Credit Supply Shocks and Human Capital: Evidence from a Change in Accounting Norms

October 31, 2018

Abstract

We exploit changes in accounting norms for bank defined benefit pension plans in Portugal to identify the effects of exogenous credit supply shocks on firm ability to attract and retain skilled workers. Using bank-firm credit exposures, matched with a census of Portuguese employees, we show that firms in a relationship with affected banks borrow less and reduce employment mostly of high-skilled workers. These 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.

Keywords: Credit Frictions, Employment, Skills, Wages

1 Introduction

Accumulating human capital is fundamental for firm long run productivity and growth (Becker 1975; Black and Lynch 1996; Katz and Murphy 1992).[1] A recent literature shows that, when facing adverse credit supply shocks, firms tend not only to downscale borrowing, investment and production, but also employment (Bentolila et al. 2015; Berton et al. 2016; Popov and Rocholl 2015; Siemer 2016). Understanding how these employment effects alter the talent pool of firms is, therefore, key to assessing whether credit shocks have long term implications on firm performance. Negative credit supply shocks could have only temporary or even positive effects on firm productivity if only the less productive workers, which are easily substitutable, leave affected firms.[2] Conversely, negative credit supply shocks could have long-term irreversible effects if high-skilled workers that have accumulated firm-specific skills leave affected firms, while entrenched less productive workers keep their jobs. Our objective is to investigate how exogenous credit supply shocks affect firm ability to retain and attract high-skilled workers.

Measuring the effects of access to credit on firm ability to retain and attract skilled workers is challenging. First, it requires a credit supply shock that is orthogonal to both bank and firm health, not contemporaneous to any important variation in labor market conditions, and takes place in good times. This is because talent retention is more crucial when talents do have rewarding outside options. Second, we need bank, firm and employee data, as well as a way to link these three layers of information. Finally, detailed employee-level information on education, experience and occupation is necessary. Our paper exploits the introduction of new accounting norms for bank defined-benefit (DB) pension plans in 2005 in Portugal as an exogenous shock to credit supply.[3] We explore the effect of this shock by

[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).

[2] Similarly, when credit shocks affect physical investment, their effects can be reversed by replenishing capital stocks once financing conditions improve.

[3] 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.

matching bank-firm credit exposures from the Portuguese credit register with a census of all Portuguese employees from private sector firms.

While, consistent with the existing literature (Berton et al. 2016; Chodorow-Reich 2014; Siemer 2016), we also show that negative credit supply shocks have a negative effect on firm total employment, we find that, in good times, the effect is stronger on the right tail of the skill distribution. Workers holding a college degree and those occupying high-skilled jobs - such as managers and specialists - are more likely to leave firms affected by an adverse credit shock. When these workers switch jobs from affected firms, they obtain better wages than ordinary switchers. Finally, these workers are less likely to start working at affected firms. These results suggest that credit supply shocks affect the talent pool of firms, with potentially long term effects on their productivity.

To obtain our results, we exploit a credit supply shock triggered by the adoption of new accounting norms for bank DB plans introduced in 2005 in Portugal - the *International Accounting Standard Nineteen* (or IAS 19). In a DB 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 DB plan liabilities are equal to the discounted value of the payments pledged to retirees based on actuarial 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 DB plan liabilities for two reasons. On the one hand, bank DB plans had to cover new types of benefits: post-employment medical care and life insurance. Actuarial assumptions, on the other hand, changed significantly: discount rates decreased and life expectancy estimates were revised upwards, leading to large actuarial losses.

The increases in the accounting value of bank pension plan liabilities resulting from IAS 19 forced banks to make large contributions to their pension plans, hence directly affecting their internal financial resources. In 2005, the total bank contributions to pension plans amounted to 2.5 billion euros, almost 20% of the Tier 1 capital of affected banks. These increases in direct contributions are 1) *heterogeneous across banks*, as both the size of bank pension plans and the magnitude of the effects on their funding status vary across banks, 2) *orthogonal to bank health*, as they result only from changes in the accounting norms that are unrelated to bank financial characteristics, 3) *orthogonal to firm employment decisions*, because pension plans are mostly held by banks in Portugal 4) *not contemporaneous to any important variation in macroeconomic or labor market conditions* as the years 2004 and 2005 were years of stable growth in Portugal.

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 of all Portuguese employees in private sector firms. The census includes detailed information on each employee's career, education, occupation and earnings. This bank-firm-employee matched dataset allows us to measure the impact of our 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 three steps. We first investigate the effect of the introduction of IAS 19 on bank-firm credit exposures in a difference-in-differences setting at the loan level. We find that on average, when facing a shock that reduces their internal resources by 20%, banks cut loan growth by around 18 pp, and are 55% less likely to start a new loan. Our specification controls for bank balance sheet and a wide range of firm characteristics. In addition, because the majority of firms borrow from several banks, we control for demand by including firm fixed effects (Khwaja and Mian 2008).

In a second step, we show that firms in a relationship with treated banks are able to offset only half of the shock by borrowing from other banks and reduce employment after the shock. A one standard deviation increase in the treatment intensity results in a decrease in loan growth by 8 pp and employment growth by 1.6 pp. To obtain this result, we build a firm-level measure of treatment intensity, which is the weighted average of the treatment intensity across all the banks a firm is borrowing from in the pre-treatment period. These results are robust to the inclusion of industry fixed effects, of multiple firm and bank controls and are stronger for small firms.

Finally, we investigate the effects of the credit supply shock on employment across worker characteristics. At the firm level, we find that employment decreases relatively more among employees with a high level of education. This result is confirmed at the individual level: high-skilled workers are more likely to leave - and less likely to start working at - affected firms.

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 2016) and firm employment (Benmelech et al. 2016; Bentolila et al. 2015; Berton et al. 2016; Acharya et al. 2015; Chodorow-Reich 2014; Popov and Rocholl 2015; Berg 2016; Hochfellner et al. 2015; Caggese et al. 2016; Siemer 2016) in three 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 more outside options. While in bad times, what we observe is that low-skilled workers are the most affected (Berton et al. 2016) with possible effect on inequality, in good times, credit supply shocks could have negative effects on the allocation of skilled workers in the economy.

Our paper also complements the literature that quantifies job reallocation effects *across firms*. Davis and Haltiwanger (1992) estimate that job creation and destruction account roughly for 20% of jobs, while Campbell and Kuttner (1996) find that reallocation shocks account for roughly half of the variance in total employment growth. Bai et al. (2015) find that the state-level deregulation of local

U.S. banking markets leads to significant increases in the reallocation of labor within local industries.[4] Babina (2016) investigates the effects of firm financial distress on employees' transition to entrepreneurship.

Finally, the paper contributes 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. Baghai et al. (2015) show 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.

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 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 the institutional details of the functioning of bank pension plans in Portugal and describes the effects of the IAS 19 accounting reform.

2.1 Bank DB Pension Plans in Portugal: an Overview

The DB plans of the Portuguese banking system have some unique specificities that contribute to the robustness of our natural experiment.

First, at the start of 2005, bank DB plans are large financial institutions that cover a large share of Portuguese employees from the banking sector. Portuguese banks started offering pension plans in the late 1980s, following the adoption of

[4] Acharya et al. (2011) looks at the effect of state-level banking deregulation in the US on the allocation of output across sectors.

the 1986 Social Security Act.[5] Bank DB plans were implemented through labor agreements between banks and 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, bank DB plans cover more than 180,000 employees, with total liabilities amounting to 9.2 billion euros, around 6% of Portuguese GDP.[6]

Second, there is a lot of heterogeneity across bank exposures to DB plans. Since the late 1980s, banks offering private pension coverage have always been coexisting 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 banking groups in Portugal are not offering pension plans. But even across banks that do sponsor a private DB plan - in fact, banks that do so account for 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.[7] Last but not least, banks are using different economic and demographic assumptions to estimate the value of their pension plan liability. Table X in the online appendix illustrates the strong heterogeneity across Bank DB plans for the 6 largest Portuguese banks.

Figure 1 plots bank pension liabilities as a percentage of bank equity in 2004 for the 10 main Portuguese banks. Bank exposure to their pension plan ranges from

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

[6]Estatisticas de Fundos de Pensoes - $http://www.asf.com.pt/NR/exeres/21E954ED-7325-4CE6-8626-11AFE2245D5A.htm$

[7]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).

0 to 104% of their 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, within the whole Portuguese economy, mostly affected only banks, as bank DB plans account for most of the private pension system in Portugal. 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. Hence, bank DB plans stand for more than 80% of the private pension plan assets under management in 2004.

The assets of bank DB plans are generally invested in a large range of financial securities. In 2005, 38% of total fund assets are invested in fixed income securities and 25% in equity.

