APPENDIX

A A model of the financial channels of labor rigidities

The aim of the present section is to provide a conceptual framework for the emergence of the financial channels of labor rigidities, which are at the core of the empirical analysis of the paper. To this end, it develops a simple model of firm decision of credit and labor demand, subject to a working-capital constraint.

The economy lives for two periods, and is populated by a profit-maximizing firm. The firm has a constant returns-to-scale technology F that employs capital and labor to produce a consumption good to be sold at price $P = 1$.[1] The firm starts the initial period with some retained earnings Π, a fixed amount of capital $\bar{K}$ and incumbent workers I (a share of the workforce of the previous period) who receive a salary w^I.[2] The firm has to choose whether to adjust the workforce by hiring new workers N in a competitive labor market.[3] To this end, it offers to them a salary w^N and incurs in a training/vacancy cost c in order for them to be productive in the final period. The firm has to pay a share λ of the total wage bill of the final period in advance, together with the full training cost c. We are assuming that, given the natural of the production activity carried out, there might be time gaps between cash inflows and wage payouts, or that it takes time for workers to become productive and the training has to be financed in advance.[4] For this reason, it needs to borrow an amount D of working capital from a banking sector.

For the present exercise, we assume that the firm starts in an unconstrained condition, in which bank credit D is available at a rate $R = 1/\beta$, where β is an intertemporal discount factor and is equal to 1 for simplicity. The firm incurs a fixed cost of operation f, and exits if is unable to honor it. In that sense, credit is only useful to transfer resources across periods, but absent any unexpected shock would have no effect on the unconstrained equilibrium. Hence, we assume for simplicity that the firm takes external credit only up to the amount needed to finance its current expenditures, but no more. Formally, the firm maximizes its value V:

$$\max_{N,D} V = AF(N + I, \bar{K}) - w^N N - w^I I - cN - f, \tag{29}$$

subject to the working-capital constraint:

$$D + \Pi \geq cN + \lambda(w^N N + w^I I), \tag{30}$$

where A is the firm TFP, and Π are retained earnings.

In normal times, when the working-capital constraint is not binding, the first-order condition with respect to new hires yields:

$$AF_L(N + I, \bar{K}) = w^N + c. \tag{31}$$

This relationship defines the optimal level of new hires N^* and as a consequence the optimal amount of credit D^* to achieve it from the working-capital constraint (30).[5]

Now suppose that the bank unexpectedly cuts its credit supply and the firm can only obtain a level $\bar{D}$.[6] In

[1]This market setting comes at no loss of generality, and can be easily extended to a monopolistically competitive environment.

[2]We do not model the determination of the incumbents' salary. That would arguably depend on current market wages, past wage levels in case of downward wage rigidity and some incurred training cost.

[3]De facto, this amounts to analyzing a setting with decreasing returns to scale in the short run, and necessarily ignores any feedback effect on fixed capital investment through labor-capital complementarity in production.

[4]Another way to rationalize this constraint is by limited enforcement in labor contracts. Before production takes place, the firm promises salaries w^I and w^N to incumbents and new hires, respectively. However, it can renege on the promise and defaults on his payroll, in which case the workers are able to seize only a fraction of the production. To relax this problem, the firm pays a fraction of the wage bill upfront.

[5]Notice that in this case the incumbents' salaries have no effect on the optimal level of hiring. Moreover, we do not allow the firm to fire incumbents. We discuss the effect of this assumption below.

[6]Remember that in our empirical analysis we do not have a direct measure of credit spreads at the loan level. Hence, we model the credit shock as a decrease in credit supply below the level that would be optimally demanded by firms. In any case, the two settings are isomorphic in our simple model, as any suboptimal level of

this case, the firm's working-capital constraint yields the firm's labor demand as:

$$\bar{N} = \frac{(D + \Pi) - \lambda w^I I}{c + \lambda w^N}. \tag{32}$$

The credit tightening has a negative impact on the firm's value, summarized by the shadow value of credit.

Result 1 *A negative credit shock decreases firm value:*

$$\left.\frac{\partial V}{\partial D}\right|_{D=\bar{D}} = \mu = \frac{AF_L(\bar{N} + I, \bar{K}) - w^N - c}{c + \lambda w^N}, \tag{33}$$

where μ is the shadow value of the working-capital constraint (30)*.*

The effect on firm's value through new hires:

$$\frac{\partial N}{\partial D} = \frac{1}{\lambda w^N + c} - \frac{\lambda}{\lambda w^N + c}\left(\frac{\partial w^I}{\partial D} I + \frac{\partial I}{\partial D} w^I\right) \tag{34}$$

highlights that a credit tightening can affect them not only directly, but also through the effect on incumbents wages and employment. Yet, if we assume that the incumbents' wages are fully inflexible (which, at least in nominal terms, is almost entirely the case in Portugal) and that firings are not feasible or optimal (see discussion below), then the term in parentheses of the previous expression cancels out, and we can state the following:

Result 2 *The elasticity of employment to credit around the optimal undistorted quantities is:*

$$\varepsilon_{L,D} = \frac{\partial \log L}{\partial \log D} = \frac{N^*}{N^* + I} + \frac{\lambda w^I I - \Pi}{(\lambda w^N + c)(N^* + I)}. \tag{35}$$

We interpret the first term as the labor-as-investment channel, which depends on how much the firm wants to extend its workforce with respect to the current one (the elasticity of new hires to credit is always 1 in this setting). The second term represents instead the labor-as-leverage channel: The greater the incumbents' wages w^I, or the greater the share of the wage bill λ that has to be paid in advance, or the smaller the retained earnings Π from the previous period, the stronger the amplification of a credit shock from the labor-as-leverage channel will be on new hires.[7] The leverage effect through a firm's exposure to the compensation-policy component of its labor share, which we identify in the empirical analysis, exactly proxies this leverage effect in the model through the greater incumbents' wage level.

As a matter of fact, this amplification result might not be per se a signal of firm unprofitability, as it is possible that retained earnings Π do not fall too much for greater levels of labor share in the past, if the firm has a good operating margin in the aggregate after taking capital costs and other costs into account. In the data, the labor share is indeed negatively correlated with past profits. The variation in labor costs conditional on a certain level of profitability is exactly what the empirical exercise measures. What matters for the leverage effect to materialize is that a firm is exposed to rigid labor costs that it has to honor. Controlling for different degrees of productivity, such as value added per employee and overall TFP, helps distinguishing whether what one observes in the data is the results of simple overpayment or a leverage effect on an otherwise productive firm.[8]

Result 3 *Given Π, a greater incumbents' labor share to finance (proxied by $\lambda w^I I$) amplifies the employment elasticity to credit, and further raises the TFP threshold below which a firm exits the market.*

Discussion Given the necessary complication that analyzing the discontinuity in the hiring/firing decision would entail with respect to the discontinuity in adjustment costs at the 0 point, our model does not include

credit supplied by banks can rationalize an increase in credit spreads through the shadow value of liquidity for the firm.

[7]Keep in mind that λ and Π do not affect the optimal amount of hiring in the undistorted state.

[8]Keep in mind that the employment elasticity does not directly depend on future profitability and is not attenuated by it. If anything, future profitability would lead to a greater effect on impact through the investment channel, as firms would hire more in the optimal undistorted case.

optimal firing due to TFP shocks or market conditions. In principle, the presence of implicit or explicit firing costs would arguably determine a pecking order from the least to the most protected workers. A way to rationalize this could be either by assuming firing costs that are increasing in tenure (which is for sure part of the story in Portugal) or the possibility that tenured incumbents accumulate firm-specific human capital through which they hold up the firm's operations, or general skills that they could use in increasing their bargaining power with the firm. However, these dynamics would not eliminate the leverage effect, given that the workers creating the most leverage are at the same time the most skilled and likely essential to the firm operations.

Incumbents wages w^I can be high for different reasons, which are left unmodeled here given the static nature of the model. Consistently with Card et al. (2017) or Kline et al. (2019), one would expect wages to incorporate part of the training costs in which the firm had incurred in order for the workers to be productive, given their implicit lower substitutability with outsiders. Moreover, risk-sharing consideration between firms and workers might affect wage dynamics (Guiso et al., 2005, 2013). For example, Xiaolan (2014) shows that the optimal contract to provide insurance to workers against negative productivity shocks, while at the same time providing the incentives for high-skill workers to remain in the firm, necessarily implies a degree of downward wage rigidity and an increasing trajectory over time as a function of human capital accumulation. In other words, in Xiaolan's setting downward rigidity in compensation is not determined by explicit firing costs, but by risk-sharing considerations. These kinds of dynamics are exactly what one should have in mind regarding the way in which labor-as-investment turns into labor-as-leverage in our framework.

From the empirical analysis, it is clear that the amplification of a credit shock, which in this setting is isomorphic to a cash-flow shock, is predominantly driven by leverage.[9] Thus, the effects on exit can almost surely be attributable to the labor-as-leverage channel.[10] The labor-as-investment channel instead, absent any non-convexity in training costs, should at most eliminate new hires but, given the presence of capital in place and incumbent workers, it is unlikely to drive exit. Labor-as-investment plausibly creates amplification through the effect that it has on wage dynamics over time, which is not captured in this static model, but does not per se generate a greater volatility of firms' employment and investment decisions to cash-flow shocks. Put differently, in this very simple model working capital is needed to create the leverage effect through incumbents wages, but does not create amplification per se. In fact, training and vacancy costs expose the firms to financing costs, but firms might react to cash-flow shocks by scaling them back in a proportionate way. For example, a firm having to finance 80 percent of the wage bill in advance will exhibit the same elasticity of employment as a firm having to finance only 20 percent, provided that they receive the shock in a similar proportional amount. Hence, the elasticity of hiring to cash-flow, absent other channels, should be 1 in the simple model, which is why the overall elasticity of employment is the hiring share itself.

It is important to point out that, even if one would generally expect the labor-as-investment and labor-as-leverage channels to frequently coexist and possibly reinforce each other, these two channels are separate on a substantive level, and it is conceivable that they can exist independently. In the model, labor-as-leverage implicitly depends on the presence of the working-capital constraint, which makes labor akin to an investment good. However, it is possible to conceive other situations in which its effects would materialize even in the absence of an investment channel. In fact, it is possible that the presence of other fixed or complementary costs at firm level would set the leverage effect in motion, even if workers immediately generate the cash flow needed for their payments. In a similar way, if a firm had projects or other expenses that need priority financing for the firm to operate, the need to finance them would determine a real effect on employment and other forms of investments if costs are rigid. As long as the cash inflows that the workers generate are used by the firm to finance other prioritized payments, the quasi-fixity of labor will once again reverberate on new hiring and even firing decisions

[9]An alternative possibility is that the firm is hit by the credit shock at a point in time when it needs to replace a high share of its incumbent workers, and the credit shock makes it impossible to pay the training costs for new hires, thus leaving the firm in the impossibility to produce. Through such a mechanism, exit would also depend on the labor-as-investment channel. However, in our sample there is no evidence that firms with high incumbents' turnover face higher exit rates. Results are available upon request.

[10]The effect of the credit shock might also translate into a greater volatility of capital investment and eventually a greater exit probability, given that the decrease in D diminishes firm value. In turn, stronger leverage effects from past rigid costs, by distorting more a firm employment decision, might amplify the effect on V, consistently with the empirical results.

for the less attached workers.

All these arguments do not dismiss the labor-as-investment channel as irrelevant: to some extent, the channel creates an exposure to credit fluctuations through investment costs (which might have a leverage effect later on), and the fact that firms do not seem to insure themselves against the exposure to short-term liquidity risk is still puzzling, given that training costs are possibly long-term and easily predictable.

B Data description and cleaning

B.1 Available datasets

B.1.1 Labor market data: Quadros de Pessoal

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. The data are collected and managed by the Ministry of Labour and Social Solidarity, that 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.[11]

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 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 included comprehends workers' gender, age, detailed occupational code (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), detailed educational level, qualification within the firm (managerial qualification, specialized workforce or generic workers, besides trainees). At the contract level it is possible to know the precise hiring date, the kind of 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 information on 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.[12]

The unique worker identifier is based on the workers' social security number, and given the extensive work on the part of the Ministry to control and certify the quality of the data in this administrative dataset, the coverage and reliability of the data is quite high (except for the discrete break in coverage for only a subset of firms in 2010

[11]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. This also means that in our analysis the "survivors" sample is not necessarily a balanced sample.

[12]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 three broad categories.

due to the new reporting requirement in the *Relatório Único*. Given that other datasets in our analysis cannot cover the same time-span, we only focus on years from 2005 to 2013 (but potentially control for observables up to 2003 in some empirical exercises).

We use the QP to extract information regarding wage policies at the firm level. This is the dataset we use in order to compute AKM firm level fixed effects, which describe what component of workers' compensation is firm specific and pertains to average firm wage policy. We compute AKM fixed effects thourgh an AKM regression, which is a wage regression at the worker level on firm and worker fixed effects and other workers' characteristics. The firm fixed effect captures overall generosity of payments while the individual fixed effect should capture unobservable skills. In our AKM specifications we control for sex, a third polynomial of age and educational categories dummies, all variables present in QP itself. We run the AKM regressions on worker level data from 2003 to 2008.

B.1.2 Firm level financial statement data: Central de Balanços

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 in its present form covering the universe of firms is based on information reported in the starts in 2006, even if almost 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 actually have a very high coverage of firms' balance sheets for 2005 as well. Before 2005 the CB maintained by the Bank of Portugal was actually a survey only for the biggest firms in the country. However, given the substantially lower coverage of the population of firms before 2005, we do not rely on that data.
After 2009, in order for the data to comply with international accounting standards, there has been a major 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 personally 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 a great amount of information on firms' balance sheets and income statements, even if the harmonization process between 2009 and 2010 makes it at time difficult if not impossible to keep consistent records for all balance sheet variables in the dataset. We use the dataset to obtain information on total assets, fixed assets, current assets total debt (not just bank 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. We computer value added from this dataset by adding back employee related expenditures to the firm EBITDA (which should correspond to subtracting expenditures on intermediate goods from total sales).

Given the dataset time-consistent coverage of firms operating in Portugal, we use it to identify firm exits as well. The procedure to identify a firm exit combines different criteria. Firstly, we rely on the CB on categorization of whether a firm is active, suspended activity or closed down. Secondly, we flag all the cases in which the firm will end up having 0 employees the next year but does have a positive number of employees in a given year. Thirdly, we actually check whether a firm disappears from the dataset in any given year that is not 2013 and does not re-appear at any time (and does not simply have, consequently, a gap in the data). Lastly, we label as exits the instances in which a firm disappears for more than two years, as it is likely that if the identifier reappears later it has just been reassigned to another firm (an assumption that seems to be validated by the observation that when such instance takes place the firm seems different in terms of size and sector between the

two periods). In all the cases we select the criterion of exit, in case a firm matches more than one at different points in time, by looking at the case in which the firm "closed down" with the highest number of employees or, if ties are not resolved, with the lowest EBITDA.

B.1.3 Credit exposure level dataset: Central de Responsabilidades de Crédito

The *Central de Responsabilidades de Crédito* (henceforth CRC), is the credit registry of the Central Bank of Portugal. The dataset features available for our period of analysis (up to 2013) features bank-firm exposures above EUR50 by the universe of Portuguese credit institutions at the monthly level. The dataset does not contain credit exposure by foreign banks towards Portuguese firms, but can obviously contain credit from Portuguese banks to foreign owned firms residing and operating in Portugal.[13]

The dataset is regularly employed 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. From 2009 onwards, but unfortunately not before, it is possible to obtain information closer to loan-level (i.e. it is possible to keep track of exposures which consist into the sum of loans with very detailed similar characteristics instead of seeing an aggregate number by kind of coarsely defined exposure) and more details about the exact maturity of each exposure and the collateral posted by each firm, if any (real collateral or guarantees, fraction of the value of the loan backed by it). Given the nature of our analysis and the period of interest, we mostly focus on obtaining a consistent representation of the information available in the dataset before 2009. For our analysis and given the time frequency in other data sources we average debt exposures at the yearly level. We use "regular" credit in our specifications as measure of credit, which corresponds to credit in good standing and in use by the firm. Credit is defined as short-term if the maturity is below 1 year or it is a credit line with undefined maturity (post-2009 data) or 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 underfined maturity because the latter category of credit lines comprehends all those exposures that, once withdrawn by the customer, should undergo renegotitation 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 remainder in regular credit.

