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Credit supply and human capital: evidence from bank pension liabilities

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Abstract

We identify the effects of exogenous credit constraints on firm ability to attract and retain skilled workers. To do so, we exploit a shock to the value of the pension obligations of Portuguese banks resulting from a change in accounting norms. Using bank-firm credit exposures that we match with a census of all Portuguese employees, we show that firms in a relationship with affected banks borrow less and reduce employment mostly of high-skilled workers. High-skilled workers are more likely to exit and less likely to join affected firms. Overall, credit market frictions might have long lasting effects on firm productivity and growth through firm accumulation of human capital.

JEL classification: G21, J21, J24

Keywords: Credit Frictions, Employment, Skills, Wages

Non-technical Summary

Human capital is an important determinant of firm productivity. The allocation of skilled workers across firms is therefore crucial for growth, and even more so in a knowledge-driven economy. This paper shows that workers' ability to switch firms increases with their skills, due to better outside options. As a result, firms facing exogenous negative shocks - such as tighter financing constraints - face a decrease in the skill intensity of their workforce. Overall, our results suggest that negative shocks related to financial market imperfections can distort the allocation of skills in the economy. To obtain these results, we exploit exogenous variations in firm financing constraints stemming from a shock to the pension liabilities of Portuguese banks in 2005. The shock, which resulted from a change in accounting norms, had a negative and heterogeneous impact on the financial health of the banks sponsoring pension plans. Using comprehensive data linking banks to all Portuguese firms, and firms to all their employees, we show that sponsor banks subsequently reduced credit to firms and that firms in a relationship with these sponsor banks had a lower access to credit. We then investigate the effects on employment across skills and find that the share of skilled workers decreases in affected firms. More precisely, workers with a college degree or occupying skill-intensive jobs - such as managers or specialists - are more likely to leave affected firms and will enjoy a wage premium when they switch firms. Skilled workers are also less likely to join affected firms.

We exploit the introduction of new accounting norms for defined-benefit plans - the International Accounting Standard Nineteen (IAS 19) - in Portugal in 2005 as a shock to bank pension liabilities and their credit supply. In a defined-benefit plan, the bank pledges retirement benefits to employees according to a formula that is a function of each employee's age, tenure and salary. Thus, the defined-benefit plan liabilities are equal to the discounted value of the payments pledged to retirees based on accounting assumptions on discount rates, retirement age, wage growth and life expectancy. The introduction of IAS 19 resulted in large and heterogeneous increases in the accounting value of bank defined-benefit plan liabilities for two reasons. Defined-benefit plans had to cover new types of benefits, and the accounting assumptions, on the other hand, changed significantly: the discount rate decreased while life expectancy estimates were revised upwards.

We identify the effects of the introduction of IAS19 on credit supply and firm employment by matching all bank-firm credit exposures with a census of Portuguese employees. Bank-firm credit exposures come from the Portuguese Credit Register, which collects the credit exposures of all banks and firms in Portugal since 1980 at a monthly frequency. We combine the Credit Register with data from bank, firm and defined-benefit plan financial statements. We then match this dataset with the yearly census of all private sector firms in Portugal, containing detailed information on each employee's career, education, occupation and earnings. This bank-firm-employee matched dataset allows us to study the impact of the shock not only on total firm employment, but also its effects across workers with different skill levels.

Using regression analyses, we show that the share of skilled workers decreases at affected firms and that high-skilled workers are twice more likely to leave affected firms than low-skilled workers. In addition, we study wage changes for switchers and find that college and high-school educated workers experience higher increase in wages after leaving affected firms than after leaving unaffected firms. Regarding the effect on entrants, we also find evidence that entry rates for high-skilled workers at constrained firms are lower following the credit shock.

Overall, our results suggest that regulators should take into consideration how changes in accounting norms and more generally in the regulation of the financing sector can have spill-over effects on the economy. Any policy aiming to reduce credit market imperfections - such as public ratings, accredited certifications for SMEs, information sharing through credit registers, credit guarantees - might also attenuate the distortionary effects of credit market imperfections on the allocation of talent.

1 Introduction

There is a broad consensus that human capital is an important determinant of firm productivity and growth, and that its role might be even more crucial in a knowledge-driven economy (Black and Lynch 1996; Katz and Murphy 1992).[1] Recent literature shows that, when facing adverse credit supply shocks, firms tend to downscale borrowing, investment, and employment (Berton et al. 2018; Bentolila et al. 2017; Jiménez et al. 2017; Siemer 2016). However, little is known about how exogenous credit constraints affect firm ability to accumulate human capital.

In this paper, we show that the skill intensity of the labour force decreases in firms facing exogeneous credit supply shocks. Two mechanisms are at play. First, skilled workers are more likely to leave credit-constrained firms than unskilled workers. The wage premium these skilled workers enjoy when switching from credit-constrained to unconstrained firms suggests that they voluntarily leave for better opportunities. Second, skilled workers are less likely to start working at credit-constrained firms. Overall, these results suggest that credit supply shocks might have long run effects on the productivity of firms and the allocation of talent in the economy.

To estimate the effects of credit constraints on firm human capital, we exploit the adoption of new accounting norms - the *International Accounting Standard Nineteen* (IAS 19) - for bank defined-benefit (DB) pension plans in Portugal in 2005. In a DB plan, banks pledge retirement benefits to their employees. The accounting value of the liabilities of a DB plan is the net present value of these payments. To arrive at this value, the regulator defines 'actuarial' assumptions on the discount rate, the retirement age, the expected wage growth of beneficiaries as well as their life expectancy. In 2004, Portuguese banks had DB plans of heterogeneous size, ranging from 0% - for banks that were relying on the national social security system for their employees - to more than 100% of their common equity. This heterogeneity resulted from institutional changes that had affected

[1] Human capital increases output per worker through three main channels: it facilitates the adoption and the use of new technologies (Acemoglu and Zilibotti 2001), it leads to modern organizational changes (Caroli and Van Reenen 2001), and it has positive externalities on the productivity of other workers (Moretti 2004).

bank decisions to offer a private DB plan and the structure of these DB plans since the 1980s.

The adoption of IAS 19 led to a 35% increase in the accounting value of the liabilities of bank DB plans, resulting in a decline in the internal resources of sponsor banks. IAS 19 required both the inclusion of new benefits to DB plans and a change in the 'actuarial assumptions' used to estimate the DB plan obligations: the discount rate is decreased while the life expectancy of covered workers is increased. To comply with the regulation relative to the funding of DB plans, banks had to make large direct contributions to the pension plans and to deduct most of the increases from their regulatory capital.[2] In 2005, the total contributions of banks to their DB plans hence amounted to 2.5 billion euros, or 21% of their equity. The effects of the adoption of these new accounting norms on bank financial resources are: 1) heterogeneous across banks, because of the ex-ante heterogeneity in the share of employees covered by the DB plans; 2) not related to any changes in macroeconomic or financial conditions as the changes are triggered only by the harmonization of accounting rules across countries; 3) specific to banks, and only to a sub-sample of these banks, as the private pension system in Portugal does not cover any other sector of the economy except the financial and the telecommunication sectors; 4) of a large magnitude, and in good times, which allows to identify how exogenous financing constraints can affect firm ability to attract and retain human capital; 5) not anticipated in magnitude and coverage, as the conditions of the implementation of IAS19 in Portugal are only determined in 2005, the year of the shock.

We identify the effects of the credit supply shock triggered by the introduction of IAS 19 on firm employment by matching all bank-firm credit exposures with a census of Portuguese employees. Bank-firm credit exposures come from the Portuguese credit register that covers the credit exposures of all banks and firms in Portugal since 1980. We combine the credit register with data from bank, firm and DB plan financial statements. We then match this dataset with a census

[2] In another context, Rauh (2006) exploits firm mandatory contributions to their pension funds as an exogenous shock to internal financial resources and investigates the effect on firm investment.

of all Portuguese employees in private sector firms. The census includes detailed information on each employee's career, level of education, occupation and earnings. This bank-firm-employee matched dataset allows us to measure the impact of the credit supply shock not only on firm employment, but also on diverse other employment outcomes such as wages, career dynamics and talent allocation or retention.

Our analysis follows two steps. In a first step, we confirm and quantify the well-known effects of credit supply shocks on firm borrowing and employment (Berton et al. 2018; Chodorow-Reich 2014; Siemer 2016). To do so, we document that the introduction of IAS 19 led affected banks to reduce credit supply. We find that, on average, when facing a shock that reduces their internal resources by 20%, banks cut loan growth by around 18 percentage points and are 55% less likely to start a new loan. Our favourite specification includes a wide range of bank balance sheet characteristics as well as firm fixed effects to control for firm demand for credit (Khwaja and Mian 2008). We then show that firms in a relationship with treated banks borrow less and reduce employment *only* after the shock. While prior to the shock, treated and control firms face similar trends, treated firms experience a relative decrease of 8 pp in loan growth and a decrease of 1.7 pp in employment growth following the credit supply shock. To obtain these results, we build a firm-specific indicator of treatment intensity and measure the effect of the treatment in a difference-in-differences specification. These results are robust to different measures of treatment intensity, to the inclusion of 52 industry fixed effects, of a large set of firm and bank controls, and are stronger for small firms. The effects of the credit supply shock are also stronger in Portuguese high-growth industries, such as the hospitality and food and the information and telecommunication industries.

In a second step, after establishing the effects of the credit supply shock on firm borrowing and employment, as well as its exogeneity to firm characteristics, we investigate the impact on firm human capital. We obtain three new results.

Our first finding is that, in good times, the employment of skilled workers is more affected by credit constraints than the employment of unskilled workers. This results in a relative decrease in the skill intensity of firms affected by credit supply shocks. We identify workers' skills using detailed census information on both their level of education and the skill-intensity of their occupation. We then estimate a difference-in-differences specification at the firm level where the dependant variable is the growth of employment across four categories of education and five occupations. In these specifications, we control for a large set of firm characteristics and for industry fixed effects. We find that the 8 pp relative decrease in loan growth leads to a decline of 3.6 pp in the employment growth of high-skilled workers. Thus, we document an elasticity of skilled employment to credit supply of 45%, while the corresponding elasticities for high school-, middle school- and elementary school-educated workers are equal to 26%, 22% and 15%.

Our second result is that the relative decrease in the employment of high-skilled workers partly results from skilled workers leaving affected firms likely for better opportunities. We estimate a linear probability model at worker level where we control for worker characteristics and firm fixed effects. We show that high-skilled workers are twice more likely to leave affected firms than low-skilled workers. To shed additional light on the reasons for this higher exit rate for skilled workers, we estimate a triple difference-in-differences model explaining wage changes for switchers. The granularity of the data allows us to include worker fixed effects, and thus ensure that unobservable worker characteristics do not bias the estimates. Following the credit shock, college and high-school educated workers experience a 2.4% and, respectively, 2.7% higher increase in wages after leaving affected firms than after leaving unaffected firms. These findings are consistent with the talent drain hypothesis: educated workers switch to benefit from better opportunities in firms that are not affected by the shock.

Our third result is that high-skilled workers are also less likely to join firms that are affected by credit supply shocks. Overall, these results suggest that in good times credit-constrained firms struggle to retain and attract skilled workers.

Our paper adds to the growing literature on the effects of bank financing constraints on lending (Paravisini 2008; Ivashina and Scharfstein 2010; Chava and Purnanandam 2011; Puri et al. 2011; Berg 2018; Jiménez et al. 2017) and firm employment (Benmelech et al. 2016; Bentolila et al. 2017; Berton et al. 2018; Acharya et al. 2018; Chodorow-Reich 2014; Popov and Rocholl 2018; Berg 2018; Hochfellner et al. 2015; Caggese et al. 2018; Siemer 2016) in two ways. First, we are able to precisely quantify how a decrease in bank internal resources translates into a decrease in credit supply, as we focus on a credit supply shock triggered by a change in accounting norms that is orthogonal to both bank and firm health. This change is due to the harmonization of accounting standards across countries, and not to changing macroeconomic, financial, or fiscal conditions that could simultaneously induce economic distress on banks and firms. Second, we can identify the effect of credit supply shocks on talent retention and on the workforce composition, as the credit supply shock occurs in good times, when high-skilled workers have good outside options. While Berton et al. (2018) document that, in bad times, low-skilled workers are more affected by credit supply shocks, with implications on inequality, we show that in good times, bank financial health affects the allocation of skilled workers in the economy.

We also contribute to the recent literature on the effects of firm financing constraints on firm ability to retain and attract talents. By looking at an exogenous credit supply shock, we are able to examine how the pool of workers within the firm varies with firm access to external funds, even in the absence of financial distress. Baghai et al. (2015) find that the pool of talented workers significantly deteriorates when firms are close to bankruptcy, and Brown and Matsa (2016) that talented workers tend to apply less to firms in financial distress. We show that credit constraints have a negative impact on the skill intensity of otherwise healthy firms and that the effect is is higher in growth firms. In related work, Caggese et al. (2018) argue that constrained firms might prefer to fire workers with shorter tenures, which have the smallest firing costs but the largest potential for future productivity growth.[3]

Finally, our paper also complements the literature that investigates the allo-

[3]In subsequent work, Fonseca and Van Doornik (2019) show that skill intensity and capital expenditures increased jointly at credit-constrained firms in Brazil after 2005. 2005 is both the adoption year of a bankruptcy reform that relaxed credit constraints (Ponticelli and Alencar 2016) and the starting year of a dramatic boom in the market of raw materials. As firms that are ex-ante more likely to be credit-constrained are younger, smaller and more productive, and therefore more likely to benefit from this positive shock to the Brazilian economy, we interpret the results as unique evidence on the complementarity between skills and capital.

cation effects of financial shocks in the economy. Bai et al. (2018) find that the state-level deregulation of local U.S. banking markets leads to significant increases in the reallocation of labor within local industries. Acharya et al. (2011) look at the effect of state-level banking deregulation in the US on the allocation of output across sectors. Finally, Babina (2016) investigates the effects of firm financial distress on employees' transition to entrepreneurship.