2.2 The Accounting of Bank DB Plans

Accounting norms are crucial in the assessment of the value of a pension plan assets and liabilities, which can directly affect the financial flexibility of the sponsor bank.

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 retirees. The bank has to fund pension liabilities with dedicated assets.

The calculation of the accounting value of a DB plan assets and liabilities is based on actuarial assumptions that are defined by accounting norms at the bank, national (before 2005) or international levels (after the implementation of IFRS in 2005). When they vary, these actuarial assumptions lead to *actuarial gains or losses*. There are two primary sets of actuarial assumptions. Economic assumptions deal with the discount rate, wage growth, inflation and the expected

[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

long-term rate of returns on assets. Demographic assumptions, on the other hand, include 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 *actuarial losses*.

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* in its balance sheet and make prudential deductions from Tier 1 capital.

The sponsor of a DB plan is required to make cash contributions to the pension plan when the pension plan is "underfunded". A pension plan is considered underfunded when the market value of the plan assets is less than the present discounted value of the pension liabilities. Such a situation may result from *actuarial losses*. In this case, required contributions are defined by a legally specified formula.

Prudential deductions from Tier 1 capital were introduced in 2002 by Bank of Portugal to shield bank capital from deferred actuarial losses. The bank can indeed defer the reporting of part of the actuarial losses in the income statements 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 and deducted from Tier 1 capital. Thus, banks facing an increase in actuarial losses have to monitor closely their capital levels to remain compliant.

Figure 2 illustrates how a 50 million Euros increase in the accounting value of a bank DB plan liabilities can lead to contributions and prudential deductions. The technical annex provides more detail on the exact accounting rules that drive contributions and prudential deductions.

INSERT FIGURE 2

[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 - and 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 the online appendix.

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 led to a large increase in bank cash contributions to their DB plans, hence affecting directly their internal financial resources while resulting also in prudential deductions from Tier 1 capital.

The introduction of IAS19 in 2005

In 2005, the adoption of IAS 19 - 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 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 X of the online appendix shows, while other IFRS rules affected the accounting value of equity and the income statement, none had such a large impact.

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. This extension accounted for about 50% of the increase in the value of bank DB plan liabilities. Second, two major actuarial assumptions - the discount rate and life expectancy -, were revised. On the one hand, 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. Life expectancy of female workers, on the other hand, 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 3 decomposes the aggregate effect of the adoption of IAS 19 on bank liability into its three components: the benefit extension, change in the rate assumptions, and change in the mortality tables.

INSERT FIGURE 3

Figure 4 plots the aggregate variations in the bank DB plan assets and liabilities over the years and illustrates the effect of the adoption of IAS19 on the value of bank pension plan liabilities. Section X in the online appendix shows extracts from the second largest Portuguese bank 10-K financial statements regarding the extension of pension benefits and how the accounting value of the liabilities has been affected.

INSERT FIGURE 4

While the adoption of the IFRS norms, amoung which IAS 19, was approved by the European Parliament in July 2002 for an implementation as of 1 January 2005, the effect of IAS 19 on Portuguese bank DB plan liabilities and contributions was not anticipated before 2005 for the following reasons. First, the exact parameters of the implementation of IAS 19, such as the conditions of the recognition of actuarial gains and 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, the institutional environment added some uncertainty in Portugal. It was only in February 2005 that Bank of Portugal published an amendment, Notice 2/2005, on the specific treatment of actuarial losses in Portugal. In the meantime, banks were discussing intensively with the Central Bank about the treatment of contributions and the possible exemption of some pension liabilities. Hence, in 2004, CGD pensions liabilities for the length of service provided up to 31 December 2000 are transferred to the National Pension system to attenuate the public deficit that the Portuguese Government was running at the time and to spare CGD from the IAS 19 shock. Subsequently, in November 2005, Millenium BCP - the largest Portuguese banking group and pension provider- proposed that their pension liability be also transferred.[11] While BCP's request was initially rejected, later on, in 2011, in the context of the Tripartite Agreement to substantially reduce public debt and end the sovereign crisis, the Portuguese Government did transfer the entire bank pension plans into public ownership.

The Effects on Bank Internal Financial Resources and Regulatory Capital

Figure 5 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: 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 5

Banks also had to make significant deductions from their Tier 1 capital to account for the deferred actuarial losses, i.e. the share of actuarial losses that were above the *regulatory corridor*, and did not need to be declared as losses in the current income statements.

The fact that, during 2005, banks had to make substantially larger pension contributions and prudential deductions than in previous years, provides strong evidence that the funding shock was largely unanticipated.

Overall, he 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 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)

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

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, as the exact conditions of the implementation of IAS19 in Portugal are only determined the year of the shock.

3 Data Overview and Treatment Measures

3.1 Data Sources

We obtain our final sample by merging four databases: the Portuguese credit register, the Bank of Portugal bank balance sheet data, bank DB plan data from the Bank of Portugal Financial Stability Department, 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 history.

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 data back to 1995. We hence build five variables that provide information

[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.

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, (4) an indicator for whether it had any history of defaults, and (5) the number of banks the firm is in a relationship with.

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 this database with a second one 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, we hence have information on 350,000 firms and on the complete career history of 3 million workers.

The Portuguese census asks employers to report each employee's socio-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.

The Portuguese census database also includes key firm level data such as total sales, year of creation, number of employees, the legal and ownership structures of the firms, 5 digit industry identification number, parish and county information, as well as unique firm identifiers. We use the unique firm identifiers to match the census database with the credit register.

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 are hiring at least one worker.[14] We then use the unique firm identifier to match the yearly census information with our monthly balanced panel of bank-firm exposures and 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 plan data.

For our main empirical analyses - on firm borrowing and employment, and 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.[15] We also restrict the sample to firms with a positive credit exposure in 2004 for these analyses, as our measure of treatment intensity is based on firm credit exposures ex-ante. Our final sample hence includes a total of 161,202 firms, 59 banks, 426,119 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

[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.

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

[15] The analysis of switchers, which focuses on the employment outcomes of workers that have switched jobs, covers the wider 2003-2007 period.

3.3 Measuring Treatment

We measure the intensity of the treatment, i.e. the bank funding shock triggered by the adoption of IAS19, first, at the bank level, second, at the firm level.

At the bank level, the $TreatmentIntensity_{bank}$ variable is the bank exposure to their pension fund ex ante, measured by the ratio of the bank DB plan liabilities to the bank equity in 2004. This ratio captures the magnitude of the shock by scaling the size of the DP pension plan to the bank internal funds as proxied by the bank equity. All our results are robust to 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 C3 in the online appendix).

Figure **??** illustrates the heterogeneity of the treatment - as measured by the ratio of bank DB plan liability to the bank equity - across the 10 largest Portuguese banks. Not only there is strong heterogeneity in the treatment, but the magnitude of the treatment is not related to the bank size, as measured by the bank total assets. Table 1 confirms that our variable $TreatmentIntensity_{bank}$ varies significantly across banks: the average and the median are at 40%, the 10^{th} percentile 0% and the 90^{th} percentile 104%. Table XX in the online appendix shows that even within the 6 largest banks, the treatment intensity varies from XX to XX%.

At the firm level, the $TreatmentIntensity_{firm}$ variable is the average treatment intensity among all banks lending to a firm weighted by their relative credit exposures to this firm during the pre-treatment period. Table 1 shows that the variable $TreatmentIntensity_{firm}$ amounts to 0.39 on average 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.

To facilitate estimations, we allocate banks, firms and workers to treatment and control groups based on the distribution of the $TreatmentIntensity_{bank}$ and $TreatmentIntensity_{firm}$ variables. At the bank level, the variable $TreatmentDummy_{bank}$ takes the value one for banks with a treatment intensity above the median, with a ratio of DB plan liability to the bank equity below 40%. At the firm level, the variable $TreatmentDummy_{firm}$ indicates firms for which more than half of their credit exposures is to banks treated with high intensity. We hence have 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/firms as banks/firms with $TreatmentDummy$ equal to 1.

INCLUDE TABLE 1

3.4 External Validity

Portugal offers an ideal experimental setting for our identification; not only because of the policy experiment and the access to unique data, 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 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 XX shows in the online appendix, 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. 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.[16] 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.[17]

[16]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.

[17]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.

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 (see Figures A and B in the online appendix), its rigidity is relatively high, which ensures that any effect we observe on worker flows might only be biased downwards (Blanchard and Portugal 2001).[18]

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).[19]

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 XX 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 regulatory capital that affected banks heterogeneously. In this section, we investigate the effects of the shock on, first, bank credit supply, looking at changes in bank-firm credit exposures, second, firm total borrowing.