B.1.4 Banks balance sheet dataset: Balanço das Instituições Monetárias e Financeiras

The "Balanço das Instituições Monetárias e Financeiras" (henceforth BBS) is the balance-sheet dataset for credit institutions that we employ. It is a proprietary dataset of the Bank of Portugal with the balance sheets of the universe of financial monetary institutions operating in the country. The dataset is utilized by officers of the bank in order 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) it is possible to see which is the kind of counterparty involved (i.e. the kind of institution, government, private or non-governmental body, creditor or debtor), the maturity of the item in question if relevant (time deposits, on demand deposits, interbank long-term or short-term exposures) and the nationality of the counterparty (extra-EU or each EU country separately). The data are reported at the monthly level.

The measure of interbank funding which is the basis of our instrument is computed from this dataset 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 (obviously not a central bank).

[13] We do not believe that this fact could be a source of significant bias in any of our results, as the Portuguese economy mostly features relatively small and arguably bank-dependent firms, and for the biggest firms it is more likely for them to access directly debt markets instead of creating ties with foreign banks. Most foreign banks, moreover, operate Portugal incorporated subsidiaries in the country, the credits of which would regularly appear in the CRC.

In matching the BBS and the CRC, we also took care of harmonizing and making bank definitions consistent across datasets given the existence of many mergers and acquisitions in the Portuguese banking system during the period. 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 in order to make sure that credit flows across institutions were rightly accounted for, and definitions of bank codes across datasets and across time were consistent.

B.1.5 Banks balance sheet dataset: Sistema Integrado de Estatísticas de Títulos

The *Sistema Integrado de Estatísticas de Títulos* (henceforth SIET) is a proprietary dataset of the Bank of Portugal. It includes debt securities (i.e. banknotes, commercial papers, bonds, etc.) with maturity both short term (up until 1 year) and long term (more than 1 year), and capital (i.e. shares and other means of participations) but neither derivatives nor REPOs. For both debt securities and capital, SIET collects data about emissions and portfolio holdings. For emissions, SIET collects flows and stocks relative to national issuers, on a title-by-title and issuer-by-issuer bases. For portfolio holdings, SIET collects flows and stocks on an investor-by-investor and title-by-title basis. Through SIET we obtain holdings of sovereign debt, or more in general any government-issued debt instrument held by banks on their balance sheet.

B.1.6 Commuting zone definitions

Given the relevance of the concept of commuting zone, especially for the analysis of labor market reallocation, we obtained data on the definition of commuting zones for Portugal from Afonso and Venâncio (2016).

B.1.7 Labor market data: Occupational Information Network

Given the availability of definitions of occupations at the worker level in the QP, we were able to obtain occupation characteristics through the Occupational Information Network (O*NET) database. The O*NET database is a widely used database in labor economics and is the primary source of data in the United States for categorization of occupation characteristics. It is based on the combination of the analysis of responses to questionnaires on occupations administered to sampled employers and employees, and is updated four times a year with new data or updates to current categorizations.

We used O*NET in order to create indexes on job categorizations in terms of education, experience and training requirements. For each occupation a categorization is provided regarding the level of experience required (with possible scores ranging from 1 to 12, from less than high-school to post-graduate level), the level of previous experience (from 1 to 11, from none to more than 10 years), the level of on-site training (classes, courses, instructions sessions organized by the employer) or on-the-job training (that is, work carried out under the supervision of more experienced workers) required to being able to carry out the required tasks (from 1 to 9, from a short demonstration to years of training). Moreover, we also extracted for each occupation the categorization of the "job zone" (with a score from 1 to 4 in ascending order of "sophistication" of required vocational preparation levels), which is a further categorization created by expert O*NET analysts that combines all the previous four categories in a unique index. We obtained a separate occupational index as well for each category by averaging the scores, taking into account the frequency of each score for each response.

In order to combine the data, we first worked on making profession definitions consistent across time in our dataset, and then merged our occupational code to O*NET through a ISCO08-ONETSOC10 crosswalk. Given the change in occupational codes from the *Classificação Nacional de Profissões* (CNP94) to the new *Classificação Portuguesa das Profissões* (CPP2010) in 2010 in order to update the categorization and making in compliant to the *International Standard Classification of Occupations* (ISCO2008) categorization, we created a crosswalk based on the frequency of cross-occupational code changes from 2009 to 2010 in the QP within the same firms. We used the cross-walk in Hardy et al. (2018) to merge our ISCO08 codes to (ONET)SOC10 (Standard Occupational Codes). We then averaged all the occupational scores and indexes obtained from ONET across occupations in order to obtain a time consistent 3-digits ISCO08 occupational categorization.[14]

[14]The fact that obviously the occupational categorizations are neither bijections nor injections across sets made

We used O*NET version 23.3, and more specifically the education, training and experience files.[15]

B.2 Sample selection

In order to prepare the data for the analysis in our event-study, we need to combine all the different sources of data available, and perform cleaning checks to obtain a relevant sample of analysis depending on variables availability and firms' and banks' characteristics.

Given that the focus of our analysis is predominantly the adjustment of employment and other real variables as a function of the different measures that we label as different sources of "labor rigidities" in the text, the main firm-level dataset around which we combine the other datasets is the QP.

First, we perform some quality checks on the QP and remove workers' for which identifiers are not consistent over time.[16] We then select only workers listed as "employees", full-time, between 16 and 65 years of age, and receiving a full wage in the October of every year (e.g. not on sick leave or other forms of leave).[17] As regards monetary balance-sheet variables, wages and credit variables, we deflate all nominal values in the analysis by the 2013 consumer price index.[18]

In order to define the final sample of analysis we merge all datasets and select firms based on some defined criteria. Given that we are interested in both firm dynamics and employment adjustment, we mostly consider firms present both in QP and CB.[19] We restrict our attention to firms in mainland Portugal, and exclude from the sample industries like 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 of course 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.[20][21]

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 the instrument is computed those banks for which foreign interbank funding is actually intra-banking-group funding from the foreign headquarter to the Portuguese subsidiary.[22]

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it difficult in some cases to reassign the occupational codes. We tried to use the official crosswalk at first, but noticed that it created very big discontinuities for the frequency of observation of some professions. We noticed on the other hand that within firms changes in occupational codes seemed to be very consistent, and as such a more valid "revealed preference" categorization on the part of employers of their employees actual occupation. We then decided to limit ourselves to a 3-digits categorization in order to have a meaningful number of workers for occupation, and in order to minimize the inconsistencies in the cross-categorizations of occupational codes between CNP and CPP.

[15] `https://www.onetcenter.org/dictionary/23.3/excel/education_training_experience.html`

[16] For the period 2005-2013 the problem is actually marginal.

[17] We also remove records with unreasonable number of hours worked and perform other sanity checks or within-worker's records harmonization on other variables, such as date of birth, hiring dates, workers' characteristics.

[18] For the productivity estimation the deflation of nominal values is performed at a much greater level of detail and precision depending on each item and industry. We refer the reader to Appendix C for the details of the estimation.

[19] Most of the firms with partial state ownership are not in CB. Hence, they can be included in the most basic analyses, but not in those that feature firm balance-sheet controls.

[20] Considering firms already existing in 2005 allows us to have at least 3 years of pre-period in our event study framework. We implicitly exclude entrants in the three years before 2009 from the event study analysis.

[21] We focus on relatively big firms, at least by Portuguese standards, as we are interested in measuring employment adjustment at the firm level, which becomes increasingly noisy and lumpy for very small firms, and because of the fact that the QP coverage of Portuguese firms is full for relatively big firms but decreases for very small firms after 2009.

[22] The cases for which this happens are very few and do not represent more than 1 percent of total credit at any point time. We cannot disclose any detail on the names of the banks in question.

To limit the influece of outliers in the regressions, we drop firms in the top 2.5 percentile of positive credit variation between the pre- and post-periods. For the same reason we drop all the firms with a percentage of exposure-amount growth above the top 2.5 percent of the distribution in the exposure level specifications. This effectively amounts to eliminating more than 2.5 percent of firms for those particular regressions, but we still think that this kind of cut is more sensible than leaving the firms in the estimation sample without accounting for all their loans.

Our final sample spans 14,846 firms and 31 banks.[23]

C Production function estimation

C.1 Productivity and output elasticities estimation

For the estimation of output elasticities, markups and ultimately revenue total factor productivity (TFPR) we use different methodologies. First of all, we consider a three-factors of production gross output (y) function, where factors are labor (l), physical capital (k) and an intermediate input (m). We consider both a simple Cobb-Douglas specification where the elasticity of substitution among the factors of production is restricted to be 1 and a translog specification, which relaxes the above assumption. The (log-)production function is thus expressed as a function of log-inputs as:

$$y_{i,t} = f(l_{i,t}, k_{i,t}, m_{i,t}) + \omega_{i,t} + \varepsilon_{i,t} \tag{36}$$

where $f(l_{i,t}, k_{i,t}, m_{i,t})$ is

$$\beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} \tag{37}$$

in the Cobb-Douglas case, and:

$$\beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + \sum_{x \in \{l,k,m\}} \beta_{xx} x_{i,t}^2 + \sum_{j \in \{l,k,m\}, j \neq x} \sum_{x \in \{l,k,m\}} \beta_{jx} j_{i,t} x_{i,t} \tag{38}$$

in the translog case. ω in the equation represents the firm's level of technical efficiency (or total factor productivity, TFP).[24]

In our estimation gross output is measured as total firm sales (coming from QP when available and using CB firm revenues, which correspond to the QP definition of sales, for all other firms), deflated by 2-digit industry gross output deflators. Labor is measured as the firm wage bill (coming from QP when available or using CB total salaries for all other firms), which differently from total headcount (or full-time equivalent count) partially accounts for labor quality, and is deflated by the consumer price index. The intermediate input is the sum of the cost of intermediate goods and supplied services, deflated by 2-digit industry intermediate inputs deflators. For physical capital we use a capital series that we constructed following the perpetual inventory method (PIM) in the baseline specifications or the book value of (net) fixed assets (both tangible and intangible). In the latter case the book value of (net) fixed assets is deflated by 2-digit industry capital goods formation deflator.[25] For the PIM on the other hand we estimate the following equation:

$$K_{i,t} = (1 - \delta_{i,t}) K_{i,t-1} + \frac{I_{i,t}}{def_t} \tag{39}$$

[23]Most of the regressions which require also balance-sheet variables consists of 13,804 firms, while the sample of surviving firms consists of 11,802 firms. At least for the employment and balance-sheet items regressions, though, results are virtually unchanged if we just restrict our attention to specifications in which fixed effects that do not require the CB are utilized (see 4), and cover the entire sample.

[24]The CES production function is a specific case of the general translog production function, and can be obtained by applying a second order Maclaurin approximation (which implies the parameterization of the Cobb-Douglas case as point around which the approximation is performed) to the log of $y = (\sum a_x x_i^{\rho})^{\frac{\nu}{\rho}}$. The CES entails some specific parameters restrictions with respect to an unconstrained translog specification, which should thus be considered as a more general specification.

[25]All the price indexes for Portugal, apart from the CPI, are obtained from the OECD STructural ANalysis Database (STAN) (`http://www.oecd.org/sti/ind/stanstructuralanalysisdatabase.htm`).

at the firm level. Instead of using the book value of yearly depreciation for fixed assets, we use a level of 7 percent for all firms.[26] From 2009 onwards we can measure directly firm level capital investment form the cash-flow statement (unavailable for earlier years) as the total yearly capital expenditure in both tangible and intangible capital formation. For the other years, or when the variable is missing, we use the variation in book fixed assets, deflated by the yearly capital goods formation deflator, as a measure of investment. We take the earliest year available level of fixed assets, deflated by the industry capital goods formation deflator, as starting value for the series. For incumbents firms in the dataset, the earliest year is 2005, and their starting value of real capital is thus just an approximation. We use the results based on PIM capital as our baseline.[27]

The estimation is carried out yearly, for all firms in the CB from 2005 to 2013, at a level of aggregation that is close to the 2-digit industry level.[28] For the estimation of output elasticities we remove from the dataset firms with a revenue labor share lower than or greater than 1 percent, firms with a revenue material labor share lower than 10 percent or greater than 1, and the firms with a sum of labor and material shares above 1.2. We also drop the lowest and highest 1-percent quantiles of labor and material shares. We are left with 275,093 unique firms and 139,735 firm-year observations on average.

Firm level (log) TFP is calculated as the residual from the estimation of the production function according to the various specifications. The estimated residual, the productivity shock, can be written as

$$\xi_{i,t} = \hat{\omega}_{i,t} + \nu_{i,t} = \omega_{i,t} + \varepsilon_{i,t} \tag{40}$$

where $\hat{\omega}$ represents the "transmitted" component of productivity (that is, the one that the firm takes into account while making input decisions) and $\nu_{i,t}$ should represent an unexpected shock. Given that the residual $\nu_{i,t}$ in the estimation might also arise because of any measurement error in output, inputs and prices, we calculate productivity either as the full residual from the production function estimation, or the residual

$$\hat{\omega}_{i,t} = \hat{y}_{i,t} - \hat{f}(l_{i,t}, k_{i,t}, m_{i,t}) \tag{41}$$

where $\hat{y}_{i,t}$ is obtained as the estimated gross output from a regression of output on a third order polynomial of all inputs of production. The latter form aims to eliminate any component of the realization of gross output that appears not to be related to the planned input choice, and remains unexplained by it, thus limiting the concern on the influence of measurement error. In the main text we show results based on this latter measure of productivity, but our results are qualitatively unchanged regardless of the measure we use. We use the full residual, as standard in the literature, for the productivity decomposition.[29]

The estimation of output elasticities and productivity generally presents problems related to the nature of input choice itself. On the one hand, input choice is likely to be very strongly correlated with (expected) productivity itself, and as such the direct estimation of the log production function by OLS would very likely be subject to biases given endogeneity determined by simultaneity.[30] On the other hand, there is generally an implicit selection bias for the firms observed in the dataset, given that more productive firm tend to be more resilient in normal times.

We address the first issue by following the literature in industrial organization on the identification by means

[26] 7% is less than the maximum level of depreciation tax deduction that firm would get by deflating capital the most each year. For this reason, even if imperfect, it is a plausible measure of yearly depreciation. Given that we are unable to decompose in a time-consistent way the subcomponents of capital formation, the approximation is necessary.

[27] Our results are qualitatively insensitive to the measure of fixed capital that we used for the estimation of output elasticities and productivity, and in many cases are also almost quantitatively indistinguishable.

[28] Given that there is a change in industry definitions in QP (see Appendix B) and some subgroups are small, we aggregate some of the subgroups. The resulting industry definitions are conceived to be time-consistent across the different CAE versions of industrial definitions.

[29] See Petrin and Sivadasan (2013) for a similar exercise.

[30] Given Portugal's labor market institutional features, it would not look unreasonable to consider labor as a quasi-fixed input in production, with a greater degree of flexibility than capital but still less flexible. Our method of estimating labor elasticity is consistent regardless of this matter, but if labor not a fully flexible input in production it cannot be utilized to estimate firms' markups.

of proxy variables (Olley and Pakes (1996); Levinsohn and Petrin (2003)).[31] This methodology consists into substituting unobserved productivity in the production function by a proxy variable, a choice variable assumed to have an invertible mapping with productivity itself. In our case, we use the intermediate input as the proxy variable (as in Levinsohn and Petrin (2003)).