The rest of the paper is organized as follows. Section 2 describes the institutional background of bank pension plans in Portugal, the IAS 19 accounting reform, and its effect on both the accounting value of bank pension plans and on the financial situation of banks. Sections 3 introduces the data. Section 4 and Section 5 present the identification strategy and the results on, respectively, firm access to credit and human capital. Section 6 concludes.

2 Institutional Background: Bank Pension Plans and the IAS 19 Reform

This section presents institutional detail on bank DB pension plans in Portugal and describes the effects of the IAS 19 accounting reform on banks.

2.1 Bank DB Pension Plans in Portugal: an Overview

The characteristics of the system of private DB plans in Portugal make it an ideal setting to address our research question for the following reasons.

First, at the start of 2005, bank DB plans are large financial institutions that cover a large share of Portuguese employees working in the banking sector. Portuguese banks started offering pension plans following the adoption of the 1986 Social Security Act.[4] In the late 1980s, all the main Portuguese banks implemented DB plans through labor agreements with the unions. One of the fundamental factors in the development of these pension funds was the tax incentive, as banks can deduct from taxes the contributions to their pension plans. At the end of 2004,

[4]Decreto-lei 396/86, de 25 de Novembro https://dre.tretas.org/dre/8413/decreto-lei-396-86-de-25-de-novembro

bank DB plans cover more than 180,000 employees, with total liabilities amounting to 9.2 billion euros, around 6% of Portuguese GDP (Autoridade de Supervisao de Seguros e Fundos de Pensoes).[5]

Second, there is a lot of heterogeneity across bank exposures to DB plans. Since the late 1980s, banks offering private pension coverage have always coexisted with banks that do not have pension obligations for their employees, such as small banks - for which the fixed costs of implementing of a DB plan would be too high - and foreign banks. Hence, in 2005, 9 out of 22 Portuguese banking groups covered in our analysis are not offering pension plans. But even across banks that do sponsor a private DB plan - and, in fact, banks that do so account for over 80% of the banking sector assets - there is a lot of heterogeneity in the size of their pension plans. One of the reasons is that there has been a consolidation of the Portuguese banking sector since the 1990s, with banks making acquisitions of competing banks with or without pension plans. Another reason is that some banks, such as Caixa Geral de Depositos, the largest Portuguese bank, transferred part of their pension plan obligations to the public sector in the beginning of the 2000s, so that in 2005 a large share of their employees are covered by the National Social Security Pension Scheme.[6] Table C.1 in the online appendix illustrates the strong heterogeneity across Bank DB plans for the 6 largest Portuguese banks.[7]

Figure 1 plots bank pension liabilities as a percentage of bank equity in 2004 for the 6 main Portuguese banks. Bank exposure to their pension plan ranges from 19% to 133% of equity, is highly heterogeneous across banks and not correlated with the size of the bank.

INSERT FIGURE 1

Third, we are able to exploit an accounting reform that mostly affected only

[5] $http : //www.asf.com.pt/NR/exeres/21E954ED - 7325 - 4CE6 - 8626 - 11AFE2245D5A.htm$

[6] At end 2004, with the publication of Decree Laws nos. $240 - A/2004$ of 29 December and $241 - A/2004$ of 30 December, CGD employee retirement and survivors' pensions liabilities for the length of service provided up to 31 December 2000, were transferred to Caixa Geral de Aposentacoes (CGA). The CGD Pension Fund, by way of compensation, transferred the provisions set up to cover the referred to liabilities, to CGA. Liabilities totalled EUR 2,510 million in the beginning of 2004, with EUR 1,434 million of assets having been transferred during the year (CGD Annual Report, 2005).

[7] Data are publicly available in each bank 2004 and 2005 annual reports.

banks, as bank DB plans account for most of the private pension system in Portugal (80%). The private pension sector in Portugal covers indeed only two sectors: banking and telecommunications.[8] The rest of the population is covered by the National Social Security Pension Scheme.

2.2 The Accounting of Bank DB Plans

Accounting norms are key to the valuation of a DB plan liabilities. Variations in accounting norms for DB plans can therefore affect the financial resources of sponsor banks, as these banks have to comply with the regulation on the funding status of their DB plans.

In a DB pension plan, the bank pledges retirement benefits to employees according to a formula that is a function of each employee's age, tenure and salary. Thus, a bank sponsoring a DB pension plan has a financial liability equal to the present discounted value of the payments pledged to current and future retirees. The bank has to fund pension liabilities with dedicated assets.

The calculation of the accounting value of a DB plan liabilities relies on actuarial assumptions. These actuarial assumptions are defined by the regulator at the national level - before 2005 -, or at the international level - after the implementation of IAS19 in 2005. Actuarial assumptions include both economic assumptions on the discount rate, the wage growth rate and the inflation rate, and demographic assumptions on life expectancy, retirement age and rate of employment termination before retirement. The level of discount rate is the actuarial assumption which, if revised, can lead to the highest changes in the accounting value of the DB plan liabilities.

The financial situation of a DB pension plan can affect the sponsor bank financial flexibility through two channels: the *funding* channel - when the sponsor has to make direct cash contributions to the pension fund -, and the *accounting* channel - when the sponsor has to recognize *actuarial losses*, i.e. losses resulting from changes in actuarial assumptions, in its balance sheet and make prudential

[8] Our specifications include industry fixed effects which relieve some concerns that our results would be driven by the telecommunication industry being also affected by the reforms. Our results are also robust to excluding this sector of the economy.

deductions from Tier 1 capital.

The sponsor of a DB plan is required to make cash contributions to the pension plan to ensure that the DB plan is never "underfunded": i.e. the market value of the plan assets is higher than the present discounted value of the pension liabilities. Cash contributions might be needed following *actuarial losses* and are defined by a legally-specified formula.

In addition, in 2002, Bank of Portugal introduced prudential deductions from Tier 1 capital to shield bank capital from deferred actuarial losses. A bank can indeed defer the reporting of most of the actuarial losses in the income statements to subsequent years, by amortizing these actuarial losses over a period of 10 to 20 years.[9,10] These deferred actuarial losses are reported separately in the bank financial statements. However, they have to be deducted from Tier 1 capital. As a result, banks facing an increase in actuarial losses have to reflect them closely in their capital levels, even if not in the income statement.

Section B in the online appendix provides more detail on the accounting rules of DB plans in Portugal before IAS 19. Figure B.1 illustrates how a 50 million Euros increase in the accounting value of a bank's DB plan liabilities can lead to contributions and prudential deductions.

2.3 The Introduction of IAS 19 as a Source of Variations in Bank Internal Financial Resources and Regulatory Capital

The introduction of IAS 19 on January 1st 2005 resulted in a large increase in the accounting value of bank DB plan liabilities. As a result, sponsor banks had to make large cash contributions to their DB plans as well as prudential deductions from Tier 1 capital.

[9] Pension expenses on the income statements are calculated as the sum of the forecasted annual pension commitments - also known as the "service cost" of the plan - the interest cost of the plan and the amortization amounts of the actuarial losses, net of the expected return on the plan's assets.

[10] The share of the actuarial losses that can be deferred and hence not declared as losses in the account statement is defined by the *corridor rule* that we describe in Section B of the online appendix.

The introduction of IAS19 in 2005

The adoption of IAS 19 in 2005, in the context of the implementation of the IFRS norms in Portugal, led to an increase in bank DB plan liabilities of around 35%, from 9.2 to over 12 billion Euros. The objective of IAS 19 was to harmonize the accounting rules for employee pension benefits across countries. While the introduction of IFRS rules concerned all major banks and firms in Portugal, IAS 19 was the only IFRS rule that led to direct cash contributions. In addition, as Table C.3 of the online appendix shows, while other IFRS rules also affected the accounting value of equity and the income statement, none had such a large impact on bank financial situation.

The increase in bank DB plan liabilities following the adoption of IAS19 resulted from two major changes. First, the range of benefits covered by bank pension plans was extended to post-employment medical care and life insurance, which were previously covered by the national security system. This extension accounted for about 50% of the increase in the value of bank DB plan liabilities. Second, two major actuarial assumptions were revised, namely the discount rate and life expectancy. The discount rate used to calculate the present value of bank DB plan liabilities was revised downwards by 50 basis points - from 5.25% to 4.75% - to better match the long maturities of the obligations. The decrease in the discount rate accounted for approximately 25% of the effect of IAS19 on pension fund liabilities. In turn, the life expectancy of female workers was revised upwards, accounting for the remaining 25% of the effect. Before the introduction of the IAS19 standards, actuaries indeed used one single life expectancy table for both male and female employees. The new rules required gender-specific tables, adjusting for the higher life expectancy of female employees.

Figure 2 decomposes the aggregate effect of the adoption of IAS 19 on bank liability into its three components: the benefit extension, the change in the actuarial assumptions, and the change in the mortality tables.

INSERT FIGURE 2

Figure 3 plots the aggregate variations in the bank DB plan assets and liabilities over the years and illustrates the effect adopting IAS 19 on the value of bank pension plan liabilities. Additionally, we provide in Section F in the online appendix extracts from the second largest Portuguese bank 10-K financial and pension plan statements. These illustrate how the accounting value of the liabilities has been affected.

INSERT FIGURE 3

Portuguese banks did not anticipate the magnitude of the effects of IAS 19 on the liabilities of their DB plans and the resulting contributions before 2005 for the following three reasons. First, even if the European Parliament approved the adoption of new accounting standards in July 2002 for an implementation as of January 1st 2005, the exact parameters of the new accounting standards were only defined in 2004. In particular, the conditions of the recognition of actuarial losses were fully defined only in December 2004 by the *Amendment to IAS 19 Employee Benefits: Actuarial Gains and Losses, Group Plans and Disclosures*. Second, Bank of Portugal defined the accounting treatment of actuarial losses in Portuguese Banks following IAS 19 only in February 2005 (*Notice 2/2005 of Bank of Portugal*). Third, the possible exemption of some pension liabilities was actively debated until end of 2005. In 2004, CGD pensions liabilities for the length of service provided up to 31 December 2000 are transferred to the National Pension system in part to spare CGD from the IAS 19 shock. Subsequently, in November 2005, Millenium BCP - the largest private Portuguese banking group - proposed that their pension liability be also transferred.[11] While BCP's request was initially rejected, a similar context in 2011 was met with a favourable outcome, as the Portuguese Government did transfer the entire bank pension plans into public ownership as part of the tripartite agreement with the ECB, EC and the IMF.

The Effects on Sponsor Bank Internal Financial Resources and Regulatory Capital

[11] https://www.cmjornal.pt/economia/detalhe/millennium-bcp-propoe-transferencia-de-fundo-de-pensoes

Given the large and broadly unanticipated effect IAS 19, sponsor banks had to make substantial contributions as well as deductions from regulated capital in order to recognize the new actuarial losses. Figure 4 shows bank cash contributions to their pension plans from 2003 to 2007. In 2005, banks were required to increase their contributions to pension plans because of the 35% increase in bank DB plan liability resulting from IAS 19. The effect is large: direct bank contributions to their pension plans spike in 2005, amounting to 2.35 billion euros, which represents 20% of the equity of affected banks.

INSERT FIGURE 4

Banks also had to make significant deductions from their Tier 1 capital to account for most of the actuarial losses, as the share that could be exempted under the *regulatory corridor* was negligible. The fact that, during 2005, banks had to make substantially larger pension contributions and prudential deductions than in previous years provides additional evidence that the funding shock was largely unforeseen.

Overall, the richness of this institutional setting allows us to exploit a funding shock that is: 1) heterogeneous across banks, because of the significant ex-ante heterogeneity in the coverage of the pension plans; 2) not related to any changes in macroeconomic or financial conditions as it is triggered only by the harmonization of accounting rules across countries; 3) specific to banks, and only to a sub-sample of these banks, as the private pension system in Portugal does not cover any other sector of the economy except the financial and the telecommunication sectors; 4) of a large magnitude, and in good times, which allows to identify how exogenous financing constraints can affect firm ability to attract and retain human capital; 5) not anticipated in magnitude and coverage, as the conditions of the implementation of IAS19 in Portugal are only determined the year of the shock.

3 Data Overview and Treatment Measures

This section describes the data, the construction of the sample of analysis and the treatment variables, and discusses the external validity of the empirical framework.

3.1 Data Sources

We obtain our final sample by merging four databases that are all using unique firm and bank identifiers: the Portuguese credit register, bank balance sheet data, bank DB pension plan data, and the Quadros de Pessoal database, the Portuguese census.

3.1.1 Bank-firm Exposures: The Portuguese Credit Register

We obtain bank-firm credit exposures from the Portuguese credit register. The credit register is held by the Bank of Portugal and covers *all bank loans* above 50 euros granted to firms from 1980 to present. For each month and bank-firm exposure, the credit register provides information on both the lenders' and the borrowers' identities, as well as on the amount of credit that is outstanding, along with borrowers' repayment position.

We construct a balanced panel of monthly bank-firm exposures that covers the 2004-2006 period in the following way. First, we aggregate all outstanding loans in monthly bank-firm credit exposures. Second, for each bank-firm pair, we fill all months for which the pair is not in the credit register with a zero exposure. Hence, if bank b lends to firm f and the loan is repaid after a year, the bf pair will be in our data during the entire sample period, even though the bank-firm exposure will be equal to zero for two out of the three years of the analysis.[12]

We also extract the credit history of each firm from the credit register by tracking their records back to 1995. With this, we build four variables that provide information on the firm credit history: (1) the average loan size of the firm over the previous 10 years - or since the firm start date -, (2) the number of months with positive credit exposures, (3) an indicator for whether the firm is in default at the time of the analysis, and (4) an indicator for whether it had any history of defaults.

[12]For the purpose of our analysis, we exclude loans granted by non financial and monetary institutions, which account for less than 5 per cent of total credit in Portugal.