[18]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. These lower flows come from both lower job creation and destruction, and from lower worker flows given job creation and destruction.

[19]**?** 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

4.1 Changes in Credit Supply

4.1.1 Main Result

To estimate the aggregate effects on bank credit supply and verify whether the parallel trend assumption holds, we first plot changes in bank loan exposures to firms since 2004 across the two groups of banks: the treated banks and the control banks.

INCLUDE FIGURE 6

Figure 6 shows that, while lending evolved similarly until mid 2005 across control and treated banks, lending by treated banks grew twice more slowly than lending by control banks from mid 2005 to the beginning of 2006. The lag of six months we observe before the effect kicks 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, where the dependent variable is the bank-firm exposure growth rate 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:

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

In addition to easing the interpretation and comparability of the estimates, this growth measure has good statistical properties, as it is symmetric around zero and restricted to finite values.[20]

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

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

The dependant variable $Credit\ Growth_{b,i}$ is the change in bank b's exposure to firm i 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.[21]

INCLUDE TABLE 4

Column 1 in Table 4 confirms the aggregate result in Figure 6: the growth in 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 6 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 would vary between the pre and the post periods. This is all the more relevant as we observe from Table 1 that treated banks are significantly larger and less capitalized than control banks. The vector $BankControls_b$ includes the logarithm of assets, the equity ratio, a measure of liquidity - liabilities maturing within one year to total assets -, the ratio of bonds outstanding to assets, and the ratio of non-performing loans to total lending, in the pre-treatment period, i.e., in 2004.

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

[21] Table A.2 in the online appendix shows that results are robust to clustering at the banking 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)

Similarly, $Firm_i$ is a vector of firm controls that include our five variables on firm credit history, as well as the number of banking relationships in the pre-treatment period.

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 by a treated bank to the supply of credit by 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 17 percentage points lower than the growth rate of its exposure to a control bank.

Column 4 suggests that the result is confirmed also in this specification using the treatment intensity as a dependant variable: banks with larger pension liabilities relative to their equity tend to increase their credit exposure to firms less 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 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 than 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 negative coefficients in columns 6 and 7 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: a dummy that equals one if a new loan is granted in the post-treatment period to a firm that had a zero-exposure to this bank in the pre-treatment period to measure new lending, and a dummy variable that is equal to one when a credit exposure that was positive in the pre-period becomes null 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 at the "intensive margin" of lending, when we restrict the sample to bank-firm exposures that are strictly positive in the pre-treatment period, banks reduce their existing credit exposures to firms by around 19 pp. This sample is also restricted to firms that employed at least one worker in the pre-treatment period. To facilitate tracking the impact of the credit shocks through the Portuguese economy, from banks to individual workers, we will carry this sample of 161,202 firms through the rest of the paper.

4.1.2 Robustness Tests

Tables XX, YY and ZZ in the Online Appendix includes a series of robustness tests. First, Column 1 in Table **??** 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, which 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, and focusing on them eliminates potential noise in the estimates from including smaller institutions. In addition, these six main banks homogeneously implemented the other IFRS rules in 2005.

Table YY and ZZ in the Online Appendix show that the results are robust to various definitions of the dependent variables and the treatment variables. In Table YY, 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 ZZ, 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 by comparing the change in borrowing by treated firms versus the change in borrowing by control firms between the pre and the post periods in a difference-in-differences analysis. To do so, we first sum the monthly loan exposures of each firm across all banks in each month to obtain a monthly measure of firm total borrowing. 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 then estimate the following specification:

$$\begin{aligned} Credit\ Growth_i = Industry_s + \beta Treatment_i + \\ + \gamma FirmControls_i + \gamma MainBankControls_i + e_i \end{aligned} \tag{2}$$

where $Credit\ Growth_i$ is the change in the total credit exposure of firm i between the pre and post-period using again the Davis and Haltiwanger (1992) growth measure. $Treatment_i$ 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 firms that have total non-zero credit exposures in the pre-period.

The coefficient of the $TreatmentDummy$ in Column 1 in Table 5 suggests that firms are not able to fully substitute credit from a treated bank with credit from a control bank when the treated bank is affected by the shock. 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 relieves the concern that the differences between treated and control firms are not driving the results. We indeed observe from Table 1 that treated firms are significantly smaller. The vector of firm controls

$FirmControls_i$ includes the following 12 controls at the firm level: total sales, total credit, the number of bank relationships, 5 indicators for bad credit history, starting capital, age, number of employees and debt to income ratios.

INCLUDE TABLE 5

The specification in Column 3 is saturated with two-digit SIC industry fixed effects. In Column 4, we add average bank characteristics along the same dimensions as for the bank-firm analysis, but weighted by ex-ante relative credit exposures. In Columns 5 to 7, we replicate the models of Columns 2 to 4 using the treatment intensity measure as dependent variable. Consistently, firm borrowing decreases when firm exposure to treated banks increases.

4.2.2 Heterogeneity of the Effects

In a second step, we replicate our analysis across several sub samples split along our main firm characteristics: age, size, productivity and wage level.

Table 6 explores how the results vary in the cross-section of treated firms. We group firms in quartiles in function of their age, size, average hourly wage paid and average product per worker in 2004. Then, we study the impact on the lower and upper quartiles across each of these characteristics. The coefficient estimates point to a generalised negative effect of the shock on credit exposures across all the groups, but with stronger effects on young, smaller and less productive firms, as measured by worker hourly wage and sales per workers. This result shows that it is more difficult to substitute credit from an affected bank with credit from a unaffected bank for small and less productive firms. As shown in the existing literature, young, small and less productive firms are more vulnerable to credit supply shocks.

INCLUDE TABLE 6

Finally, Table **??** in the online appendix shows that the effects persist across the main industrial sectors in Portugal.

5 Firm Human Capital

We investigate the effects of the credit supply shock on firm total employment and on the characteristics of workers who leave and of those who join affected firms. Workers with different skills may have different preferences and incentives to leave or join firms facing a lower access to credit. In addition, worker mobility is also determined by the extent to which their human capital can be generally applied in the economy. Among all workers who may leave or not join a firm that has a lower access to credit, the more educated are likely to be especially critical for the firm's future growth and productivity.

5.1 Skill Composition of the Labor Force

We first show that the credit supply shock affects firm total employment.

To do so, we create a variable that sum the total number of workers at the firm level and across each level of education, before collapsing our sample into two sub-periods, the pre-treatment period and the post treatment period, taking the average of each variable over each sub-period.

We then estimate the following model:

$$\begin{aligned} Employment\ Growth_i = Industry_s + \beta Treatment_i + \\ + \gamma Controls_i + e_i \end{aligned} \tag{3}$$

where $Employment\ Growth_i$ is the change in the total number of employees - and across each level of education - of firm i between the pre and post-period using the Davis and Haltiwanger (1992) growth measure.

INCLUDE TABLE 7

The results in Table 7 suggest that firms reduce employment after facing an adverse credit supply shock. Column (1) first indicates the effect of the treatment on total employment growth. We find that employment growth at treated firms is 1.7 pp lower than for control firms.

Figure 7 shows the dynamics of the coefficient: we observe that treated and control firms experience similar employment growth in 2003 and 2004, but that treated firms increase employment less than control firms the year they face the credit supply shock.

We then investigate the effects across levels of education. There are several reasons why the employment of educated workers might be more impacted by the credit supply shock. One possibility is that these workers are more expensive, and so because the firm is credit constrained, these are the first workers the firm decides to fire. Alternatively, educated workers might prefer to work in firms with better opportunities. Another possibility, however, would be that firms fire first the less educated workers that are more easily substituable, as firm-specific human capital is likely to be complementary to a worker's level of education. Whether human capital will decrease at affected firms is therefore an empirical question.

Columns (2) to (5) of Table 7 suggest that the higher the level of education, the stronger the effect of the shock: the effect is three times larger for workers with a college degree than for workers with up to elementary school education. More precisely, employment growth at treated firms is 1.2 pp lower than for control firms for workers with up to elementary school education, but 3.6 pp lower for workers with a college education.

Figure 8 shows the dynamics of the coefficients across levels of education: while treated and control firms experience similar employment growth of college-educated workers in 2003 and 2004, treated firms increase employment less of this category of workers than control firms the year they face the credit supply shock.

5.2 Worker Flows across Skills

We then run worker-level regressions to better identify the effects across skills and alleviate some concerns that the specifications at the firm level might raise. For example, if worker characteristics such as age or tenure vary 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. The larger effect on the employment growth of educated workers might also come from them switching to the control group, while uneducated workers stay unemployed. Alternatively, changes in growth rate are likely to be higher when initial values are low, amplifying the effect on educated workers, as the share of college-educated workers is ex-ante lower in firms on average. Finally, worker-level specifications also allow to disentangle the effects on worker separation versus hiring.