The estimation is subdivided in two stages: in the first stage output is non-parametrically regressed on the inputs (and importantly, the proxy variable, which is an input in our case), in order to retrieve expected output and an estimate of the residual:[32]

$$y_{i,t} = \phi(l_{i,t}, k_{i,t}, m_{i,t}) + \varepsilon_{i,t} \tag{42}$$

We follow De Loecker and Warzynski (2012) and Ackerberg et al. (2015) in the estimation of all the relevant output elasticities at the second stage, which allows for consistent estimation even in presence of dynamic effects of the labor choice on the other inputs. The second stage estimation relies on the assumption that productivity at the firm level follows a Markov process:

$$\omega_{i,t} = g(\omega_{i,t-1}) + \eta_{i,t} \tag{43}$$

For a given guess of parameters β one can obtain an estimate of productivity:

$$\hat{\omega}_{i,t}(\beta) = \hat{\phi} - (\hat{\beta}_l l_{i,t} + \hat{\beta}_k k_{i,t} + \hat{\beta}_m m_{i,t}) \tag{44}$$

for the Cobb-Douglas case of

$$\hat{\omega}_{i,t}(\beta) = \hat{\phi} - \left(\hat{\beta}_l l_{i,t} + \hat{\beta}_k k_{i,t} + \hat{\beta}_m m_{i,t} + \sum_{x \in \{l,k,m\}} \hat{\beta}_{xx} x_{i,t}^2 + \sum_{j \in \{l,k,m\}, j \neq x} \sum_{x \in \{l,k,m\}} \hat{\beta}_{jx} j_{i,t} x_{i,t} \right) \tag{45}$$

in the translog case. One can thus non-parametrically regress $\hat{\omega}_{i,t}$ on its own lag and obtain the estimated innovation to productivity $\nu_{i,t}(\beta)$). It is then possible to estimate all the output elasticities and subsequently TFP by GMM relying on moment conditions of the form:

$$\mathbb{E}[\eta_{i,t}(\beta) z^j] = 0 \qquad j \in \{l, k, m\} \tag{46}$$

in the Cobb Douglas case and

$$\mathbb{E}[\eta_{i,t}(\beta) z^j] = 0 \qquad j \in \{l, k, m\} \tag{47}$$

$$\mathbb{E}[\eta_{i,t}(\beta) z^j z^h] = 0 \qquad j, h \in \{l, k, m\} \tag{48}$$

in the translog case. The z variables are instruments for the various inputs. Given the standard assumptions on input dynamics, k can be a valid instrument of itself, whereas we use lags of labor and intermediate inputs as instruments, and according interactions for higher order terms.[33][34][35]

We address the problem of possible selection bias of firms into the dataset by trying to control for the probability of survival in the law of motion of productivity, as suggested in Olley and Pakes (1996). We actually augment the estimation of Equation (43) by adding the estimated survival probability obtained by fitting a probit model on year dummies and input levels.[36]

[31] The proxy-variable approach is the most frequently used in the industrial organization literature. Alternatives are fixed effects, first order conditions, the dynamic panel approach or the use of plausible instruments.

[32] We use a third order polynomial of inputs in this first stage regression.

[33] In order for lags of wage bill and intermediate inputs to be valid instrument for their respective current values, one would need the prices to be correlated over time, an assumption that is quite plausible and surely confirmed in our data as regards the dynamics of wages.

[34] In the Cobb Douglas case we also add orthogonality conditions for the lag of capital and the second lag of intermediate inputs. Given the amount of parameters to estimate and the computing time required for the procedure, we do not add overidentifying restrictions in the translog case.

[35] If labor was indeed a dynamic input, the estimation of its elasticity would remain consistent anyway, as the orthogonality condition would a fortiori be valid for its lag.

[36] We carried out a the same procedure by augmenting Equation (43) with the estimated failure probability as in Antunes et al. (2016), but did not notice any material difference in final outcomes.

We compute productivity and elasticities for robustness by estimating the Cobb-Douglas and translog productions functions by straight OLS as well, adding year fixed effects to the estimation. All results in the main body of the paper are qualitatively (and quantitatively) robust to these different estimation procedures.

In the Cobb-Douglas case the estimated coefficients for each input are also output elasticities, which are consequently fixed within each industry (the Cobb-Douglas specification does not admit any variation in input revenue shares and elasticities across firms within the same estimation sample). In the translog case, on the other hand, the elasticity of substitution across any inputs is not restricted to be 1 and elasticities can vary depending on each firms' input mix utilized. For any input x, given the other two inputs j and h, the estimated output elasticity can be obtained as:

$$\hat{\theta}^x_{i,t} = \hat{\beta}_x + 2\hat{\beta}_{xx}x_{i,t} + \hat{\beta}_{xj}j_{i,t} + \hat{\beta}_{xh}h_{i,t} \tag{49}$$

Tables D.22 and D.23 show average estimates of input elasticities using all the different estimation methodologies, and with different measures of the capital input. Reassuringly, the estimated elasticities and markups are in line with the recent studies performing similar estimations (Blattner et al. (2019) for Portugal, Fonseca and Van Doornik (2019) for Brazil and Lenzu and Manaresi (2018) for Italy).

C.2 Markups and marginal products

The estimation of output elasticities makes it possible to also estimate firms' markups and evaluate the marginal revenue product of inputs in production.

In order to estimate firm level markups, we rely on the procedure laid out by De Loecker and Warzynski (2012), who use the first-order condition of the flexible inputs to impute the ratio of prices to costs. We use the intermediate input for this task, given that, as discussed above, labor is likely to be a dynamic input in our context, and is surely subject to some degree of adjustment costs. The markup can be obtained as

$$\hat{\mu}_{i,t} = \hat{\theta}^m_{i,t}\left(\frac{P_{i,t}Q_{i,t}}{P^m_{i,t}M_{i,t}}\right) \tag{50}$$

As in De Loecker and Warzynski (2012), we can only imperfectly measure the expenditure share of materials in gross output, given the likely presence of measurement error in the estimation of Equation (36). For this reason, we divide gross output in equation (50) by $\exp(\hat{\varepsilon}_{i,t})$, the residual from the first stage regression in the production function estimation procedure. Per De Loecker and Warzynski (2012) this correction helps eliminating any variation in expenditure shares coming from variation in output not correlated with $\phi(l_{i,t}, k_{i,t}, m_{i,t})$, that is "output variation not related to variables impacting input demand".[37]

Given the estimated markups and elasticities, it is possible to obtain estimates of the distortion in labor and capital utilization, namely the differences (gaps) between their estimated marginal products and their cost. Taking into account a model in which firms compete monopolistically and choose their input demand level at each period, we can derive revenue marginal product (MRP) as

$$MRP^X_{i,t} \equiv \frac{\partial(P_{i,t}(Q_{i,t})Q_{i,t})}{\partial X_{i,t}} = \underbrace{P_{i,t}\frac{\partial Q_{i,t}}{\partial X_{i,t}}}_{VMP^X_{i,t}}\underbrace{\left(1 + \frac{Q_{i,t}}{P_{i,t}}\frac{\partial P_{i,t}}{\partial Q_{i,t}}\right)}_{\mu^{-1}_{i,t}} = \theta^X_{i,t}\frac{P_{i,t}Q_{i,t}}{X_{i,t}}\frac{1}{\mu_{i,t}} \tag{51}$$

and as such MRP - cost gaps as

$$\text{MRPK-cost gap}_{i,t} = \hat{\theta}^k_{i,t}\frac{P_{i,t}Y_{i,t}}{K_{i,t}}\frac{1}{\hat{\mu}_{i,t}} - R_{i,t} \tag{52}$$

$$\text{MRPL-cost gap}_{i,t} = \hat{\theta}^l_{i,t}\frac{P_{i,t}Y_{i,t}}{L_{i,t}}\frac{1}{\hat{\mu}_{i,t}} - W_{i,t} \tag{53}$$

$R_{i,t}$ consists of the depreciation rate, which we keep at 7 percent as in the PIM exercise, and the average interest

[37] We mainly focus on the estimates of markups and marginal products coming from the Ackerberg et al. (2015) translog specification, as in the Cobb-Douglas case elasticities do not vary within industry, and as such markups for instance are solely determined by the ranking in corrected expenditure shares, and not by possible variation in output elasticities and inputs utilization.

rate paid by the firm on its debt, which is the ratio of interest expenditures to total debt. When the information is missing, similarly to Fonseca and Van Doornik (2019) we impute interest rates as the average yearly interest rate at the 2-digit industry level.[38] For the average wage $W_{i,t}$, we divide the total wage bill by the number of employees (either taken from the QP when available, or as the full-time equivalent count in the CB for the remaining firms).[39]

These gaps convey information on how much a firm is constrained in the demand for an input (in case the gap is positive) or is overusing it and likely the optimal downward adjustment in its usage is hindered by adjustment costs (negative gaps).

Table D.24 displays our estimates of costs, marginal revenue products and gaps. Even in this case, quite reassuringly, our estimates of gaps are in the same ballpark of magnitude of recent studies performing similar exercises (Blattner et al. (2019) for Portugal, Fonseca and Van Doornik (2019) for Brazil and Lenzu and Manaresi (2018) for Italy).

[38]It is not possible to obtain more precise interest rates estimates for different kind of loans and credit instruments for the years of the analysis. The variation in results is minimal if using finer definitions of industry.

[39]For this estimation, one would ideally want to have more precise estimates of the marginal costs of inputs of production than the average yearly estimates of firm wage and user cost of capital. Reassuringly, studies in which data allow to gauge the distinction between average and marginal cost levels do not seem to find dramatic differences in gaps estimated according to the different costs definitions (see Lenzu and Manaresi (2018) for the difference in estimated gaps using average versus marginal wages.

D Appendix Tables

Table D.1: Average prevailing interest rates on non-financial bank loans

	ST rates	MT rates	LT rates	Euribor - 1y
2005	4.57	4.14	4.04	2.33
2006	5.23	4.72	4.66	3.44
2007	6.13	5.58	5.54	4.45
2008	6.76	6.12	5.97	4.81
2009	4.69	4.10	3.78	1.62
2010	4.23	3.32	2.99	1.35
2011	5.72	4.55	3.85	2.00
2012	6.33	5.16	3.87	1.11
2013	5.91	4.99	3.46	0.54

Yearly (simple) average of monthly rates on loans for non-financial corporations.
Short term loans defined as loans with maturity less than one year. Medium term loans defined as loans with maturity between 1 and 5 years. Long term loans defined as loans with maturity greater than 5 years.
Source: Monetary and financial statistics, Bank of Portugal.

Table D.2: Share of secured credit, firm level

	(1) ST	(2) LT	(3) Diff.
Sh. secured loans	0.25	0.50	
Sh. secured credit	0.40	0.62	0.22***
	(0.43)	(0.40)	138.46
Sh. fully secured credit	0.21	0.38	0.17***
	(0.33)	(0.40)	122.03
Sh. financial collateral	0.04	0.07	0.03***
	(0.18)	(0.21)	33.11
Sh. real collateral mortgage	0.07	0.21	0.14***
	(0.23)	(0.35)	121.83
Sh. personal guarantee	0.37	0.50	0.14***
	(0.42)	(0.42)	83.50
N	140592	131845	

The table refers to all firms in a CRC-QP match in the sectors of analysis (excluding, agriculture, mining, energy production and distribution and construction). The share of secured loans refers to the actual share of loans that have any sort of collateralization backing it. All other statistics are aggregated at the firm level and refer to shares of total regular credit available to firms.
Column (3) shows the results of t-test for the difference of the means, T-stats reported.

Table D.3: Firm level descriptive statistics, sample of analysis - workforce composition

	Mean	SD	p25	p50	p75
Pre - 2009					
Share of managers	0.13	0.15	0.02	0.09	0.17
Specialized workers	0.33	0.27	0.10	0.24	0.52
Generic workers	0.51	0.31	0.22	0.56	0.79
High education	0.11	0.17	0.00	0.05	0.12
Medium education	0.47	0.24	0.28	0.45	0.65
Low education	0.42	0.29	0.16	0.41	0.65
Under 30	0.25	0.17	0.12	0.22	0.35
Att. incumbents	0.68	0.19	0.58	0.72	0.82
Post - 2009					
Share of managers	0.15	0.18	0.04	0.10	0.19
Specialized workers	0.37	0.27	0.14	0.31	0.56
Generic workers	0.47	0.30	0.20	0.50	0.73
High education	0.13	0.19	0.00	0.07	0.16
Medium education	0.52	0.24	0.34	0.52	0.70
Low education	0.35	0.27	0.10	0.32	0.55
Under 30	0.18	0.16	0.07	0.15	0.27
Att. incumbents	0.55	0.23	0.40	0.58	0.73

Descriptive statistics for the full (unbalanced) sample of analysis, with N=14,864 distinct firms. All workforce decomposition variables from QP.

Table D.4: Robustness: instrument effects on credit post-2010

	(1)	(2)	(3)	(4)	(5)
			$\Delta D_{st,2013-2010}$		
$\Delta D_{i;st,2010-2006}$	-0.220***	-0.231***	-0.253***	-0.254***	-0.251***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Z_i	0.240	-0.041	-0.148	-0.176	-0.154
	(0.277)	(0.257)	(0.260)	(0.262)	(0.261)
W. Sov.				-0.980+	
share in Q4-2009, 2005 banks				(0.588)	
W. Sov.					-1.242*
share in Q4-2009, 2009 banks					(0.629)
Firms	12883	12865	12061	12061	11882
Fixed effects	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes

The regressions refer to the empirical specification in equation (4) in the text.
See the table 4 for the list of further controls and fixed effects in the regressions.
The sample consists of firms with (short-term) credit relationships in 2010.
Columns 4 and 5 control directly for firms (weighted) exposure to banks average sovereign debt holdings over assets in 2009 (Q4), either considering banks with which the firms has a relationship in 2005 (4) or 2009 (5).
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.5: Employment regressions, first stage

	(1)	(2)	(3)	(4)	(5)
			S_i		
Z_i	-1.761***	-1.706***	-1.716***	-1.702***	-1.766***
	(0.301)	(0.276)	(0.280)	(0.285)	(0.293)
Firms	14846	14830	13833	13806	11802
Sample	Complete	Complete	Complete	Complete	Survivors
Fixed effects	No	Yes	Yes	Yes	Yes
Controls	No	No	Fail b.c.	Yes	Yes

The table shows the estimation results of the first stage regressions of the credit variation S_i on the instrument Z_i. All regressions feature firm and time fixed effects.
See the table 4 for the list of controls and fixed effects in the regressions.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6: Employment regressions, reduced form

	(1)	(2)	(3)	(4)
		$log(\#emp)_{i,t}$		
Z_i	-0.123**	-0.120**	-0.120**	-0.152***
	(0.051)	(0.052)	(0.053)	(0.054)
Firms	14830	13833	13806	11802
Sample	Complete	Complete	Complete	Survivors
Fixed effects	Yes	Yes	Yes	Yes
Controls	No	Fail b.c.	Yes	Yes

All regressions feature firm and time fixed effects. See the table 4 for the list of controls and fixed effects in the regressions.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7: Hours regressions

	(1)	(2)	(3)	(4)
	$log(\#\ hours)_{i,t}$		$log(\#\ base\ hours)_{i,t}$	
S_i	0.067*	0.085*	0.067*	0.085*
	(0.034)	(0.035)	(0.034)	(0.035)
Firms	13806	11802	13806	11802
EFF. WID F	34.56	35.55	34.56	35.55
Sample	Complete	Survivors	Complete	Survivors

The dependent variables are either the total amount of work hours (columns 1 and 2) or the total amount of normal contract hours, which does not comprehend extraordinary or overtime hours of work.
See the table 4 for the list of controls and fixed effects in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.8: Employment - wage bill regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	$Employees_{i,t}$		$Wage\ bill_{i,t}$		$Base\ wage\ bill_{i,t}$	
S_i	0.069*	0.083*	0.100**	0.122**	0.102**	0.116**
	(0.031)	(0.033)	(0.038)	(0.041)	(0.038)	(0.040)
Firms	13806	11802	13806	11802	13806	11802
EFF. WID F	34.56	35.55	34.56	35.55	34.56	35.55
Sample	Complete	Survivors	Complete	Survivors	Complete	Survivors

The dependent variable in these regressions is the ratio of the number of workers (or the wage bill) to the average level of the pre-period corresponding amount.
The outcome variable is winsorized at the top 1% level.
See the table 4 for the list of controls and fixed effects in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.9: Heterogeneous employment regressions: Contracts

	(1)	(2)	(3)	(4)
	$Permanent\ w_{\cdot i,t}$		$Temporary\ w_{\cdot i,t}$	
S_i	0.098+	0.158*	0.174	0.145
	(0.057)	(0.062)	(0.147)	(0.150)
Firms	13657	11681	11829	10129
EFF. WID F	37.00	38.37	31.02	32.94
Sample	Complete	Survivors	Complete	Survivors

The dependent variable in these regressions is the ratio of the number of specific workers to the average level of the pre-period corresponding amount. As such, the regressions are defined only for the firms for which the kind of worker is present in the pre-period (even if missing values for some years are possible).
Temporary workers are workers hired with a fixed-term contract.
The outcome variable is winsorized at the top 1% level.
See the table 4 for the list of controls and fixed effects in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.10: Heterogeneous employment regressions: Education

