Productivity slowdown and firm exit: The ins and outs of banking crises*

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Abstract

This paper studies the adverse long-term impact of a decline in lender health on aggregate productivity. I develop a simple model of productivity-enhancing investment where firm exposure to fragile banks leads to losses on both the intensive and the extensive margin. The model is consistent with the surge in exits and prolonged drop in productivity growth observed in Spain in the aftermath of the 2008 financial crisis. The model also highlights the existence of a bias in the measurement of observable TFP growth during an episode of heightened exit. Using data on Spanish firm-bank relationships and bank bailouts, I implement an exit-adjusted measure of productivity growth and use it to quantify the output loss attributable to the financial friction. A decade after the crisis, output growth from the extensive margin recovers but the same is not true of the output level. The output shortfall from the intensive margin proves much more persistent, with the growth gap only beginning to narrow towards the end of the sample period. Together, these dynamics amount to a cumulative loss of 3% of pre-crisis GDP over ten years.

Keywords: banking crises, firm investment, productivity, endogenous exit
JEL Classifications: E22, G01, G21, G33

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1 Introduction

The 2008 financial crisis brought about a renewed interest in the relationship between credit access and productivity growth. Countries suffering from banking crises experienced sharp contractions in economic activity followed by particularly sluggish recoveries. A striking example is the Euro periphery, where aggregate productivity collapsed and has yet to bounce back to pre-crisis levels (see Figure 1).[1]

This paper studies the extent to which a deterioration in lender health can have a long-lasting impact on aggregate productivity dynamics. Tentative evidence from Spain shows that the sharp decline in productivity following the financial crisis was accompanied by a simultaneous surge in firm exit, as portrayed in Figure 2. I propose a framework in which bank distress gives rise to the type of joint exit and TFP growth dynamics which are observed in the Spanish post-crisis data and apply it to quantify the long-term cost of the financial friction in a way which takes into account potential spillovers from excessive firm closures.

The model I develop is a simple model of firm dynamics with productivity-enhancing investment which illustrates how a negative shock to credit availability followed by an episode of elevated firm exits can give rise to a downward bias in the observable TFP decline. The model features a set of firms linked to banks whose internal cost of funds determines whether a firm is liquidated or allowed to continue. Firm productivity in a given period depends on last period's investment and a stochastic efficiency component. Whenever a firm is hit by a bad efficiency shock, its current investment and continuation value decline, making it more prone to being closed down. The financial friction generated by an increase in banks' discount factor operates through two distinct channels: first, by inducing premature terminations among the less efficient borrowers of affected banks and second, by reducing the incentive to invest in future firm productivity.

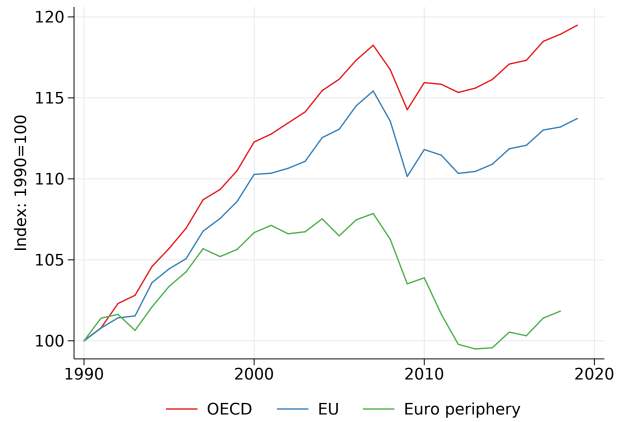
I proceed by devising a method for measuring the output loss from a banking crisis and apply it to data on close to 300,000 Spanish non-financial corporations linked to their banks. Drawing on a unique provision which barred Spanish savings banks from operating outside their home region until 1988, I show how regional variation in the concentration of these banks can be harnessed for the identification of the exit bias in an empirical exercise which draws inspiration from the theoretical model.

A year-by-year analysis reveals that bank distress primarily manifests itself through heightened exits in the early post-crisis years and through diminished productivity growth in the later years. In addition, I find that output growth from the extensive margin eventually recovers while the growth gap from the intensive margin only starts narrowing towards the end of the sample period, implying a much more persistent output shortfall. Together, these dynamics amount to a cumulative loss of 3% of pre-crisis GDP over ten years.

Several features of the Spanish economy make it especially well suited for studying the effect of

[1] The Euro periphery refers to Greece, Ireland, Italy, Spain, and Portugal.

Figure 1: Productivity in the OECD



Note: The figure shows the unweighted average of countries with available data since 1990. The Euro periphery refers to Greece, Ireland, Italy, Spain, and Portugal. Source: OECD.

banking crises. First, the corporate sector has traditionally almost exclusively relied on bank credit as a source of external finance, owing to the fact that a negligible fraction of firms are listed on the stock market and very few issue publicly traded debt.[2] Second, the adoption of the Euro and the accompanying decline in real interest rates fueled a credit boom which left many firms highly leveraged going into the crisis and made them susceptible to debt overhang and rollover risk once the credit crunch set in.[3] Finally, the severity of the crisis prompted the dismantling of the entire savings banks sector which previously accounted for roughly half of the total amount of credit.[4]

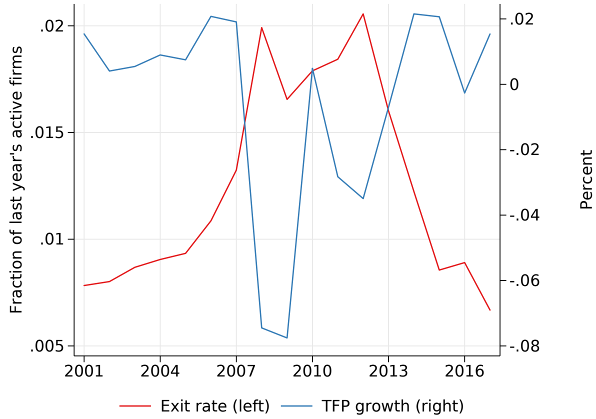
Related literature This paper is related to several strands of the literature. The first strand is concerned with the relationship between finance and productivity, the direction of which is a priori ambiguous. On the one hand, better access to credit can increase productivity by spurring innovation – a channel which has been emphasized by the literature on financial development and growth (see Popov (2018) for a survey). On the other hand, easy credit access can lead to productivity losses from resource misallocation. For example, Gopinath et al. (2017) document an increase in the dispersion of the marginal return to capital in southern European countries in the period of declining real interest rates predating the adoption of the Euro.

[2] Less than 1% of the 4.5 million firms on which I have legal status information are classified as listed on the stock market. As for publicly traded debt, Bentolila, Jansen and Jiménez (2018) find an average of five large issuing firms between 2002 and 2010.

[3] Real interest rates fell by approximately 10 percentage points between 1995 and 2006 and average debt-to asset ratios of non-financial corporations rose from 15% in 2000 to 20% in 2006. The real interest rate refers to the difference between the nominal corporate lending rate and that year's GDP deflator, which are obtained from Eurostat and the Bank of Spain. Debt-to-asset ratios are taken from my firm-level sample.

[4] See Figure A.1 in the Appendix for the evolution of savings banks' market share.

Figure 2: Firm exit and productivity growth in Spain



Note: Exits refer to firm liquidations and bankruptcies. Source: Author's computations using Orbis.

Aghion et al. (2019) unify the direct investment and the indirect allocation channel in a model of innovation-based growth with credit constraints and show how these opposing channels can give rise to an inverted-U relationship between credit access and productivity growth. In their setup, the allocation channel deters productivity growth under favorable credit conditions by allowing unproductive firms to remain longer on the market. This runs counter to my own findings and the ones in Garcia-Macia (2017), who finds that the productivity slowdown in Spanish manufacturing is fueled by the intensive as well as the extensive margin.

The papers by Aghion et al. (2019) and Garcia-Macia (2017) come closest to my own, as they both study how financial conditions shape productivity dynamics in a setting with endogenous firm exit. My paper differs from theirs in two ways. First, by using information on firm-bank relationships, I am able to explicitly trace the source of the financial friction to each firm's main providers of external funds, whose health serves as a more direct measure of the credit constraint. Second, my framework is not constrained by an interpretation of the productivity-enhancing investment as knowledge, since in principle it can include any type of expenditure that raises a firm's productivity, like for instance investment in organizational capital.

The second major strand of the literature relevant to this paper is the one studying the real effects of the bank lending channel in quasi-experimental settings. Papers in this literature consistently document a decline in economic activity following shocks which introduce variation in bank credit availability. For example, Peek and Rosengren (2000) use geographic variation in Japanese bank penetration of U.S. markets to document a decline in U.S. construction activity following the Japanese banking crisis. This, and other related papers such as Ashcraft (2005), identify shocks to credit supply that originate outside the markets under study thus making them plausibly orthogonal to local credit demand. However, they are unable to measure the effect of the credit shock at the individual firm level.

In a more recent paper, Chodorow-Reich (2014) applies the approach developed by Khwaja and Mian (2008) to a dataset of syndicated loans matched with employment data from 2,000 U.S. firms spanning a wide size range. The paper shows how the deterioration in bank health following the 2008 crisis led to larger employment losses at firms with pre-crisis relationships to weak banks. While my dataset does not possess the same degree of granularity, it does allow for analyzing a wider range of firm-level outcomes, most notably investment and productivity.

The increase in the availability of credit register data which covers the universe of loans reported to a country's financial authority has resulted in a recent proliferation of papers using this type of data to study the relationship between credit access and real economic activity. These papers generally do not look at the effect on productivity, and those that do, typically do not emphasize the role of the exit margin. For example, Bentolila, Jansen and Jiménez (2018) and Cingano, Manaresi and Sette (2016) find significant adverse effects of weak-bank attachment on post-2008 employment and investment at Spanish and Italian firms, respectively, but stop short of analyzing trends in TFP. Manaresi and Pierri (2019) and Blattner, Farinha and Rebelo (2019), on the other hand, find sizable TFP losses in Italy and Portugal owing to a weakening of the banking sector, but stop short of a decomposition of the share due to the extensive margin. I contribute to this literature by adding the exit dimension to an analysis of productivity dynamics in the face of bank fragility.

The remainder of the paper is structured as follows. Section 2 lays out the theoretical model, while Section 3 introduces the data and discusses the main stylized facts. Section 4 develops a strategy for the measurement of exit-adjusted productivity and Section 5 discusses the main results. Section 6 performs a counterfactual analysis of the cost of the financial friction, while Section 7 concludes.

2 Model

The productivity slump afflicting countries which had previously undergone banking crises points to a connection between bank health and aggregate productivity. This raises the question of the mechanism underlying their joint occurrence. To discipline the discussion of how bank fragility can stymie growth and have a long-lasting effect on aggregate productivity, I develop a model of firm dynamics with endogenous productivity which, despite its simplicity, is able to reproduce the main stylized facts observed in the data.

The model features a set of atomistic firms, each owned by a single bank. The matching between firms and banks is exogenously given and is assumed to be fixed over time. Static firm-bank connections are also a feature of the dataset used in this paper and are backed by evidence pointing to the stability of lending relationships over the business cycle.[5]

[5] See Chodorow-Reich (2014) for evidence on the stickiness of lender-borrower relationships among U.S. firms.

In each period $t = \{1, 2, ...\}$ a firm produces A_t, interpreted as TFP, and spends amount $Z_t = z_t A_t$ to enhance its productivity. Future TFP also depends on a stochastic component, θ_t, which determines the extent to which the firm's investment contributes to its growth and, as such, can be interpreted as the firm's efficiency or ingenuity. Productivity evolves according to the following law of motion:

$$A_{t+1} = \theta_t f(z_t) A_t \ ,$$

where $f(\cdot)$ is an increasing and concave function of investment with $f(0) = 1$.

For simplicity, I abstract from any agency frictions between banks and firms. A firm maximizes its value for the bank that owns it, effectively placing the bank in complete control over the firm's decisions. The problems facing a bank in a given period are twofold: whether or not to keep a firm afloat and, should that be the case, how much to invest in its future productivity. These decisions are akin to the ones that banks in the real world must make on a regular basis: they determine whether or not to initiate bankruptcy proceedings for some of their clients and they decide how much credit to extend to new and existing borrowers.

In the model, a bank uses its internal cost of funds, R, to evaluate the firms it controls and to decide the optimal course of action on their behalf. An increase in R signifies that the bank is in more urgent need for cash and may prefer to prematurely liquidate a firm which, under a lower R, would be considered valuable enough to keep afloat. A higher R also implies that the bank discounts future profits more heavily, which acts as a disincentive to invest in productivity. The internal cost of funds therefore serves as a measure for bank health, with higher R signifying a weaker / less healthy bank.