3.1.2 Bank Level Data

We collect bank level data from two different databases of the Bank of Portugal. We first use the Bank's Monetary and Financial Statistics that contain monthly information on bank balance sheets. We match these data with a second database with yearly information on bank DB plans. Bank balance sheet data is at the bank level and available for the 59 Portuguese banks in 2004, while bank DB plan data is at the banking group level, covering the 13 Portuguese banking groups that sponsored employee pension plans over the period of analysis. Bank DB plan data include the total assets and liabilities of each DB plan, the disaggregated actuarial variations, the pension expenses, as well as the cash contributions of the sponsor bank to the DB plan.

3.1.3 Employee-level Data: Quadros de Pessoal

To investigate the effects of the credit supply shock on labor market outcomes, we use the Quadros de Pessoal database, a census of all private sector firms in Portugal that employ at least one worker. The census is conducted each October by the Portuguese Ministry of Employment and provides detailed information on the workforce of each firm. In addition, each firm and each worker entering the database are assigned a unique time-invariant identifying number that allows us to follow firms and workers over time. Over our 2004-2006 sample period, the available information covers 350,000 firms and the complete career history of 3 million workers.

The Portuguese census asks employers to report each employee's social and demographic characteristics, employment start and end dates, as well as an extensive set of job characteristics, such as the type of employment, job title, wage and hours worked per year.[13] Socio-demographic characteristics include years of experience, level of education, year of last promotion, age, gender and nationality.

We use two variables to measure a worker's human capital: the worker level of education and the type of occupation. We first group workers into four levels

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

of education: up to elementary education, middle school education, high school education and college education.[14] Second, we follow Caliendo et al. (2015) and Mion and Opromolla (2014) and group workers into five occupations based on the worker classification available in the Quadros de Pessoal. In the matched employer-employee data set, each worker, in each year, has to be assigned to a category following a compulsory classification of workers defined by the Portuguese law (Decreto Lei 121/78 of July 2nd 1978). The classification is based on the tasks performed and the skill requirements, and each category can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. On the basis of this hierarchical classification, we partition the available categories into the following five occupations. We assign "Top executives (top management)"; "Intermediary executives (middle management)"; "Supervisors, team leaders" to *Managers*; "Higher-skilled professionals" to *High-skilled Operational Occupations*, "Skilled professionals" to *Skilled Operational Occupations*; "Semi-skilled professionals" to *Semi-skilled Operational Occupations*, and the remaining category "Non-skilled professionals" to *Non-skilled Occupations*.

Finally, in addition to worker characteristics, the Portuguese census database also includes key firm level data such as total sales, starting capital, year of creation, number of employees, the legal and ownership structures of the firms, 5 digit industry identification numbers as well as parish and county information.

3.2 Sample Construction

We build our sample in the following way. First, we keep all the private firms from the non-financial sector of the economy that hired at least one worker in the pre-treatment period.[15] We then use the unique firm identifier to match the yearly census information with our monthly balanced panel of bank-firm exposures. We add the variables on firm credit history from the credit register. Finally, we use the bank identifier in the credit register to merge this dataset with the bank balance sheet and DB pension plan data.

[14] These four levels of education correspond to 6, 9, 12, and 16 years of education.

[15] We, therefore, drop financial firms, state-owned companies and entrepreneurs.

For the main empirical analyses - on firm borrowing and employment, as well as on worker career outcomes - , we define the pre-treatment period as the year 2004 and the post-treatment period as the years 2005 to 2006.[16] We also restrict the sample to firms with a positive credit exposure in 2004, as the measure of treatment intensity at firm level is based on firm credit exposures in the pre-treatment period. As a result, the final sample includes a total of 161,202 firms, 59 banks, 333,788 bank-firm exposures and more than 2 million employees working at these firms in 2004. Tables 1 and 2 provide summary statistics on banks, firms, and employees in this final sample.

INCLUDE TABLE 1

INCLUDE TABLE 2

3.3 Measuring Treatment

We define both bank-specific and firm-specific measures of the treatment intensity.

At the bank level, the $Treatment\ Intensity_b$ variable is the bank exposure to their DB plan ex-ante, measured by the ratio of the bank DB plan liabilities to bank equity in 2004. This ratio captures the magnitude of the shock by scaling the size of the DB pension plan to bank internal funds as proxied by the bank equity. All our results are robust when using as alternative measures the ratio of the change in pension liabilities due to IAS19 to the bank equity, the ratio of the 2005 cash contribution to the bank equity, and the ratio of pension liabilities to banking assets (see for example Table D.3 in the online appendix).

Figure 1 illustrates the heterogeneity of the treatment variable across the 6 largest Portuguese banks.[17] The ratio of DB plan liabilities to bank equity varies from 19% to 133%. The magnitude of the treatment is related neither to the size of the bank, as measured by total assets, nor to its equity ratio. Table 1 confirms that the variable $Treatment\ Intensity_b$ varies significantly across banks in the

[16] The analysis of switchers, which focuses on the employment outcomes of workers that have switched jobs, extends until 2007, in order to track workers that left at the end of 2005 and 2006.

[17] The data is publicly available in the financial reports of these 6 banks and reported in Table C1 in the online appendix.

total sample: the average and the median are at 40%, the 10^{th} percentile 0% and the 90^{th} percentile 104%.

At the firm level, the $Treatment\ Intensity_f$ variable is the weighted average of the treatment intensity of the banks the firm borrows from. It is calculated as follows:

$$Treatment\ Intensity_f = \sum_{b=k} \alpha_{k,f} \times Treatment\ Intensity_k,$$

where

$$\alpha_{b,f} = \frac{Loan_{b,f,2004}}{\sum_{b=k} Loan_{k,f,2004}}.$$

Hence $\alpha_{b,f}$ measures the relative credit exposure of firm f to bank b during the pre-treatment period, i.e. in 2004.

Table 1 shows that the variable $Treatment\ Intensity_f$ averages 0.39 and has a standard deviation of 0.28. In the first 10th percentile, there are firms borrowing only from non-affected banks, while the 90th percentile and above captures single-bank firms borrowing from banks treated with high intensity.

The summary statistics in Table 1 also indicate that the median firm in the control group is very similar to the median firm in the treated group along the following characteristics: size, age, credit history and composition of the workforce.

To facilitate the interpretation of the estimates, we also allocate banks, firms and workers to treatment and control groups based on the distribution of their respective measure of treatment intensity. At the bank level, the variable $Treatment\ Dummy_b$ takes the value one for banks with a treatment intensity above the median, i.e. with a ratio of DB plan liability to equity above 40%. At the firm level, the variable $Treatment\ Dummy_{firm}$ indicates firms for which more than half of their pre-period credit exposures originated from banks treated with high intensity. The assignment leads to 13 treated banks and 46 control banks, associated with 80,846 treated firms and 80,356 control firms. In the rest of the paper, we identify "treated" banks or firms when their $Treatment\ Dummy$ equals 1.

INCLUDE TABLE 1

3.4 External Validity

Portugal offers an ideal laboratory to address our research questions not only because of the policy experiment, but also because the Portuguese economy has some unique characteristics that are useful for our analysis.

First, in line with other European Union countries, Portugal is a bank-based economy. We therefore measure the cost of credit frictions through the lending channel in a country where banks are the main source of firm external funding. In 2004, Portuguese banks held more than 70 per cent of the total financial system's assets, and bank loans corresponded to more than 120% of GDP (Constancio et al. 2009). As Figure A.1 from the online appendix shows, the ratio of the bank assets to GDP is above the OECD average, but of the same magnitude as in Germany and the Netherlands.

Second, in 2004, the development and integration of the Portuguese financial system are close to the EU average (refer to Table A.1 in the online appendix). Since the 1980s, the liberalisation of the economy, coupled with the participation in the Euro area, have fostered the growth of the financial sector. The privatisation of the Portuguese public banks, which started in 1989, was virtually completed in 1995.[18] Private banks started to operate in late 1984, and, during the 1990s some foreign groups were already operating in Portugal, with a total market share of more than 10 per cent in 2004 (Figure A.2 in the online appendix).[19]

Another interesting feature about the Portuguese economy is its labor market. While the structure of the labor market is close to the one of other OECD countries in terms of sectoral composition and firm size (Figure E.2 in the online appendix), its rigidity is relatively high, which ensures that any effect we observe on worker flows might only be biased downwards.[20]

[18]The market shares of state-owned banks in terms of the banking system's assets decreased from more than 74% in 1990 to around 24% in 1996, remaining stable from then on. The market share of the public banking group that still prevails corresponds to that of Caixa Geral de Depositos.

[19]The increase in the market share of foreign banks in 2000 was largely due to the acquisition of a large domestic bank - Banco Totta & Acores - by a foreign bank - Santander.

[20]Despite an unemployment rate of only 6.1 per cent, very similar to the US one in 2004, flows of workers into unemployment are indeed three times lower in Portugal than in the US (Blanchard and Portugal 2001). These lower flows come from both lower job creation and destruction, and from lower worker flows given job creation and destruction.

While job flows are much lower in Portugal than in the US, wages are relatively flexible, which allows us to investigate the effects of job displacement triggered by the credit supply shock on wages. The average wage spell in Portugal is 13 months, about 2 months less than in the Euro Area (Druant et al. 2009). Despite the rigidity imposed by the existence of mandatory minimum wages and the presence of binding wage floors determined by collective agreements, firms still retain the ability to circumvent wage agreements to absorb demand shocks (Constancio et al. 2009).[21]

Finally, our analysis covers years of stable GDP and credit growth in Portugal, with no major changes in the dynamics of its labor market (see Figure E.1 in the online appendix).

4 Firm Access to Credit

We exploit the introduction of IAS19 in 2005 as a shock to bank internal funds and regulated capital. In this section, we investigate the effects of the shock on, first, bank credit supply - looking at changes in bank-firm credit exposures -, and second, on firm total borrowing.

4.1 Changes in Credit Supply

4.1.1 Main Result

To estimate the aggregate effects on bank credit supply and test the parallel trend assumption, we first plot changes in corporate lending by treated versus control banks.

INCLUDE FIGURE 5

Figure 5 shows that the growth in lending by treated banks slows down relatively to the growth in lending by control banks from mid-2005, while it followed a parallel trend from 2003 to 2005. The lag of six months we observe before the

[21] Blanchard (2006) claims that wage flexibility might be limited in Portugal in 2006 since this wage cushion has been partly used by firms from 2000 to 2005.

effect is visible in the data is consistent with banks only having to report the financial situation of their DB plan at the end of the year, and with the fact that the institutional details of the implementation of IAS 19 were only fully defined in the first semester of 2005. In addition, part of the bank-firm exposures come from revolving lines of credit, which are negotiated ex-ante for a given period of time.

We further investigate the effects of the funding shock on bank credit supply in a difference-in-differences model at the bank-firm level. The dependent variable is the growth rate of the bank-firm credit exposures between the pre- and the post-periods. The pre-period is the year 2004 and the post-period covers the years 2005 and 2006. We collapse our monthly panel of bank-firm exposures in these two sub-periods by taking the average of each bank-firm exposure over each sub-period, following Bertrand et al. (2004). We then compute the growth rate in each bank-firm exposure using the Davis and Haltiwanger (1992) growth measure:

$$Credit\ Growth_{b,f} = \frac{Credit_{b,f,post} - Credit_{b,f,pre}}{\frac{1}{2}(Credit_{b,f,pre} + Credit_{b,f,post})},$$

where $Credit\ Growth_{b,f}$ is the exposure of bank b to firm f. In addition to easing the interpretation and comparability of the estimates, this growth rate has good statistical properties as it is symmetric around zero, bounded in the range $[-2; 2]$, and it can accommodate both entry and exit.[22]

We estimate the effect of the funding shock on bank exposure to firms using the following specification:

$$\begin{aligned} Credit\ Growth_{b,f} = {} & Firm_f + \beta Treatment_b + \\ & + \gamma BankControls_b + e_{b,f} \end{aligned} \tag{1}$$

The dependent variable $Credit\ Growth_{b,f}$ is the change in bank b's exposure to firm f between the pre and the post periods. $Treatment_b$ is either our treatment dummy or the treatment intensity variable at the bank level depending on the specification. We cluster standard errors at the banking group $\times$ industry levels.[23]

[22]For a thorough explanation of the statistical advantages of using this growth measure, please refer to the technical annex in Davis and Haltiwanger (1992).

[23]Table D.1 in the online appendix shows that results are robust to clustering at the banking

INCLUDE TABLE 4

Column 1 in Table 4 confirms the aggregate result of Figure 5: the growth of bank-firm credit exposures between the pre and the post periods is 17 percentage points lower for treated banks versus control banks.

Column 2 shows that our result is robust to including a large set of bank and firm characteristics as control variables. While we observe from Figure 5 that the parallel trend assumption holds between control and treated banks, we include a large set of bank characteristics to further ensure that any differences across control and treated banks do not drive our result. This alleviates the concern that the relationship between bank characteristics and lending could vary between the pre and the post periods. The vector $BankControls_b$ includes the logarithm of assets, the capital ratio, a measure of liquidity - assets maturing within one year to total assets -, the ratio of bonds outstanding to assets, loans-to-assets, short term liabilities to assets and the ratio of non-performing loans to total lending, all calculated in the pre-treatment period, i.e., in 2004. Similarly, $Firm_f$ is a vector of firm controls that includes the four measures of firm credit history.

Column 3 controls further for firm demand for credit by including firm fixed effects (Khwaja and Mian 2008). We, therefore, compare the supply of credit of a treated bank to the supply of credit of a control bank *to the same firm*. The point estimate of β suggests that, for a given firm, the growth rate of its exposure to a treated bank is also 17 percentage points lower than the growth rate of its exposure to a control bank.

Column 4 suggests that the result also holds also in a specification using the treatment intensity, instead of the treatment dummy, as independent variable: banks with larger pension liabilities relative to their equity tend to increase less their credit exposure to firms after the introduction of IAS 19.