	(1)	(2)	(3)	(4)	(5)	(6)
	$High\ educ._{i,t}$		$Medium\ educ._{i,t}$		$Low\ educ._{i,t}$	
S_i	0.030	-0.048	0.222**	0.271***	0.057	0.065+
	(0.138)	(0.133)	(0.071)	(0.080)	(0.036)	(0.036)
Firms	9539	8228	13699	11710	12679	10833
EFF. WID F	30.45	32.25	33.01	34.07	38.51	41.89
Sample	Complete	Survivors	Complete	Survivors	Complete	Survivors

The dependent variable in these regressions is the ratio of the number of specific workers to the average level of the pre-period corresponding amount. As such, the regressions are defined only for the firms for which the kind of worker is present in the pre-period (even if missing values for some years are possible).
High educated obtained at least an undergraduate degree. Medium educated workers completed high school or an equivalent level professional school. Low educated workers did not complete high school or an equivalent professional school.
The outcome variable is winsorized at the top 1% level.
See the table 4 for the list of controls and fixed effects in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.11: Robustness: Almeida et al. (2011) identification, effects on fixed investments

	(1)	(2)
	$log(fixed\ assets)_{i,t}$	
S_i	0.017	0.031
	(0.074)	(0.120)
$S_i \cdot exp\_lt_i$		-0.025
		(0.119)
exp_lt_i	-0.090***	-0.095***
	(0.015)	(0.026)
Firms	11799	11799
Sample	Survivors	Survivors

The regressions refer to the empirical specification in equation (8) in the text.
The treatment is interacted with a dummy variable equal to 1 if the firm has long-term debt maturing in the first two semester of 2009. As a consequence, we instrument the interacted treatment with the interaction of the same dummy and the baseline instrument Z_i. We also control for the dummy variable itself, interacted with the post-period dummy to allow for different rends depending on the long-term debt maturing soon after the credit shock.
The regressions are carried out on the sample of firms surviving up to 2013.
See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.12: Average wage regressions

	(1)	(2)
	$log(Avg.\ wage)_{i,t}$	$log(Avg.\ wage)_{inc08;i,t}$
S_i	0.018	0.023
	(0.015)	(0.017)
Firms	13806	13804
EFF. WID F	34.56	34.56
Sample	Complete	Complete

The dependent variable for column 1 is the logarithm of the average wage for all employees. The dependent variable for column 3 is the logarithm of the average wage for incumbent workers in 2008 who remain in the firm. See the table 4 for the list of controls and fixed effects in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.13: Regressions by attachment

	(1)	(2)
	$log(Att.\ empl.)_{i,t}$	$log(Low\ att.\ empl.)_{i,t}$
S_i	0.040	0.104*
	(0.028)	(0.049)
Firms	13726	13198
EFF. WID F	37.21	36.63
Sample	Complete	Complete

The dependent variable for column 1 is the logarithm of the number of attached employees in 2008, whereas the dependent variable for column 2 is the logarithm of the number of less attached employees in 2008. We define attached workers as workers present in the firm for the entirety of the pre-period. We define less attached employees as all other incumbent employees present in the firm in 2008.
See the table 4 for the list of controls and fixed effects in the regressions. All regressions feature the full set of fixed effects and controls.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.14: Loan level regressions: productivity

	(1)	(2)	(3)	(4)
		$\Delta D_{i;st,pre-post}$		
FD_b, $Low\ TFP$	-2.237***	-2.347***	-2.318***	-2.235***
	(0.276)	(0.308)	(0.256)	(0.264)
, $Med.\ TFP$	-1.941***	-2.314***	-2.278***	-2.457***
	(0.309)	(0.312)	(0.268)	(0.274)
, $High\ TFP$	-2.376***	-1.927***	-2.346***	-2.245***
	(0.294)	(0.274)	(0.275)	(0.263)
Firms	9206	9206	12703	12703
Firm FE	Yes	Yes	No	No
Other FE	No	No	Yes	Yes
TFP Measure	CD ACF	TSLOG ACF	CD ACF	TSLOG ACF

In columns 1 and 3 TFP is the residual of a CD three factors production function, whereas in columns 2 and 4 the production function is TSLOG. The estimation always follows De Loecker and Warzynski (2012); Ackerberg et al. (2015). In columns 1 and 2 firm fixed effects control for unobservable firms' characteristics time-trends. In columns 6-7 we control for fixed effects for observables, but no firm fixed effect. Samples are firms with loans with more than one bank (essential to identify the firm fixed effect) across all specifications in the table.
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 to the year 2014.
Sample sizes depend on availability of non-missing variables in CB.
Standard errors in parentheses, clustered at the firm and bank-by-3 digits industry level.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.15: Regressions by CD productivity bins (Ackerberg et al. (2015))

	(1)	(2)
	$log(\#emp)_{i,t}$	$P(exit)_{i,t}$
S_i, $Low\ TFP$	0.070+	-0.033*
	(0.037)	(0.013)
, $Med.\ TFP$	0.087*	-0.015
	(0.042)	(0.013)
, $High\ TFP$	0.080+	-0.017
	(0.042)	(0.016)
Firms	13287	13277
WID F	10.84	11.47
Sample	Complete	Complete
Firm FE	Yes	No
Other FE	Yes	Yes

See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls. In addition to that specification we control for average TFP in 2005 and 2006 (estimated according to to the method proposed in De Loecker and Warzynski (2012); Ackerberg et al. (2015) by means of a three factors of production gross output Cobb-Douglas production function). TFP can be estimated for less firms than the full samples depending on availability of the variables to compute it in CB. Moreover, given that we cannot control for unobservable characteristics in the exit specification through firm fixed effects any more, we try to characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failed up until the year 2014.
We control linearly for the baseline effect of productivity.
In the exit specification the fixed effects are interacted with year dummies, whereas the controls are kept constant and not interacted with any year dummy. In the employment specifications all variables are interacted with a post-period dummy.
Sample sizes depend on availability of non-missing variables in CB.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.16: Regressions by OLS CD productivity bins

	(1) $log(\#emp)_{i,t}$	(2) $P(exit)_{i,t}$
S_i, $Low\ TFP$	0.048	-0.023+
	(0.037)	(0.012)
, $Med.\ TFP$	0.104*	-0.026+
	(0.042)	(0.016)
, $High\ TFP$	0.088*	-0.019
	(0.045)	(0.017)
Firms	13287	13277
WID F	10.91	10.64
Sample	Complete	Complete
Firm FE	Yes	No
Other FE	Yes	Yes

See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls. In addition to that specification we control for average TFP in 2005 and 2006 (estimated by OLS by means of a three factors of production gross output Cobb-Douglas production function). TFP can be estimated for less firms than the full samples depending on availability of the variables to compute it in CB. Moreover, given that we cannot control for unobservable characteristics in the exit specification through firm fixed effects any more, we try to characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks failed up until the year 2014.
We control linearly for the baseline effect of productivity.
In the exit specification the fixed effects are interacted with year dummies, whereas the controls are kept constant and not interacted with any year dummy. In the employment specifications all variables are interacted with a post-period dummy.
Sample sizes depend on availability of non-missing variables in CB.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.17: Regressions by OLS TSLOG productivity bins

	(1) $log(\#emp)_{i,t}$	(2) $P(exit)_{i,t}$
S_i, $Low\ TFP$	0.079*	-0.029*
	(0.040)	(0.015)
, $Med.\ TFP$	0.070+	-0.019
	(0.038)	(0.013)
, $High\ TFP$	0.080+	-0.020
	(0.041)	(0.015)
Firms	13287	13277
WID F	10.87	11.50
Sample	Complete	Complete
Firm FE	Yes	No
Other FE	Yes	Yes

See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls. In addition to that specification we control for average TFP in 2005 and 2006 (estimated by OLS by means of a three factors of production gross output translog production function). TFP can be estimated for less firms than the full samples depending on availability of the variables to compute it in CB. Moreover, given that we cannot control for unobservable characteristics in the exit specification through firm fixed effects any more, we try to characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failed up until the year 2014.
We control linearly for the baseline effect of productivity.
In the exit specification the fixed effects are interacted with year dummies, whereas the controls are kept constant and not interacted with any year dummy. In the employment specifications all variables are interacted with a post-period dummy.
Sample sizes depend on availability of non-missing variables in CB.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.18: Regressions by TSLOG productivity bins (Ackerberg et al. (2015))

	(1) $log(\#emp)_{i,t}$	(2) $P(exit)_{i,t}$
S_i, $Low\ TFP$	0.080*	-0.034*
	(0.039)	(0.015)
, $Med.\ TFP$	0.077*	-0.015
	(0.037)	(0.012)
, $High\ TFP$	0.072	-0.022
	(0.045)	(0.017)
Firms	13287	13277
WID F	11.12	11.59
Sample	Complete	Complete
Firm FE	Yes	No
Other FE	Yes	Yes

See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls. In addition to that specification we control for average TFP in 2005 and 2006 (estimated by the Ackerberg et al. (2015) methodology by means of a three factors of production gross output translog production function). TFP can be estimated for less firms than in the full samples depending on availability of the variables to compute it in CB. Moreover, given that we cannot control for unobservable characteristics in the exit specification through firm fixed effects any more, we try to characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failed up until the year 2014.
We control linearly for the baseline effect of productivity.
In the exit specification the fixed effects are interacted with year dummies, whereas the controls are kept constant and not interacted with any year dummy. In the employment specifications all variables are interacted with a post-period dummy.
Sample sizes depend on availability of non-missing variables in CB.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.19: Reallocation and TFP by labor share - full dataset

	(1) $exit_{i,t}$	(2) $\Delta\log(emp)_{i,t+1}$	(3) $\Delta\log(ftemp)_{i,t+1}$	(4) $\Delta\log(fixed\,cap.)_{i,t+1}$
$TFP_{i,t} \cdot \mathbb{1}(labsh\_q. = 1)$	-0.0370***	0.0298***	0.0267***	0.0183+
	(0.0049)	(0.0069)	(0.0067)	(0.0105)
$\cdot\,\mathbb{1}(labsh\_q. = 2)$	-0.0390***	0.0339***	0.0325***	0.0249*
	(0.0051)	(0.0070)	(0.0069)	(0.0115)
$\cdot\,\mathbb{1}(labsh\_q. = 3)$	-0.0400***	0.0352***	0.0334***	0.0274*
	(0.0053)	(0.0069)	(0.0070)	(0.0110)
$\cdot\,\mathbb{1}(labsh\_q. = 4)$	-0.0454***	0.0444***	0.0413***	0.0322**
	(0.0049)	(0.0069)	(0.0070)	(0.0105)
$\cdot\,Post\ Lehman_t \cdot$	0.0005	-0.0001	0.0000	-0.0014
$\cdot\,\mathbb{1}(labsh\_q. = 1)$	(0.0010)	(0.0035)	(0.0032)	(0.0048)
$\cdot\,\mathbb{1}(labsh\_q. = 2)$	0.0005	-0.0049	-0.0055	-0.0107
	(0.0008)	(0.0036)	(0.0034)	(0.0066)
$\cdot\,\mathbb{1}(labsh\_q. = 3)$	0.0011	-0.0059	-0.0064	-0.0062
	(0.0010)	(0.0042)	(0.0041)	(0.0056)
$\cdot\,\mathbb{1}(labsh\_q. = 4)$	0.0027+	-0.0095***	-0.0087**	-0.0119*
	(0.0015)	(0.0027)	(0.0028)	(0.0056)
$asinh(VA/emp)_{2005-2008}$	-0.0112***	-0.0031*	0.0014	0.0077+
	(0.0011)	(0.0013)	(0.0013)	(0.0040)
Firms	178294	170044	169324	176376
N	802568	767934	762156	845980
Industry FE	Yes	Yes	Yes	Yes
Labor share quartile by post-Lehman FE	Yes	Yes	Yes	Yes

The regressions refer to the empirical specification in equation (20) in the text. A different coefficient is jointly estimated for each labor share bin, and a variation of slope is estimated for the years post 2008.
Labor share is computed as the average ratio of employment costs over value added for the years from 2005 to 2008. In all specifications a control for the average value added per employee in the period from 2005 to 2008 is added.
All regressions feature 3-digits industry fixed effects, and labor share quartile by post-Lehman dummy fixed effects.
The sample consists of all firms in QP matched with CB for which TFP can be computed (with the exclusion of the energy and construction sector).
All variables refer to the outcomes from t to $t+1$. We measure employment either as total headcount of full time equivalent employment, as reported in CB. The exit regression excludes the year 2005, given the CB structure.
Standard errors clustered at the 3-digits industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.20: Marginal revenue products - cost gaps regressions

	(1)	(2)	(3)
	$MRPL_{i,t}$	$MRPL_{book;i,t}$	$Avg.\ wage_{i,t}$
S_i	-0.993+	-0.987	0.018
	(0.599)	(0.606)	(0.015)
Firms	11710	12005	13806
WID F	29.34	29.06	35.63
Sample	Complete	Complete	Complete

MRPLs are expressed in thousand euros.
In columns 1 the MRPL is obtained given estimation of output elasticities with capital computed through PIM.
In column 2 MRPL is obtained given estimation of output elasticities with book value of capital.
Outcome variables are winsorized at 0.5^{th} and 99.5^{th} percentiles.
See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls.
Regressions are run on the full sample for all firms for which it was possible to calculate the MRP-cost gaps.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.21: Wedge regressions

	(1)	(2)	(3)
	$Lab.\ wedge_{i,t}$	$Cap.\ wedge_{i,t}$	$Mat.\ wedge_{i,t}$
S_i	-0.0080+	0.0023	-0.0081
	(0.0047)	(0.0049)	(0.0092)
Firms	11710	12823	12988
WID F	29.34	35.37	34.90
Sample	Complete	Complete	Complete

Outcome variables are winsorized at 0.5^{th} and 99.5^{th} percentiles.
See Table 4 for a list of the added controls and fixed effects present in the regressions. All regressions feature the full set of fixed effects and controls.
Regressions are run on the full sample for all firms for which it was possible to calculate the input wedges.
Standard errors clustered at the bank-industry pair level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.22: Revenue elasticities and markups, PIM capital

	CD		TSLOG		ACF CD		ACF TSLOG	
	Mean	IQR	Mean	IQR	Mean	IQR	Mean	IQR
θ^L	0.20	0.13	0.21	0.18	0.22	0.11	0.21	0.19
	(0.0001)		(0.0003)		(0.0001)		(0.0003)	
θ^K	0.03	0.02	0.03	0.03	0.02	0.01	0.03	0.02
	(0.00003)		(0.00005)		(0.00001)		(0.00004)	
θ^M	0.74	0.19	0.73	0.21	0.71	0.14	0.72	0.21
	(0.0002)		(0.0003)		(0.0002)		(0.0003)	
RS	0.97	0.04	0.97	0.05	0.96	0.02	0.96	0.04
	(0.0001)		(0.0001)		(0.0002)		(0.0001)	
μ					1.33	0.34	1.26	0.16
					(0.0009)		(0.0003)	

The table displays descriptive statistics regarding firm-level production function parameters, returns to scale and markups. Mean, interquartile ranges and block bootstrapped standard errors (by firm) for the mean. We show estimates for the two specifications of the gross production function (Cobb-Douglas and translog) and two methodologies we use. The first two columns are estimated by simple OLS, whereas the second two are estimated following the method by Ackerberg et al. (2015), which accounts for endogeneity in the choice of inputs use and we correct for firm selection. See appendix C for details regarding the estimation procedure. Returns to scale are computed as $\sum_X \theta^X_{i,t}$ $X \in \{L, K, M\}$. Markups are estimated according to the method laid out by De Loecker and Warzynski (2012), see appendix C.2 for details regarding the estimation procedure.
The table results are based on estimates of the production function where capital is measured according to the perpetual inventory method (PIM).