To make these ideas more precise, let V_t^c denote the value from allowing a firm to continue and V_t^e denote the value of exit. Firm value in period t is then given by $V_t = \max(V_t^c, V_t^e)$, where V_t^c satisfies the Bellman equation

$$V_t^c = \max_{z_t} A_t (1 - z_t) + \frac{1}{R} E_t V_{t+1} \ . \tag{1}$$

For the purpose of illustrating the basic properties of the model, I forgo a full-fledged structural estimation and instead impose a set of assumptions motivated primarily by their simplicity. In particular, I assume the function $f(\cdot)$ transforming investment into the endogenous component of productivity growth to take the form

$$f(z) = 1 + \phi z^{\alpha} \ , \quad \phi > 0 \ , \quad \alpha \in (0, 1) \ .$$

I assume bank health R to be constant over time for ease of exposition. This assumption is imposed now for convenience and will be relaxed later on. Additionally, firm efficiency θ is assumed to follow an AR(1) process with normal i.i.d. shocks:

$$\log(\theta_{t+1}) = \rho_\theta \log(\theta_t) + \sigma_\theta \epsilon_{t+1} \ , \quad \rho_\theta \in (0,1) \ , \quad \epsilon_t \sim N(0,1) \ .$$

Together, these assumptions imply that the value from allowing a firm to continue depends on current productivity and a factor which varies with the ratio θ_t/R:

$$V_t^c = v^c\left(\frac{\theta_t}{R}\right) A_t \ .$$

Assuming that $V_t^e = v^e A_t$, where v^e is an exogenous constant, the value of the firm becomes:

$$V_{t+1} = A_{t+1} \max\left(v^c\left(\frac{\theta_{t+1}}{R}\right), v^e\right) = \theta_t f\left(z_t\right) A_t \max\left(v^c\left(\frac{\theta_{t+1}}{R}\right), v^e\right) \ . \tag{2}$$

Combining (1) and (2) yields the functional equation

$$v^c\left(\frac{\theta_t}{R}\right) = \max_{z_t} 1 - z_t + \frac{\theta_t}{R} f\left(z\right) E \max\left(v^c\left(\frac{\theta_{t+1}}{R}\right), v^e\right) \ , \tag{3}$$

which can be solved for numerically.

The assumptions needed to arrive at equation (3) make it possible to derive a concise and intuitive condition for firm survival which only depends on the ratio between firm efficiency and bank health. In order to make it to the next period, a firm's continuation value must exceed the value from exiting, which for increasing $v^c(\cdot)$ implies that

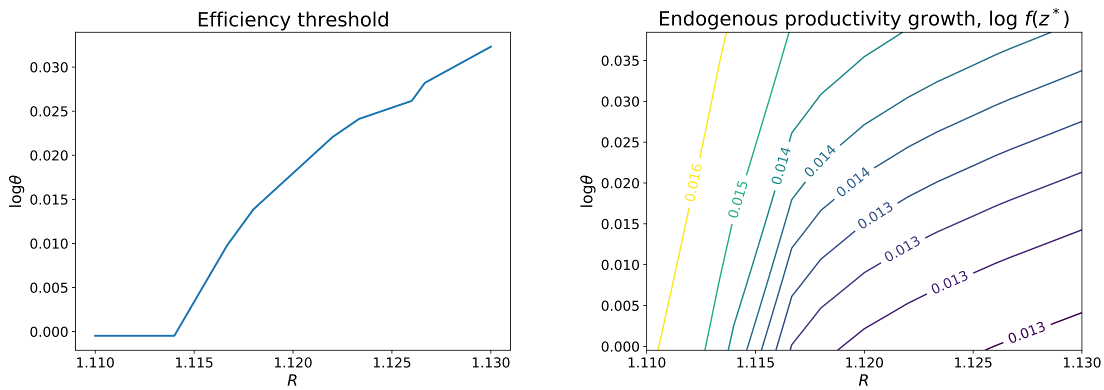
$$\frac{\theta_t}{R} > \gamma \quad \text{where} \quad v^c(\gamma) = v^e \ . \tag{4}$$

Put differently, the firms which exit in a given period do so either because their current efficiency is too low or because the bank they belong to is too weak. Another implication of equation (4) is that even the lowest level of R, corresponding to the healthiest bank, has an associated efficiency threshold γR below which firm exit is the optimal outcome. This gives a natural interpretation to the additional exits caused by an increase of R as excessive, or premature, exits.

I solve the model for different values of time-invariant R by iterating to convergence on the continuation value v^c evaluated at discrete points on a θ-grid. Table A.1 in the Appendix reports the parameter values used for solving the model. Parameters $(\rho_\theta, \sigma_\theta)$ describing the distribution of firm efficiency are derived, respectively, from the sector-level autocorrelation and the standard deviation of productivity growth.

The grid spans two standard deviations above and below the mean of the stationary distribution. Optimal investment z_t is restricted to the interval $(0, 1)$, which, together with the stability condition

Figure 3: Optimal bank decisions



preventing the value function from diverging, imposes the following restriction on R and ϕ:

$$\frac{R}{1+\phi} > \overline{\theta} \ ,$$

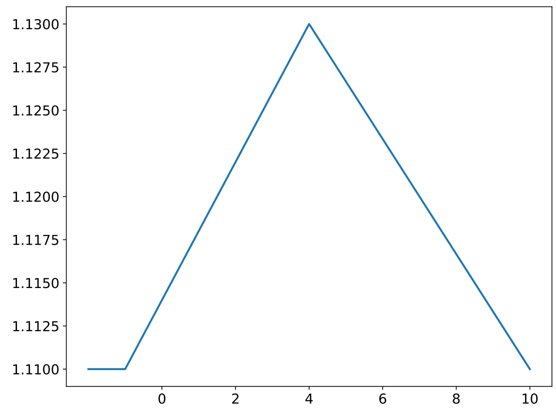
where $\overline{\theta}$ is the maximal θ-value on the grid and satisfies $\log(\overline{\theta}) = 2\sigma_\theta/\sqrt{1-\rho_\theta^2}$. [6]

The optimal course of action for banks of varying quality is depicted in Figure 3. The left panel shows the exit frontier to be increasing in the cost of funds, confirming the earlier intuition that a bank which is more strapped for liquidity prefers closing down its less efficient firms – firms which to a less constrained bank are worth maintaining. The right panel shows how the endogenous component of TFP growth varies with firm efficiency and bank health. Keeping efficiency constant, a weaker bank's diminished investment translates into a smaller contribution to TFP growth. Conversely, among the firms belonging to the same bank, the more efficient ones grow faster due to more funds being devoted to enhancing their productivity.

Having passed these basic sanity checks, the model can now be harnessed to study the aggregate impact of a sudden deterioration in bank health. I model the financial crisis as a temporary deviation of R from its benchmark value and allow the value and policy functions to vary over time. Figure 4 shows the time path assumed for R. For each period during which R differs from the benchmark, I obtain the value function by backwards induction and solve for the optimal level of z. Equipped with optimal exit and investment rules for the entire time path of R, I simulate a large number of firms subject to period-by-period innovations in their efficiency and heightened levels of bank distress at the time of the crisis. In crisis periods, firms behave according to the exit and investment rules corresponding to the elevated value of R. For the sake of comparison,

[6] Constraining investment to lie between $(0, 1)$ implies that the firm only relies on internal funds to invest in future TFP. This assumption can be easily relaxed by allowing z to be non-negative, thereby introducing debt financing in the model. This extension, however, would not add much more generality given that the model in its current form treats banks and firms as an inseparable entity.

Figure 4: Time path of R during the crisis



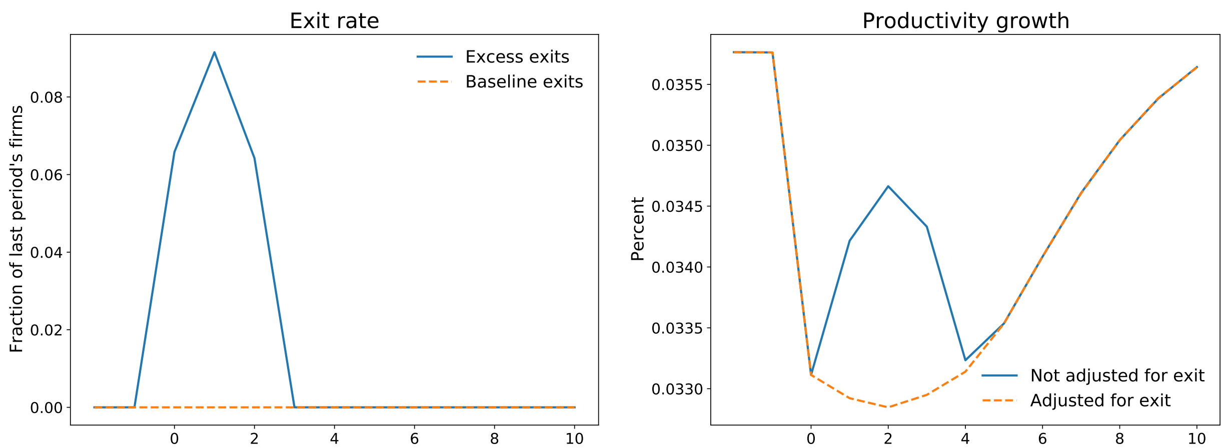
I also compute the counterfactual productivity which would ensue if exiting firms were allowed to continue.

Figure 5 reports the result of the simulation exercise described above. The solid line in the left panel represents the exit rates obtained under crisis levels of bank health, while the dashed line represents exit in the benchmark case. The benchmark level was chosen so that all firms survive, enabling the interpretation of crisis-time exit rates as excess exits caused by the financial friction. As expected, the crisis causes a build-up in exits followed by a gradual decline to their original level.

The solid line in the right panel shows the productivity growth obtained by discarding exiting firms – which is how one would measure aggregate productivity growth in the data. The shape is reminiscent of Figure 2 shown earlier, with productivity growth dipping on impact, briefly recuperating only to drop again before finally converging back to pre-crisis levels. The model also reproduces the concomitant increase in firm exit accompanying the shortfall in productivity growth. When liquidations are at their highest, the surviving firms are the ones whose high efficiency warrants investment even from a crisis-stricken bank. This explains why average productivity growth among survivors actually goes up after the initial fall. As exits abate and the pool of survivors becomes less skewed toward high-efficiency firms, TFP growth drops once again.

Counterfactual TFP growth, which includes exiting firms and is represented by the dashed line, is persistently below its observable counterpart for much of the crisis period, pointing to the existence of a bias in the measurement of productivity in times of heightened bankruptcies. A useful analogy is the relationship between labor productivity and unemployment: an increase in unemployment raises measured labor productivity because it is the least productive workers who lose their jobs. This disparity illustrates how a surge in exits can mask the true cost that financial crises inflict on productivity growth, which over time accumulates into a persistent shortfall in the productivity level.

Figure 5: Aggregate outcomes during the crisis



The main takeaway from the model is that the financial friction induced by a decline in bank health affects productivity both through the extensive margin, by tilting the composition of the surviving firms towards the more productive ones, and through the intensive margin, by reducing the resources devoted to enhancing productivity. The model has shown how the extensive margin can distort the true loss of banking crises, making the case for a productivity measure which corrects this bias. The remainder of the paper is devoted to deriving such a measure from data at the firm-bank level.

3 Data and stylized facts

Before moving on to the details of how to measure exit-adjusted firm productivity, an overview of the data is in order. This section describes the economic environment in Spain around the time of the financial crisis of 2008 and develops a measure of bank health which is shown to be negatively related to firm survival and observed productivity growth. This makes the Spanish banking crisis an ideal testing ground for the workings of the theoretical model just described.

3.1 Data sources

I combine several data sources to obtain a linked firm-bank dataset spanning the period between 2000-2017 in Spain. On the firm side, I use data on financial accounts from merged historical vintages of Bureau van Dijk's Orbis dataset. Combining vintages is important since any single vintage only retains the most recent ten years of balance sheet data per firm. The resulting sample accounts for approximately 72% of Spanish gross output and the firm-size distribution closely reflects the one observed in aggregate data (Kalemli-Ozcan et al. (2015)). The comprehensive coverage of the lower end of the firm-size distribution constitutes a major advantage of Orbis over other widely used firm-level datasets – such as Worldscope or Compustat – and makes it preferable especially in the case of Spain, where the vast majority of firms are unlisted small- or medium-sized enterprises.[7]

I drop firm-year observations with non-positive values for total assets, tangible fixed assets, and number of employees as well as entries with negative liabilities and net worth. Nominal quantities are deflated using sector-specific GDP deflators. As a further quality check, I only keep observations which satisfy basic accounting identities.[8] To obtain TFP values at the firm level, I impose a Cobb-Douglas production function with tangible fixed assets as the capital input and the number of employees as the labor input. I then apply the Wooldridge (2009) extension of Levinsohn and Petrin (2003) to obtain output elasticities for each two-digit industry and compute TFP as the production function residual.

In addition to yearly balance sheet information, the historical Orbis database also contains information on firms' status of activity and bank affiliation. The status of activity is used to determine whether a firm exits in a given year, which can happen if the firm is in the process of liquidation or is undergoing bankruptcy proceedings.[9,10] As for the bank affiliation, each firm can report the names of up to ten credit institutions with which it had a relationship. I consider a firm's relationship to a given bank to also imply borrowing from that bank, an assumption commonly made in the literature on firm-bank relationships.[11] One caveat of the bank relationship variable is that it does not have a time stamp, meaning that it is impossible to determine when the relationship started. This shortcoming is mitigated by evidence pointing to the stickiness of bank-borrower relationships over the cycle.[12]

On the bank side, I collect publicly available information from the Bank of Spain on the amount of government aid received by banks during the 2009-2012 restructuring of the financial system. I complement the bailout data with information on total risk-weighted assets obtained from the 2010 stress tests conducted by the European Banking Authority. Additionally, I collect information on bank branches and market shares, broken down at the three-digit regional level, from the Spanish Association of Private Banks (AEB) and the Spanish Confederation of Savings Banks (CECA). I hand-match the banks by their name due to the lack of a common bank identifier across the different sources.