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 2002-2008 period:

$$Pr(Leavingthefirm)_{i,j,t} = Firm_j + Year_t + \beta Post_t \times Treatment_j$$
$$+WorkerControls_{i,t} + FirmControls_{j,t} + e_{i,j,t}$$

$Pr(Leavingthefirm)_{i,j,t}$ is a dummy variable indicating whether worker i leaves firm j in year t, $Firm_j$ is a vector or firm fixed effects, $Year_t$ a vector of year fixed effects. $Post_t \times Treatment_j$ is a dummy variable that takes the value of one after 2005 if the firm has been affected by the credit supply shock and zero otherwise. The coefficient β measures the increase in the probability of a worker leaving the firm after it has been affected by the credit supply shock. We also include a set of individual worker characteristics that could affect the probability of leaving prior to bankruptcy events:$WorkerControl_{i,t}$ includes a polynomial of age and tenure. The vector of firm fixed effects $Firm_j$ accounts for time-invariant differences in turnover across firms that may occur for reasons other than bankruptcy. The $FirmControl_{j,t}$ vector include year-industry, year-firm size, year-firm age, year-firm average wage fixed effects that account for the evolution of the optimal composition of workers across sectors, firm size, age and average wage. 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. Finally, we cluster standard errors at the banking group $\times$ industry level, and results are robust to clustering at the firm level.

Results are reported in Table 8. In column (1), we find that a lower access to credit is associated with an increase in the probability of a worker leaving the firm, as the coefficient β is positive, and statistically and economically significant. This estimate implies that the probability of workers leaving a firm is 0.4 percentage points higher when the firm is affected by the credit supply shock. In columns (2) to (10), we analyze the composition of workers who leave affected firms. An important pattern that emerges is the increase in the propensity of workers to leave affected firms as their level of education increases, in Columns (2) to (5). Hence, college-educated workers have a 0.1 percentage point higher probability of leaving a treated firm than workers with only elementary school education.

Columns (6) and (10) replicate the estimations, along a measure of worker skill pre-defined by the Portuguese Ministry of Employment.[22] Accordingly, every year when reporting to *Quadros de Pessoal*, firms have to allocate workers to a given skill category, determined both by the worker's level of education and by the complexity of the tasks they undertake within the firm.[23] When relying on this alternative classification, the results are even stronger. Managers or higher-skilled workers have a 2 percentage points higher probability to leave after the firm is affected by the credit supply shock, while lower-skilled workers have only a 0.1 percentage point higher probability.

INCLUDE TABLE 8

Next, we investigate whether the composition of workers that join affected firms vary 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:

[22] The worker classification by skill level was established by means of Decree 121/78, from 2 July 1978. Caliendo et al. (2015) use this classification to study how firm reorganization impacts productivity.

[23] The official worker classification includes eight layers: top management, middle management, supervisors, higher-skilled professionals, skilled professionals, semi-skilled professional, non-skilled professionals, and apprentices. We group the first three layers under managers, and we exclude apprentices, who account for an insignificant share of the labor force in 2004

$$Pr(Joiningthefirm)_{i,j,t} = Firm_j + Year_t + \beta Post_t \times Treatment_j$$
$$+WorkerControls_{i,t} + FirmControls_{j,t} + e_{i,j,t}$$

$Pr(Joiningthefirm)_{i,j,t}$ is a dummy variable indicating whether worker i leaves firm j in year t

Tables 9 reports the results.

INCLUDE TABLE 9

Finally, Table 9 focuses on hiring, as we estimate, for each worker, the probability that they will start a new employment relationship with a treated or a control firm. According to column (1), a worker is 0.2 percentage points less likely to start working at an affected firm. Columns (2) to (10) suggest that most of the effect comes from the most educated workers. While firms facing a credit supply shock are able to attract unskilled workers to replace the unskilled workers that have left, these firms are unable to do so with high-skilled workers and hence to replace the lost human capital. A high-skilled workers, either with a college degree (column 5) or a manager (column 6) has a 2.6 - 2.8 percentage point lower probability to join a firm after it is affected by a credit shock. We here extend the results in Brown and Matsa (2016) and Baghai et. al (2018) showing that even without facing financial distress, a lower access to credit can dampen firm ability to attract skilled workers and hence affect firm growth and productivity over the long run.

5.3 Wage Outcome: Evidence of Voluntary Turnover

The results we find on highly educated workers leaving affected firms might be a consequence of firms dismissing the most expensive employees, or, oppositely, workers voluntarily leaving firms with lower growth opportunities. While there is evidence in the labor literature that job displacements result in significant earning losses for the affected workers (Jacobson et al. 1993; Couch and Placzek 2010), the effect on wages would be the opposite if highly educated workers leave affected firms voluntary for better work opportunities.

We identify the differential effect of the credit shock on the wages of workers who switch with the following model:

$$Log(HourlyWage)_{i,t} = Worker_i + Year_t + \alpha D_{it} + \beta D_{it} \times Treatment_j + WorkerControls_{i,t} + e_{it}$$

$Log(HourlyWage)_{i,t}$ is the average hourly wage of a worker, D_{it} is a dummy variable indicating whether worker i switched jobs at date t. $D_{it} \times Treatment_j$ takes the value one if the worker swtiches from a firm that is affected by the credit supply shock after 2005. We include year and individual fixed effects, so that the estimated effects on wages reflect the precise impact of switching jobs, and not of individual characteristics or of changes in the economic context. We also separate workers along the four groups of education.

INCLUDE TABLE 10

Table 10 shows that workers that leave affected firms experience a higher wage increase than average switchers, and that the effect is mostly driven by high-school and college educated workers. This result is consistent with educated workers switching to benefit from better opportunities in firms that are not affected by the shock.

6 Conclusion

Using a exogeneous shock to bank internal resources, we document how credit supply affect firm employment in good time. We show that having access to credit affects not only firm employment but also the composition of the work force. In good times, firms affected by a credit supply shock are likely to lose human capital relatively to their unaffected competitors, which might them dampen its future productivity and growth. Overall, we document the long run effect of credit market frictions.

References

Acemoglu, D. and F. Zilibotti (2001). Productivity differences. *The Quarterly Journal of Economics 116*(2), 563–606.

Acharya, V. V., T. Eisert, C. Eufinger, and C. W. Hirsch (2015). Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans. *Working Paper*.

Acharya, V. V., J. Imbs, and J. Sturgess (2011). Finance and Efficiency: do Bank Branching Regulations Matter? *Review of Finance 15*(1), 135–172.

Babina, T. (2016). Destructive creation at work: How financial distress spurs entrepreneurship. *Working Paper*.

Baghai, R., R. Silva, V. Thell, and V. Vig (2015). Talent in Distressed Firms: Labor Fragility and Capital Structure. *Working paper*.

Bai, J. J., D. R. Carvalho, and G. M. Phillips (2015). The Impact of Bank Credit on Labor Reallocation and Aggregate Industry Productivity. *Working Paper*.

Becker, G. S. (1975). Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education, Second Edition.

Benmelech, E., C. Frydman, and D. Papanikolaou (2016). Credit Market Disruptions and Employment during the Great Depression: Evidence from Firm-level Data. *Working Paper*.

Bentolila, S., M. Jansen, G. Jiménez, and S. Ruano (2015). When Credit Dries up: Job Losses in the Great Recession. *Working Paper*.

Berg, T. (2016). Got Rejected? Real Effects of not Getting a Loan. Technical report.

Berton, F., S. Mocetti, A. Presbitero, and M. Richiardi (2016). Banks, firms and jobs. Technical report.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics 119*(1), 249–275.

Black, S. E. and L. M. Lynch (1996). Human-capital investments and productivity. *The American economic review 86*(2), 263–267.

Blanchard, O. and P. Portugal (2001). What Hides behind an Unemployment Rate: Comparing Portuguese and US Labor Markets. *American Economic Review*, 187–207.

Brown, J. and D. A. Matsa (2016). Boarding a Sinking Ship? An Investigation of Job Applications to Distressed Firms. *The Journal of Finance 71*(2), 507–550.

Caggese, A., V. Cunat, and D. Metzger (2016). Firing the Wrong Workers: Financing Constraints and Labor Misallocation. *Working Paper*.

Caliendo, L., G. Mion, L. D. Opromolla, and E. Rossi-Hansberg (2015). Productivity and organization in portuguese firms. Technical report, National Bureau of Economic Research.

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Caroli, E. and J. Van Reenen (2001). Skill-biased organizational change? evidence from a panel of british and french establishments. *The Quarterly Journal of Economics 116*(4), 1449–1492.