Table D.23: Revenue elasticities and markups, book v. of capital

	CD		TSLOG		ACF CD		ACF TSLOG	
	Mean	IQR	Mean	IQR	Mean	IQR	Mean	IQR
θ^L	0.20	0.13	0.21	0.18	0.23	0.14	0.21	0.18
	(0.0001)		(0.0003)		(0.0002)		(0.0003)	
θ^K	0.03	0.02	0.03	0.03	0.02	0.01	0.04	0.02
	(0.00003)		(0.00005)		(0.00001)		0.00005	
θ^M	0.74	0.19	0.73	0.21	0.72	0.17	0.71	0.20
	(0.0002)		(0.0003)		(0.0002)		(0.0003)	
RS	0.97	0.04	0.97	0.05	0.97	0.02	0.95	0.04
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
μ					1.34	0.33	1.25	0.14
					(0.0008)		(0.0002)	

The table displays descriptive statistics regarding firm-level production function parameters, returns to scale and markups. Mean, interquartile ranges and block bootstrapped standard errors (by firm) for the mean. We show estimates for the two specifications of the gross production function (Cobb-Douglas and translog) and two methodologies we use. The first two columns are estimated by simple OLS, whereas the second two are estimated following the method by Ackerberg et al. (2015), which accounts for endogeneity in the choice of inputs use and we correct for firm selection. See appendix C for details regarding the estimation procedure. Returns to scale are computed as $\sum_X \theta^X_{i,t}$ $X \in \{L, K, M\}$. Markups are estimated according to the method laid out by De Loecker and Warzynski (2012), see appendix C.2 for details regarding the estimation procedure.
The table results are based on estimates of the production function where capital is measured as the net book value of balance sheet.

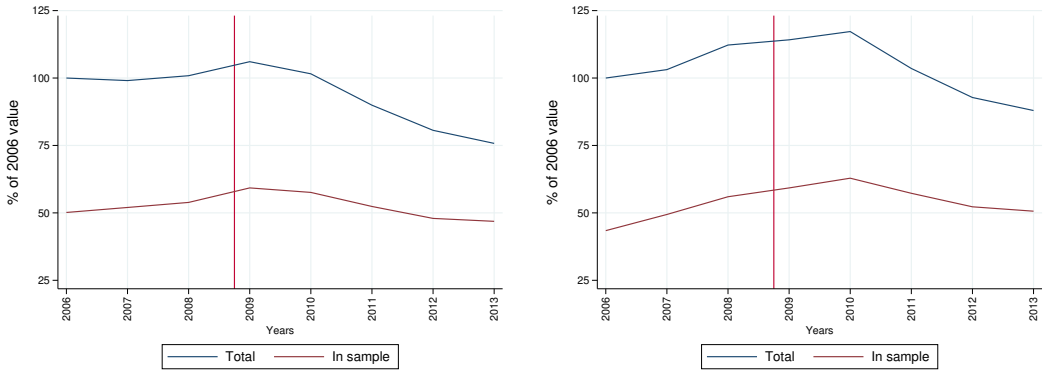
Table D.24: MRPs, user costs and gaps, full CB

	Mean	p50	p10	p90	Mean	p50	p10	p90
Panel A								
r	0.07	0.05	0.00	0.14				
w	10.59	9.27	5.21	17.35				
Panel B	PIM capital				Book v. capital			
MRP^L	13.39	10.53	3.64	25.54	13.19	10.29	3.96	24.64
	(0.0271)				(0.0262)			
MRP^K	0.38	0.21	0.06	0.83	0.33	0.18	0.05	0.68
	(0.0010)				(0.0010)			
$Lab. Gap$	2.37	1.23	-4.19	9.81	2.20	0.93	-3.68	8.80
	(0.0153)				(0.0136)			
$Cap. Gap$	0.23	0.09	-0.09	0.70	0.18	0.05	-0.10	0.54
	(0.0010)				(0.0009)			

Panel A reports descriptive statistics regarding the distribution of measured interest rates and firm level (average) wages. Interest rates are measured as the ratio of interest expenses of the firm over the total stock of debt (as reported in CB, which comprehends both bank debt and any other form of debt financing for the firm). The average wage is simply calculated as the ratio of salaries to employees, where total salaries are taken from CB and employees are either employment as measured from QP or full time equivalent employment from CB is the former data is missing.
Panel B reports descriptive statistics regarding marginal products and marginal products-cost gaps. The labor marginal product and gap are measured in thousands of Euros. Block bootstrapped standard errors (by firm) displayed for the means. We report statistics both for the marginal products and gaps based on elasticities and values of variables when capital is computed according to the perpetual inventory method (PIM) or the net book value.
See appendix C.2 for details regarding the computations.

E Appendix Figures

Figure E.1: Credit dynamics in Portugal

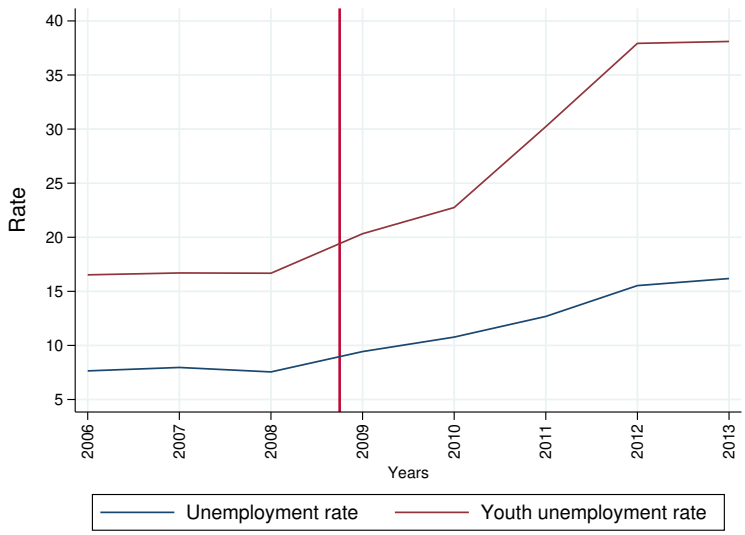


(a) Total regular credit

(b) Long-term regular credit

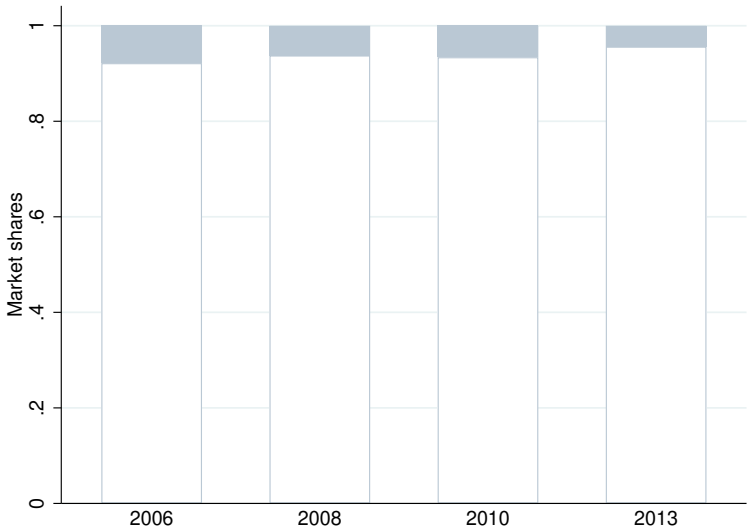
The Figures show the time series for the aggregate amount of total regular (left) and long-term credit (right) for the firms and banks in the sample. Total regular credit is credit not overdue or in renegotiation available to the firm. Long-term credit is any credit exposure with maturity greater than one year, with the exclusion of credit lines with no maturity. The red dotted line splits the sample in pre-period and post-period. Totals are expressed as a percentage total regular credit in 2006.
Source: *Central de Responsabilidades de Crédito* merged with *Quadros de Pessoal* (left), *Central de Responsabilidades de Crédito* merged with *Quadros de Pessoal* and banks' balance sheets (right), authors' calculations and sample selection.

Figure E.2: Unemployment rate



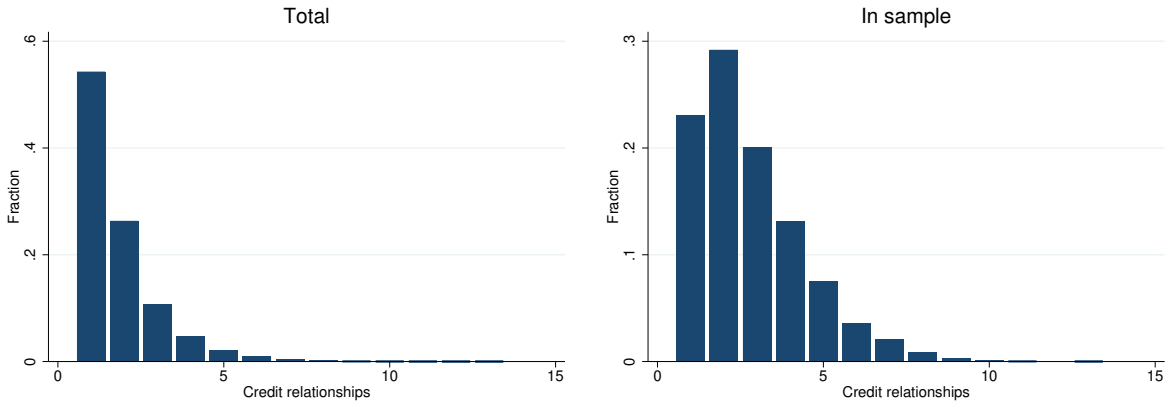
The Figure shows the time series of the unemployment rate in Portugal, both for all workers (blue) and for workers below 25 years old (red).
Source: OECD.

Figure E.3: Bank concentration by total regular credit



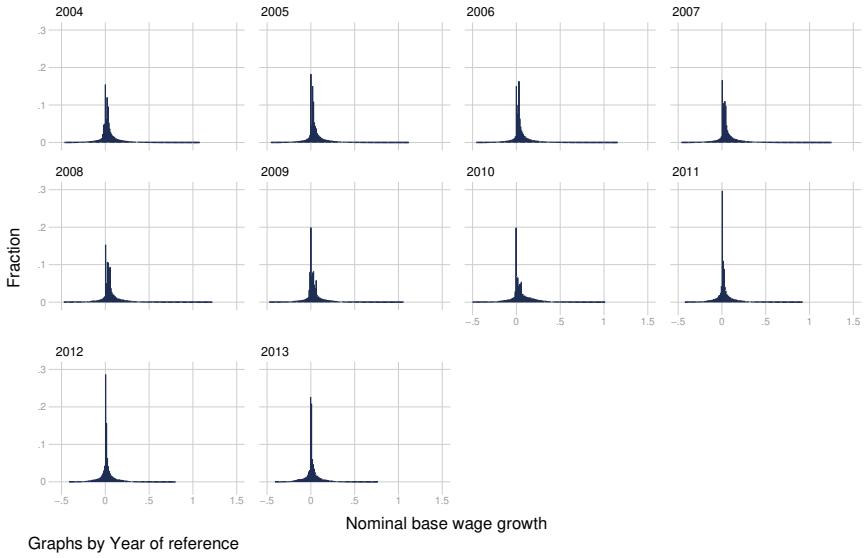
Banking groups market shares in terms of total regular credit, top 10 vs. all other banks. The sample of reference is all firms in QP with credit. Only banks surviving up to 2009 are included, consistently with the sample definition for the empirical event study.
Source: *Central de Responsabilidades de Crédito* merged with *Quadros de Pessoal*, authors' calculations and sample selection.

Figure E.4: Number of credit relationships



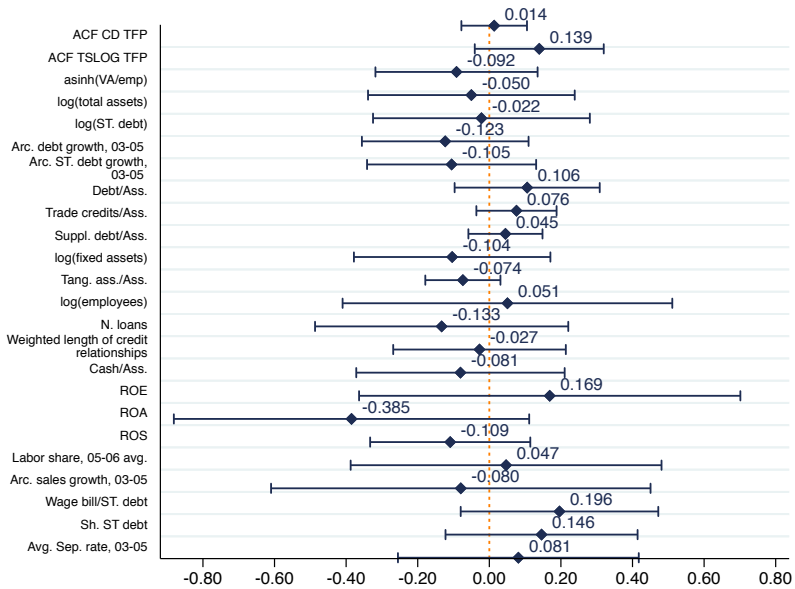
The Figure shows the distribution of the number of credit relationships by firm in 2005 for all firms with credit and in the QP (left) and for the firms in the sample of analysis (right).
Source: *Central de Responsabilidades de Crédito* merged with *Quadros de Pessoal*, authors' calculations and sample selection.

Figure E.5: Distribution of nominal base-wage growth in Portugal



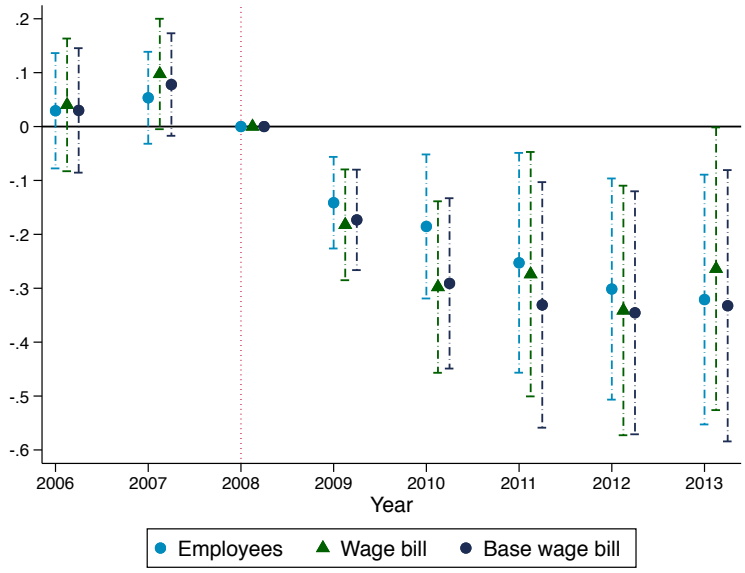
Distribution of the nominal base-wage growth at the worker's level in Portugal, by year. Base wage comprehends only regular compensations, without accounting for any overtime payments, and refers to the October of each year. Source: Full *Quadros de Pessoal* dataset, cleaned for inconsistent workers' identifiers. Authors' calculations and sample selection.

Figure E.6: Balance checks (Borusyak et al., 2019)



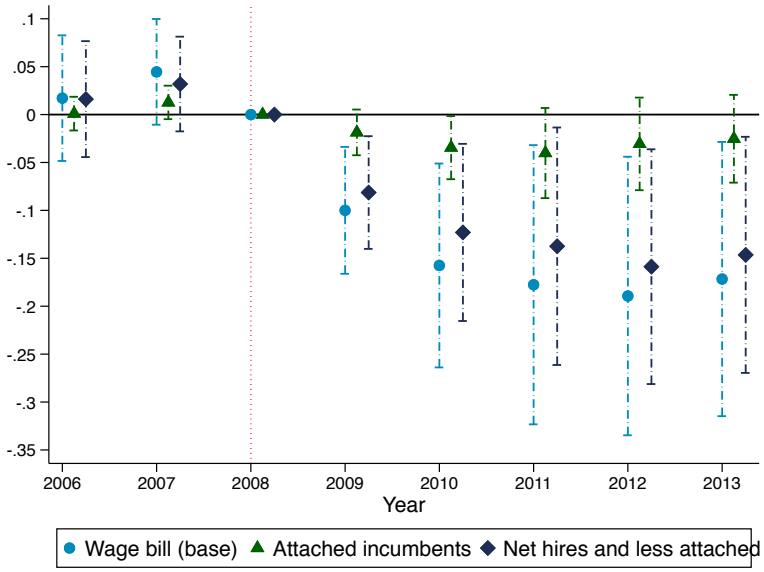
The Figure shows the coefficients (with 95% confidence intervals) of pairwise regressions of the standardized value of each variable in 2005 (unless reported otherwise) on the (standardized value of the) instrument Z_i. The regressions are run at the bank level, and all regressors are weighted bank exposures to firm characteristics, according to the method exposed in (Borusyak et al., 2019). Before weighting firm characteristics at the bank level, the variables are regressed on the fixed effects used throughout the analysis in the paper (see Table 4 for a list), and residuals are calculated and used in the analysis. Standard errors robust to heteroskedasticity.