[7]SMEs made up 66% of the 2006 Spanish wage bill and the average value-added share of listed firms in manufacturing is approximately 14% (Garcia-Macia (2017)).

[8]The data cleaning process closely follows Gopinath et al. (2017).

[9]I do not consider (de)-mergers as exits.

[10]Note that the timing of firm exit is somewhat imprecise. For most exiting firms there is a gap of several years between the last valid observation and the year when the status changed to inactive. In those cases, I define the exit year to be the year immediately following the firm's last observation. This assumption is also made in other papers looking at firm exit, e.g. Aghion et al. (2019).

[11]See for example Kalemli-Ozcan, Laeven and Moreno (2022) and Laeven, McAdam and Popov (2018).

[12]See Chodorow-Reich (2014) and Giannetti and Ongena (2012).

3.2 Institutional background

A unique feature of the Spanish banking system at the onset of the crisis was the presence of a special type of savings banks called *cajas*.[13] By 2007, the *cajas* accounted for about half of the total amount of credit and their failure was at the epicenter of the banking crisis.

The *cajas* were originally established by local governments, churches, and welfare societies to offer local banking services to traditionally underserved segments of the Spanish economy, such as small businesses and the middle- and working classes. As such, the *cajas* included local governments among their stakeholders and had a strong territorial basis. The geographic restrictions were gradually lifted during the 1980s as *cajas* were lobbying for branching deregulation in order to improve their ability to compete with commercial banks. The limits were initially extended to the regional level and completely removed in 1988, when *cajas* were allowed to expand outside their region of origin.[14]

Despite the ensuing regional diversification, firms located in regions where *cajas* held a strong market position in 1988 are more likely to have a relationship with these institutions eighteen years later. This persistence points to the existence of a spatial aspect to lending, whereby banks may prefer lending to local businesses because they possess better knowledge of them. This idea will be exploited in the creation of the exit-adjusted measure of productivity.

Several attributes set the savings banks apart from commercial banks – the other major segment of the Spanish banking sector – and contributed to their demise. First, the savings banks lacked clear procedures for recapitalization in case of insolvency, which led to delays in their restructuring once the crisis hit and ultimately proved fatal. Second, they were not listed on the stock market, which meant they were less subject to market discipline and were unable to raise capital in response to the crisis. Finally, they were partially controlled by regional governments, which led to inefficiencies and made them susceptible to political capture (Santos (2017)).

3.3 Bank health at the time of the crisis

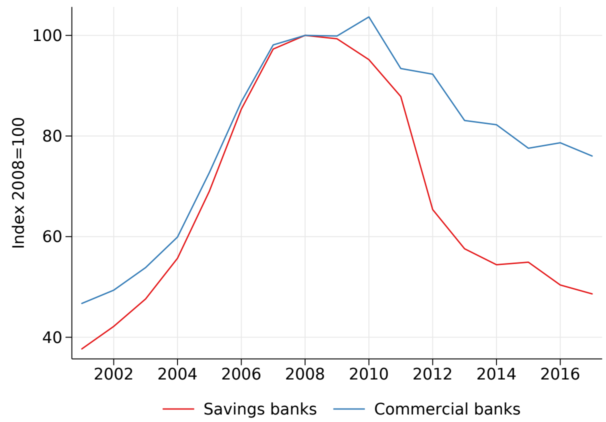
The Spanish banking sector was severely hit by the 2008 financial crisis and its restructuring required government support amounting to 65.5 billion euros, or roughly 5.5% of Spanish GDP (Bank of Spain (2019)). The reform process started in 2009-2010 with the government intervening in 33 institutions by either nationalizing them or facilitating their takeovers by other banks. Further nationalizations took place in subsequent years and the consolidation process culminated in Spain's request for financial assistance from the European Financial Stability Facility in June 2012.

For the purpose of my analysis, I classify a bank as weak if it was subject to any form of government intervention since the onset of the crisis, be it in the form of a liquidity injection, recapitalization or takeover. This results in a total number of 37 institutions, further collapsed

[13] In what follows, I use the terms *cajas* and savings banks interchangeably.

[14] See Illueca, Norden and Udell (2014) and Fernández-Villaverde, Garicano and Santos (2013).

Figure 6: Evolution of credit by bank type



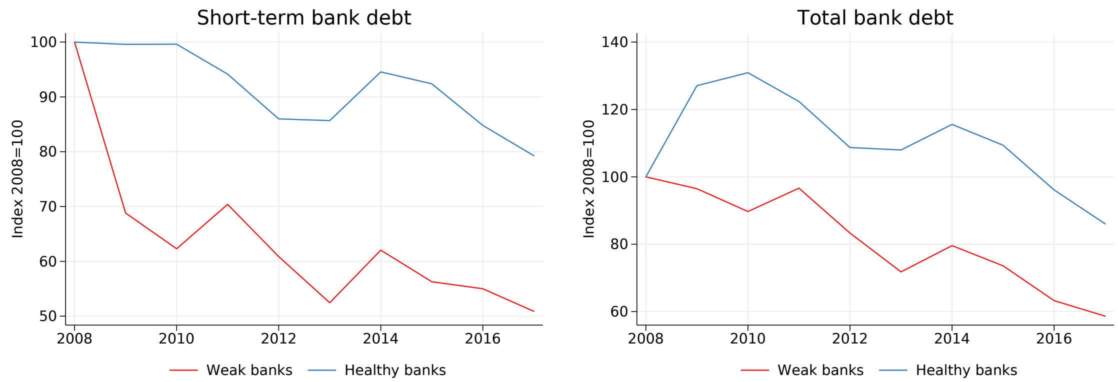
Note: This figure shows the evolution of real credit from commercial and savings banks computed as total credit from all banks in each category. The sample consists of all Spanish banks active in a given year and is therefore a superset of the banks present in the firm-level data. Source: AEB and CECA.

into 13 entities due to the mergers occurring as part of the restructuring process (see Table A.2 in the Appendix for details). I normalize the amount of government aid by the risk-weighted assets of each entity to obtain a continuous measure of bank weakness ranging between 0 (healthy bank) and 0.25 (weakest bank). For firms with multiple bank relationships, I measure lender health as the average weakness of all banks linked to any such firm.

My sample of weak banks consists entirely of savings banks. While all banks suffered losses from non-performing loans, solvency concerns were concentrated in the *caja* sector, which was effectively wiped out once these institutions were forced to convert into commercial banks.[15] These losses translated into a credit crunch which was more pronounced for savings banks than for commercial banks. Figure 6 plots the total amount of credit by bank type and shows that savings banks contracted lending considerably more in the post-crisis years, after having slightly outpaced commercial banks before the crisis. A similar pattern emerges when looking at bank debt in the firm data. The left panel of Figure 7 shows a sharp post-crisis fall in the short-term debt of firms tied to weak banks and a much milder decline for firms with healthy bank relationships. Consistent with the trend observed in the bank-level data, the total bank debt of firms borrowing from troubled banks remains below its 2008 level throughout the entire post-crisis period, whereas in the case of healthy banks it only starts falling in 2010 and does so at a slower rate than for weak banks. The fact that the sources in Figures 6 and 7 align is reassuring, given that only a subset of savings and commercial banks are present in the firm-level data.

[15] By July 2012, 43 out of the 46 *cajas* active in 2006 were involved in the restructuring process and all of them were forced to convert into commercial banks as part of the agreement signed between Spain and the European Financial Stability Facility (EFSF (2012)). By 2017, only 12 former *cajas* still existed.

Figure 7: Evolution of firm debt by bank health



Note: This figure shows bank debt from matched firm-bank data. Short-term debt refers to maturities of one year or less. Firms in the weak-bank category are firms which have a relationship with at least one distressed bank. The sample is restricted to firms in manufacturing, transportation, accommodation, information, and professional sectors. In an average year, there are 58,050 firms in the healthy-bank category and 12,206 firms in the weak-bank category. Debt amounts are summed over all firms in each category.

It is worth noting that credit growth was already declining in 2007, as is evident in Figure 6. This is consistent with evidence from Bentolila, Jansen and Jiménez (2018), who have access to the universe of Spanish corporate loans and use a similar set of weak banks to show that the latter started rationing credit in late 2007. The timing of the credit collapse is not surprising given that 2007 marks the end of the economic boom and accompanying real estate bubble which started in 1999.

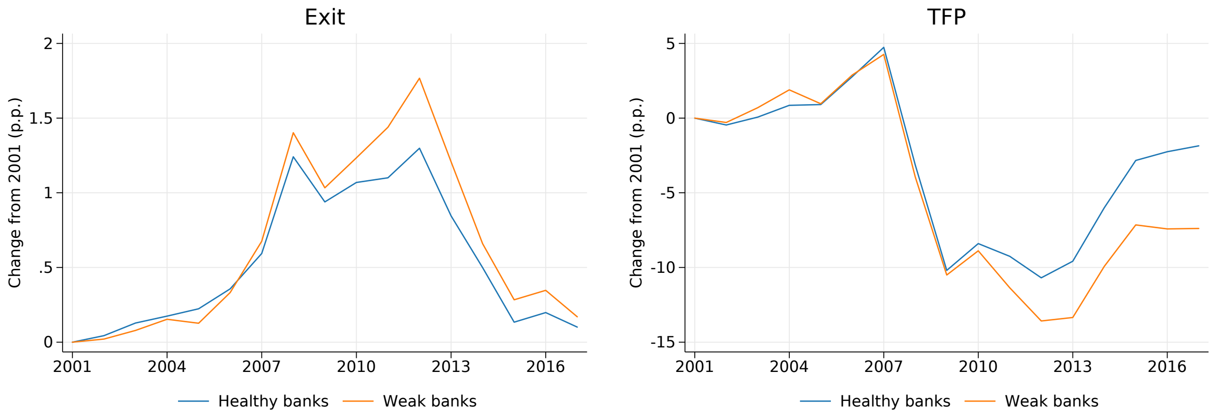
3.4 Borrower characteristics

Having outlined the classification between weak and healthy banks, I now turn to the characteristics of the firms borrowing from each bank type. The identification of the lender-health effect on firm productivity rests on the assumption that firms are as-good-as-randomly assigned to their banks.

The evolution of firm exit and productivity, broken down by bank health, suggests that the crisis marks the start of a growing divergence between firms exposed to banks of differing quality. Starting in 2007, the performance gap between firms tied to weak and healthy banks widens both in terms of survival odds and productivity: the former exhibit higher relative exit rates and suffer greater contractions in their productivity level (see Figure 8). This represents a clear departure from the pre-crisis period, during which exit rates and productivity were moving at a similar pace for the two groups of firms.

Further evidence supporting the absence of systematic differences between the clients of weak and healthy banks prior to the crisis is presented in Table 1. The last column reports the normalized difference statistic for several firm characteristics, which is computed following Imbens

Figure 8: Firm outcomes by bank health



Note: This figure shows average exit rates (left) and productivity growth (right) for firms exposed to weak and healthy banks.

and Wooldridge (2009).[16] The number of bank relationships is the only variable with an absolute value of the normalized difference above 0.25 – which is the threshold for a significant difference – implying that firms tied to distressed banks had on average more bank connections going into the crisis. As for the remaining variables, Table 1 shows that the firm sample is well balanced along a broad range of characteristics.

Table 1 also shows the share of firms in the construction and real estate industries for both bank types. Weak banks are only marginally more exposed to these sectors, which rules out the possibility that the main results of the paper are driven by the bursting of the real estate bubble which predated the crisis. To further ensure that bank affiliation is not in fact a proxy for the industries in which firms operate, all future exercises include sector controls.

The evidence presented so far assuages concerns of selection on observable characteristics. There is, however, the possibility that firms associate themselves with weak banks for reasons which are unobserved but related to firm performance. To address this, I run linear panel regressions of exit probability and productivity growth on the bank variable and include firm-level fixed effects to absorb any confounding unobserved characteristics. To account for aggregate and local demand effects, I also include 2-digit sector $\times$ 3-digit region $\times$ year fixed effects. The baseline specification is given by:

$$y_{it} = \beta \ \mathrm{BW}_i \times \mathrm{Post}_t + X_{it-1}\delta + \alpha_i + \alpha_{s,r,t} + \epsilon_{it} \ , \tag{5}$$

where y_{it} denotes the outcome of interest, BW_i is the average weakness of a firm's banks as measured by the aid-to-assets ratio, $Post_t$ is an indicator for the period starting in 2007, and X_{it-1} is a vector

[16] I prefer the scale-free normalized difference statistic over the more commonly used t-statistic because the latter is increasing with the number of observations, which is problematic in large samples.

Table 1: Pre-crisis descriptive statistics by bank affiliation

	Healthy banks (Control)		Weak banks (Treated)		
	Mean	Std. dev.	Mean	Std. dev.	Nrm. diff.
Exits	0.011	0.104	0.009	0.096	-0.012
TFP growth	0.020	0.337	0.024	0.346	0.009
TFP level	0.881	0.283	0.867	0.294	-0.033
Log value added	-0.470	1.174	-0.310	1.238	0.094
Log employees	2.303	1.119	2.463	1.172	0.098
Log tangible assets	-1.913	1.947	-1.696	1.961	0.079
Log total assets	0.194	1.381	0.393	1.460	0.099
Debt / assets	0.204	0.199	0.203	0.199	-0.003
Average pre-crisis TFP	0.019	0.193	0.023	0.192	0.014
Average pre-crisis debt / assets	0.165	0.167	0.170	0.167	0.022
Number of banks	1.680	0.951	2.463	1.496	0.442
Construction / real estate	0.211	0.408	0.240	0.427	0.050

Note: Sample consists of 165,188 control firms and 45,205 treated firms. A firm is considered treated if it has a relationship with at least one weak bank. Variables are measured in 2006. The last column represents the normalized difference test from Imbens and Wooldridge (2009).

of lagged controls including firm size, indebtedness and productivity.