Column 5 shows that the magnitude of the effect is still large and highly significant when we restrict the sample only to banks offering pension coverage. This

group level (22 clusters). In our main analysis, however, we cluster at banking group $\times$ industry levels to account for possible correlation in the firm-level residuals induced by including industry fixed effects (Petersen 2009). This also ensures that we have a sufficiently high number of clusters (Cameron and Miller 2015) specification provides additional robustness for the possibility of non-random firm-bank matching, which may occur if firms dealing with banks that sponsor pension plans are systematically different from firms dealing with banks without any pension obligation. With this specification, we show that the effect is not driven by including the latter type of banks, which tend to be smaller banks, more local, and possibly more relationship-based.

In Columns 6 and 7, we show that the funding shock also has an effect on the "extensive margin" of lending: the coefficients in columns 6 (negative) and 7 (positive) suggest that treated banks are, respectively, less likely to start new relationships with firms, and more likely to end existing relationships with firms. To obtain this result, we build two new variables. First, we measure new lending with a dummy that equals one if a new loan is granted in the post-treatment period to a firm that has a zero-exposure to this bank in the pre-treatment period. Second, a dummy variable that is equal to one when a credit exposure that is positive in the pre-period becomes zero in the post treatment period. We then estimate equation (1) in a Logit model with these two variables as dependant variables.

Finally, the results in Columns 8 and 9 suggest that banks reduce their existing credit exposures to firms by the same amount when we restrict the sample to the 333,788 bank-firm exposures of the 161,202 firms that use credit and employ at least one worker in 2004. Because we have the history of these firms from QP, we can include a wider set of controls. Hence, firm characteristics in Column 8 include the four measures of credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure. Column 9 includes firm fixed effects. To follow the impact of the credit shock through the Portuguese economy, from banks to individual workers, we will work with this constant sample of firms in the rest of the paper.

4.1.2 Robustness Tests

Tables D.1, D.2 and D.3 in the Online Appendix include a series of robustness tests. First, Column 1 in Table D.1 offers a sensitivity analysis to bank capital buffers. The coefficient on the interaction term suggests that treated banks with lower capital buffers tend to cut lending more than highly capitalized banks. This is another way to measure the treatment intensity. While in all specifications in Table 4, standard errors are clustered at the banking group $\times$ industry levels, Columns 2 to 4 show that results are robust to clustering standard errors at the banking group level only. Finally, Columns 5 to 7 show that the results are robust to restricting the sample to the six main banks in Portugal. These banks jointly account for 87% of the banking assets in Portugal in 2004. Focusing on them eliminates potential noise in the estimates from including smaller institutions. In addition, these six main banks homogeneously implemented the complete set of IFRS rules in 2005.

Table D.2 and D.3 in the Online Appendix show that the results are robust to various definitions of the dependent variables and the treatment variables. In Table D.2, we replicate the main specifications using the delta log as dependant variable instead of our credit growth measure, as in the existing literature. One limit of using the delta log is that it puts more weight on very small loans whose size can easily be multiplied. This accounts for the larger coefficient we observe with this specification. In Table D.3, we define the treatment intensity variable as the *change* in bank pension liabilities to bank equity.

4.2 Firm Total Borrowing

4.2.1 Main Result

We now investigate whether the treatment affects firm access to credit.

Figure 6 shows that credit growth differs between treated and control firms after 2005, the year of the shock. Before 2005, treated and control firms face parallel trends in credit growth, which suggests that the treatment is exogenous to firm unobservable characteristics. The figure plots the coefficient estimates of the treatment dummy in a panel model where the dependant variable is the yearly growth rate in credit at the firm level. The controls include the firm characteristics and 52 industry fixed effects. To obtain the growth rate in credit at the firm level, we sum the loan exposures of each firm across all banks.

We then collapse our sample into the pre-treatment period and the post treatment period by taking the average of the firm monthly borrowing over each period. We estimate the following specification:

$$\begin{aligned} Credit\ Growth_f = Industry_s + \beta Treatment_f + \\ + \gamma FirmControls_f + \gamma AverageBankControls_f + e_f \end{aligned} \tag{2}$$

where $Credit\ Growth_f$ is the change in the total credit exposure of firm f between the pre and post-period using again the Davis and Haltiwanger (1992) growth measure. $Treatment_f$ is our treatment measure - the treatment dummy or the measure of treatment intensity - here at the firm level. Because our treatment measure is computed based on relative bank-firm exposures in the pre-treatment period, we restrict the sample to the 161,202 firms that have total non-zero credit exposures in the pre-period. Standard errors are clustered at the firm main banking group × industry levels.

Table 5 reports the results. The coefficient of the $TreatmentDummy$ in Column 1 suggests that firms are not able to fully substitute credit from treated banks with credit from control banks when the treated banks are shocked. We find that credit growth is 8 percentage points lower for treated firms relatively to non-treated firms.

Column 2 shows that this result is robust to including a large set of firm characteristics as control variables, which further alleviates the concern that differences between treated and control firms might drive our results. The vector of firm controls $FirmControls_i$ includes all the controls at the firm level: the four measures of credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure. The coefficient of our treatment dummy remains stable, suggesting that differences across control and treated firms do not account for the significant differences in credit growth observed since 2005 across the two groups of firms.

INCLUDE TABLE 5

Column 3 adds 52 two-digit SIC industry fixed effects without any effect on our result.

Finally, in Column 4, we control for the "average" characteristics of the banks the firm is in a relationship with in the pre-period, weighted by relative credit exposures in the pre-period. The coefficient decreases only slightly.

Columns 5 to 7 confirm that the result holds when we use the treatment intensity measure instead of the treatment dummy as dependent variable. In these three columns we estimate the same specification as in Columns 2 to 4. Consistently, firm borrowing decreases when firm exposure to treated banks increases.

4.2.2 Heterogeneity of the Effects

This section explores how the effect of the credit supply shock varies across industries and firm size.

We first estimate Model (2) by industry. Panel A of Table 6 displays the results. The credit supply shock has a negative effect on firm borrowing across all samples. The coefficient, however, is larger in the Information and Communication as well as in the Hospitality and Food industries. Both industry segments have had the largest productivity growth in Portugal since 2005. This implies that credit shocks might be particularly harmful to growing sectors, which tend to have a larger number of smaller firms.

In fact, Panel B shows that smaller firms are more affected. Overall, this analysis suggests that the effect is larger on growth rather than value firms, as small firms tend to have faster productivity growth.

Credit supply shocks are therefore likely to have large long run effects if they affect industries with the highest productivity growth. These long run effects might be amplified if affected firms struggle to retain and attract skilled workers.

INCLUDE TABLE 6

5 Firm Human Capital

In this section, we investigate the effects of the credit supply shock on firm total employment and on the skill composition of the labor force. Workers with different skill, knowledge or experience may have different preferences and incentives to leave or join firms facing a credit supply shock, as well as different outside opportunities. Among all workers who may leave or not join a firm that has a lower access to credit, the most skilled ones are likely to have the largest impact on the firm's future growth and productivity.

5.1 Skill Composition of the Labor Force

We first show that credit supply affects firm total employment even in good times. While there is large empirical evidence on the effects of credit supply shocks on firm employment in bad times (Benmelech et al. 2016; Bentolila et al. 2017; Berton et al. 2018; Acharya et al. 2018; Chodorow-Reich 2014; Popov and Rocholl 2018; Hochfellner et al. 2015; Siemer 2016), little is known about what happens in good times.[24]

To do so, we collapse our sample into two sub-periods, the pre-treatment - 2004 - and the post treatment periods - 2005 and 2006 -, taking the average number of employees at the firm level over each sub-period. We then estimate the following model:

$$\begin{aligned} Employment\ Growth_f = \beta Treatment_f + \mu Industry_s + \\ + \gamma FirmControls_f + e_f \end{aligned} \tag{3}$$

where $Employment\ Growth_f$ is the change in the total number of employees of firm i between the pre and post-period using the Davis and Haltiwanger (1992) growth measure, $Industry_s$ is a vector of 52 industry dummies and $Controls_s$ is a vector of firm characteristics measured in the year 2004. As previously, firm

[24] Jiménez et al. (2017) and Alfaro et al. (2018) find no effect of the credit supply shock they exploit in good times. They both use shocks that originate in bank weaknesses and argue that they are exogenous to individual firms. However, this approach is less useful to study the mobility of human capital, because it is vulnerable to reverse causality/simultaneity. Industry or regional shocks weaken bank health and simultaneously affect the outside opportunity of workers.

characteristics include our four measures of credit history, the logarithm of total sales, the logarithm of the number of employees, firm age, product per worker and workforce tenure, as well as indicator variables for the legal organization of the firm and the ownership type - private, public or foreign.

INCLUDE TABLE 7

The coefficient estimate of the $TreatmentDummy$ in Column 1 of Table 7 suggests that the 8 percentage points lower credit growth that treated firms experienced compared to control firms translated into a 1.7 percentage point lower employment growth. Hence, credit supply shocks affect firm growth opportunities in good times, resulting in a lower employment growth. The elasticity of employment to credit supply we measure is 22%, which is of comparable but smaller magnitude than the one Berton et al. (2018) obtain in bad times (36%). Berton et al. (2018) employ a very close identification strategy using loan-level data to control for demand with firm fixed effects. These two results are consistent with firms having a better access to internal funds to fund future growth in good times, while having to rely more on credit in bad times.

Figure 7 shows the dynamics of the coefficient of the treated dummy in a panel version of model (3) with firm and year fixed effects. We observe that treated and control firms experience similar employment growth in 2003 and 2004, but that treated firms diverge from the trend, decreasing employment relatively to control firms the year they face the credit supply shock.[25] We then investigate whether the effect of the credit supply shock on firm employment varies across worker skills. There are at least two reasons why the employment of skilled workers might be more impacted by credit supply shocks in good times. First, these workers are more expensive and tend to work under less flexible contracts. Therefore, these are the last workers firms might decide to hire when firms are credit constrained. Second, skilled workers already employed at affected firms might prefer to switch to firms with better opportunities. Outside options might be even more attractive in good times. Oppositely, credit-constrained firms might fire first the less skilled

[25] We cannot show the employment growth rate in 2002 as QP data are not available before 2002.

workers that are more easily substitutable, as firm-specific human capital is likely to be complementary to a worker's level of education. Therefore, whether human capital will decrease relatively in affected firms and, if so, whether this is the result of firing or voluntary exit is an empirical question.

To address this question, we use the average number of employees at the firm level over each sub-period and across four levels of education - elementary school, middle school, high school and college - and five levels of occupation - non-skilled, semi-skilled, skilled, high-skilled workers, and managers. Table 2 provides summary statistics on the average number of workers employed by treated and control firms, across levels of educations and occupations. Workers with high human capital are relatively scarce. 67% of the workers in Portugal do not have a high school degree in 2004. Only 11% of firm employees have a college degree. This is likely to put them in a relatively better bargaining positions in the hiring and wage setting negotiations.

We estimate the following model for each subgroup of workers:

$$\begin{aligned} Employment\ Growth_{f,j} &= \beta Treatment_f + \mu Industry_s + \\ &+ \gamma FirmControls_f + \epsilon_{f,j} \end{aligned} \tag{4}$$

where $Employment\ Growth_{f,j}$ is the change in firm f's number of employees of category j between the pre and post-period using the Davis and Haltiwanger (1992) growth measure. $Industry_s$ is the vector of 52 industry dummies and $Controls_f$ is the vector of firm characteristics measured in the year 2004.

Columns 2 to 5 of Table 7 provide the results across levels of education. We observe that employment growth increases less at firms affected by the credit supply shock mostly for highly educated workers, while the effect for the less educated ones is smaller and only slightly significant. In particular, the elasticity of employment to credit supply for college-educated workers is higher than the average and equal to 45% (=3.6/8). The corresponding elasticities are equal to 26% and 22% for high school- and middle school-educated workers, respectively, and only 15% for workers with elementary school education. Overall, the effect is three times larger for workers with a college degree than for workers with up to elementary school education. The lower employment growth for college-educated workers hence accounts for more than 20% of the total effect of the credit supply shock, even though college-educated workers account only for 10% of the workforce.[26]

Figure 8 shows the dynamics of the coefficient on the treated dummy in a panel version of model (3) with firm and year fixed effects and across levels of education. While treated and control firms experience similar employment growth of college-educated workers in 2003 and 2004, following the credit supply shock treated firms increase employment less than control firms particularly for this category of workers.

Then Columns 6 to 10 of Table 7 provide the results by types of occupation. Firms that are more affected by the credit supply shock increase less the employment of workers in high-skilled occupations. There is almost no effect on workers in non-skilled occupations.

As a robustness check, Table D.5 in the online appendix restricts the sample to firms with 5 employees or more. While the effect is of relatively smaller magnitude, which is consistent with larger firms being able to substitute various sources of funding, it is again mostly driven by educated workers employed in skill-intensive occupations. In Table D.6, we replicate the results above, using the measure of treatment intensity, instead of the treatment dummy. Again, the negative effects on high-skilled workers - defined either by education or by occupation - are the strongest. The higher the intensity of the treatment, the larger the differential effect in the growth rate of skilled employment.