Figure E.7: Employment and wage-bill regressions: event study, reduced form



The dependent variables in these regressions are the ratios of the number of employees and the wage bill (total and base) over the average of their levels in the pre-period (2006-2008). 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 or wage bill with respect to the 2008 level.
See Table 4 for the list of controls and fixed effects in the regressions. All regressors and fixed effects are interacted with a year dummy.
Number of firms: 11,802, survivors sample.
95% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.8: Wage bill adjustment by tenure: event study

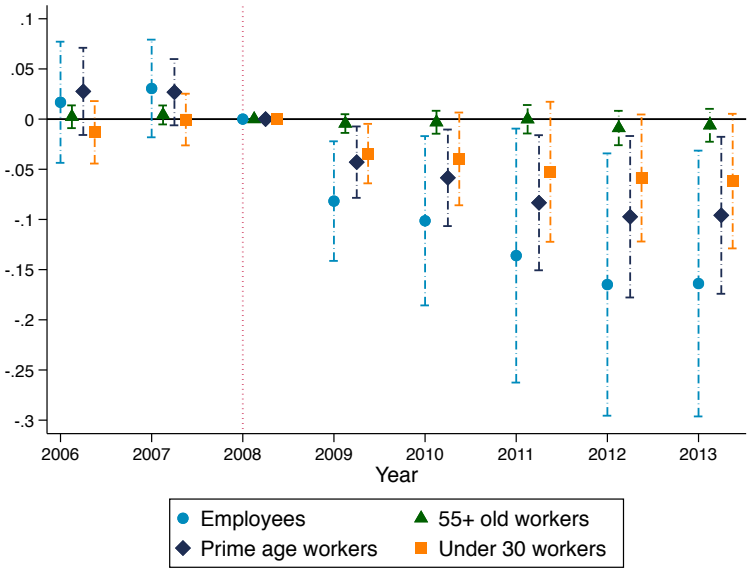


The dependent variables in these regressions are the ratio of the the base-wage bill going to employees of the specific category over the average level of base-wage bill in the pre-period (2006-2008). By construction, the sum of the coefficients for the attached incumbents and net hires should be equal to the overall base-wage bill effect. In the specifications the coefficients for 2008 are normalized to 0, so that all the other coefficients should be interpreted as the effect on the percentage variation of (each kind of) wage bill with respect to the 2008 level.
Attached incumbents are defined as workers present at the firm for the entirety of the pre-period, and net hires are all other workers (less attached workers or hires/separations in the post period). In order to get a sense of the implied elasticities of adjustment, one should divide the estimated coefficient by the share of wage bill going to attached workers in the pre-period.
The sample includes only survivor firms (N = 11,809), but is not balanced. The graph displays the effect of a negative shock.
See Table 4 for the list of controls and fixed effects present in the regressions. All regressors and fixed effects are interacted with a year dummy.
95% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.9: Qualifications regressions, event study

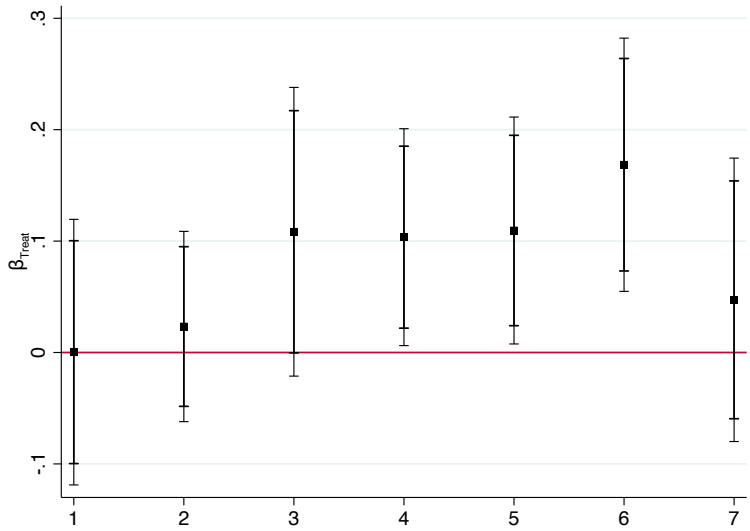
The dependent variables in these regressions are the ratios of the total number of employees and the number of employees by qualification over the average number of employees in the pre-period (2006-2008). See Appendix B.1.1 for more details. In the specifications the coefficient for the year 2008 are 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 Table 4 for the list of controls and fixed effects in the regressions. All regressors and fixed effects are interacted with a year dummy.
See Table D.3 for descriptives statistics on the relative shares of workers in the workforce in the pre- and post-period.
Number of firms: 11,802, survivors sample. Pre-period sh. of managers: 13%. Share of specialized workers: 33%. 95% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.10: Age regressions, event study



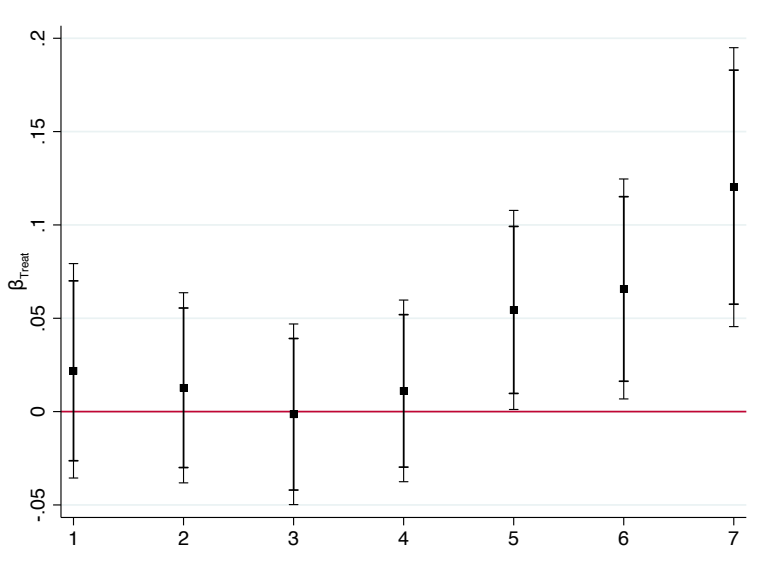
The dependent variables in these regressions are the ratios of the total number of employees and the number of employees by age over the average number of employees in the pre-period (2006-2008). See Appendix B.1.1 for more details. In the specifications the coefficient for the year 2008 are normalized 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 Table 4 for the list of controls and fixed effects in the regressions. All regressors and fixed effects are interacted with a year dummy.
See Table D.3 fothe r descriptives statistics on the relative shares of workers in the workforce in the pre- and post-period.
Number of firms: 11,802, survivors sample. Pre-period share of under 31: 25%. Share of above 54: 8%.
95% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.11: Employment regressions by labor-share bins, survivors sample

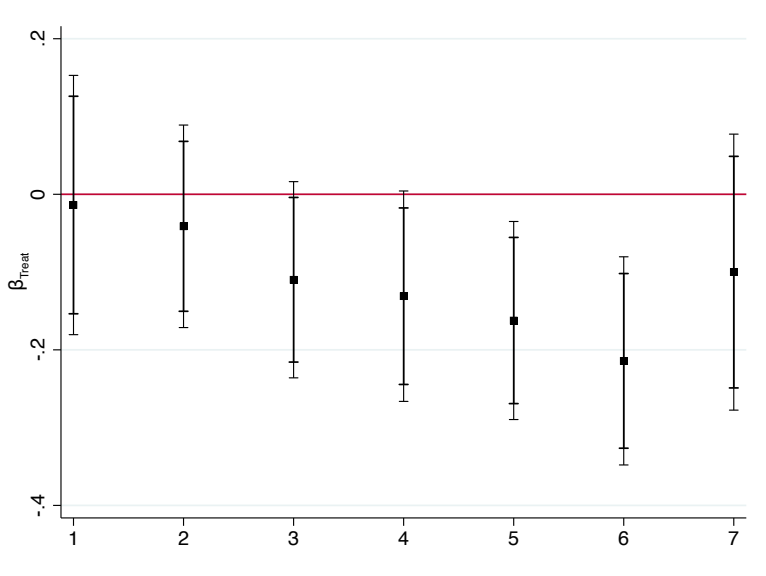


We estimate a coefficient for each of the seven labor-share bins, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels).
See Table 4 for the list of controls and fixed effects in the regressions. All fixed effects and controls are interacted with a *post* dummy.
Number of firms: 11,768, survivors sample.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.12: Regressions by labor-share bins, reduced form



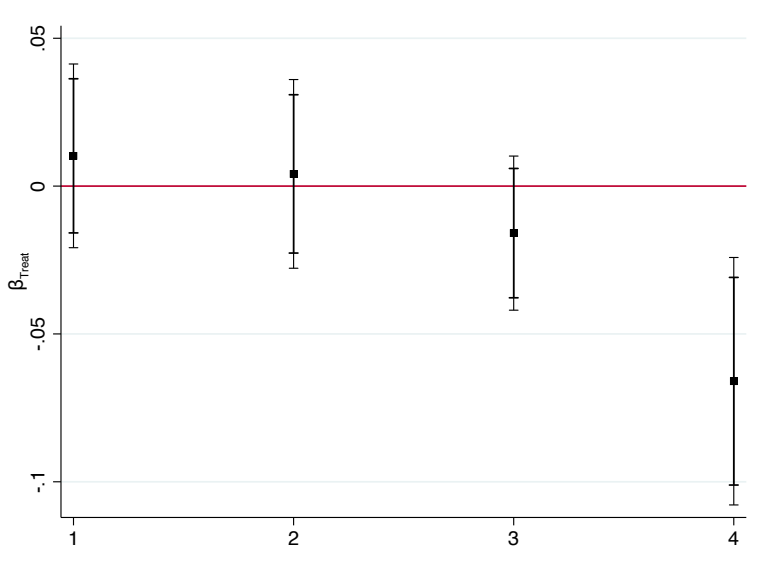
(a) Exit



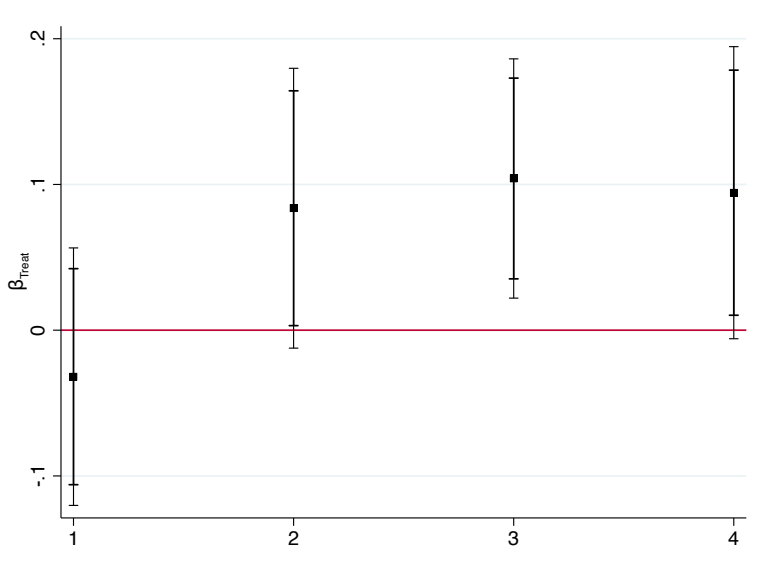
(b) Employment

We estimate a coefficient for each of the seven labor-share bins, while controlling for baseline effects linearly and for the interacted instruments. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels).
See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects any more, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit specification. In the employment specification all fixed effects and controls are interacted with a *post* dummy.
Number of firms: 13,750 (exit), 13,760 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.13: Regressions by labor-share quartiles



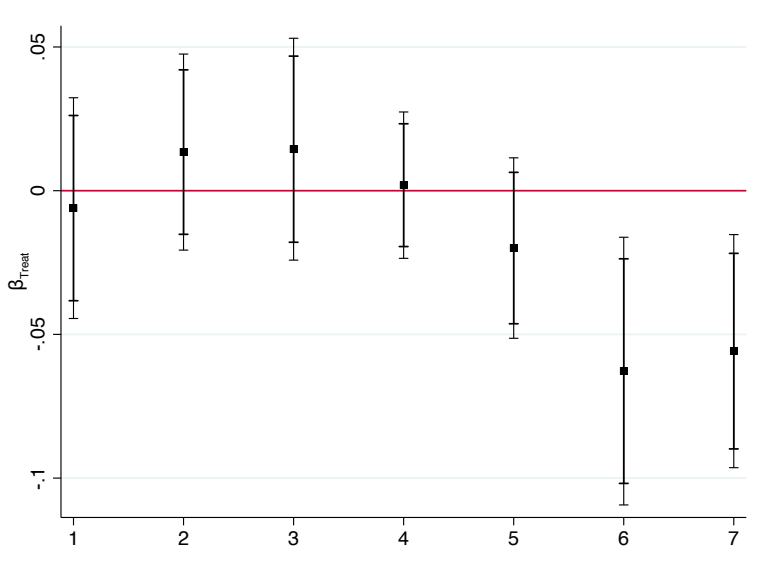
(a) Exit



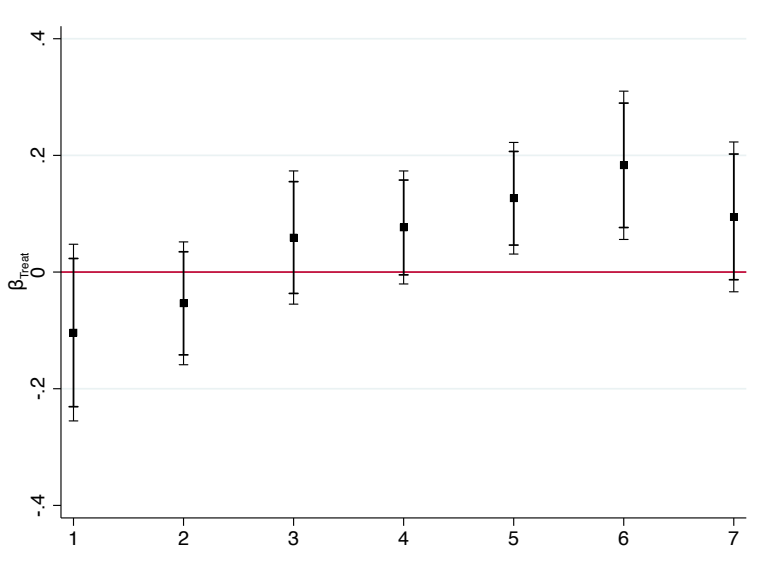
(b) Employment

We estimate a coefficient for each of the four labor-share quartiles, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument.
See Table 4 for the list of controls and fixed effects present in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,750 (exit) and 13,760 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.14: Regressions by residualized labor-share bins