The choice of controls is fairly standard in the literature (see e.g. Aghion et al. (2019)). Last period's productivity is included to account for catch-up dynamics while firm size, as measured by employment and total assets, is meant to absorb the easier access to credit markets enjoyed by large firms. Leverage is included in order to make sure that the bank effect is not influenced by the amount borrowed. Note that stand-alone coefficients for bank weakness and the post-crisis period cannot be estimated due to collinearity with firm and year fixed effects respectively.

It is worth pointing out that all panel specifications in this paper, including equation (5), use two-way clustering of the standard errors by firm and year. This allows for the error terms to be correlated both across different year-observations for the same firm and across different firm-observations in the same year. This is a more general setup than is typical in the literature, which mostly uses one-way clustering at the firm or sector level.[17] Under two-way clustering, a significant coefficient on a variable indicates that the variable still matters in the presence of serially correlated firm shocks as well as in the presence of aggregate shocks affecting all firms in a given year.

The results from estimating equation (5) are shown in the first two columns of Table 2. The coefficient on bank health is highly significant and implies that, all else equal, moving from an unaffected bank to the worst-hit bank increases a firm's probability of exit by $0.07 \times 0.25 = 1.8$ percentage points per year and decreases its productivity growth by $0.08 \times 0.25 = 2$ percentage points per year. The rich fixed effects specification rules out the possibility that the weak-bank

[17] See, for example, Kalemli-Ozcan, Laeven and Moreno (2022) and Bentolila, Jansen and Jiménez (2018), Laeven, McAdam and Popov (2018). To my knowledge, mine is the first paper to study lender effects at the firm level using clustering along the time dimension.

Table 2: Weak banks and firm outcomes

	(1) Exits	(2) Δ TFP	(3) Exits	(4) Δ TFP
Bank weakness × post-crisis	0.071**	-0.083***	0.070**	-0.081***
	(0.023)	(0.019)	(0.023)	(0.020)
Bank weakness × log total assets $_{t-1}$			0.003	-0.006
			(0.007)	(0.027)
Log TFP $_{t-1}$	-0.008***	-0.519***	-0.008***	-0.519***
	(0.002)	(0.017)	(0.002)	(0.017)
Log employment $_{t-1}$	-0.004***	0.048***	-0.004***	0.048***
	(0.001)	(0.005)	(0.001)	(0.005)
Log total assets $_{t-1}$	-0.001*	0.051***	-0.001*	0.051***
	(0.001)	(0.005)	(0.000)	(0.005)
Debt / assets $_{t-1}$	0.027***	-0.003	0.027***	-0.003
	(0.007)	(0.004)	(0.007)	(0.004)
Firm FE	Yes	Yes	Yes	Yes
Sector × region × year FE	Yes	Yes	Yes	Yes
R^2	0.158	0.343	0.158	0.343
Observations	2,035,706	1,970,771	2,035,706	1,970,771

Note: This table shows results from estimating a linear panel model of exit probability and TFP growth of the form described in equation (5). Post-crisis refers to years 2007 and above. Sector refers to 2-digit NACE Rev. 2 categories. Region refers to 3-digit NUTS categories. Standard errors are clustered at the firm and year level.

effect is merely an artifact of a borrower composition more skewed towards vulnerable firms, or towards firms operating in badly hit industries or regions. It is also worth stressing the fact that the bank effect is unaffected by firm size, as implied by the insignificant interaction between bank health and total assets (Columns 3-4 of Table 2). This underscores the point that all firms borrowing from weak banks suffered, regardless of their size.

The main findings are robust to a number of alternative specifications and sample variations. Appendix Table A.4 shows that the bank coefficient retains its sign and significance when including 4-digit industry fixed effects (Columns 1-2), when excluding firms with multiple bank relationships (Columns 5-6), as well as when excluding firms in problematic sectors such as construction and real estate (Columns 7-8).

The results in Table 2 can be viewed through the lens of the theoretical model described in Section 2, where weak banks' urgent need for cash affects productivity both directly, through credit rationing, and indirectly, by raising the bar for acceptable borrower quality. The higher exit rate observed among firms tied to weak banks is suggestive of the latter mechanism, the effects of which are missed if one only looks at realized productivity growth among survivors and can give rise to sample selection bias. In what follows, I lay out a strategy for quantifying the economic impact of lender health while accounting for premature firm exit among the clients of weak banks.

4 Empirical strategy

The post-crisis surge in exits associated with weak bank exposure leaves open the possibility that the firms hardest hit by their lending relationships are forced to close and are thereby omitted from the productivity analysis. To address the resulting sample selection bias, I apply a commonly used two-step procedure which involves separately modeling firm survival and productivity growth (Heckman (1976)).

The validity of the exercise rests on finding a variable which (i) is useful in predicting firm survival and (ii) can be omitted from the main equation because it only affects productivity growth through the impact it has on selection. I use information on firm location to serve this purpose. The exclusion restriction cannot be tested directly, but I offer evidence which argues in favor of using geographic variation to correct for sample selection.

4.1 Regional bank exposure of Spanish firms

Bank relationships tend to be local, for reasons which might have to do with banks possessing better knowledge of local business conditions. Spain is no exception, as is evident from the fact that in my sample of firms, being attached to a weak bank is highly correlated with the regional share of branches belonging to those banks in 1988, i.e. before the savings banks were allowed to expand nationally (see Appendix Table A.3). This suggests that eighteen years later, firms are still more likely to borrow from banks which traditionally held strong market positions in their region of operation.

To the extent that banks are more willing to lend to local firms, a shock which affects one region's banks more severely leaves the firms located in that region with fewer viable alternative lenders. This, in turn, could translate into worse firm outcomes in regions more exposed to weak banks once the crisis hits. In addition, one might expect firms with existing ties to weak banks to be disproportionately affected due to the difficulty of switching between lenders.[18]

A priori, this line of reasoning can conceivably be applied to both survival and productivity growth: firms in regions with many weak banks may have a harder time substituting away from these banks, which could make them more prone to failure and/or lead to lower investment in productivity. In the data, however, it turns out that a high regional concentration of weak banks, by offering fewer alternative funding sources, significantly affects exits but not productivity. The exercise performed to establish this finding consists of estimating linear panel models of firm exit

[18]The discussion surrounding alternative lenders may seem inconsistent with the premise of static bank relationships on which the results of the paper are based. With a slight modification, however, the alternative-lender argument can be made in the presence of time-invariant bank ties. Recall that a firm's bank measure is the average health of its lenders. The same average health for a firm in a low- as opposed to a high-density region is likely the result of a more diverse lender composition in the former compared to the latter. In other words, a firm in a low-density region is more likely to have a healthy bank in its lender mix and is therefore more likely to be able to use this bank to substitute away from its ailing banks. The discussion therefore does not depend on firms seeking out *new* banks, which would involve changing their overall bank measure.

and productivity growth of the form:

$$y_{it} = \beta \ \mathrm{BW}_i \mathrm{Post}_t + \gamma \ \mathrm{WD}_r \mathrm{Post}_t + X_{it-1}\delta + \alpha_i + \alpha_{s,coast,t} + \epsilon_{it} \ , \tag{6}$$

where WD_r is a dummy equal to one if region r's weak-bank density in 1988 is above the median. Note that region fixed effects cannot be included because bank density is constant within a region. Instead, I account for the possibly asymmetric impact of the real estate bubble by including an indicator for the coastal provinces where the credit boom and house price bubble were strongest in the lead-up to the crisis (Bentolila, Jansen and Jiménez (2018)). The remaining controls are defined as in equation (5).

In order to test whether the weak-bank effect varies with the regional concentration of weak banks, I augment the specification in (6) with the interaction between the two variables. The estimation equation then becomes:

$$y_{it} = \beta \ \mathrm{BW}_i \mathrm{Post}_t + \gamma \ \mathrm{WD}_r \mathrm{Post}_t + \phi \ \mathrm{BW}_i \mathrm{WD}_r \mathrm{Post}_t + X_{it-1}\delta + \alpha_i + \alpha_{s,coast,t} + \epsilon_{it} \ . \tag{7}$$

Before turning to a detailed discussion of the results, it is worth emphasizing the merit of using the 1988 bank branch allocation as a proxy for regional weak-bank density. The advantage of the 1988 measure is that it is the result of legislative barriers unrelated to economic conditions outside the savings banks' home region. This avoids the possible endogeneity of contemporaneous weak-bank concentration, which is influenced by the conscious decision of weak banks on where to expand and may therefore depend on firm performance in target regions.

The results from estimating equations (6)-(7) are shown in Table 3. The first column shows the total effect of regional weak-bank density on firm exit to be significantly positive while holding individual lender health constant. The second column decomposes the regional effect based on the health of a firm's own lenders and shows that it is entirely driven by firms with existing relationships to troubled banks, i.e. the firms with a non-zero bank weakness measure. These findings are consistent with the narrative laid out above, in which the bank concentration of a firm's region captures the quality of potential alternative lenders and affects exit on top of the role played by the firm's own weak banks.

This evidence establishes the first condition that the regional instrument must satisfy, namely that it is a good predictor of exit. The second condition for the validity of the regional instrument is that, controlling for bank affiliation and other firm characteristics, it is unrelated to productivity growth. The data appears to support this claim.

Looking at the last two columns of Table 3, which perform the same exercise as the first two columns only using TFP growth as the dependent variable, it appears that a higher regional concentration of weak banks does not impact local firms' ability to grow, while individual bank

Table 3: Regional weak-bank density and firm outcomes

	(1) Exit	(2) Exit	(3) Δ TFP	(4) Δ TFP
Bank weakness × post-crisis	0.071**	0.049**	-0.049*	-0.041
	(0.023)	(0.017)	(0.021)	(0.028)
High weak-bank density in 1988 × post-crisis	0.001*	0.000	0.001	0.001
	(0.000)	(0.000)	(0.002)	(0.002)
Bank weakness × high weak-bank density in 1988 × post-crisis		0.048*		-0.016
		(0.021)		(0.037)
Log TFP $_{t-1}$	-0.008***	-0.008***	-0.518***	-0.518***
	(0.002)	(0.002)	(0.019)	(0.019)
Log employment $_{t-1}$	-0.004***	-0.004***	0.050***	0.050***
	(0.001)	(0.001)	(0.005)	(0.005)
Log total assets $_{t-1}$	-0.002*	-0.002*	0.048***	0.048***
	(0.001)	(0.001)	(0.005)	(0.005)
Debt / assets $_{t-1}$	0.028***	0.028***	-0.003	-0.003
	(0.007)	(0.007)	(0.004)	(0.004)
Total effects				
Bank weakness		0.061		-0.046
(Std.err.)		0.020		0.023
High weak-bank density in 1988		0.001		0.001
(Std. err.)		0.000		0.002
Firm FE	Yes	Yes	Yes	Yes
Sector × coastal region × year FE	Yes	Yes	Yes	Yes
R^2	0.141	0.141	0.325	0.325
Observations	1,968,004	1,968,004	1,907,065	1,907,065

Note: This table shows results from estimating a linear panel model of exit probability and TFP growth of the form described in equations (6)-(7). Post-crisis refers to years 2007 and above. Weak-bank density refers to the share of bank branches belonging to weak banks in a given region. Sector refers to 2-digit NACE Rev. 2 categories. Coastal regions include provinces along the Mediterranean Coast and in the Balearic and Canary Islands. Standard errors are clustered at the firm and year level.

health does.[19,20]

The significant effect of regional bank density on firm exit and the lack thereof on productivity growth constitute the cornerstone of the identification strategy and as such deserve a more detailed discussion. One explanation for why the effect is present for exits and not productivity growth could be that a shock large enough to affect exit, by posing an immediate threat to the firm, prompts a stronger reaction in terms of seeking out alternative lenders. A shock that does not endanger the firm's survival may therefore have a more muted response by comparison.

[19]The magnitudes of the bank effects in Table (3) are slightly different from the baseline specification reported in Table (2) mainly due to the omission of 3-digit-level regional fixed effects in the former.

[20]The lack of a significant relationship between regional density and productivity is reinforced by the fact that, when looking at the pre-crisis years alone, firms located in regions with a stronger *caja* presence were no different in terms of their TFP growth than similar firms in regions less exposed to these institutions (see Appendix Table A.5). This reduces the possibility that high-density regions were special in a way that might have to do with firm productivity. The caveat of this result is that it relies on contemporaneous year-by-year densities which could suffer from the endongeneity issues discussed above. That is why for the main results I prefer the 1988 measure which predates regional deregulation.

Note that the response in question is not the one prompted by the firm's own banks – which is significant for both exit and productivity growth – but rather the added effect of being surrounded by weak banks. As such, it is possible to imagine a credit shock differentially affecting the two outcomes depending on whether it threatens the firm's survival. If, under its existing bank affiliation, a firm's ability to cover its costs and stay afloat is at stake, it gives the firm a strong impetus to try to find funding elsewhere – and a firm which happens to be in a region with better banks has a higher chance of succeeding. If, on the other hand, the credit shock only affects firm investment plans, some firms might forgo those plans rather than seek out other lenders thereby diluting the regional effect.