5.2 Worker Separations across Skills

In this section we discuss estimates from worker-level regressions. These regressions allow us to better identify the effects across skills, to differentiate between worker inflows and outflows, and they alleviate concerns that the specifications at the firm level might raise. For example, if worker characteristics such as age or

[26] Table D.4 in the online appendix reproduces Table 7 using a more disaggregated classification of workers by years of education. The effects are maintained.

tenure varied across levels of education, age or tenure effects could be driving the results. We, therefore, control for polynomials of age and tenure in worker-level regressions. In addition, the larger effect on the employment growth of highly-skilled workers might be a result of highly-skilled workers switching to non-treated firms in case of separation, while uneducated workers remain unemployed. If so, this would mechanically bias upwards the gap in the coefficients between skilled versus unskilled workers in the firm-level specifications. However, this gap should be insignificant in worker-level specifications where we estimate the individual probabilities of separation and entry. Finally, changes in growth rates are likely to be mechanically higher when initial values are low, hence amplifying the effect on educated workers. This concern is relevant because the share of highly-skilled or college-educated workers in 2004 in our sample is as low as 11%.[27]

We formally test whether the credit supply shock is associated with an increase in the probability that workers leave the firm by estimating the following panel model over the 2003-2006 period:

$$\begin{aligned} Pr(Leavingthefirm)_{i,f,t} = {} & \beta Post_t \times Treated_f + \\ & + \alpha Firm_f + \eta Year_t + \phi WorkerControls_{i,t} + \\ & + \gamma FirmControls_{f,t} + \epsilon_{i,f,t} \end{aligned} \tag{5}$$

$Pr(Leavingthefirm)_{i,f,t}$ is a dummy variable indicating whether worker i leaves firm f in year t. $Post_t \times Treated_f$ is a dummy variable that takes the value of one after 2005 if the worker leaves a firm that has been affected by the credit supply shock and zero otherwise. $Firm_f$ is a vector of firm fixed effects that accounts for time-invariant differences in turnover across firms, while $Year_t$ is a vector of year fixed effects to capture macroeconomic trends that can affect turnover. The coefficient β hence measures how the probability that a worker leaves a firm varies

[27] Because you cannot lose half of a worker, when you lose one educated worker, the effect on the growth rate might be amplified. Let us consider four companies with each 4 unskilled workers, and 1 manager. Say that the probability to leave is 25% for all categories of workers. One firm loses 1 manager, and each firm loses one unskilled worker. Then the average growth rate is -50% for managers and -25% for unskilled workers, while the probability to leave is the same.

for workers employed by treated firms versus workers in control firms after the credit supply shock. We also include a set of worker time-varying characteristics that could affect the probability of leaving: $WorkerControl_{i,t}$ includes a polynomial of age and tenure. The $FirmControl_{f,t}$ vector includes a large set of fixed effects that account for the evolution of the optimal composition of workers across sectors, firm size, age and ex-ante wage: year $\times$ industry, year $\times$ firm size quartiles , year $\times$ firm age quartiles, year $\times$ firm average wage quartiles, and an interaction term between firm-level product per worker in the pre-treatment period and year, in order to control for pre-exiting trends in productivity, at firm level. Our results are thus not driven by the possibility that, for example, firms that are affected by the shocks are also from industries/size quartile/age quartile/wage quartile where more educated employees are leaving. The effect is also robust to pre-existing differences in productivity level. Finally, we cluster standard errors at the banking group $\times$ industry level and results are robust to clustering at the worker level.

Table 8 reports the result. In Column 1, we find that lower access to credit is associated with an increase in the probability that workers leave the firm, as the coefficient β is positive, as well as statistically and economically significant. This estimate implies that the probability of the average worker to leave the firm is 1 percentage point higher when the firm is affected by the credit supply shock. As Table 2 shows, ex-ante, workers from treated and from control firms have the same probability of leaving.

We then show that the effect of the credit supply shock on the probability that a worker leaves the firm increases with the worker's skills. The results in Columns 2 to 5 of Table 8 suggest that the propensity of workers to leave affected firms is higher when workers are more educated. More precisely, the effect is twice larger for college and high-school educated workers than for workers with less than a high-school degree, with respectively a 1.4 pp and a 0.7 pp increase in the probability to leave. This result also stands across types of occupation: Columns 6 in the bottom part of the table indicates that workers in highly-skilled intensive occupations have a 2.5 percentage point higher probability to leave affected firms after the shock.

INCLUDE TABLE 8

Finally, the first panel on Figure 9 plots the dynamics of the difference in the probability to leave for college-educated workers in treated firms versus control firms. The strongest effect on leavers can be observed at the end of 2006, suggesting that the impact of the credit shock on worker separations lasts for two years.

5.3 Wage Outcome: Evidence of Voluntary Turnover

The previous result on separations by skill is consistent with two hypotheses. Either affected firms struggle to retain talents, or oppositely, they voluntarily dismiss the most expensive workers.

In this section, we disentangle between talent retention inability or voluntary firm reorganization. For this, we investigate the evolution of wages for workers who switch away from treated firms versus regular switchers, in a triple difference-in-differences wage panel model. Existing labor literature shows that when workers exit as a result of firing or firm closures, they incur significant earning losses (Jacobson et al. 1993; Couch and Placzek 2010). However, if workers self-select into firms with better growth opportunities, we should observe a positive effect on the wages of treated switchers, after the credit shock.

We identify as follows the differential effect of the credit supply shock on worker wages, by analysing whether treated workers switching after the credit shock receive a wage premium or a discount:

$$\begin{aligned} Log(HourlyWage)_{i,t} = {} & \beta Switcher_{i,t} \times Treated_f \times Post_t + \alpha Switcher_{i,t} + \\ & + \gamma Switcher_{i,t} \times Post_t + \theta Treated_f \times Post_t + \\ & + \mu Switcher_{i,t} \times Treated_f + Worker_i + Year_t + \epsilon_{i,f,t} \end{aligned} \tag{6}$$

$Log(HourlyWage)_{i,t}$ is the log of the average hourly wage of a worker i in year t.[28] $Switcher_{i,t}$ is a dummy variable indicating whether worker i switched to a different job since the previous year. We restrict the estimation sample to workers that in 2004 were employed by either a treated or a control firm. Thus, $Treated_f$

[28]The hourly wage does not include bonuses and variable income.

allocates workers to 0/1 groups, depending on whether they were employed by a control or a treated firm in 2004. We then keep the full employment history of workers that appear in QP every year, since 2002 to 2007, therefore identifying switchers from 2003 to 2007. $Post_t$ is a dummy variable that takes the value of one after 2005. The coefficient β of the triple interaction $Switcher_{i,t} \times Treated_f \times Post_t$ hence measures the sensitivity of the switching wage to the credit shock, by isolating the effect on workers leaving affected firms in the post-period. We include in the estimations combinations of the variables present in the triple interaction: $Switcher_{i,t}$, $Switcher_{i,t} \times Post_t$, $Treated_j \times Post_t$ and $Switcher_{i,t} \times Treated_f$. The dummies for $Treated$ and $Post$ are included in the worker and, respectively, year fixed effects. We estimate the model for the whole sample of workers and by education. To account for the non-linear effect of age on wages, all models include a second-degree polynomial in worker age. Standard errors are clustered at worker level and reported in brackets. In Table D8 in the online appendix we cluster the same specification at two-digit industry level.

INCLUDE TABLE 9

Table 9 shows that workers that leave affected firms experience a higher wage increase after the shock than previous to it and relative to switchers from non affected firms. Most importantly, the effect is mostly driven by high-school and college educated workers who experience a 2.7% and, respectively, 2.4% increase in wages after leaving affected firms. This result confirms that treated firms experience a loss of talent: educated workers switch to benefit from better opportunities in firms that are not affected by the shock.

5.4 Hiring across Skills

Next, we investigate whether the composition of workers that join affected firms varies after a firm is affected by a credit supply shock. If firms are not able to retain skilled workers but are still able to attract them, then the overall talent pool in the organization may be unaffected by the lower access to credit.

We analyze the ability of firms affected by a credit supply shock to attract skilled workers by estimating the following specification:

$$
\begin{aligned}
Pr(Joiningthefirm)_{i,f,t} = \beta Post_t \times Treated_f + \\
+ \alpha Firm_f + \eta Year_t + \phi WorkerControls_{i,t} + \\
+ \gamma FirmControls_{f,t} + \epsilon_{i,f,t}
\end{aligned}
\tag{7}
$$

This specification is the same as the one on employee separation reported in Table 8 except that $Pr(Joiningthefirm)_{i,f,t}$ is a dummy variable that takes the value one if worker i joins firm f in year t.

Table 10 reports the results. We first note that while the estimate of β in Column 1 is negative, which implies that affected firms attract fewer employees, the magnitude is very small. An average worker is only 0.1 percentage points less likely to start working at an affected firm. However, columns 2 to 5 indicate that the effect varies significantly by level of education. Following the shock, the probability that a firm will hire a worker with a college degree is 1.7 percentage points lower for affected firms. Not only are these firms losing talent as indicated in Table 8, but they are unable to replace the lost human capital by attracting highly skilled employees in sufficiently large numbers.

INCLUDE TABLE 10

The second panel on Figure 9 shows the dynamics of the difference in the probability that a college-educated worker enters a treated firm versus a control firm. The strongest effect on entrants can be observed at the end of 2005, immediately following the shock. While the entry rates seem to recover later on, the effect is not offset, and firms would plausibly need time to recover the lost firm-specific capital.

We here extend the finding of Brown and Matsa (2016) and Baghai et al. (2015). Even without facing financial distress, credit-constrained firms can struggle both to attract and to retain skilled workers. Through this human capital channel, credit supply shocks might affect firm growth and productivity over the long run.

6 Conclusion

Using an exogenous shock to bank internal resources, we document how access to credit affects firm ability to attract and retain skilled workers. We show that impaired access to credit affects not only firm total employment, but also the composition of the workforce. In good times, credit supply shocks hurt the accumulation of human capital in affected firms relatively to their unaffected competitors. This outcome could reduce the potential for future productivity and growth at these firms. Overall, we document the long run effects of credit market frictions.

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A. FIGURES

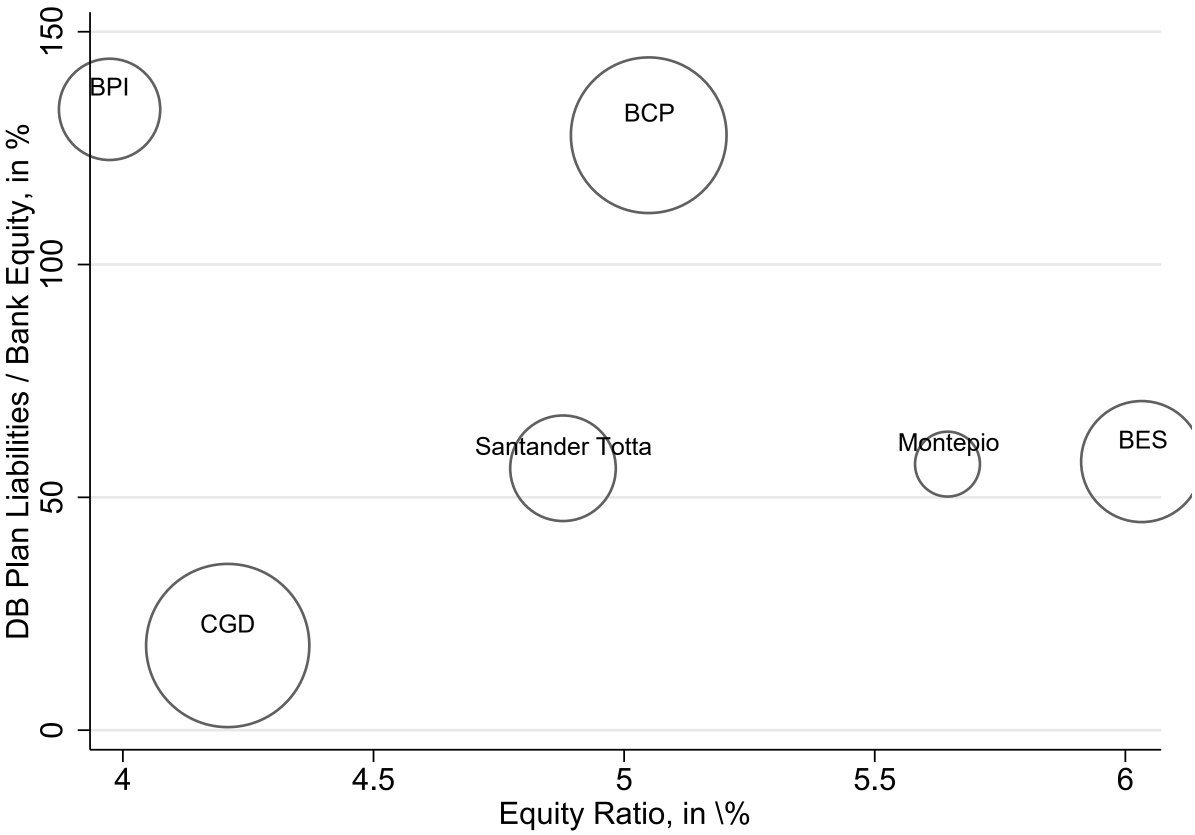

Figure 1. The Heterogeneous Exposure of the 6 Main Portuguese Banks to their DB Plans

This figure shows bank exposure to DB plans - measured as the ratio of the pension plan liabilities to bank total equity - for the 6 main Portuguese banks at the end of 2004 as a function of their equity ratio in 2004. The size of the symbol is proportional to the bank total assets. These 6 banks stand for 87% of total bank assets in Portugal. Data comes from the 2004 annual reports.