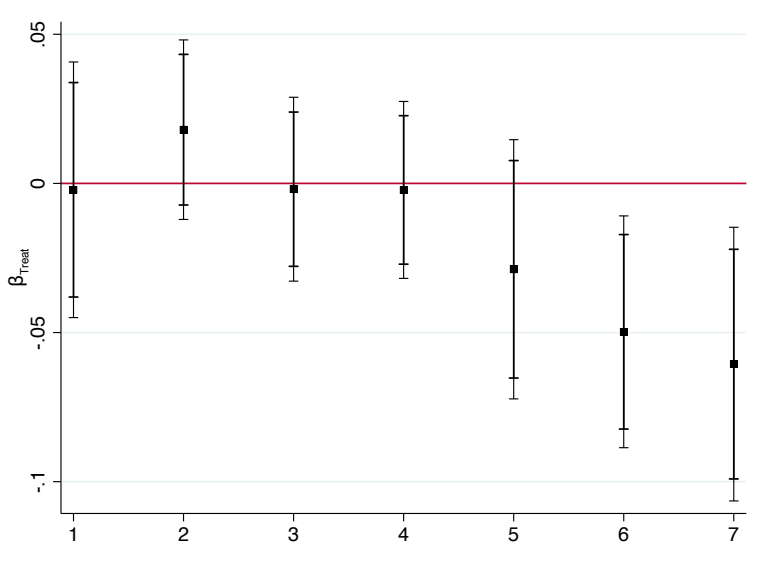
(a) Exit



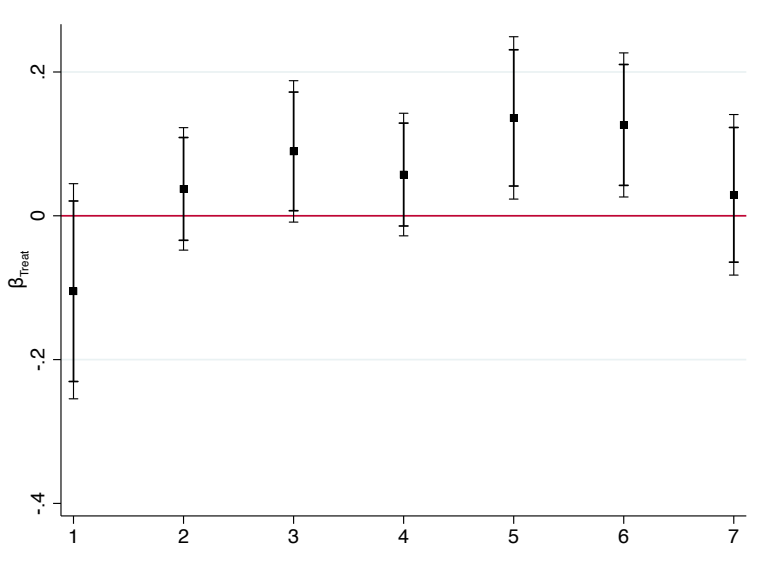
(b) Employment

We obtain the residualized labor shares by calculating the residuals in a regression of the labor share over value added per employee (2005-2006 average values) and the set of fixed effects that we control for in the regressions. We estimate a coefficient for each of the seven labor-share bins, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument.
See Table 4 for the list of controls and fixed effects present in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,740 (exit) and 13,750 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.15: Regressions by labor-share bins (alternative measure)



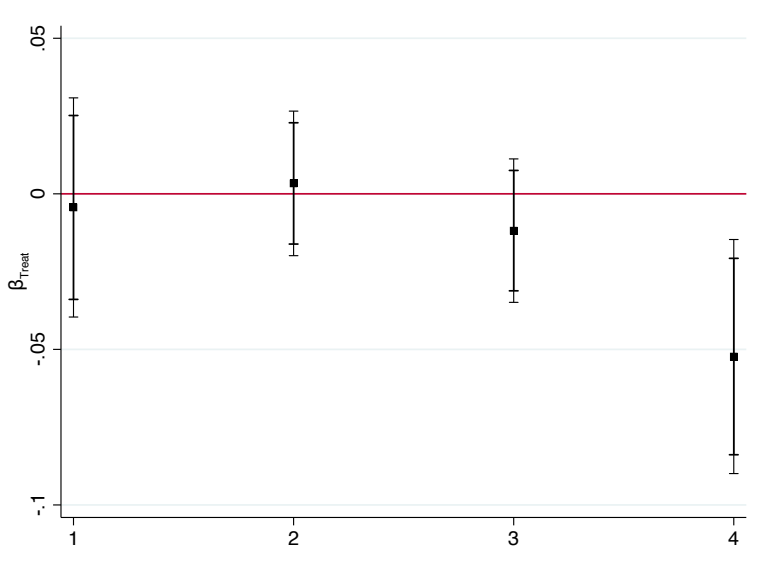
(a) Exit



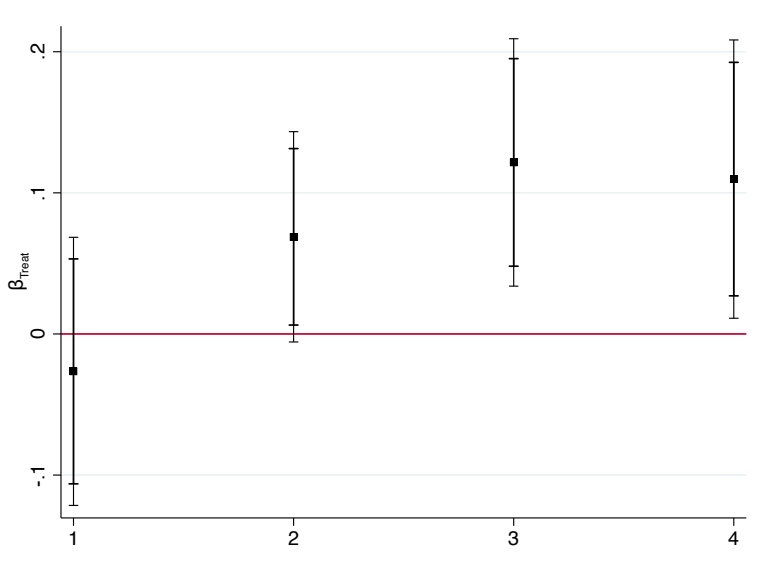
(b) Employment

The alternative labor-share measure uses wage bills calculated from the QP as a measure of labor costs. We estimate a coefficient for each of the seven labor-share bins, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument.
See Table 4 for the list of controls and fixed effects present in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,714 (exit) and 13,724 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.16: Regressions by labor-share quartiles in sales



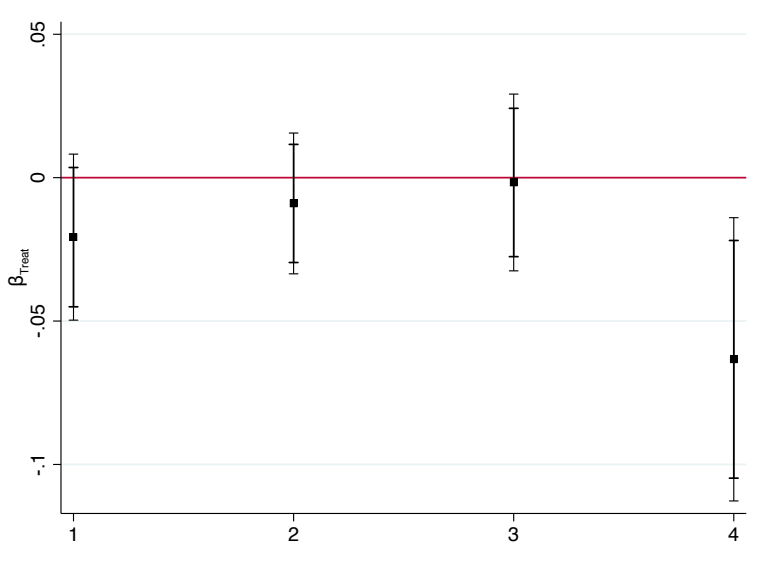
(a) Exit



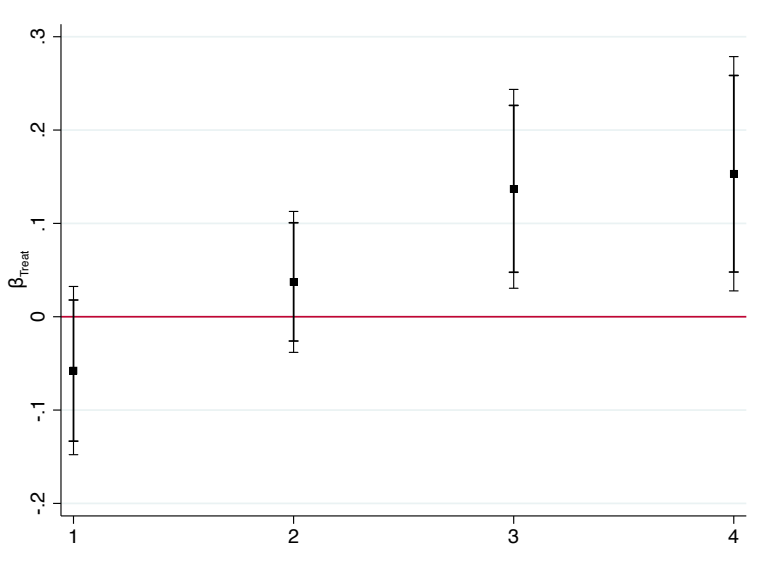
(b) Employment

We estimate a coefficient for each of the seven labor-share bins, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total sales.
See Table 4 for the list of controls and fixed effects present in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
In order to be consistent with the value added specifications, we use sales per employee instead of value added per employee as the measure of labor productivity.
Number of firms: 13,750 (exit) and 13,760 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.17: Regressions by labor-share bins (2007-2008 averages)



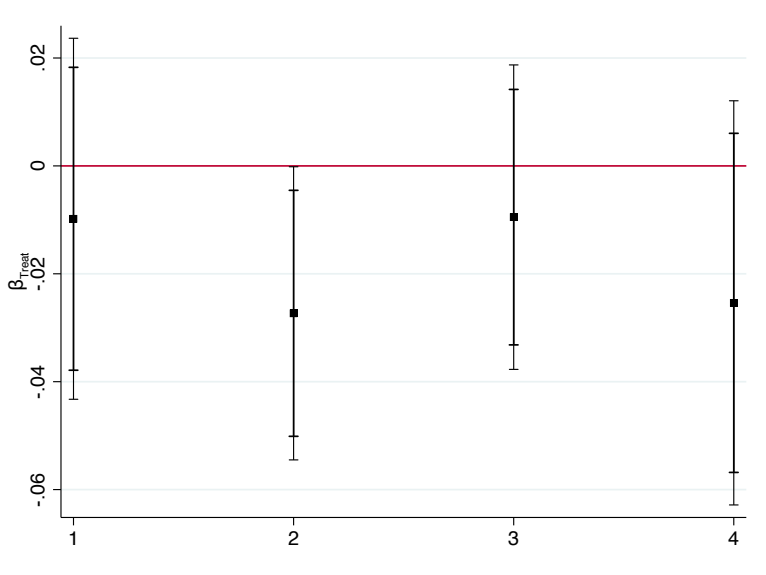
(a) Exit



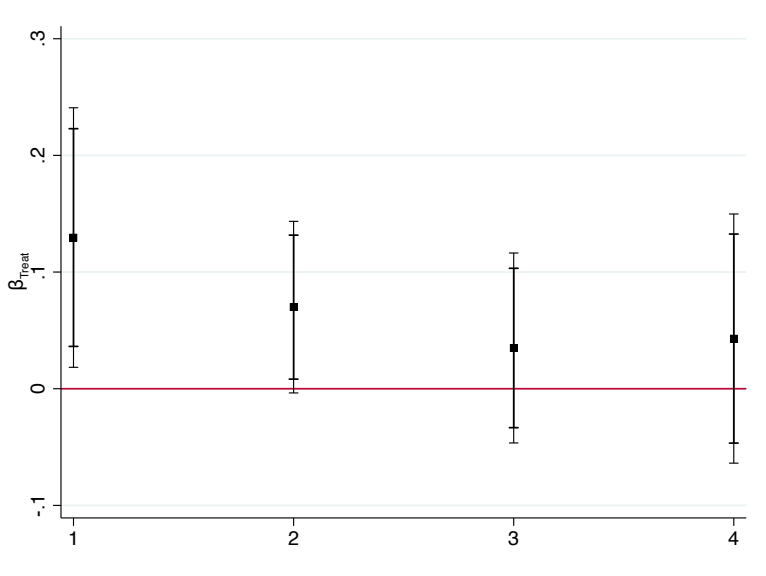
(b) Employment

The alternative labor-share measure uses wage bills calculated from the QP as a measure of labor costs. We estimate a coefficient for each of the seven labor-share bins, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2007-2008 levels).
See Table 4 for the list of controls and fixed effects present in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,750 (exit) and 13,760 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.18: Regressions by leverage bins



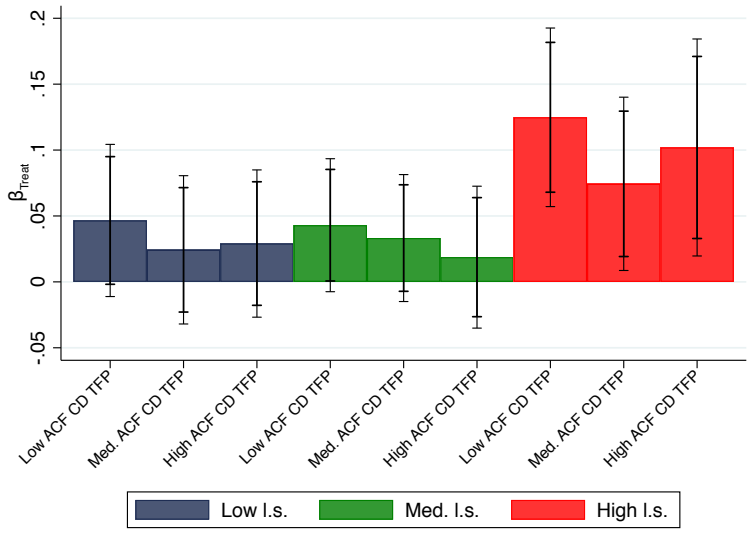
(a) Exit



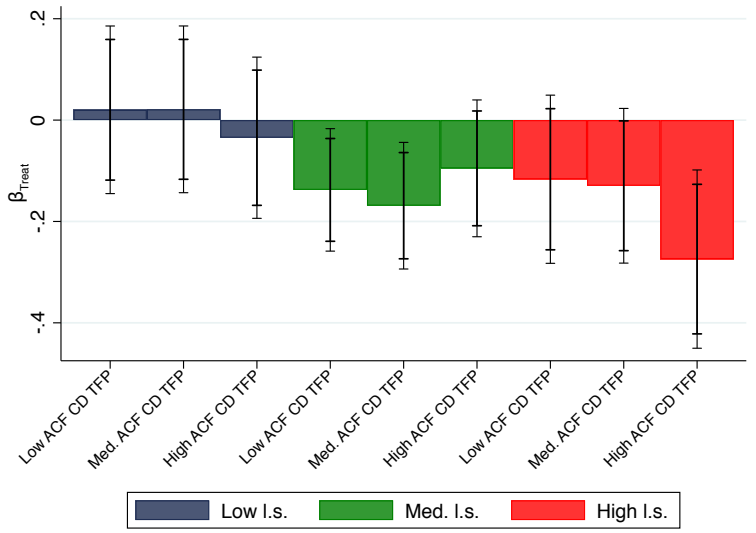
(b) Employment

We estimate a coefficient for each of the four leverage quartiles, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument. Leverage is defined as the ratio between total regular credit to total assets (2005 levels).
See Table 4 for the list of controls and fixed effects present in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the bank-firm matching by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,796 (exit) and 13,806 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.19: Regressions by labor-share and productivity bins, reduced form



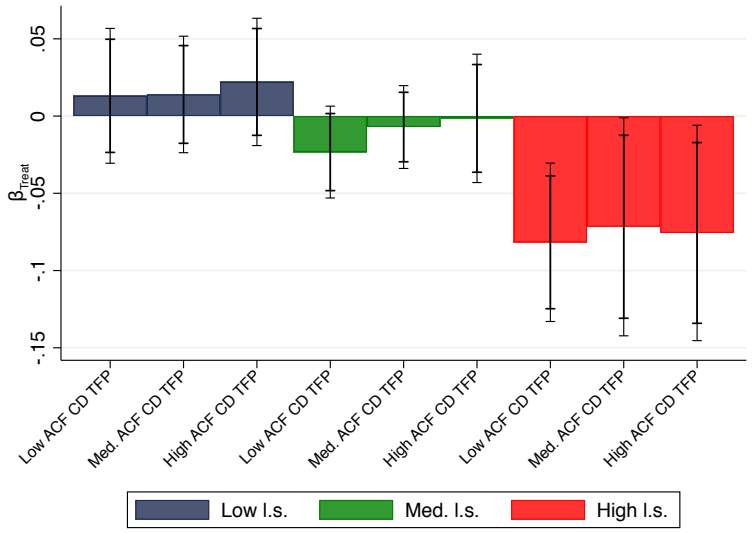
(a) Exit



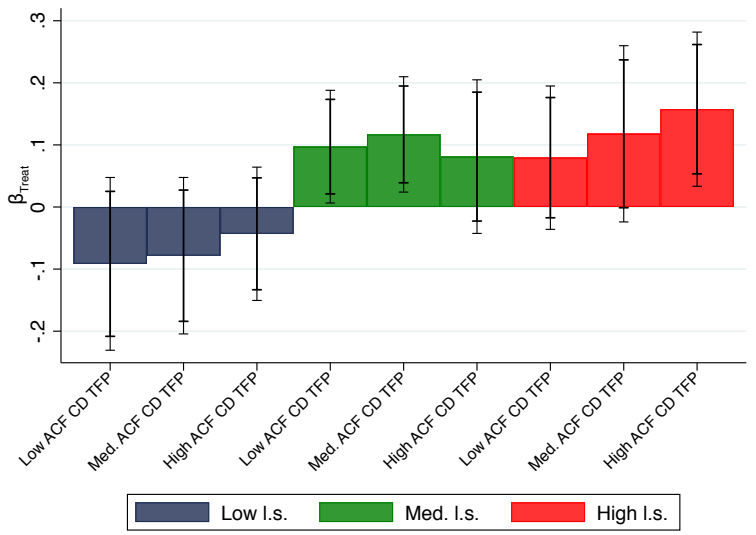
(b) Employment

We estimate a coefficient for each of the nine interacted bins, while controlling linearly for baseline effects and their interaction. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels). Productivity is estimated on a 3-inputs gross sales Cobb-Douglas production function following Ackerberg et al. (2015), by 2-digit industrial sectors.
See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,248 (exit) and 13,258 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.20: Regressions by residualized labor-share and productivity bins