The validity of the regional instrument is most important when the bank effect on exit is strongest: if sample selection on the bank variable were random, then focusing on the performance of surviving firms alone would yield an accurate measure of the overall bank effect. The years when the decline in bank health has a strong impact on exit are also the years when the narrative underpinning the identification strategy is most plausible: when the bank shock is primarily a shock to survival, the drive to switch between lenders is strongest, making regional differences in alternative lending opportunities most likely to matter. That is why the exercise performed in Appendix Table (A.6), which shows that in the first half of the post-crisis period the exit channel takes precedence over the productivity channel, reinforces the credibility of the regional instrument during those years.

Taken together, the evidence presented in this section shows that information contained in a firm's region of operation is useful in predicting firm exit while leaving productivity unaffected, making it a suitable candidate in addressing the sample selection bias.

4.2 Correcting for sample selection

With an adequate instrument for the selection equation in hand, I now turn to describing the correction procedure. The relationship of interest involves the impact of bank health on post-crisis productivity growth. I consider 2007 to be the first year of the crisis and track how firm-level TFP growth varies with bank attachment in each subsequent year, up until the end of my sample period in 2017.[21]

In order to account for the bias originating from premature exit among weak-bank customers, I augment the equation for productivity growth with a term reflecting the effect of bank health on firm survival. Specifically, I estimate the following model for each post-crisis year t:

$$\Delta TFP_{it} = X_{1it}\beta_t + u_{1it} \tag{8}$$

$$surv_{it} = \mathbb{1}[X_{2it}\delta_t + v_{2it} > 0] \ , \tag{9}$$

[21] The choice of the first crisis year is based on the timing of the credit crunch, which, according to Section 3.3, started in 2007.

where X_1 contains lagged firm characteristics (TFP level, size, indebtedness) as well as average pre-crisis TFP growth and leverage. The vector of controls in the selection equation, X_2, includes region indicators in addition to all the variables in X_1. The error terms u_1 and v_2 are assumed to be jointly normal:

$$u_1 \sim N(0, \sigma) \quad v_2 \sim N(0, 1) \quad Corr(u_1, v_2) = \rho \ ,$$

which, together with equations (8) and (9), implies that the expected TFP growth of surviving firms can be written as:

$$E(\Delta TFP_{it} | X_{it}, surv_{it} = 1) = X_{1it}\beta_t + \gamma\lambda(X_{2it}\delta_t) \ , \tag{10}$$

where the last term represents the sample selection bias and $\lambda(.)$ is a known function of the predicted values from the selection equation.[22]

The inclusion of pre-crisis averages in both selection and productivity equations is meant to absorb any unobserved firm characteristics, which, owing to the cross-sectional nature of the regressions, cannot be controlled for with firm-level fixed effects.[23] This is implicitly assuming that if firms associating themselves with weak banks differ in fundamental ways from the ones choosing healthy banks, these differences are reflected in pre-crisis firm characteristics. I use past TFP growth and leverage because they encapsulate, respectively, firm quality and the degree of dependence on external funds. Taken together, these controls rule out scenarios in which weak banks took on highly leveraged, poor quality customers during the boom years for reasons having to do with an intrinsically higher risk appetite, a desire to compete for market share in new regions, or the political interests of their shareholders.

5 Results

Table 4 estimates the sample selection model for each post-crisis year. The first panel pertains to bias-adjusted productivity growth (equation 8) whereas the second panel reports the results from probit models of firm survival (equation 9). The coefficient on the correction term λ is also reported at the bottom of the table along with its standard error. A coefficient significantly different from zero indicates the presence of a sample selection bias.

Before interpreting the results, it is worth pointing out that Table 4 uses regional indicators in the selection equation. The coefficients on bank health and all other control variables remain almost unchanged after replacing the regional indicators with 1988 bank branch shares, as shown

[22] The model specification follows Heckman (1976). The functional form of $\lambda(.)$ is known as the inverse Mills ratio and is equal to the ratio between the PDF and complementary CDF of the normal distribution.

[23] It is possible to extend the model to a panel design which corrects for sample selection in the presence of endogenous regressors and unobserved heterogeneity (see Semykina and Wooldridge (2010)). While more general, this approach assumes that the firm attributes influencing bank attachment are also time-invariant, which means that they must be present before the crisis. The only loss of generality in my approach is the assumption that those attributes can be captured by pre-crisis productivity growth and leverage.

in Appendix Table A.7. Table A.7 also shows the effect of weak-bank concentration on selection to be negative and highly significant for the first part of the post-crisis period, in line with the discussion from Section 4.1. The fact that the coefficients from the two specifications closely align alleviates concerns about the region indicators picking up local conditions unrelated to the 1988 branch allocation.[24]

Turning to the results in Table 4, poorer bank health is generally associated with lower productivity growth and survival odds, echoing the findings from the panel models of Section 3. The time variation in the magnitude and significance of the effect, however, offers novel insights into how bank health operates over the cycle along the intensive and extensive margins. The different dynamics of the two margins underscore the importance of distinguishing between the two channels.

Both productivity and survival probabilities plunge on impact, yet over the next three years the former effect weakens to the point of becoming statistically insignificant, while the latter remains strongly negative. In the following years, the productivity effect picks up and by the end of the sample period, the trend is reversed, with TFP growth taking heavy losses compared to only mild ones in terms of firm survival. Put differently, the bank effect on exit fades with the acuteness of the crisis, while the effect on productivity growth intensifies as financial conditions improve.

The correction term λ turns from highly significant between 2007-2013 to borderline significant or insignificant thereafter. This suggests that the need to adjust for the sample selection bias becomes less stringent over time as the exit margin slowly loses importance.

Table 4 also reports the coefficients on the remaining control variables, which mostly follow expected trends. Leverage is negatively related to next-period TFP growth and survival probability, suggesting that debt overhang impairs firm performance. Previous-period TFP level is positively associated with survival – a finding which at the same time acts as a validity check for the productivity measure.

Firm size, as proxied by employment and total assets, is positively associated with productivity growth, suggesting that larger firms are better at enhancing their performance, possibly due to better access to resources. Somewhat surprisingly, this ability does not seem to help prevent exit for most of the post-crisis period, as larger firms appear less likely to make it to the next period. This could be driven at least in part by regulatory hurdles targeting larger firms which may limit their ability to downsize in response to a crisis. For example, Spanish labor law subjects firms with over 50 employees to more stringent employment protection. Laeven, McAdam and Popov (2018) exploit this provision to show that firms below the employment threshold are better able to adapt to the credit shock.

[24]The main difference between the two sets of results comes from the sample selection effect which is larger and more precisely estimated in the specification using regional indicators. This could be due to the fact that, by being an imperfect measure of weak-bank density, regional branch shares do not provide the necessary variation to reliably identify selection effects. That said, the regional indicators are still good predictors of exit, as shown by the high F-statistic documented in Appendix Table A.8.

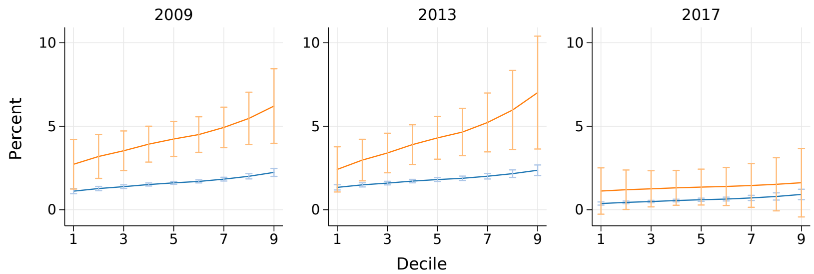
Table 4: Effect of weak banks on productivity growth

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
ΔTFP (1)											
Bank weakness	-0.098***	-0.047	-0.051	-0.043	-0.212***	-0.093**	-0.146***	-0.090**	-0.090**	-0.101**	-0.102**
	(0.024)	(0.028)	(0.030)	(0.030)	(0.031)	(0.033)	(0.035)	(0.035)	(0.035)	(0.035)	(0.038)
Log TFP $_{t-1}$	-0.202***	-0.244***	-0.264***	-0.232***	-0.206***	-0.187***	-0.188***	-0.180***	-0.183***	-0.180***	-0.177***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Log employment $_{t-1}$	0.008***	0.027***	0.023***	0.015***	0.022***	0.029***	0.031***	0.019***	0.020***	0.019***	0.017***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log total assets $_{t-1}$	0.046***	0.048***	0.058***	0.051***	0.041***	0.035***	0.029***	0.035***	0.034***	0.034***	0.032***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Debt / assets $_{t-1}$	0.023***	-0.039***	-0.040***	-0.052***	-0.052***	-0.047***	-0.066***	-0.053***	-0.058***	-0.054***	-0.063***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Pre-crisis avg. Δ TFP	0.008	0.011	0.029***	0.007	0.026***	0.001	0.016*	0.028***	0.021**	0.010	0.013
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Pre-crisis avg. leverage	-0.061***	-0.002	-0.040***	-0.016	-0.011	-0.015	-0.019*	-0.029**	-0.021*	-0.011	0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Selection (2)											
Bank weakness	-1.750***	-1.714***	-1.557***	-1.798***	-1.587***	-1.431***	-1.279***	-1.072**	-0.657	0.492	-0.937
	(0.250)	(0.211)	(0.237)	(0.239)	(0.252)	(0.263)	(0.305)	(0.377)	(0.492)	(0.595)	(0.652)
Log TFP $_{t-1}$	0.086**	0.082***	0.157***	0.195***	0.267***	0.274***	0.287***	0.215***	0.232***	0.204***	0.308***
	(0.027)	(0.023)	(0.024)	(0.023)	(0.023)	(0.022)	(0.025)	(0.028)	(0.037)	(0.042)	(0.054)
Log employment $_{t-1}$	-0.039*	-0.059***	-0.105***	-0.118***	-0.119***	-0.122***	-0.095***	-0.031	-0.024	-0.088***	-0.116***
	(0.016)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)	(0.016)	(0.018)	(0.024)	(0.026)	(0.035)
Log total assets $_{t-1}$	-0.139***	-0.103***	-0.049***	-0.058***	-0.071***	-0.029*	-0.026	-0.020	-0.003	0.051*	0.064*
	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.016)	(0.017)	(0.023)	(0.025)	(0.032)
Debt / assets $_{t-1}$	-0.241**	-0.203**	-0.376***	-0.808***	-1.095***	-1.266***	-1.048***	-0.968***	-0.862***	-0.877***	-1.018***
	(0.083)	(0.065)	(0.065)	(0.059)	(0.057)	(0.055)	(0.064)	(0.074)	(0.094)	(0.102)	(0.128)
Pre-crisis avg. Δ TFP	0.021	-0.045	-0.032	-0.119	0.057	-0.038	0.031	-0.056	-0.072	-0.002	0.006
	(0.063)	(0.056)	(0.061)	(0.061)	(0.064)	(0.060)	(0.073)	(0.085)	(0.112)	(0.115)	(0.153)
Pre-crisis avg. leverage	-0.106	-0.246**	0.043	0.260**	0.406***	0.616***	0.514***	0.711***	0.573***	0.897***	1.198***
	(0.104)	(0.081)	(0.086)	(0.083)	(0.083)	(0.082)	(0.095)	(0.113)	(0.141)	(0.160)	(0.213)
Sector controls	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2
Region controls	2	2	2	2	2	2	2	2	2	2	2
λ	0.032	0.042	0.057	0.056	0.043	0.036	0.035	0.026	0.028	0.032	0.046
Std. err. of λ coeff.	0.009	0.012	0.010	0.010	0.009	0.009	0.009	0.011	0.013	0.013	0.013
ρ	0.110	0.126	0.171	0.173	0.136	0.114	0.112	0.086	0.097	0.118	0.174
σ	0.291	0.331	0.336	0.323	0.318	0.317	0.312	0.297	0.286	0.274	0.266
Observations	103,164	98,813	96,355	91,062	84,991	78,662	72,884	68,043	62,724	58,530	44,424

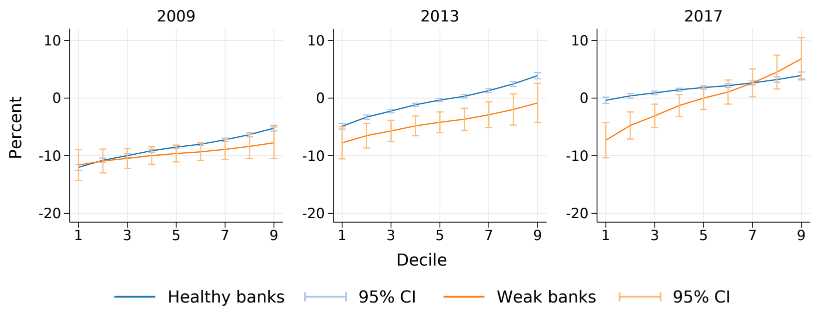
Note: This table shows results from estimating selection-bias-adjusted models of productivity growth of the form described in equation (10) for each year. The λ-term represents the sample selection bias. Sector refers to 2-digit NACE Rev. 2 categories. Region refers to 3-digit NUTS categories.