Chava, S. and A. Purnanandam (2011). The Effect of Banking Crisis on Bank-Dependent Borrowers. *Journal of Financial Economics 99*(1), 116–135.

Chodorow-Reich, G. (2014). The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Constancio, V., A. C. Leal, M. Centeno, N. Alves, I. Correia, S. Gomes, J. Sousa, V. Almeida, G. Castro, R. Félix, et al. (2009). The Portuguese Economy in the

Context of Economic, Financial and Monetary Integration. *Banco de Portugal, Economics and Research Department*.

Davis, S. J. and J. Haltiwanger (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics 107*(3), 819–863.

Druant, M., S. Fabiani, G. Kezdi, A. Lamo, F. Martins, and R. Sabbatini (2009). How are firms' wages and prices linked: survey evidence in europe. *Working Paper, National Bank of Belgium* (174).

Hochfellner, D., J. Montes, M. Schmalz, and D. Sosyura (2015). Winners and Losers of Financial Crises: Evidence from Individuals and Firms. Technical report, Citeseer.

Ivashina, V. and D. Scharfstein (2010). Bank Lending during the Financial Crisis of 2008. *Journal of Financial economics 97*(3), 319–338.

Katz, L. F. and K. M. Murphy (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics 107*(1), 35–78.

Khwaja, A. I. and A. Mian (2008). Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *The American Economic Review 98*(4), 1413–1442.

Moretti, E. (2004). Workers' education, spillovers, and productivity: evidence from plant-level production functions. *American Economic Review 94*(3), 656–690.

Paravisini, D. (2008). Local Bank Financial Constraints and Firm Access to External Finance. *The Journal of Finance 63*(5), 2161–2193.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies 22*(1), 435–480.

Popov, A. A. and J. Rocholl (2015). Financing Constraints, Employment, and Labor Compensation: Evidence from the Subprime Mortgage Crisis. *ECB Working Paper*.

Puri, M., J. Rocholl, and S. Steffen (2011). Global Retail Lending in the Aftermath of the US Financial Crisis: Distinguishing between Supply and Demand Effects. *Journal of Financial Economics 100*(3), 556–578.

Rauh, J. D. (2006). Investment and Financing Constraints: Evidence from the Funding of Corporate Pension Plans. *The Journal of Finance 61*(1), 33–71.

Siemer, M. (2016). Firm Entry and Employment Dynamics in the Great Recession. *Working Paper*.

A. FIGURES

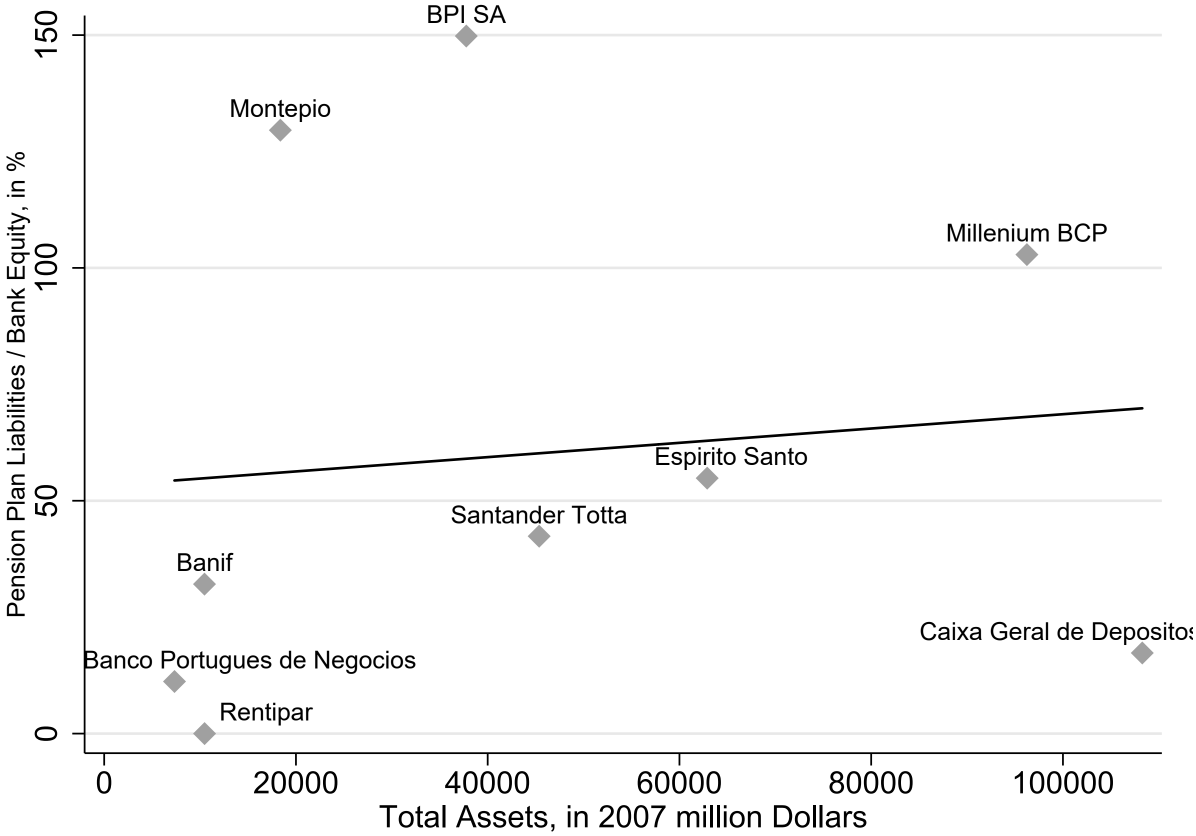

Figure 1. Bank Exposures to Pension Plans

This figure shows bank exposure to pension plans - measured as the ratio of the pension plan liabilities to bank total equity - for the 10 main Portuguese banks, at the end of 2004. These 10 banks represent 95% of total bank assets in Portugal. For confidentiality issues, we use publicly available data from Bankscope, the 2005 annual reports of each bank, and pension plan information from Instituto de Seguros de Portugal.

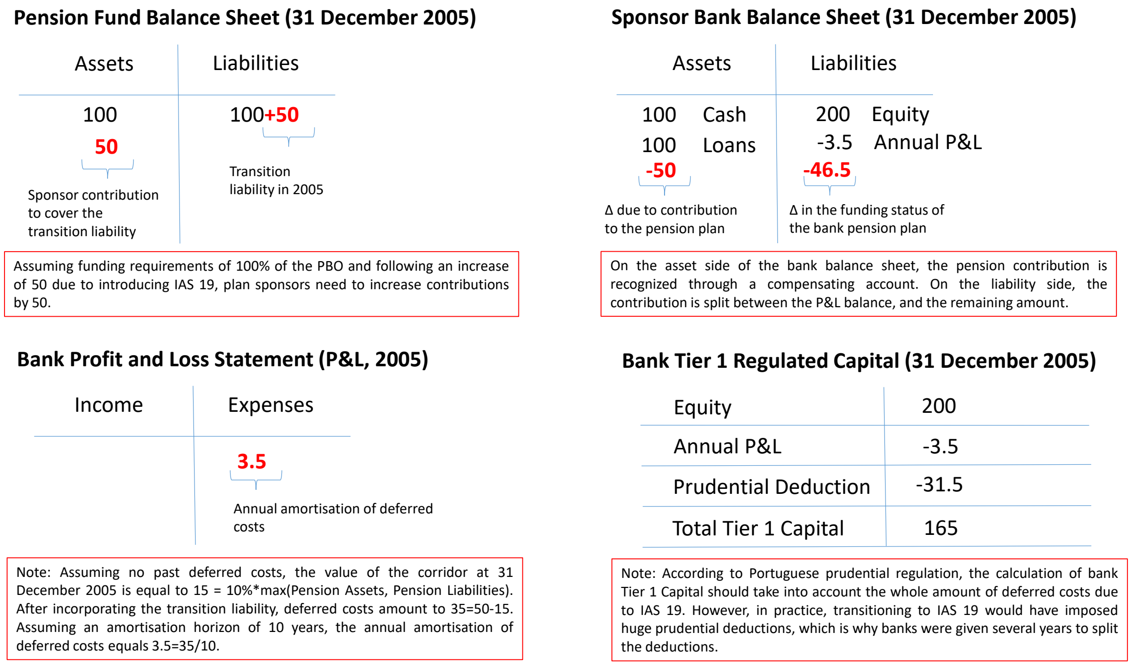

Figure 2. The Impact of an Increase in the Accounting Value of Bank DB Plan Liabilities on Bank Financial Situation

This figure uses stylised numbers to show how, based on the IAS 19 accounting standards, an increase of 50 million Euro of a bank DB-plan liabilities will affect the bank balance sheet, its income statement and its regulated capital.