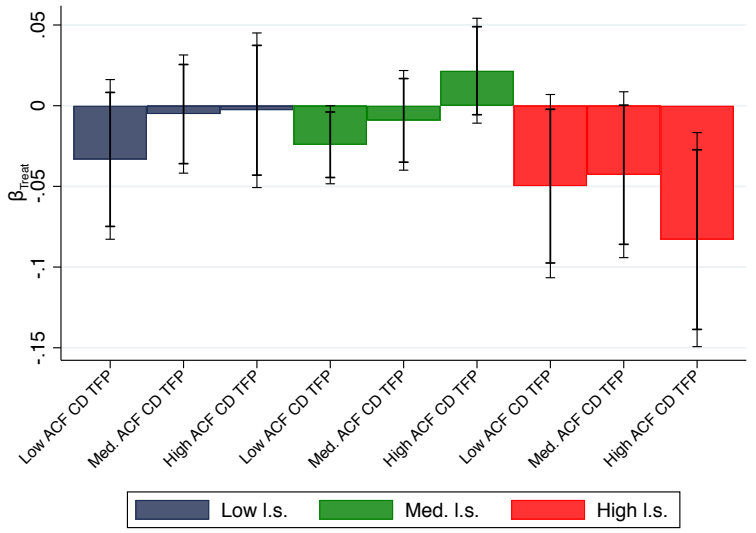
(a) Exit



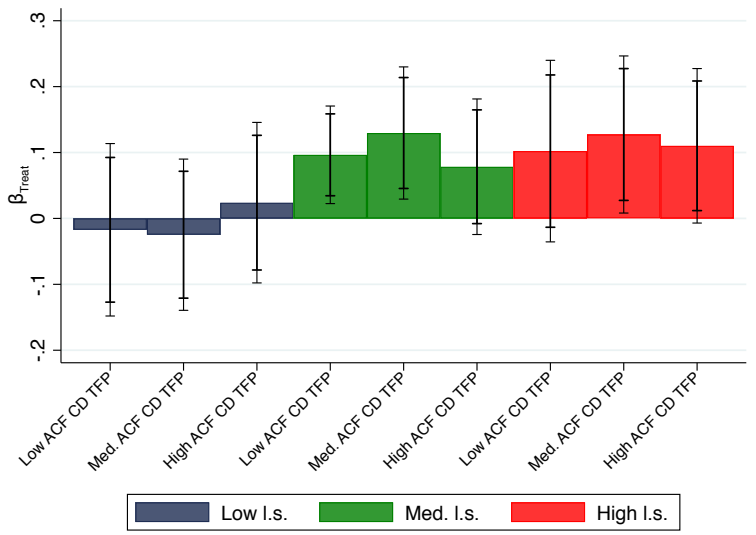
(b) Employment

We obtain the residualized labor shares by calculating the residuals in a regression of the labor share over value added per employee (2005-2006 average values) and the set of fixed effects that we control for in the regressions. We estimate a coefficient for each of the nine interacted bins, while controlling linearly for baseline effects and their interaction. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels). Productivity is estimated on a 3-inputs gross sales Cobb-Douglas production function following Ackerberg et al. (2015), by 2-digit industrial sectors.
See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,238 (exit) and 13,248 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.21: Regressions by labor-share in sales and productivity bins



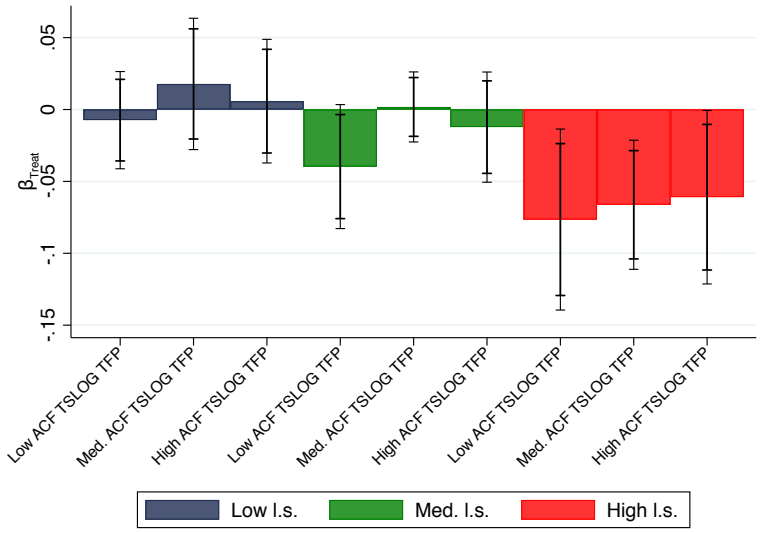
(a) Exit



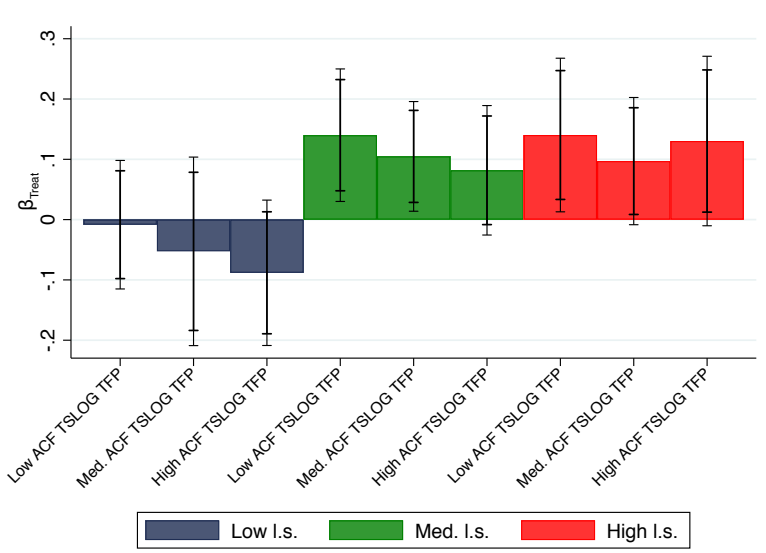
(b) Employment

We estimate a coefficient for each of the nine interacted bins, while controlling linearly for baseline effects and their interaction. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total sales (average of 2005-2006 levels). Productivity is estimated on a 3-inputs gross sales Cobb-Douglas production function following Ackerberg et al. (2015), by 2-digit industrial sectors.
See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,258 (exit) and 13,258 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.22: Regressions by labor-share and TSLOG-ACF-productivity bins



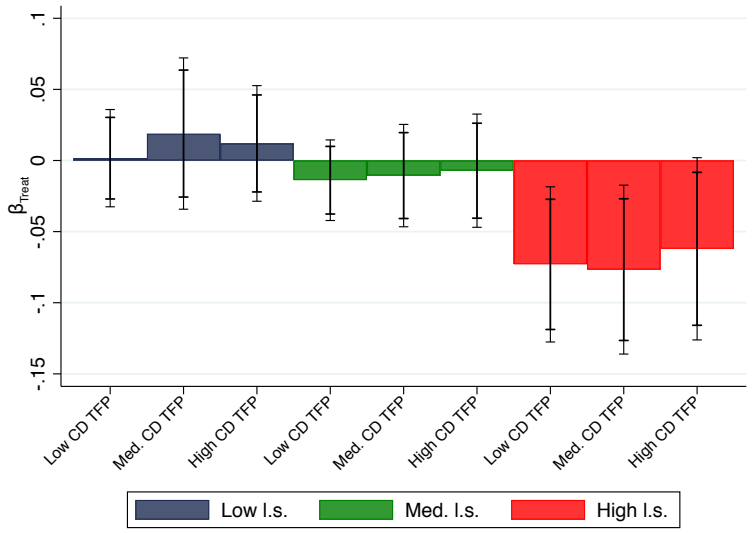
(a) Exit



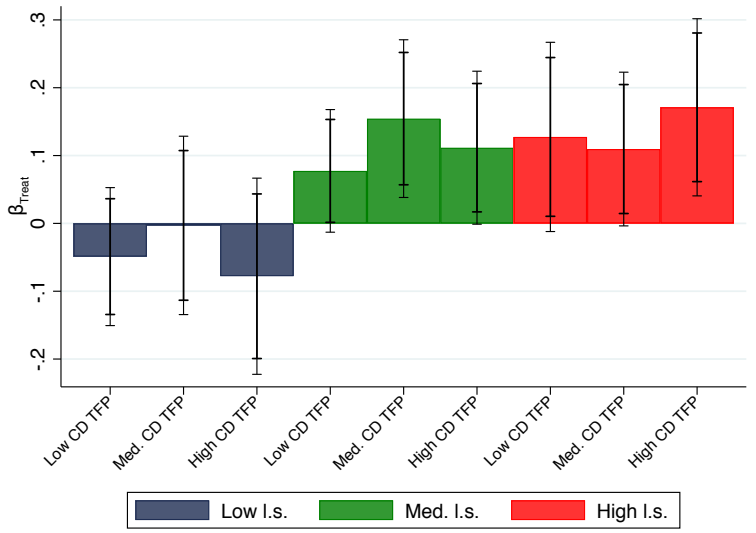
(b) Employment

We estimate a coefficient for each of the nine interacted bins, while controlling linearly for baseline effects and their interaction. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels). Productivity is estimated on a 3-inputs gross sales translog production function following Ackerberg et al. (2015), by 2-digit industrial sectors.
See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 12,927 (exit) and 12,927 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.23: Regressions by labor-share and CD-productivity bins, OLS



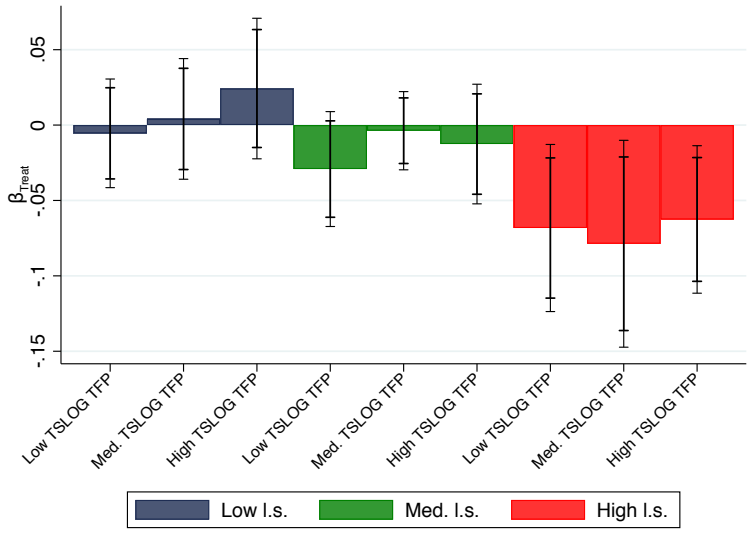
(a) Exit



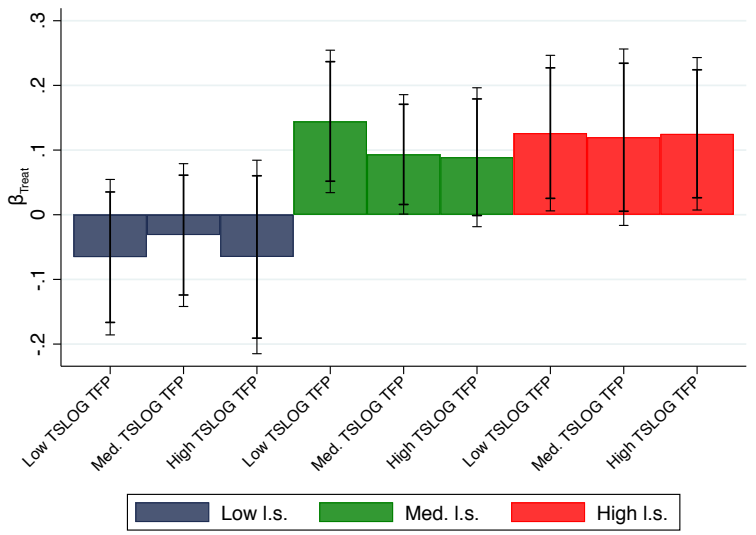
(b) Employment

We estimate a coefficient for each of the nine interacted bins, while controlling linearly for baseline effects and their interaction. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels). Productivity is estimated on a 3-inputs gross sales Cobb-Douglas production function by OLS and by 2-digit industrial sectors. See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,248 (exit) and 13,258 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.24: Regressions by labor-share and TSLOG-productivity bins, OLS



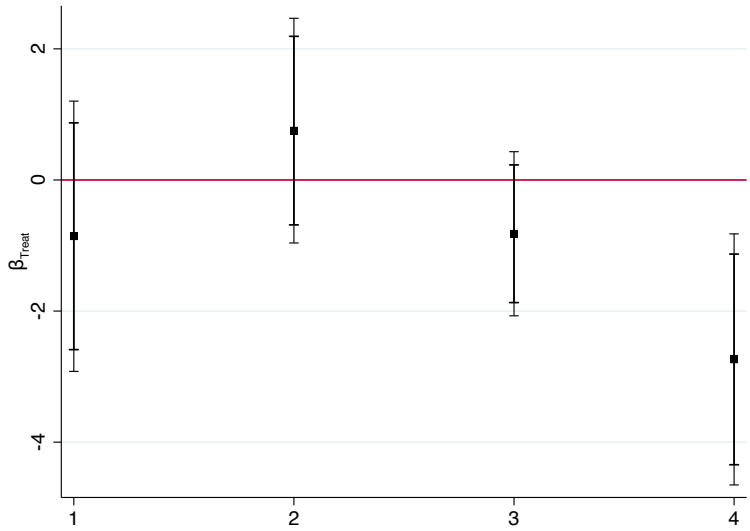
(a) Exit



(b) Employment

We estimate a coefficient for each of the nine interacted bins, while controlling linearly for baseline effects and their interaction. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels). Productivity is estimated on a 3-inputs gross sales translog production function by OLS and by 2-digit industrial sectors.
See Table 4 for the list of controls and fixed effects in the regressions. Given that we cannot control for unobservable characteristics in the exit specifications through firm fixed effects, we characterize the matching of firms to banks by augmenting the set of controls with the share of loans that each firm has with micro banks and with banks failing up to 2014.
All fixed effects are interacted with a year dummy, while regressors are constant in the exit regressions. In the employment regressions fixed effects and regressors are interacted with the Post dummy.
Number of firms: 13,248 (exit) and 13,258 (employment). Sample size depends on availability of non-missing variables in CB.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.

Figure E.25: Labor MRP-cost gap regressions by labor-share quartiles



The labor MRP-cost gap is defined as the difference between the estimated marginal revenue product of labor and the average firm wage. See Appendix C.2 for more details. We estimate a coefficient for each of the four labor-share quartiles, while controlling linearly for baseline effects. Each interacted treatment is instrumented by the interacted instrument. Labor share is defined as the ratio between employment-related costs and total value added (average of 2005-2006 levels).
See Table 4 for the list of controls and fixed effects present in the regressions. Additional controls for these specification using O*NET variables include the scores for: required education, required previous experience and required amount of training on site. Results are unchanged if these additional controls are not added. See Appendix B for a description of each of these variables, and the on-the-job training score as well.
All fixed effects and controls are interacted with a *post* dummy.
Number of firms: 13,750.
95 and 90% confidence intervals displayed, standard errors clustered at the bank-industry pair level.