Figure 9: Predicted outcomes by employment decile

(a) Exit probability



(b) Productivity growth



As for the pre-crisis controls, higher average indebtedness affects survival rates negatively for the first two crisis years, and positively thereafter. This indicates that a certain amount of cleansing may be taking place, whereby only the best of the firms with high pre-crisis debt levels make it past the first crisis years and those firms start thriving once the crisis abates. Firms which on average grew faster before the crisis also have higher productivity growth after the crisis, though the relationship is at times insignificant. This persistence is not surprising given that at least some of the factors which make a firm successful are likely acyclical.

Going back to a discussion of bank weakness, the fading effect it has on survival and the intensifying effect it has on productivity growth constitute an interesting development which deserves further attention. In particular, it is worth looking into whether there is any heterogeneity in the bank effect conditional on other firm characteristics that can help explain what is driving the alternating dynamics of the exit and productivity margins. To this end, I estimate a slightly modified sample selection model which differs from equation (10) by adding the interaction of the bank variable with all other covariates in both the selection and the TFP equation.

Figure 9 plots the resulting predicted firm outcomes by decile of pre-crisis employment levels for different post-crisis years. Panel (9a) looks at exit probabilities while Panel 9b looks at productivity growth. Focusing on year 2013, the employment gradient on exit is positive, suggesting that larger clients of weak banks are even more at risk of failing than their smaller counterparts. The opposite seems to be true for productivity growth: smaller firms borrowing from weak banks suffer more than larger ones. Together, these findings could be a cause for concern since they imply that large firms are better at cushioning the impact of a credit shock on productivity, but they are also the firms facing higher liquidation risk. To the extent that this risk materializes, the remaining firms are the ones taking the hardest hit in terms of productivity which in turn can have adverse consequences in the aggregate. This amplification dynamics could help explain why the effect on TFP growth is still present ten years after the crisis.[25]

It is also worth looking at trends in exit and productivity predating the crisis. Table A.9 presents results from running the same estimation as the one underlying Table 4, only for pre-crisis years. Despite there being signs of sample selection bias starting in 2003, the effect is not strong enough to render bank weakness significantly detrimental to productivity growth in any of the pre-crisis years. This means that in terms of productivity, firms tied to weak banks were no different from otherwise similar firms with healthy bank relationships. The same cannot be said about exits, which underscores the importance of controlling for pre-crisis firm characteristics in the post-crisis regressions.

One caveat to bear in mind when interpreting Table A.9 is that the timing of a firm's exit is imperfectly measured. In the raw data, the year of a firm's liquidation is often several years removed from the latest valid observation of other firm characteristics. That is why, in order to maximize the number of observations, I push the exit year back in time to the year following the last valid observation. This can result in prematurely counting exits and could explain some of the uptick in the bank effect in the years right before the crisis. Appendix Figure A.2 plots the predicted exit rates for firms tied to healthy banks and firms tied to the average weak bank. The difference between the two groups visibly widens after the crisis, thereby alleviating the concern that pre-crisis trends are driving the post-crisis trends.

6 Counterfactual analysis

To quantify the aggregate economic impact of the deterioration in bank health at the time of the crisis, I use the sample selection model from Section 4.2 to perform a counterfactual analysis of the output loss from the financial friction. For convenience, I restate the equations characterizing firm outcomes in a given year:

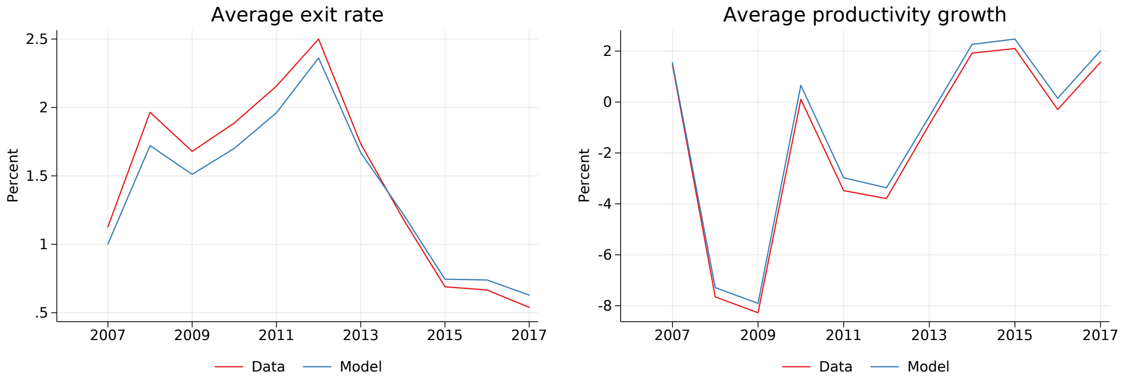
$$\Delta TFP_{it} = X_{1it}\beta_t + u_{1it} \tag{11}$$

$$surv_{it} = \mathbb{1}[X_{2it}\delta_t + v_{2it} > 0]\ . \tag{12}$$

The analysis draws inspiration from the experiment performed with the help of the theoretical

[25]Appendix Figures A.3 and A.4 show how the bank effect varies with employment in all post-crisis years. In line with the results in Table 4, the bank effect on TFP growth is initially weaker, then intensifies, while the opposite is true for exit.

Figure 10: Goodness of fit



model developed in Section 2. It starts by taking the firms active at the beginning of the crisis and drawing shocks to their survival probability and productivity growth for each post-crisis year. If, in a given year, the innovation to equation (12) clears the survival threshold, the firm makes it to the next year and produces an output level proportional to its current TFP. If, on the other hand, the condition in (12) is violated, the firm is counted as an exit for that year and its counterfactual output is retained for comparison purposes only.

Equation (12) is analogous to the condition imposed in the theoretical model requiring surviving firms' continuation value to exceed the value of exit. As in the theoretical experiment, bank affiliation plays a role in determining which firms survive and how much they produce. In the empirical exercise, the bank weakness measure enters equations (11) and (12) with a negative coefficient, which translates into lower chances of survival and a fall in productivity growth for firms whose banks are weakened by the crisis.

The experiment is run under (i) a scenario in which the health of each firm's bank is as observed in the data, and (ii) one in which all banks have the lowest level of distress. This setup parallels the analysis performed in Figure 5, which compares firm performance under constant favorable financial conditions – a proxy for tranquil times – and under elevated bank distress – a proxy for crisis times.

Firm value added is obtained by inferring factor growth from productivity growth separately in each year and plugging it in the production function underlying the TFP estimation:[26]

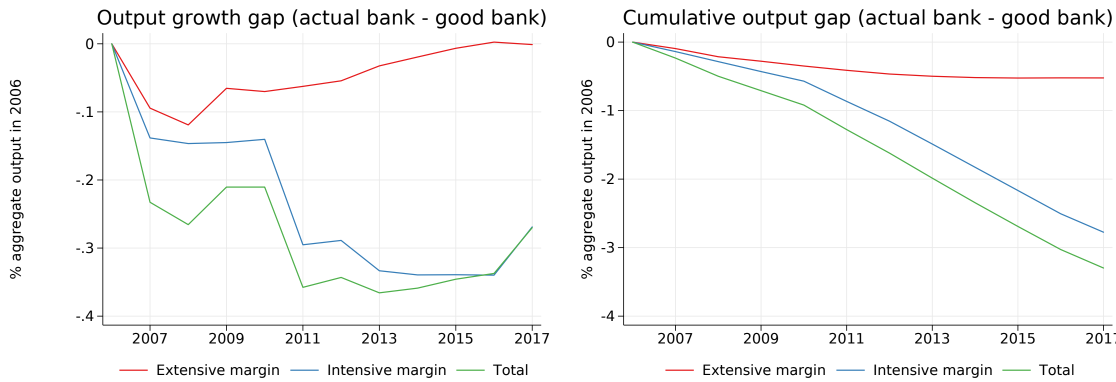
$$\widehat{\Delta x}_{it} = \beta_t x_{it-1} + \delta_t tfp_{it-1} \ , \quad x = \{k, l\} \tag{13}$$

$$va_{it} = tfp_{it-1} + \widehat{\Delta tfp}_{it} + \theta_k(k_{it-1} + \widehat{\Delta k}_{it}) + \theta_l(l_{it-1} + \widehat{\Delta l}_{it}) \ . \tag{14}$$

The difference in value added between scenarios (i) and (ii) measures by how much aggregate output would differ absent the crisis and can therefore be interpreted as the cost of the financial

[26]See Tables A.10 and A.11 in the Appendix for the estimation of factor growth from productivity growth.

Figure 11: Counterfactual



friction. The loss in output arises from the hypothetical amount produced by exiting firms and the diminished amount produced by survivors under worsening financial conditions.

Figure 10 plots exit and productivity growth from scenario (i) averaged over many simulations against the data and shows that the hypothetical firms closely mimic their empirical counterparts when exposed to lenders of the same quality.

Figure 11 plots the output gap both in terms of growth rates (left panel) and in terms of levels (right panel) along with a decomposition into the share due to exits and the share due to the productivity of survivors. The output growth shortfall from the extensive margin recovers, whereas the growth gap from the intensive margin is much more persistent and only starts narrowing towards the end of the sample period. A decade after the onset of the financial crisis, the cost attributable to it amounts to around 3% of pre-crisis GDP. The magnitude and persistence of the effect highlights the importance of looking beyond the short term in order to fully gauge the impact of financial frictions.

7 Conclusion

The aim of this paper is to study the aggregate real effects of banking crises in the medium to long run and to offer insights into the underlying forces which produce these effects. It does so by first developing a simple model of firm dynamics which endogenizes the response of productivity-enhancing investment and firm exit to a decline in lender health. The model is able to generate a surge in exits and a prolonged drop in productivity growth, both of which are prominent features of the Spanish economy in the aftermath of the 2008 financial crisis. The model also highlights the existence of a bias in the measurement of observable TFP growth during an episode of heightened exit which leads to an underestimation of the true productivity decline.

Motivated by this finding, I derive a measure of productivity from firm-level data which takes into account the disproportionately high number of liquidations among firms tied to troubled banks

– so called because they received government aid during the crisis. The exit-corrected productivity measure is obtained by estimating a sample selection model which exploits regional variation in weak-bank density as an instrument for identifying the exit bias. The sample selection model is put to work in a counterfactual analysis which estimates the output shortfall from the premature exits and lower productivity levels induced by the financial friction. I find a cumulative loss of around 3% of GDP a decade later. In addition, the output growth from the extensive margin recovers but he growth gap from the intensive margin only begins to narrow towards the end of the sample period, thereby proving much more persistent.

The estimate for the output loss presented here should be thought of as an upper bound, given that some of the advantages of a mass exodus event are not factored into the analysis. One example is the reallocation of factors that accompanies firm exit: as some businesses close, their assets are sold and their workers become available for taking up new jobs. The increased slack coming from the freeing up of resources can bring about lower factor prices which benefit surviving firms. The empirical exercise presented here seeks to grapple with this issue by allowing factor growth to respond differently in each year under the premise that some of that difference comes from aggregate exit. A more systematic approach would be to extend the theoretical model by endogenizing factor reallocation in response to a bank shock.

Another promising extension could address the observed intensification of the productivity effect as the crisis abates. One possibility is to allow for some amplification to come from the aggregate exit rate. Such amplification could arise if, for instance, the unusually high number of exits taking place at the peak of the crisis lessen the degree of competition among survivors in the following years, thereby decreasing their incentive to invest in productivity. Alternatively, it could be an artifact of inefficiencies such as labor market frictions which hamper the speed of reallocating factors. A more thorough exploration of these issues is left to future work.

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Appendix

Table A.1: Parameters for solving and simulating the theoretical model

Parameter	Description	Value
α	Technological parameter	0.72
ϕ	Technological parameter	0.068
μ_θ	Intercept of efficiency $\log(\theta)$	0.018
ρ_θ	Persistence of efficiency $\log(\theta)$	0.069
σ_θ	Standard deviation of efficiency $\log(\theta)$	0.01
v^e	Value of exit	11.92
N	Number of firms	1000
S	Number of simulations	1000
T	Number of periods	40

Table A.2: Restructuring of the Spanish savings bank sector

2009	2010	2011	2012
La Caixa	La Caixa	Caixabank	Caixabank
Caixa Girona			
Cajasol	Cajasol	Banca Civica	
Caja de Guadalajara			
Caja Navarra	Banca Civica		
Caja de Burgos			
Caja Canarias			
Caja Madrid	BFA	Bankia	
Bancaja			
La Caja de Canarias			
Caixa Laietana			
Caja de Avila			
Caja Segovia			
Caja Rioja			
CAM	Banco CAM	Banco Sabadell	
Cajasur	BBK Bank Cajasur	Kutxabank	
BBK			
Kutxa			
Vital Kutxa			
Caja Murcia	BMN	BMN	
Caixa Penedes			
Caja Granada			
Sa Nostra			
Caixa Sabadell	Unnim	Unnim Banc	BBVA
Caixa Terrassa			
Caixa Manlleu			
Unicaja	Unicaja	Unicaja Banco	
Caja Jaen			
Caja Espana	CEISS	Banco CEISS	
Caja Duero			
Caixa Catalunya	Catalunya Caixa	Catalunya Banc	
Caixa Tarragona			
Caixa Manresa			
Caixa Galicia	Novacaixagalicia	Novagalicia Banco	
Caixanova			
CCM	Banco CCM Cajastur	Liberbank	
Cajastur			
Caja de Extremadura			
Caja Cantabria			
Caja Inmaculada de Aragon		Banco Caja3	
Caja Circulo de Burgos			
Caja de Badajoz			
Ibercaja		Ibercaja Banco	

Note: This table shows the government-led mergers taking place in the aftermath of the financial crisis. By 2012, 43 out of 46 savings banks were consolidated into 13 entities which function as commercial banks. Source: CECA.