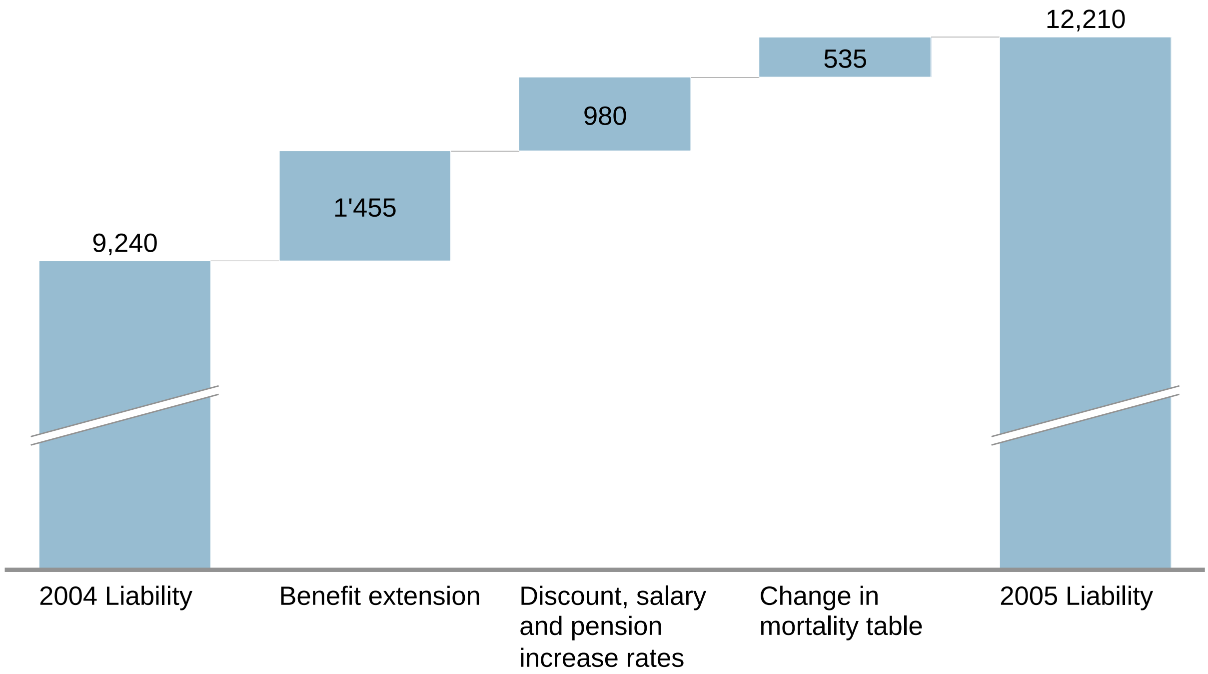

Figure 2. The Aggregate Effect of the New Accounting Standards on the DB Plan Pension Liability of Portuguese Banks

This figure illustrates the effect of the introduction of IAS 19 on the aggregated bank DB plan liabilities and decomposes the effects across its main channels. The introduction of IAS 19 resulted in a 30% increase in bank DB plan liabilities. The data is extracted from BoP's 2005 Financial Stability Report.

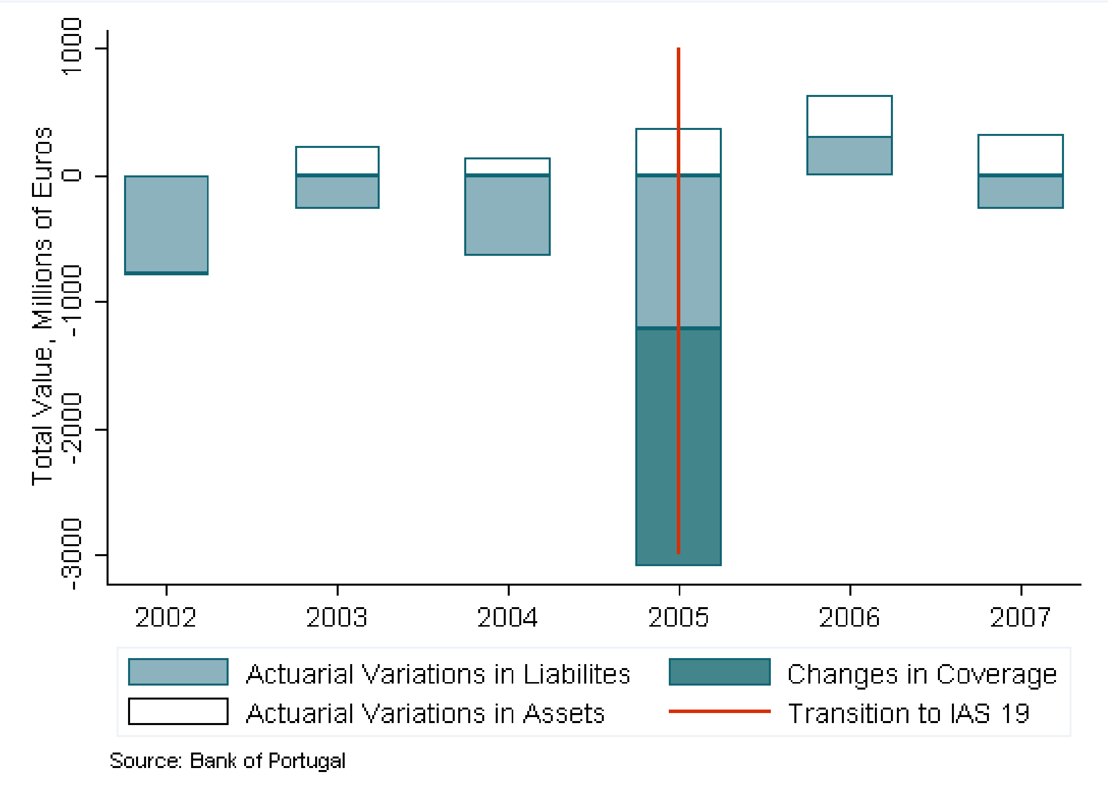

Figure 3. Aggregate Variations in Bank DB Plan Assets and Liabilities over the 2002-2007 Period

This figure shows the actuarial variations in the aggregate value of bank DB plan assets and liabilities in Portugal over the 2002-2007 period, as well as the increase in liabilities due to the extension of coverage following the introduction of IAS 19. The actuarial variations in pension liabilities stem mainly from the three channels illustrated in Figure 2.

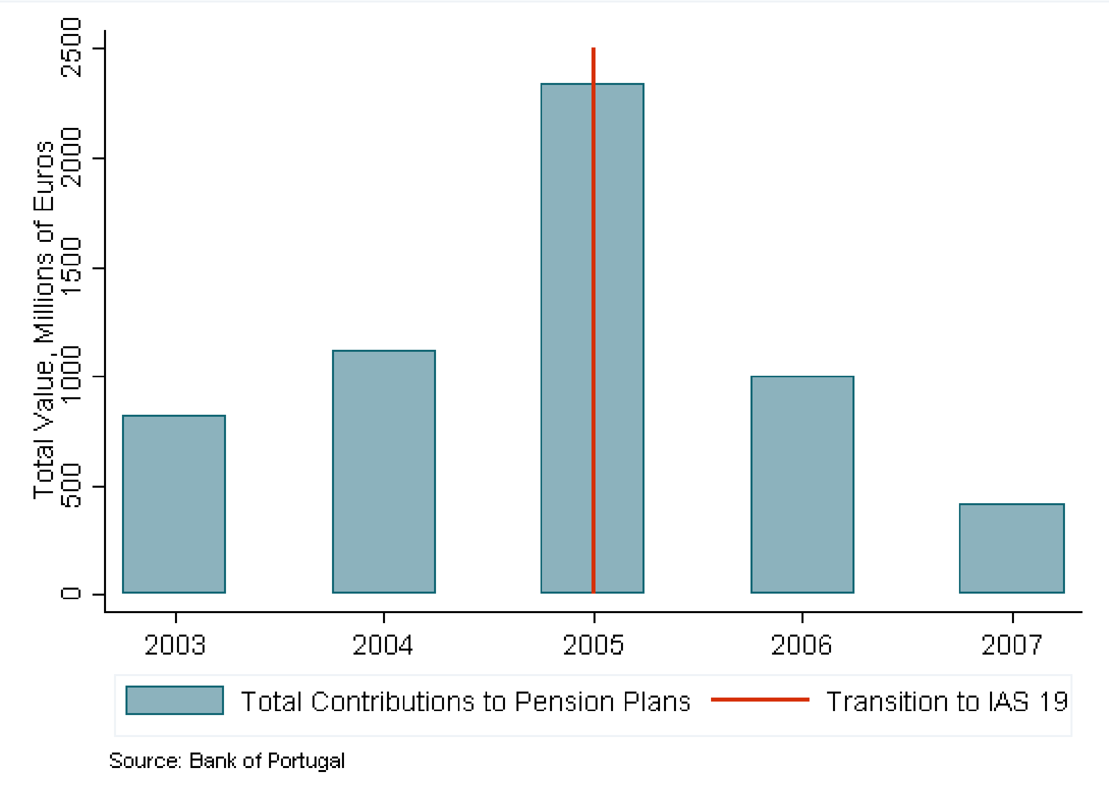

Figure 4. Aggregate Bank Direct Contributions to their DB Plans (2003-2007)

This figure shows the aggregate value of bank annual cash contributions to their DB pension plans over the 2003-2007 period. Legislation on privately funded pension plans in Portugal requires the pension benefit obligations to be funded at 100% for pensions in payment, and at 95% for employees in service. The large contributions in 2005 correspond to the increase in pension liabilities caused by the introduction of IAS19.

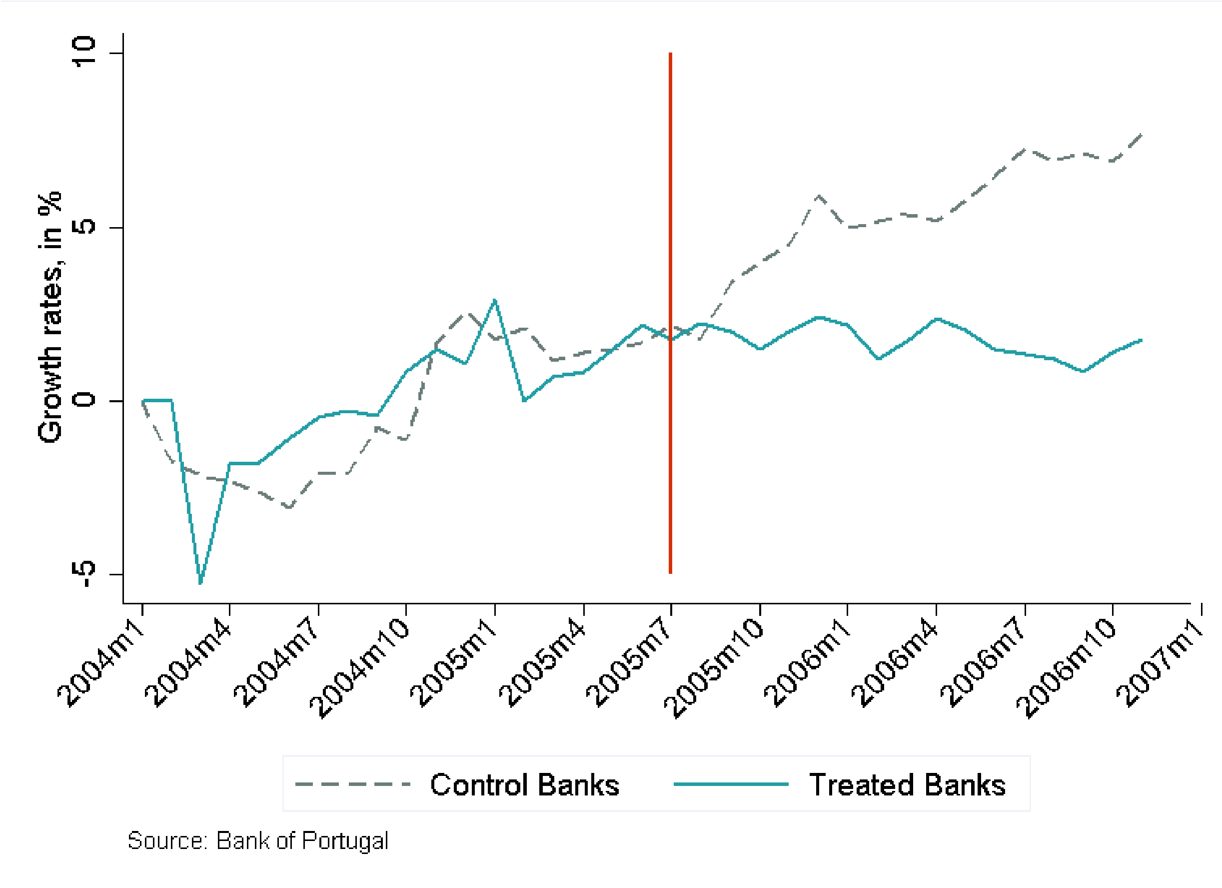

Figure 5. Evolution of Credit: Treated versus Control Banks

This figure captures the evolution of credit granted by treated and non-treated banks from January 2004 to January 2007. The two lines represent the percentage growth in credit since 2004 on a monthly basis. While credit granted by the two groups of banks evolves in parallel until 2005, since then credit exposures from treated banks experience visibly lower growth than controls.

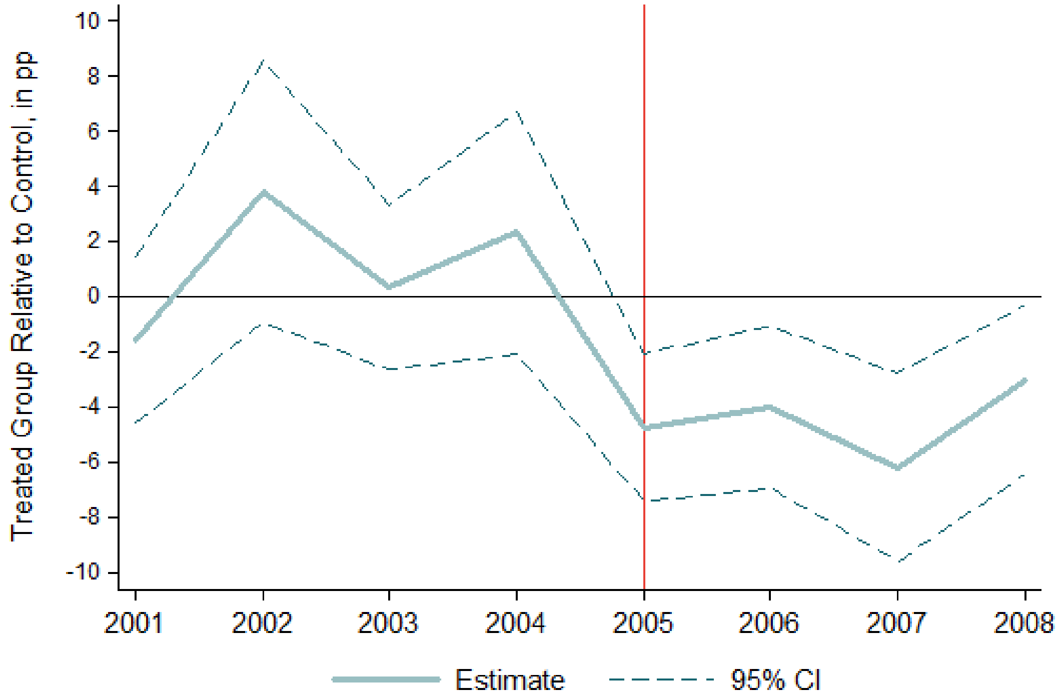

Figure 6. Yearly Differential Growth Rates of Credit of Treated Firms

This figure captures the yearly dynamics of the firm-level coefficients estimated in Table 5. The econometric model is similar to the estimation in column (3), except that the estimation is done on the yearly panel, with the year-on-year rate of growth of total credit as main dependent variable.

