3. The dependent variables are log changes of the averages before and after the shock (2009). In panel A we look at the quantities, and the dependent variables are log changes of the averages number of workers in each occupational group. In panel B we interact $S_i$with investment in machines and equipment, as in table 3. All regressions feature a full set of controls and fixed effects as detailed in the appendix section A.7. Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level: ***p < 0.01, **p < 0.05, *p < 0.1.

$\frac{n_h}{n_f} = f\left(\frac{w_{1f}}{w_{1h}}\right)$ and conditional on a level of knowledge; in other words, the firm decides on the knowledge of the production workers and on the share of domestic versus outsourced workers.

In this set-up, one unit of labor employed in production generates a unit mass of problems, which are production possibilities turned into output if they are solved using knowledge. Unsolved problems are sent to the managers at the immediate above layer. We refer the reader to Caliendo and Rossi-Hansberg, 2012 for a deeper explanation of the knowledge-based hierarchy model with heterogeneous demand.

The first order condition of the maximization problem of the firm leads to the capital labor

trade-off faced in organizing production in each layer except for the CEO:

$$\frac{k_l}{n_l} = \left(\frac{p_l}{w(cz_l + 1)} \right)^{-\sigma_l} \tag{6}$$

where $\sigma_l \equiv \frac{1}{1-\beta_l}$ is the CES elasticity of substitution between capital and labor.

This set-up allows to analyze the effect of a credit shock on the organization of firm labor. A credit shock can be seen as a shock to the cost of capital p_l, which depending on the elasticity σ_l will have heterogeneous effects on the capital-labor ratio in each layer of the hierarchy. The estimates in section 3.1 return the elasticity of substitution of each layer to a drop in the supply of credit, which is equivalent to an increase in the price of capital in this set-up. Our results highlight that the drop in credit supply has a stronger effect for skilled workers and production workers, with firms shrinking by reducing the ratio of team leaders to production workers while the span of control ratios for the layers at the top of the hierarchy are unaffected by a reduction in the supply of credit. Result are consistent with a strong use of credit by the firm to finance expenses in machines and equipment which are complementary with the knowledge of skilled workers and production workers.

D.2 Models of capital skill complementarity

The firm level response to the credit shocks can also be analyzed through the lenses of a capital skill complementarity framework (e.g. Griliches, 1969, Krusell et al., 2000 or Parro, 2013). In fact, results in section 3.1 are consistent with a credit-occupation groups complementarity mechanism: a decrease in the amount of credit that is used to finance machines and equipment has a differential effect on different occupation groups, depending on how each occupation group is complementary with the credit available to the firm.

A way to theoretically characterize the empirical results is to use a production function that is Cobb-Douglas in the managerial inputs and physical capital, and CES in the two types of production worker inputs (high and low skilled production workers) and capital-equipment. Consider for example the following production function

$$Y_{it} = A_{it} K_{ist}^{\alpha} M_{it}^{\beta} [\mu u_{it}^{\sigma} + (1-\mu)(\lambda k_{iet}^{\rho} + (1-\lambda) s_{it}^{\rho})^{\sigma/\rho}]^{\frac{1-\alpha-\beta}{\sigma}}$$

where M is the bundle of managers in efficiency unit, K_{st} is capital structure, s and u are respectively skilled workers and unskilled workers, k_e is capital equipment and A is a neutral technological shifter. Moreover, μ and λ are parameters that govern the income shares, while σ and ρ are the relevant elasticities of substitution. In particular, $\frac{1}{1-\sigma}$ is the elasticity of substitution between equipments – or skilled labor – and unskilled labor, while $\frac{1}{1-\rho}$ is the elasticity of substitution between equipment and skilled labor. This set-up allows to test for the existence of capital-skill

complementarity – if $\sigma > \rho$ the model validates the existence of capital-skill complementarity – and indirectly for the impact of a change in the amount of capital equipment available to the firm financed through short term credit on the relative skill demand and skill premium. The empirical estimates in section 3.1 confirm the existence of capital-skill complementarity for both production workers and skilled workers. While a formal test of the mechanism would require detailed information on the use of credit by occupation groups which are not available in our dataset, the results of section C.7 points toward a strong capital-skill complementarity mechanism in the data.