Table A.3: Persistence of regional bank attachment

	Weak-bank attachment in 2006
Weak-bank density in 1988	0.140***
	(0.007)
Sector controls	Yes
R^2	0.007
Observations	183,905

Note: The sample consists of firms active in 2006. Weak bank attachment is a dummy equal to 1 if a firm has a relationship with at least one weak bank. Sector refers to 2-digit NACE Rev. 2 categories. Weak-bank density refers to the share of bank branches belonging to weak banks in a given region.

Table A.4: Robustness: Weak banks and firm outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Exits	Δ TFP	Exits	Δ TFP	Exits	Δ TFP
Bank weakness × post-crisis	0.074**	-0.069**	0.050**	-0.073**	0.072**	-0.051*
	(0.025)	(0.018)	(0.018)	(0.026)	(0.024)	(0.019)
Log TFP $_{t-1}$	-0.008***	-0.531***	-0.007***	-0.538***	-0.011***	-0.488***
	(0.002)	(0.017)	(0.002)	(0.017)	(0.002)	(0.017)
Log employment $_{t-1}$	-0.004***	0.044***	-0.003***	0.056***	-0.005***	0.056***
	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)
Log total assets $_{t-1}$	-0.001*	0.053***	-0.002**	0.049***	-0.001	0.034***
	(0.001)	(0.005)	(0.001)	(0.005)	(0.000)	(0.005)
Debt / assets $_{t-1}$	0.027***	-0.000	0.024***	0.010*	0.027***	-0.023***
	(0.007)	(0.004)	(0.006)	(0.004)	(0.007)	(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × region × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector level	4-digit	4-digit	2-digit	2-digit	2-digit	2-digit
R^2	0.209	0.390	0.188	0.369	0.154	0.335
Observations	1,954,225	1,889,875	845,202	811,448	1,504,933	1,465,894

Note: This table shows results from estimating a linear panel model of exit probability and TFP growth of the form described in equation (5). Post-crisis refers to years 2007 and above. Region refers to 3-digit NUTS categories. Standard errors are clustered at the firm and year level. Columns 1-2 use 4-digit NACE Rev. 2 sectors; Columns 3-4 restrict the sample to firms with a single bank relationship; Columns 5-6 restrict the sample to firms in the manufacturing, transportation, accommodation, information and professional sectors.

Table A.5: Regional weak-bank density and pre-crisis Δ TFP

	Pre-crisis Δ TFP
Weak-bank density $_{t-1}$	0.005
	(0.004)
Log TFP $_{t-1}$	-0.735***
	(0.048)
Log employment $_{t-1}$	0.074*
	(0.023)
Log total assets $_{t-1}$	0.050**
	(0.009)
Debt / assets $_{t-1}$	0.008
	(0.006)
Firm FE	Yes
Sector × coastal region × year FE	Yes
R^2	0.503
Observations	550,511

Note: This table shows results from estimating a linear panel model of TFP growth. The sample is restricted to observations before 2007. Weak-bank density refers to the share of bank branches belonging to weak banks in a given region. Sector refers to 2-digit NACE Rev. 2 categories. Coastal regions include provinces along the Mediterranean Coast and in the Balearic and Canary Islands. Standard errors are clustered at the firm and year level.

Table A.6: Bank effect in different post-crisis years

	Exit		Δ TFP	
	(1)	(2)	(3)	(4)
	2007–2013	2007–2017	2007–2013	2007–2017
Bank weakness × post-crisis	0.075**	0.070**	-0.044	-0.047*
	(0.026)	(0.023)	(0.024)	(0.021)
Log TFP $_{t-1}$	-0.008**	-0.008***	-0.550***	-0.514***
	(0.002)	(0.002)	(0.022)	(0.017)
Log employment $_{t-1}$	-0.004**	-0.003***	0.048***	0.049***
	(0.001)	(0.001)	(0.006)	(0.005)
Log total assets $_{t-1}$	-0.001	-0.001*	0.055***	0.049***
	(0.001)	(0.001)	(0.007)	(0.005)
Debt / assets $_{t-1}$	0.026**	0.027***	-0.004	-0.003
	(0.008)	(0.007)	(0.005)	(0.004)
Firm FE	Yes	Yes	Yes	Yes
Sector × coastal region × year FE	Yes	Yes	Yes	Yes
R^2	0.147	0.138	0.348	0.323
Observations	1,695,705	2,046,670	1,640,893	1,981,890

Note: This table shows results from estimating a linear panel model of the form described in equation (5). Post-crisis refers to years 2007 and above. Columns 1 and 3 cover a subset of the post-crisis period. Sector refers to 2-digit NACE Rev. 2 categories. Coastal regions include provinces along the Mediterranean Coast and in the Balearic and Canary Islands. Standard errors are clustered at the firm and year level.

Table A.7: Effect of weak banks on productivity growth: Using 1988 regional weak-bank densities in the selection equation

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
ΔTFP (1)											
Bank weakness	-0.098***	-0.039	-0.048	-0.034	-0.206***	-0.089**	-0.143***	-0.088*	-0.092**	-0.111**	-0.122**
	(0.024)	(0.029)	(0.030)	(0.030)	(0.031)	(0.033)	(0.035)	(0.035)	(0.035)	(0.034)	(0.037)
Log TFP $_{t-1}$	-0.202***	-0.245***	-0.264***	-0.233***	-0.207***	-0.188***	-0.188***	-0.181***	-0.182***	-0.181***	-0.177***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Log employment $_{t-1}$	0.008***	0.027***	0.023***	0.015***	0.022***	0.029***	0.031***	0.019***	0.020***	0.019***	0.017***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Log total assets $_{t-1}$	0.046***	0.049***	0.058***	0.051***	0.041***	0.035***	0.029***	0.035***	0.035***	0.034***	0.032***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Debt / assets $_{t-1}$	0.025***	-0.037***	-0.039***	-0.049***	-0.049***	-0.043***	-0.064***	-0.052***	-0.056***	-0.055***	-0.060***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Pre-crisis avg. Δ TFP	0.008	0.011	0.028***	0.007	0.026***	0.001	0.016*	0.029***	0.019**	0.008	0.014
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Pre-crisis avg. leverage	-0.060***	-0.000	-0.041***	-0.017	-0.012	-0.016	-0.020*	-0.030***	-0.021*	-0.011	0.004
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Selection (2)											
Bank weakness	-1.767***	-1.903***	-1.672***	-1.900***	-1.747***	-1.534***	-1.714***	-1.003**	-0.701	0.503	-0.626
	(0.239)	(0.200)	(0.225)	(0.225)	(0.237)	(0.246)	(0.287)	(0.355)	(0.465)	(0.562)	(0.621)
Weak-bank density in 1988	-0.247*	-0.430***	-0.410***	-0.152	-0.381***	-0.160	-0.108	-0.110	-0.039	0.197	-0.076
	(0.101)	(0.084)	(0.091)	(0.089)	(0.090)	(0.088)	(0.103)	(0.121)	(0.155)	(0.162)	(0.209)
Log TFP $_{t-1}$	0.022	0.016	0.093***	0.138***	0.198***	0.215***	0.226***	0.167***	0.177***	0.140***	0.216***
	(0.026)	(0.022)	(0.023)	(0.022)	(0.022)	(0.021)	(0.025)	(0.027)	(0.035)	(0.041)	(0.052)
Log employment $_{t-1}$	-0.041**	-0.061***	-0.101***	-0.111***	-0.116***	-0.124***	-0.094***	-0.031	-0.023	-0.083**	-0.103**
	(0.015)	(0.013)	(0.015)	(0.014)	(0.014)	(0.014)	(0.016)	(0.018)	(0.023)	(0.025)	(0.034)
Log total assets $_{t-1}$	-0.122***	-0.083***	-0.031*	-0.043**	-0.051***	-0.009	-0.007	-0.006	0.013	0.065**	0.077*
	(0.015)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.015)	(0.017)	(0.022)	(0.024)	(0.032)
Debt / assets $_{t-1}$	-0.260**	-0.236***	-0.402***	-0.817***	-1.106***	-1.272***	-1.059***	-0.970***	-0.869***	-0.902***	-1.040***
	(0.082)	(0.064)	(0.065)	(0.058)	(0.056)	(0.055)	(0.064)	(0.073)	(0.093)	(0.101)	(0.127)
Pre-crisis avg. Δ TFP	0.051	-0.027	-0.005	-0.109	0.064	-0.025	0.025	-0.047	-0.062	-0.006	0.008
	(0.062)	(0.055)	(0.061)	(0.060)	(0.063)	(0.059)	(0.072)	(0.084)	(0.109)	(0.112)	(0.151)
Pre-crisis avg. leverage	-0.096	-0.207*	0.080	0.294***	0.437***	0.648***	0.553***	0.727***	0.603***	0.901***	1.196***
	(0.103)	(0.081)	(0.085)	(0.083)	(0.082)	(0.081)	(0.094)	(0.112)	(0.139)	(0.158)	(0.210)
Sector controls	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2
λ	0.006	0.004	0.029	0.017	0.017	0.016	0.015	0.009	0.011	0.014	0.027
Std. err. of λ coeff.	0.020	0.020	0.017	0.015	0.011	0.010	0.011	0.012	0.019	0.020	0.021
ρ	0.022	0.013	0.085	0.053	0.055	0.051	0.049	0.030	0.039	0.052	0.101
σ	0.291	0.331	0.336	0.323	0.318	0.317	0.312	0.297	0.286	0.274	0.267
Observations	104,777	99,205	96,724	91,378	85,052	78,774	72,935	68,137	64,010	59,914	46,326

Note: This table shows results from estimating selection-bias-adjusted models of productivity growth of the form described in equation (10) for each year. The λ-term represents the sample selection bias. Sector refers to 2-digit NACE Rev. 2 categories.

Table A.8: Predictive power of regions on post-crisis exit

	Exit
Bank weakness	0.045**
	(0.014)
Log TFP $_{t-1}$	-0.005**
	(0.001)
Log employment $_{t-1}$	0.002**
	(0.001)
Log total assets $_{t-1}$	0.002**
	(0.000)
Debt / assets $_{t-1}$	0.022**
	(0.006)
Region FE	Yes
Sector × year FE	Yes
R^2	0.018
Region F-test: F(41,11)	122.983
Region F-test: p-value	0.000
Observations	1,181,454

Note: This table shows results from estimating a linear panel model of exit probability for the period starting in 2007. The F-test on the regional indicators shows that regions are a strong predictor of exit. Sector refers to 2-digit NACE Rev. 2 categories. Region refers to 3-digit NUTS categories. Standard errors are clustered at the firm and year level.

Table A.9: Effect of weak banks on productivity growth

	2001	2002	2003	2004	2005	2006
ΔTFP (1)						
Bank weakness	0.003	-0.002	-0.021	0.006	-0.057	0.023
	(0.032)	(0.032)	(0.028)	(0.030)	(0.032)	(0.034)
Log TFP $_{t-1}$	-0.214***	-0.205***	-0.167***	-0.151***	-0.140***	-0.199***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log employment $_{t-1}$	0.006***	0.013***	0.017***	0.018***	0.022***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log total assets $_{t-1}$	0.053***	0.046***	0.035***	0.030***	0.026***	0.047***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Debt / assets $_{t-1}$	0.016	0.008	0.000	0.013	0.019*	-0.016
	(0.012)	(0.010)	(0.008)	(0.008)	(0.009)	(0.009)
Pre-2000 avg. Δ TFP	-0.003	0.015**	0.015**	0.026***	0.016**	0.020***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Pre-2000 avg. leverage	-0.049***	-0.044***	-0.019*	-0.019*	-0.020*	-0.013
	(0.013)	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)
Selection (2)						
Bank weakness	-0.784	-0.536	-1.340**	-1.486***	-1.632***	-1.434***
	(0.686)	(0.655)	(0.451)	(0.442)	(0.415)	(0.420)
Log TFP $_{t-1}$	0.031	0.105	0.150**	0.199***	0.279***	0.073
	(0.067)	(0.061)	(0.050)	(0.050)	(0.047)	(0.043)
Log employment $_{t-1}$	-0.043	0.001	-0.037	0.021	0.035	-0.006
	(0.043)	(0.040)	(0.030)	(0.031)	(0.027)	(0.027)
Log total assets $_{t-1}$	-0.227***	-0.249***	-0.146***	-0.134***	-0.167***	-0.146***
	(0.041)	(0.039)	(0.029)	(0.030)	(0.027)	(0.026)
Debt / assets $_{t-1}$	0.171	-0.247	-0.093	-0.061	-0.192	-0.274*
	(0.271)	(0.203)	(0.149)	(0.143)	(0.124)	(0.117)
Pre-2000 avg. Δ TFP	0.014	0.144	0.185*	-0.003	0.000	0.061
	(0.121)	(0.118)	(0.092)	(0.091)	(0.081)	(0.077)
Pre-2000 avg. leverage	-0.741**	-0.442*	-0.813***	-0.323*	-0.541***	-0.062
	(0.277)	(0.225)	(0.155)	(0.156)	(0.138)	(0.140)
Sector controls	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2	1 & 2
Region controls	2	2	2	2	2	2
λ	-0.018	0.034	0.035	0.029	0.020	0.034
Std. err. of λ coeff.	0.025	0.021	0.010	0.011	0.015	0.013
ρ	-0.063	0.119	0.141	0.117	0.079	0.123
σ	0.288	0.284	0.250	0.248	0.258	0.278
Observations	55,774	55,607	57,895	49,786	47,635	49,933

Note: This table shows results from estimating selection-bias-adjusted models of productivity growth of the form described in equation (10) for each year. The λ-term represents the sample selection bias. Sector refers to 2-digit NACE Rev. 2 categories. Region refers to 3-digit NUTS categories.