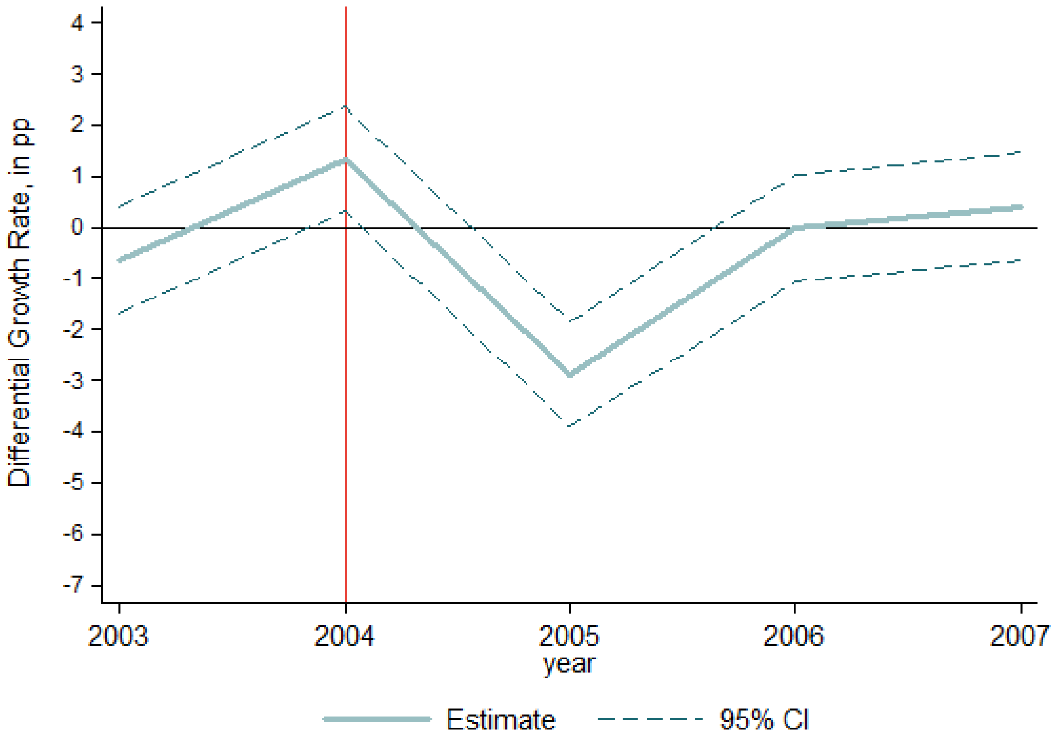

Figure 7. Yearly Differential Growth Rates of Employment of Treated Firms

This figure captures the yearly dynamics of the firm-level coefficients estimated in Table 7. The econometric model is similar, except that the estimation is done on the yearly panel, with the year-on-year rate of growth of employment as main dependent variable. The estimates are showed at the end of each year.

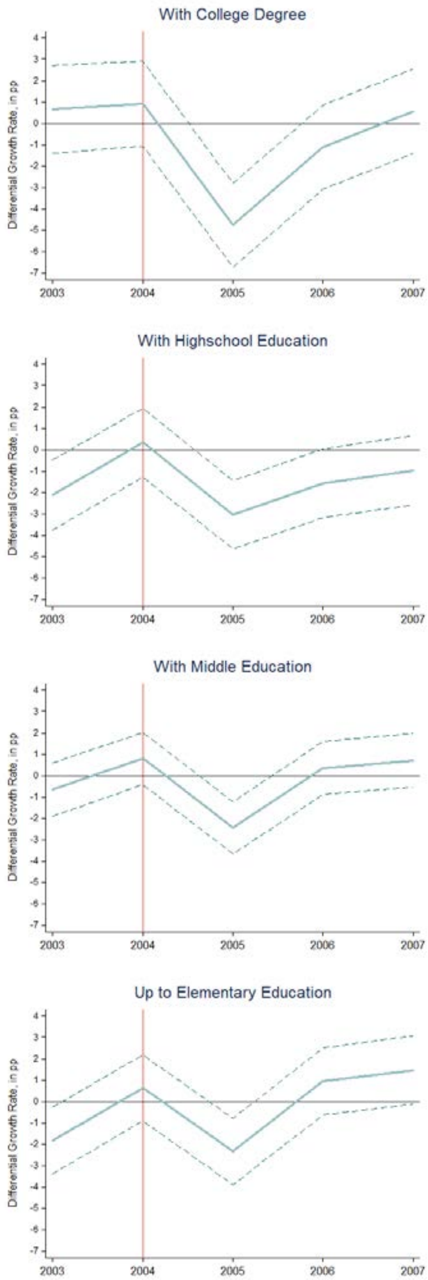

Figure 8. Yearly Differential Growth Rates of Employment, by Worker Education

This figure captures the yearly dynamics of the firm-level coefficients estimated in Table 7. The econometric model is similar, except that the estimation is done on the yearly panel, with the year-on-year rate of growth of employment as main dependent variable. Growth rates are calculated at the end of the year, over 2003 to 2007. The dotted lines show 95% confidence intervals.

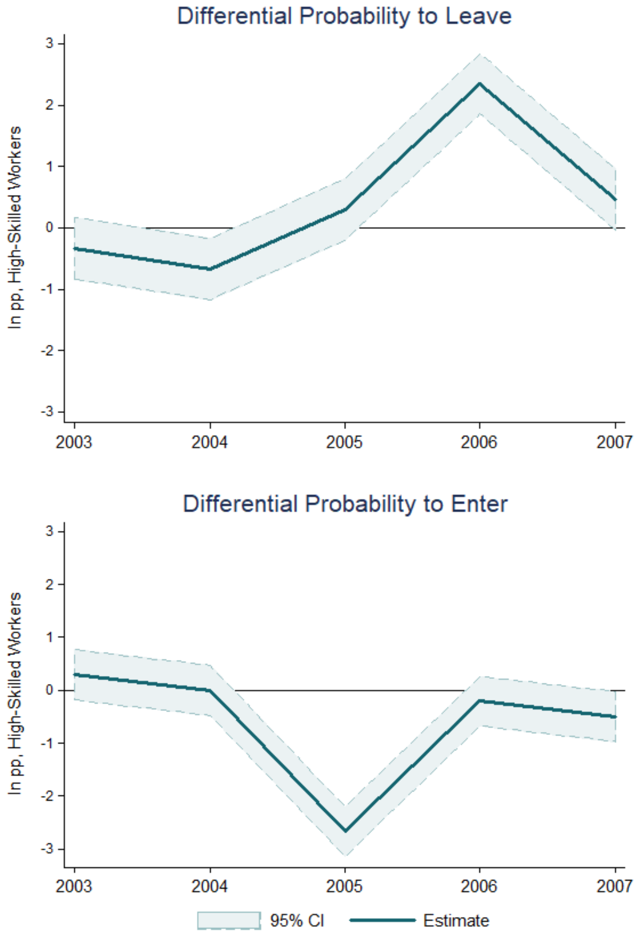

Figure 9. Yearly Differential Probabilities to Leave and to Enter a Treated Firm, for Workers with College Degree

This figure captures the dynamics of the probabilities that a worker leaves, respectively, enters, a treated firm. The yearly estimates are obtained from the specifications in Table 8 and Table 10. The dotted lines show 95% confidence intervals.

B. TABLES

Table 1. Summary Statistics: Banks and Firms

	N (1)	Mean (2)	SD (3)	P10 (4)	P50 (5)	P90 (6)
Bank DB Plan Characteristics						
Ratio of Bank Pension Liabilities to Bank Equity *(Treatment Intensity)*	333,788	0.40	0.32	0	0.40	1.04
High vs. Low intensity *(Treatment Dummy)*	333,788	0.54	0.49	0	1	1
Bank Characteristics - Treated Group						
Log(Total Assets) (EUR 000)	13	8.09	1.73	5.65	7.98	10.34
Capital Ratio	13	.08	.04	.03	.09	.13
Liquidity Ratio	13	.19	.18	.04	.14	.46
Loans to Assets	13	.74	.19	.55	.79	.93
Short Term Liabilities to Assets	13	.17	.13	.01	.19	.35
Bond Funding Ratio	13	.07	.09	.01	.06	.24
Doubtful Ratio	13	.01	.01	0	.01	.03
Bank Characteristics - Control Group						
Log(Total Assets) (EUR 000)	46	6.36	1.92	4.07	6.01	8.76
Capital Ratio	46	.11	.10	.06	.09	.24
Liquidity Ratio	46	.22	.21	.01	.14	.53
Loans to Assets	46	.79	.20	.47	.87	.98
Short Term Liabilities to Assets	46	.15	.12	.0.01	.14	.31
Bond Funding Ratio	46	.03	.06	0	.01	.06
Doubtful Ratio	46	.02	.04	.01	0.01	.06
Firm Exposure to Affected Banks						
Treatment Intensity	161,202	.39	.28	.016	.40	.79
Treatment Dummy	161,202	.50	.49	0	1	1
Firm Characteristics - Treated Group						
Total Sales (EUR 000)	80,846	758.47	2,105.67	10.78	175.01	1,531.79
Firm Age	80,846	11.70	14.09	2	8	26
% Foreign Ownership	80,846	1.86	12.98	0	0	0
% Public Ownership	80,846	.15	3.51	0	0	0
Months in the CR	80,846	72.91	40.72	16	75	120
Average Monthly Credit (Log EUR)	80,846	5.23	5.77	3.28	4.39	5.47
Current Default Dummy	80,846	.04	.20	0	0	0
Past Default Dummy	80,846	.09	.28	0	0	0
Number of Workers	80,846	12.61	81.99	1	4	20
- with low education	80,846	3.18	22.23	0	0	6
- with middle education	80,846	5.26	41.04	0	2	9
- with highschool	80,846	2.49	23.65	0	1	4
- with college	80,846	1.38	14.62	0	0	2
Average Sales per Worker (EUR 000)	80,846	87.70	422.60	3.78	37.87	164.07
Average Hourly Wage (EUR)	80,846	3.96	3.74	0	3.36	6.68
Average Workforce Tenure	80,846	5.72	4.84	1.02	4.22	12.59
Average Workforce Age	80,846	39.24	7.62	30	38.67	49.42
Firm Characteristics - Control Group						
Total Sales (EUR 000)	80,356	915.08	2,393.78	13.29	191.87	1,966.48
Firm Age	80,356	11.58	15.68	2	8	25
% Foreign Ownership	80,356	1.04	9.65	0	0	0
% Public Ownership	80,356	.25	4.73	0	0	0
Months in the CR	80,356	73.14	40.67	17	75	120
Average Monthly Credit (Log EUR)	80,356	5.46	5.91	3.66	4.59	5.79
Current Default Dummy	80,356	.08	.27	0	0	0
Past Default Dummy	80,356	.15	.35	0	0	1
Number of Workers	80,356	15.35	113.93	1	5	25
- with low education	80,846	4.09	24.21	0	1	8
- with middle education	80,846	6.45	46.42	0	2	11
- with highschool	80,846	2.86	37.99	0	1	4
- with college	80,846	1.56	23.42	0	0	2
Average Sales per Worker (EUR 000)	80,356	89.70	333.58	4.41	39.27	175.76
Average Hourly Wage (EUR)	80,356	3.61	2.55	0	3.35	6.35
Average Workforce Tenure	80,356	5.43	4.50	1.08	4.08	11.75
Average Workforce Age	80,356	38.82	7.37	30	38.25	48.5

This table reports summary statistics for all bank-firm credit exposures, bank and pension plan data as well as firm characteristics in 2004, the year before the shock. Banks and firms are separated in treatment and control groups as described in Section 3.3.

Table 2. Summary Statistics: Workers

	N (1)	Mean (2)	SD (3)	P10 (4)	P50 (5)	P90 (6)
Worker Characteristics - Treated Group						
Probability to Leave	929,861	.22	.42	0	0	1
Probability to Enter	929,861	.25	.44	0	0	1
Probability to Switch	929,861	.08	.27	0	0	1
Hourly Wage (2004 Euros)	929,861	5.84	8.49	2.54	4.05	10.5
Years of Education (Starting at 6)	929,861	8.14	4.01	4	9	15
Gender (1=Male; 2=Female)	929,861	1.42	.49	1	1	2
Age	929,861	38.40	11.23	25	37	54
Tenure in Firm	929,861	7.68	8.30	0.5	4.58	19.08
Worker Characteristics - Control Group						
Probability to Leave	1,127,250	.22	.42	0	0	1
Probability to Enter	1,127,250	.25	.43	0	0	1
Probability to Switch	1,127,250	.08	.26	0	0	1
Hourly Wage (2004 Euros)	1,127,250	5.97	8.58	2.54	4.08	11.13
Years of Education (Starting at 6)	1,127,250	7.96	4.00	4	6	12
Gender (1=Male; 2=Female)	1,127,250	1.39	.49	1	1	2
Age	1,127,250	38.52	11.21	25	37	54
Tenure in Firm	1,127,250	8.02	8.57	0.5	4.75	20.92

This table reports summary statistics for all workers of treated and control firms in 2004. A total of 2,196,014 workers is separated into treated and control groups based on the treatment of their employer.