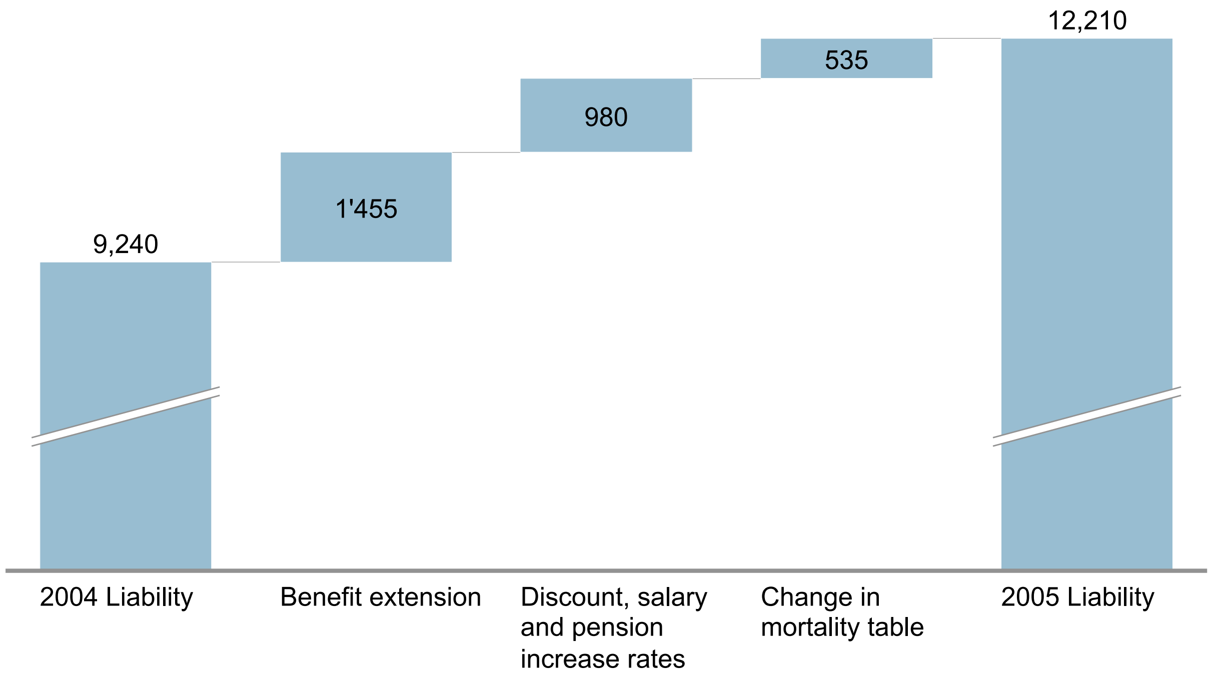

Figure 3. The Impact of IAS 19 on Bank Pension Liability

This figure illustrates the effect of IAS 19 on the aggregated bank pension plan liability, and decomposed according to the reason for its increase. The data on the total pension liability is extracted from BoP's 2005 Financial Stability Report, while the decomposition of the effect is manually collected from bank annual reports.

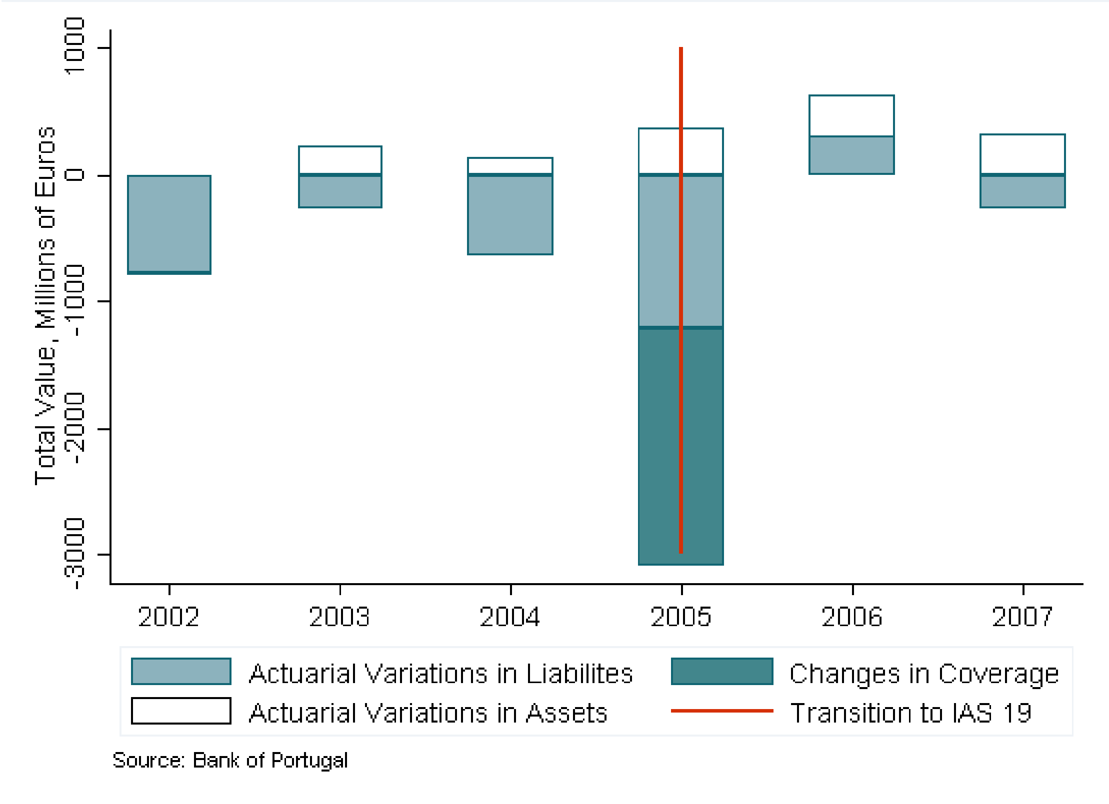

Figure 4. Aggregate Variations in Bank DB Plan Assets and Liabilities over the 2002-2007 Period

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.

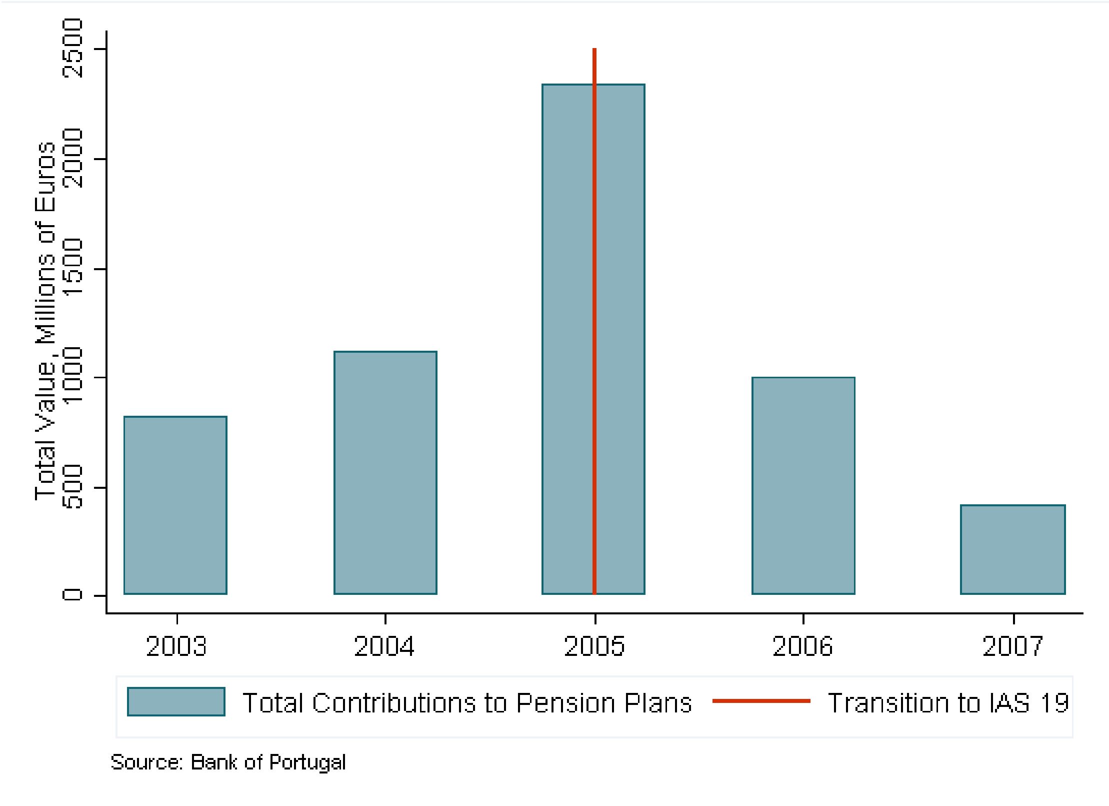

Figure 5. Bank Contributions to their DB Pension Plans (2003-2007)

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.