Table A.10: Labor growth

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Log employment $_{t-1}$	-0.061***	-0.083***	-0.067***	-0.056***	-0.051***	-0.053***	-0.049***	-0.047***	-0.044***	-0.043***	-0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log TFP $_{t-1}$	0.118***	0.160***	0.142***	0.129***	0.114***	0.119***	0.111***	0.106***	0.103***	0.103***	0.097***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Sector controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.077	0.114	0.097	0.074	0.071	0.080	0.063	0.055	0.050	0.053	0.046
Observations	160,550	155,386	158,510	154,374	148,294	142,005	137,261	134,307	131,725	125,758	102,831

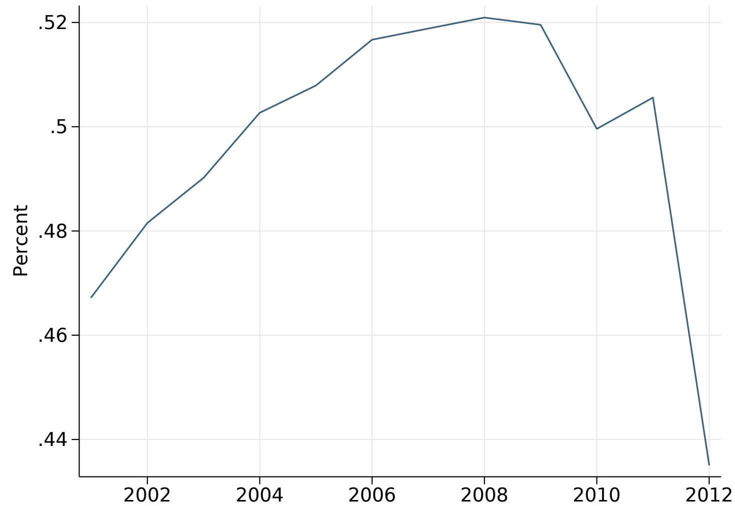
Note: This table shows results from year-by-year OLS regressions of labor growth as described in equation (13).

Table A.11: Capital growth

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Log tangible fixed assets $_{t-1}$	-0.068***	-0.142***	-0.022***	-0.023***	-0.020***	-0.018***	-0.018***	-0.032***	-0.043***	-0.040***	-0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log TFP $_{t-1}$	0.081***	0.153***	0.023***	0.042***	0.040***	0.039***	0.045***	0.067***	0.077***	0.078***	0.086***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Sector controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.038	0.119	0.011	0.012	0.012	0.012	0.017	0.020	0.031	0.026	0.037
Observations	160,550	155,386	158,510	154,374	148,294	142,005	137,261	134,307	131,725	125,758	102,831

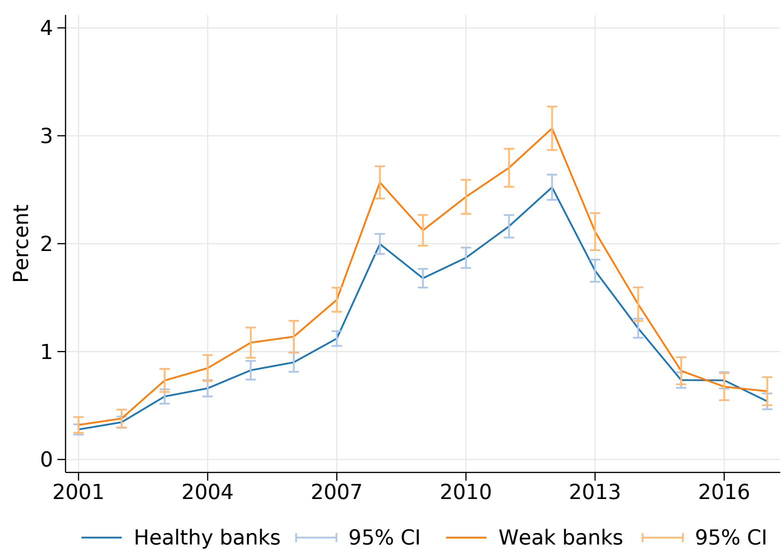
Note: This table shows results from year-by-year OLS regressions of capital growth as described in equation (13).

Figure A.1: Credit share of savings banks



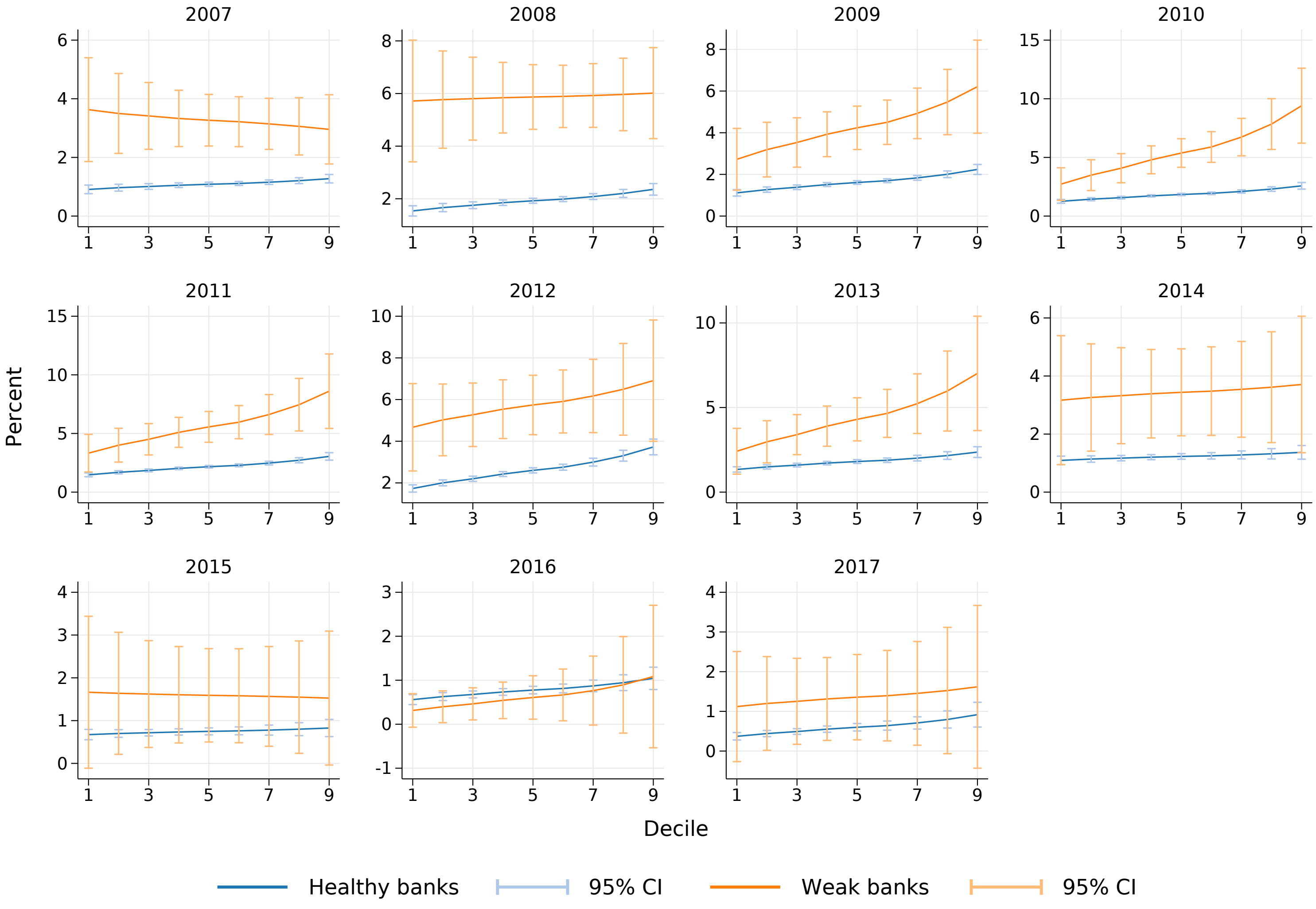
Source: AEB and CECA.

Figure A.2: Average predicted exit rate



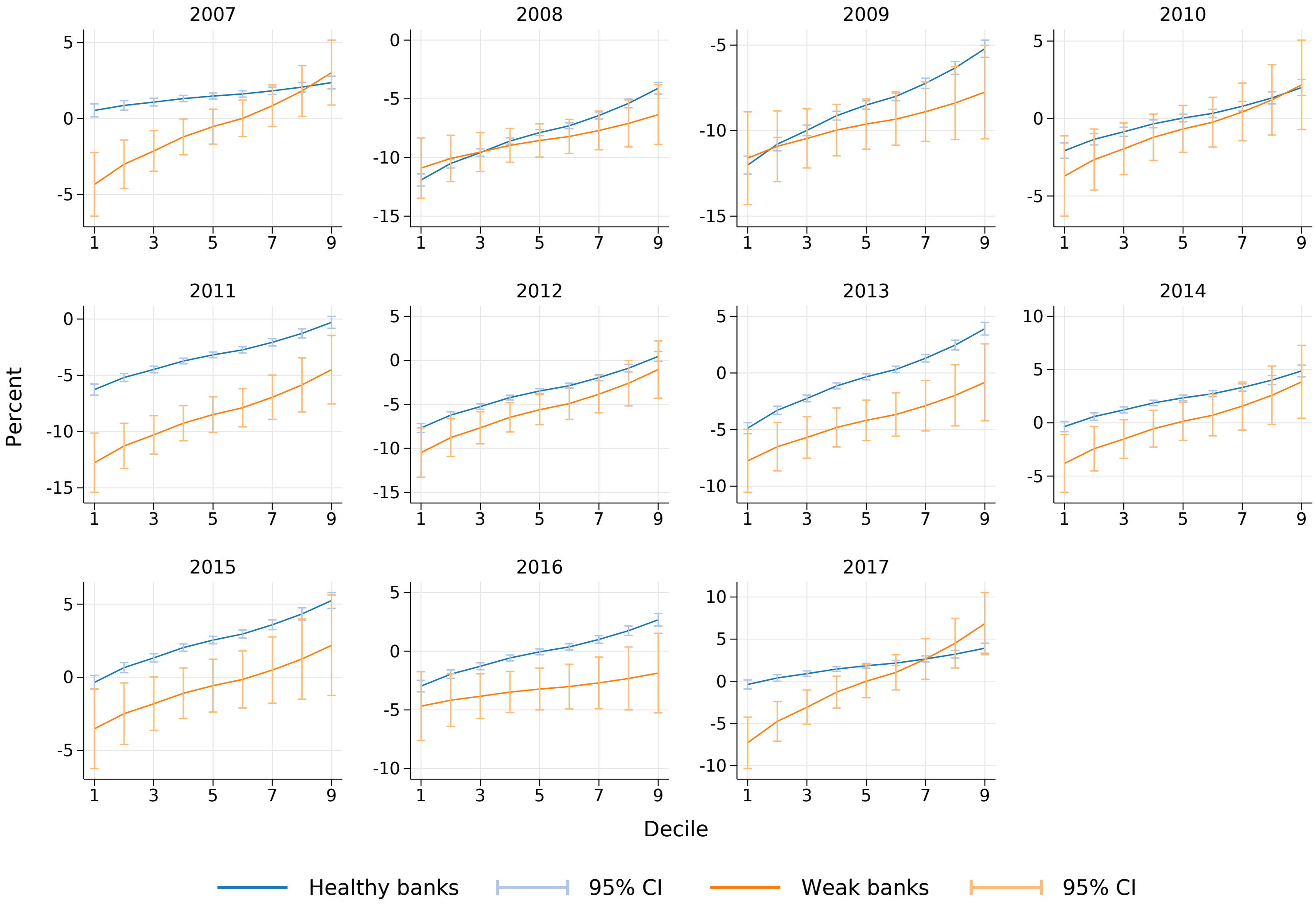
Note: This figure shows average predicted exit rates from the sample selection model described in equation (10). The orange line corresponds to firms linked to the average weak bank.

Figure A.3: Average predicted exit probability by employment decile



Note: This figure shows average predicted exit rates from a sample selection model like the one described in equation (10) only adding interaction terms between the bank variable and all other covariates in both the selection and the main equation. The orange line corresponds to firms linked to the average weak bank.

Figure A.4: Average predicted productivity growth by employment decile



Note: This figure shows average predicted exit rates from a sample selection model like the one described in equation (10) only adding interaction terms between the bank variable and all other covariates in both the selection and the main equation. The orange line corresponds to firms linked to the average weak bank.