Table 3. The Introduction of IAS 19: Description of the Treatment

Timeline	
Implementation of IAS19	January-June 2005
Pre-treatment Period	Year 2004
Post-treatment Period	Years 2005-2006
The Effect on Banks	
Treated Banks	
Number	13
% of Total Credit	56
Control Banks	
Number	46
% of Total Credit	44
Effect on Bank Internal Funds	
2005 Contribution to DB Plans	
2005 Total Amount, bln euros	2.3
Percentage of Treated Bank Equity	21
2005 Prudential Deductions	
Total Amount, bln euros	1.5
Percentage of Treated Bank Equity	14
Treatment Variables	
Treatment Dummy (Average)	0.54
Treatment Intensity (Average)	0.40
Treatment Intensity (Standard Deviation)	0.32
Main Effect on Bank-Firm Credit Exposure	
Reduction in Credit Growth for Treated Exposures	-17 pp
The Effect on Firms	
Treatment Variables	
Treatment Dummy (Average)	0.5
Weighted Treatment Intensity (Average)	0.39
Weighted Treatment Intensity (Standard Deviation)	0.28
Main Effect on Credit Growth	
Reduction in Credit Growth for Treated Firms	-8 pp
Main Effect on Employment	
Variation in Total Employment Growth	-1.7 pp
Inferred Effect on Total Employment Growth of a 10 pp Decrease in Credit Growth	- 1.9 pp

This table summarizes the characteristics and the main effects of the 2005 credit supply shock triggered by the introduction of IAS 19. Effects are computed using the estimation results in Table 4 (column 8), Table 5 (column 3) and Table 7 (column 1).

Table 4. The Impact of the Introduction of IAS 19 on Bank Lending

	Bank-Firm Credit Growth					New Lending	End Lending	Bank-Firm Credit Growth	
Sample	All				*Treatment>0*	All		Final Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment dummy	-0.168*** (0.004)	-0.191*** (0.025)	-0.177*** (0.027)			-0.550*** (0.062)	0.167*** (0.043)	-0.168*** (0.025)	-0.189*** (0.029)
Treatment intensity				-0.109*** (0.041)	-0.181*** (0.063)				
Firm Characteristics	-	Yes	-	-	-	Yes	Yes	Yes	-
Firm Fixed Effects	-	-	Yes	Yes	Yes	-	-	-	Yes
Bank Characteristics	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	426,119	426,119	319,197	319,197	236,685	426,119	426,119	333,788	269,181
R^2	0.005	0.130	0.457	0.455	0.489			0.063	0.413
Pseudo-R^2						0.236	0.031		

This table reports the coefficients of OLS and Logit estimations where the unit of observation is the loan exposure at the bank-firm level. The dependent variable is the growth of the loan exposure between the pre-treatment period (2004) and the post treatment period (2005 - 2006) in columns (1) to (5), (8) and (9). In columns (6) and (7), the dependent variables are dummy variables that indicate respectively whether a new loan is granted to a firm with currently zero exposure to the credit-granting bank and whether an existing loan exposure ends in the post-period. The independent variable $Treatment\ intensity$ is the ratio of bank pension liabilities to bank total equity in the *pre-period*, while the variable $Treatment\ dummy$ allocates banks into treatment and control groups, at the median of the $Treatment\ intensity$ variable. The initial sample comprises the universe of bank-firm exposures over the 2004-2006 period. Column (5) restricts the analysis only to bank-firm credit exposures covered by banks with a positive pension treatment. Columns (8) and (9) restrict the sample to 161,202 firms, which have positive credit and hire at least one worker in the pre-period. This sample remains constant in the subsequent analyses. We add seven numerical bank controls, including the logarithm of assets, capital ratios, liquidity ratios, loan-to-asset ratios, short term liabilities to assets, bond funding to assets, and non performing loan ratios in 2004, as well as the categorical controls for the type of credit institution. In the specifications without firm fixed effects, firm controls include our measures of the firm credit history, i.e. average volumes of credit over the previous 10 years, the number of months with positive credit exposures, and indicators for past and current defaults. In Columns (8) and (9) we have information on the whole sample of firms in 2004, and so firm controls also include the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure. Standard errors are clustered at banking group×industry levels and are reported in brackets, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 5. The Impact of the Introduction of IAS 19 on Firm Total Credit Exposure

	Credit Growth at Firm Level						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment dummy	-0.075***	-0.077***	-0.080***	-0.066***			
	(0.016)	(0.017)	(0.015)	(0.013)			
Treatment intensity					-0.179***	-0.186***	-0.150***
					(0.024)	(0.021)	(0.024)
Firm Characteristics	-	Yes	Yes	Yes	Yes	Yes	Yes
Bank Characteristics	-	-	-	Yes	-	-	Yes
Industry Fixed Effects	-	-	Yes	Yes	-	Yes	Yes
N	161,202	161,202	161,202	161,202	161,202	161,202	161,202
R^2	0.002	0.076	0.080	0.082	0.078	0.081	0.082

This table reports the coefficients of OLS regressions where the dependent variable is the growth of firm total credit exposure between the pre-treatment period, 2004, and the post treatment period, 2005-2006. The independent variable, *Treatment dummy*, separates firms into treated or control groups, depending on whether more than half of their total credit exposure in the pre-period comes from highly treated banks. The alternative independent variable, *Treatment intensity*, is the average treatment intensity across all the banks a firm borrows from in the pre-period, weighted by their relative share in the firm's total credit exposure over the same period. We start with a simple difference-in-difference estimation in Model (1) and we progressively add firm controls, i.e. our measures of credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for legal organization and ownership structure. In column (3), we add industry fixed effects. In addition, columns (4) and (7) include controls for the "average" bank - i.e., the logarithm of assets, capital ratios, liquidity ratios, loan-to-asset ratios, short term liabilities to assets, bond funding to assets, and non performing loan ratios in 2004 - weighted by each bank's credit exposure in a firm's total credit in the same year. Standard errors are clustered at banking group × industry levels and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Table 6. The Heterogeneous Impact of IAS19 on Firm Credit Exposure by Industry and Firm Size

	Credit Growth at Firm Level					
	Panel A. By Industry					
Sample	Information & Communication (1)	Hospitality & Food (2)	Wholesale Trade (3)	Transporting & Storage (4)	Manufacturing (5)	Legal & Accounting (6)
Treatment dummy	-0.112***	-0.177***	-0.078***	-0.073***	-0.051***	-0.053***
	(0.019)	(0.017)	(0.011)	(0.007)	(0.010)	(0.013)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,156	12,798	23,511	50,323	25,371	19,664
R^2	0.095	0.046	0.110	0.092	0.105	0.055

	Panel B. By Firm Size	
	Lower Quartile	Upper Quartile
Treatment dummy	-0.107***	-0.055***
	(0.016)	(0.009)
Firm Characteristics	Yes	Yes
Industry Fixed Effects	Yes	Yes
Observations	45,258	44,558
R^2	0.088	0.086

This table estimates specification (2) and, respectively, (3) as in Table 5, by industry and firm size. The dependent variable is the growth rate of firm total credit exposure between the pre-treatment period, 2004, and the post treatment period, 2005-2006. Standard errors are clustered at banking group × industry levels and reported in brackets, $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Table 7. The Impact of the Introduction of IAS 19 on Firm Employment by Education Level and Occupation Type

	Employment Growth, Firm Level				
		By Education Level			
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Treatment dummy	-0.017***	-0.036***	-0.021***	-0.018***	-0.012*
	(0.003)	(0.009)	(0.007)	(0.005)	(0.006)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	161,202	59,421	96,174	131,094	93,562
R^2	0.602	0.291	0.331	0.258	0.386
	By Occupation Type				
	Management (6)	Highly-Skilled Intensive (7)	Skilled Intensive (8)	Semi-Skilled Intensive (9)	Non-Skilled (10)
Treatment dummy	-0.013***	-0.020**	-0.001	-0.016***	-0.002
	(0.005)	(0.008)	(0.006)	(0.005)	(0.010)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	140,849	44,578	125,712	63,859	55,619
R^2	0.167	0.071	0.143	0.075	0.059

This table reports the coefficients of OLS regressions where the dependent variable is the growth rate of employment at the firm level between the pre-period (2004) and the post-period (2005 to 2006). The independent variable *Treatment dummy* splits firms into two groups based on the intensity of the treatment. All specifications are saturated with 52 two-digit industry fixed effects and control for the full set of firm characteristics available in 2004: the four measures of firm credit history, the logarithm of total sales, firm age, product per worker and workforce tenure, as well as indicators for the legal organization and the ownership structure. The initial sample includes all private firms from the non-financial sector which in 2004 had positive credit exposure and hired at least one worker. In Columns 2 to 10 the sample is restricted to firms hiring at least one worker with the specified education level or type of occupation over the three years of analysis. Standard errors are clustered at banking group $\times$ industry levels and reported in brackets, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8. The Impact of the Introduction of IAS 19 on Employee Separation by Education Level and Occupation Type

	Dummy=1 if the Employee Leaves the Firm, 0 if not				
		By Education Level			
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Post × Treated	0.010***	0.013***	0.014***	0.006***	0.008***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	7,875,424	873,317	1,616,382	3,427,894	1,923,440
R^2	0.249	0.246	0.293	0.272	0.270
	By Occupation Type				
	Management (6)	Highly-Skilled Intensive (7)	Skilled Intensive (8)	Semi-Skilled Intensive (9)	Non-Skilled (10)
Post × Treated	0.008***	0.025***	0.006***	0.005***	0.021***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	1,471,296	553,660	3,118,535	1,236,680	915,451
R^2	0.249	0.270	0.272	0.293	0.246

This table reports the coefficients of a linear model estimating the probability that a worker leaves a job. The dependent variable is a dummy variable equal to 1 when a worker leaves their firm, and 0 if the worker stays with the same firm. The independent variable *Treatment dummy* allocates workers into treated or control groups, depending on the classification of the firms they are leaving. The estimations are based on panel analysis, including a pre and a post period. The pre-period includes 2003 and 2004. The post-period includes 2005 and 2006. All specifications are saturated with firm and year fixed effects, year*industry fixed effects, as well as fixed effects for the interaction between year and quartiles for the main firm characteristics (size, age, and average hourly wage, in the pre-period). In addition, all models include an interaction term between sales per worker and year, in order to control for pre-exiting trends in productivity, at firm level. Worker characteristics include a polynomial of age and gender. The initial sample includes all private firms from the non-financial sector which in 2004 had positive credit exposure and hired at least one worker. In columns (2) to (10) the sample is restricted by worker education and occupation. Standard errors are clustered at banking group × industry levels and reported in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9. The Impact of the Introduction of IAS 19 on the Wage Outcome of Leavers by Education Level

	Log(hourly wage)				
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Switcher × Treated × Post	0.016***	0.024***	0.027***	0.002	-0.004
	(0.002)	(0.007)	(0.005)	(0.004)	(0.005)
Switcher	-0.006***	0.003	-0.004**	-0.012***	-0.011***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)
Switcher × Treated	-0.007***	-0.011***	-0.017***	-0.001	0.002
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)
Switcher × Post	0.004***	0.010*	-0.002	0.010***	0.012***
	(0.002)	(0.005)	(0.004)	(0.002)	(0.003)
Treated × Post	-0.002***	-0.012***	-0.010***	0.001	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Worker Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,329,307	555,176	1,058,686	2,199,982	1,321,446
R^2	0.909	0.899	0.901	0.875	0.858

This table reports the coefficients of a long term wage panel model, from 2002 to 2007, estimating the wage premium or discount when workers switch firms. The main dependent variable is the logarithm of average hourly wage at worker level. The main explanatory variable, $SwitcherXTreatedXPost$, is an indicator for workers who switch away from treated firms, in the post period. We include dummies for the double interactions, as well as a dummy for $Switchers$. The dummies for $Treated$ and $Post$ are included in the worker and, respectively, year fixed effects. The sample includes workers 1/ that were employed in 2004 at either treated or non-treated firms and, 2/ for which we have information on the yearly labor market history. We therefore work with a fully balanced panel at the worker-year level. In Columns 2 to 5, the sample is restricted to workers of each specified level of education. All models include a second-degree polynomial in worker age. Standard errors are clustered at worker level and reported in brackets. $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$

Table 10. The Impact of the Introduction of IAS 19 on Employee Hiring by Education Level and Occupation Type

	Dummy Variable=1 if the employee is new to the firm, 0 if not				
		By Education Level			
	All Workers (1)	College Degree (2)	High School Degree (3)	Middle School (4)	Up to Elementary School (5)
Post × Treated	-0.001***	-0.017***	-0.006***	0.005***	-0.001
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	7,875,424	873,317	1,616,382	3,427,894	1,923,440
R^2	0.373	0.379	0.423	0.401	0.386
	By Occupation Type				
	Management (6)	Highly-Skilled Intensive (7)	Skilled Intensive (8)	Semi-Skilled Intensive (9)	Non-Skilled (10)
Post × Treated	-0.007***	-0.009***	-0.000	-0.007***	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Size FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Age FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Wage FE	Yes	Yes	Yes	Yes	Yes
Year*Firm Productivity	Yes	Yes	Yes	Yes	Yes
Observations	1,471,296	553,660	3,118,535	1,236,680	915,451
R^2	0.336	0.369	0.373	0.407	0.454

This table reports the coefficients of a linear model estimating the probability that a worker enters a firm in the sample. The dependent variable is a dummy variable equal to 1 for the first year a worker enters a firm, and 0 for existing workers. The independent variable *Treatment dummy* allocates workers into treated or control groups, depending on the classification of the firms they are entering. The estimations are based on panel analysis, including a pre and a post period. The pre-period includes 2003 and 2004. The post-period includes 2005 and 2006. All specifications are saturated with firm and year fixed effects, year*industry fixed effects, as well as fixed effects for the interaction between year and quartiles for the main firm characteristics (size, age, and average hourly wage in the pre-period). In addition, all models include an interaction term between product per worker and year, in order to control for pre-exiting trends in productivity, at firm level. Worker characteristics include a polynomial of age and gender. The initial sample includes all private firms from the non-financial sector which in 2004 had positive credit exposure and hired at least one worker. In columns (2) to (10) the sample is restricted by worker education and occupation. Standard errors are clustered at banking group × industry and reported in brackets. $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$.

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