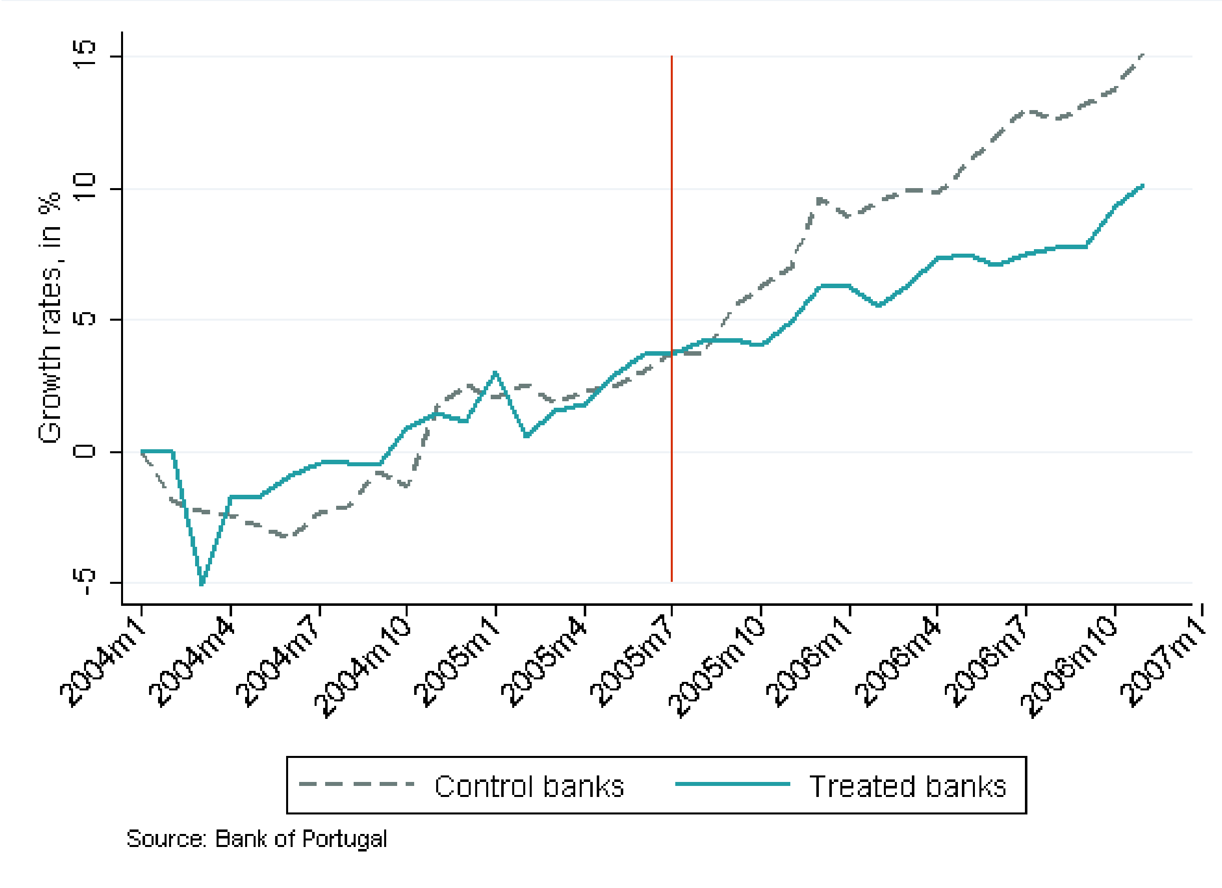

Figure 6. Evolution of Credit: Treated versus Control Banks

This figure captures the evolution of credit for 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, treated banks experience visibly lower credit growth from then on.

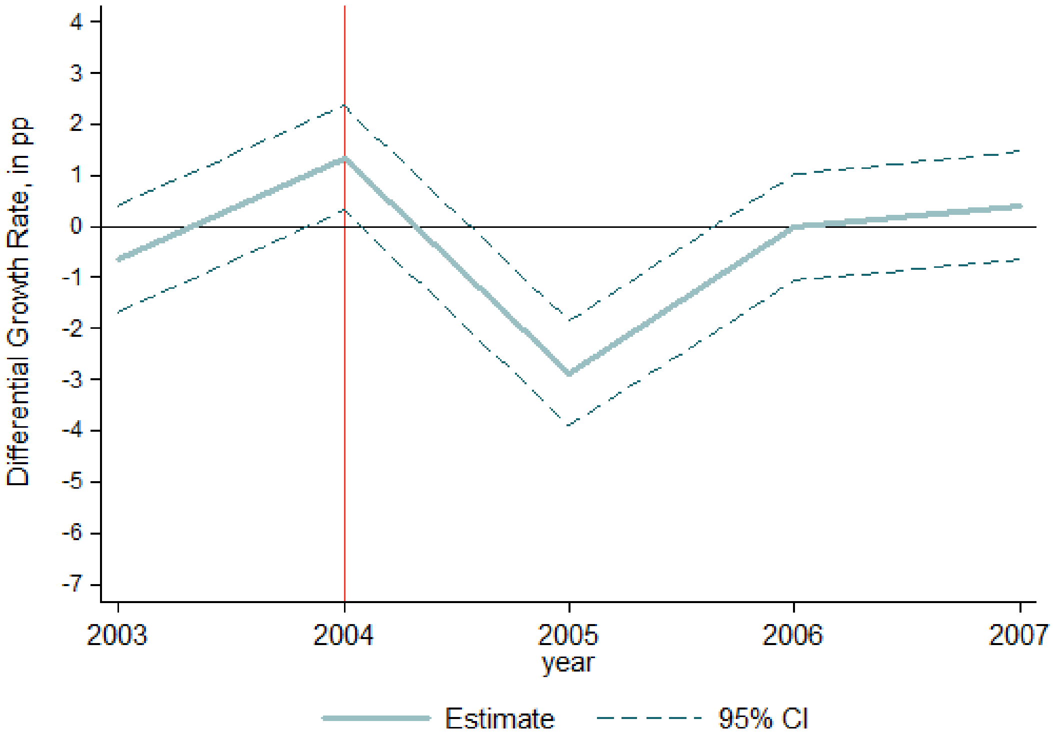

Figure 7. Yearly Differential Growth Rates of Employment of Treated Firms

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.

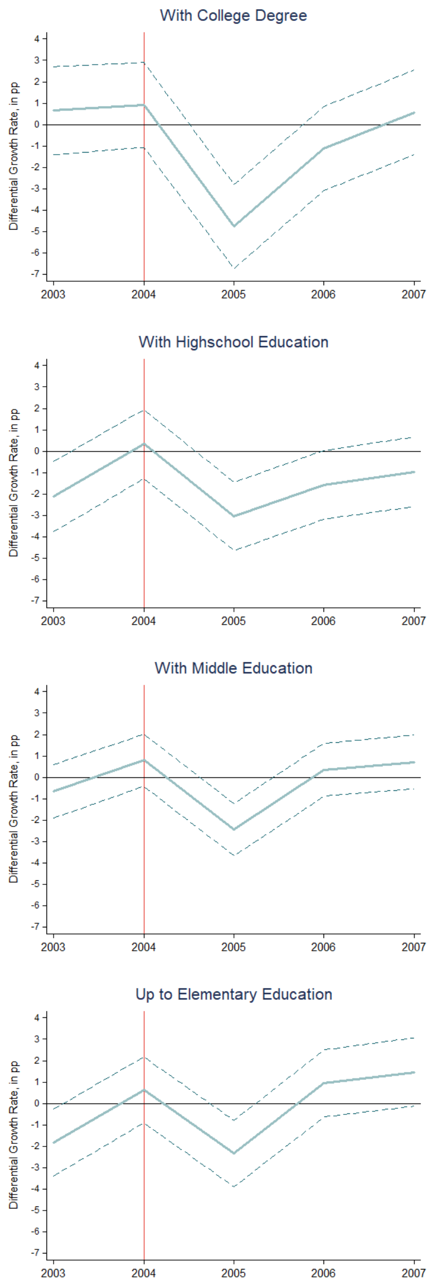

Figure 8. Yearly Differential Growth Rates of Employment, by Worker Education

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. We show growth rates over five years, 2003 to 2007.

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)*	426,119	0.40	0.32	0	0.40	1.04
High vs. Low intensity *(Treatment Dummy)*	426,119	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						
Weighted Share of Credit from Treated Banks *(Weighted Treatment)*	161,202	.39	.28	.016	.40	.79
> 50% of Credit from Treated Banks (*) *(Treatment Dummy)*	161,202	.50	.49	0	1	1
Firm Characteristics - Treated Group						
Total Sales (EUR)	80,846	758,472	2,105,675	10,786	175,014	1,531,795
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	80,846	168,789	588,012	1,900	24,420	292,986
Current Default Dummy	80,846	.04	.20	0	0	0
Past Default Dummy	80,846	.09	.28	0	0	0
Average 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	80,846	87,700	422,604	3,782	37,877	164,073
Average Hourly Wage	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)	80,356	915,088	2,393,788	13,298	191,876	1,966,484
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	80,356	288,781	813,755	4,520	39,194	618,474
Current Default Dummy	80,356	.08	.27	0	0	0
Past Default Dummy	80,356	.15	.35	0	0	1
Average 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	80,356	89,700	333,577	4,411	39,226	175,765
Average Hourly Wage	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.

Table 2. Summary Statistics: Workers

	N	Mean	SD	P10	P50	P90
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Worker Characteristics - Treated Group						
Probability to Leave	929,861	.22	.42	0	0	1
Probability to Enter	929,861	.25	.43	0	0	1
Probability to Switch	929,861	.08	.27	0	0	1
Hourly Wage (2004 Euros)	929,861	5.84	13.49	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	.27	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	Year 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 (columns 8 and 9), Table 5 (columns 3 and 6) and Table 7 (column 1).

Table 4. The Impact of the Introduction of IAS 19 on Bank-Firm Credit Exposures

	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 and columns (8) and (9) to the sample of 161,202 firms that have positive credit and hire at least one worker in the pre-period as in the subsequent analyses. Bank controls include the logarithm of assets, capital ratios, liquidity ratios, short-term liabilities to assets, bond funding ratios and doubtful ratios in 2004, and the type of credit institution. In the specifications without firm fixed effects, firm controls include 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), firm controls also include total sales, firm age, legal nature, ownership structure, product per worker and workforce turnover. Standard errors are clustered at banking group×industry levels and are reported in brackets, $^{\star}p < 0.10,^{\star\star} p < 0.05,^{\star\star\star} p < 0.01$

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 change in the firm total loan exposure from the pre-treatment period, 2004, to 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 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. measures of credit history, as well as total sales, firm age, legal nature, ownership structure, product per worker and workforce turnover, and industry fixed effects. In addition, columns (3) and (6) include controls for the "average" bank - i.e., the logarithm of assets, capital ratios, liquidity ratios, short-term liabilities to assets, bond funding ratios and doubtful ratios - weighted by their ex-ante credit exposure in a firm's total credit. 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. Cross-Sectional Effects on Total Firm Credit

	Credit Growth at Firm Level							
	Age		Size		Hourly Wage		Product per Worker	
	Q1 (1)	Q4 (2)	Q1 (3)	Q4 (4)	Q1 (5)	Q4 (6)	Q1 (7)	Q4 (8)
Treatment dummy	-0.065***	-0.099***	-0.107***	-0.055***	-0.125***	-0.049***	-0.100***	-0.057***
	(0.011)	(0.014)	(0.016)	(0.009)	(0.018)	(0.008)	(0.013)	(0.007)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,321	43,728	45,258	44,558	40,299	40,299	40,301	40,301
R^2	0.114	0.071	0.088	0.086	0.083	0.074	0.114	0.096

This table replicates Model (3) in Table 5 across different sub-samples of firms. To study whether the credit shock impacts firms differentially, we separate firms along four characteristics: age, size (number of workers in 2004), the level of wages paid to employees (average hourly wage in 2004) and a proxy for productivity (sales per worker, also in 2004). For each characteristic, we keep firms in the lower (Q1) and the upper quartiles (Q4) and run the estimations on these groups. 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: All Workers and Across Levels of Education

	Employment Growth, Firm Level				
	All Workers (1)	Up to Elementary School (2)	With Middle School Education (3)	With High School Degree (4)	With College Degree (5)
Treatment dummy	-0.017***	-0.012*	-0.018***	-0.021***	-0.036***
	(0.003)	(0.006)	(0.005)	(0.007)	(0.009)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	161,202	93,562	131,094	96,174	59,421
R^2	0.602	0.386	0.258	0.331	0.291

This table reports the coefficients of OLS regressions where the dependent variable is the growth rate of employment, at firm level, between the pre-period (2004) and the post-period (2005 to 2006). The independent variable *Treatment dummy* separates firms into treated or control groups, as in Table 5. All specifications are saturated with industry fixed effects (at two-digit SIC levels), and they include the same set of firm controls asin Table 5: credit history, total sales, firm age, legal nature, ownership structure, product per worker and workforce turnover. The initial sample includes all firms with positive credit exposure in 2004 and hiring at least one worker. In columns (2) to (5) the sample is restricted to firms hiring at least one worker with a given level of education in 2004. 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 8. Labor Market Outcomes Following the IAS 19 Shock: Worker-Level Regressions by Education. Leavers.

	Dummy=1 if the Employee Leaves the Firm, 0 if not				
		By Worker Education			
	All Workers (1)	Up to Elementary School (2)	With Middle School Education (3)	With High School Degree (4)	With College Degree (5)
Treatment dummy	0.004***	0.005***	0.004***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	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
Observations	11,161,514	2,719,313	4,870,821	2,308,887	1,242,029
R^2	0.155	0.177	0.172	0.185	0.167
	By Official Worker Classification				
	Managers (6)	Higher-Skilled Workers (7)	Skilled Workers (8)	Semi-Skilled Workers (9)	Non-Skilled Workers (10)
Treatment dummy	0.017***	0.020***	0.004***	0.001***	0.003***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,483,973	769,678	4,366,121	1,770,306	1,379,827
R^2	0.203	0.182	0.176	0.188	0.156

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 the firm she/he is working for in the previous year 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 to 2007. 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 workers in firms with positive credit exposure in 2004 and hiring 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. $^{\star}p < 0.10$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$.

Table 9. Labor Market Outcomes Following the IAS 19 Shock: Worker-Level Regressions by Education. Entrants.

	Dependent Variable=1 if a New Employee Enters a Firm, 0 for Existing				
		By Worker Education			
	All Workers (1)	Up to Elementary School (2)	With Middle School Education (3)	With High School Degree (4)	With College Degree (5)
Treatment dummy	-0.002***	0.001*	0.006***	-0.012***	-0.026***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	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
Observations	10,660,103	2,649,108	4,586,597	2,178,556	1,213,549
R^2	0.353	0.366	0.379	0.401	0.352
	By Official Worker Classification				
	Managers (6)	Higher-Skilled Workers (7)	Skilled Workers (8)	Semi-Skilled Workers (9)	Non-Skilled Workers (10)
Treatment dummy	-0.028***	-0.045***	-0.012***	0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Worker Characteristics	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	435,292	714,552	4,117,124	1,636,366	1,303,782
R^2	0.343	0.330	0.351	0.380	0.414

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 an existing worker. 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 to 2007. 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 workers in firms with positive credit exposure in 2004 and hiring 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10. Labor Market Outcomes Following the IAS 19 Shock: Worker-Level Regressions by Education. Switchers.

	Log(hourly wage)				
	All Workers (1)	Up to Elementary School (2)	With Middle School Education (3)	With High School Degree (4)	With College Degree (5)
Switcher × Treated × Post	0.006***	-0.004*	-0.001	0.005*	0.008**
	(0.001)	(0.003)	(0.002)	(0.003)	(0.004)
Worker Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,216,151	1,270,724	2,169,876	1,037,798	556,294
R^2	0.913	0.865	0.879	0.903	0.906

This table reports the coefficients of OLS regressions that estimate the earnings differential for workers who switch away from treated firms over the two years following the credit shock. The main dependent variable is the logarithm of regular hourly wages, at worker level. The specifications include data on individual workers between 2003 and 2007. We focus on workers that were employed in 2004 at either treated or non-treated firms and collect their complete labor market histories. The sample is restricted to workers which we observe in the database every year from 2003 and 2007: we therefore work with a fully balanced panel at worker-year level. In columns (2) to (5) the sample is restricted to workers of each level of education. Standard errors are clustered at banking group × industry and reported in brackets. We control for a dummy for switcher, switcher × treated, *switcher* × *post* and *treated* × *post*. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$