Does Zombie Lending Impair Innovation? *

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Abstract

This paper documents that reduced product market competition due to "zombie lending" reduces firms' incentives to innovate. It depresses patent applications and depletes the existing patent stock, particularly in high technology- and R&D-intensive sectors. We find consistent results using micro-level data from an innovation survey that includes information on unpatented innovation activities. Our results are robust to an instrumental variable approach that addresses concerns that banks are weak because they are exposed to low-performing firms. The effects are concentrated in industries in which firms with a similar technology level compete, i.e., sectors in which reduced competition is predicted to adversely affect firms' incentives to innovate. Our results highlight potential long-run externalities on productivity and innovation dynamics resulting from zombie lending.

JEL classifications: E44, E58, G20

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"A continent littered with zombie firms and broke households will never prosper." ("Europe's other debt crisis," The Economist, 2013)

1 Introduction

There is an ongoing debate about the potential negative impact of a weak banking sector on economic activity. Undercapitalized banks may extend economic downturns by continuing to lend to "zombie firms," i.e., non-viable businesses that would otherwise exit the market, thereby diverting credit away from healthier firms. Although evidence suggests that weak banks may have incentives to support zombie firms, potentially harming lending to healthy firms (see Acharya *et al.*, 2022, for an overview of the literature), the broader effects of zombie lending on economic activity remain less clearly understood. Some studies highlight concerns about negative spillovers on the productivity of non-zombie firms (see, among others, Acharya *et al.*, 2019; Blattner *et al.*, 2023; Caballero *et al.*, 2008), while others argue that the performance of healthy firms remains unaffected (Schivardi *et al.*, 2022).

This paper examines the impact of zombie lending on corporate innovation, focusing specifically on its influence within the context of product market competition. Our central hypothesis is that zombie lending significantly alters industry dynamics and—as a consequence—affects firms' incentives to pursue long-term research and development (R&D) investments or engage in other innovative activities. Understanding the potential effects of distorted bank lending incentives on innovation is essential, as innovation is a critical driver of long-term economic growth (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1994).

Our study focuses on Spain during the period following the global financial crisis (GFC), i.e., over the height of the European debt crisis. At the end of the GFC, Spanish banks, along with other southern European banks, remained weak due to insufficient recapitalizations by their respective governments (Acharya *et al.*, 2021). Even a decade later, economic growth in these countries—particularly in Spain—continues to lag behind that of core European

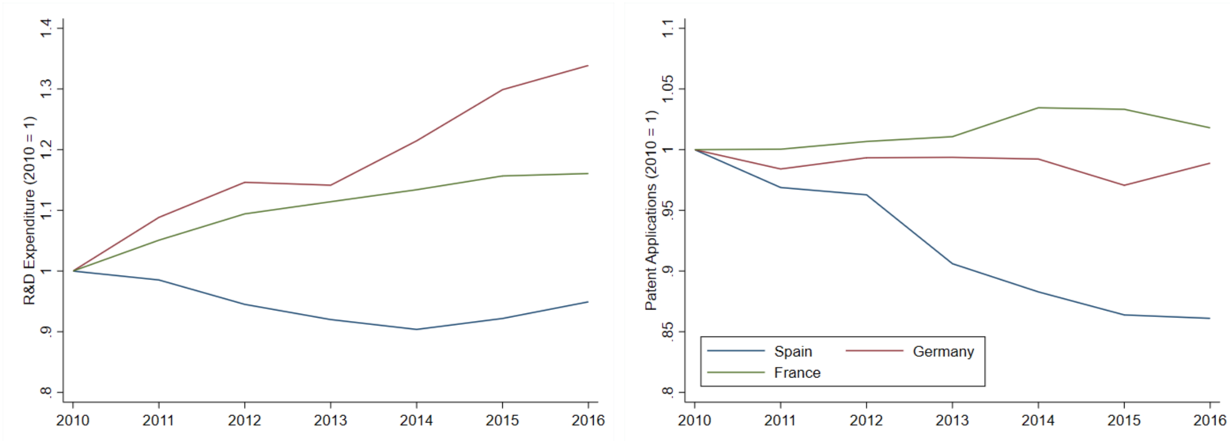

Figure 1: R&D expenditures and patent applications

This figure shows the development of R&D business expenditures (source: EUROSTAT) and patent applications (source: World Intellectual Property Organization) for France, Germany, and Spain over the 2010 to 2016 period, relative to the 2010 level.

countries, with innovation activity similarly suppressed. As illustrated in Figure 1, Spanish firms have reduced their patent applications by nearly 15% in the years after the GFC (compared to the 2010 level) and have also decreased their R&D expenditures. This decline is even more pronounced when compared to German and French firms, which have maintained or increased their patenting activity and R&D spending over the same period. Spain is thus an interesting laboratory to study the effects of zombie lending on corporate innovation.

In the first part of this paper, we investigate whether zombie lending is a key driver of the decline in innovation activity in Spain. Similar to, e.g., Schivardi *et al.* (2022), we measure the degree of zombie lending as the product of a high share of weak firms in an industry and the degree to which banks in the same industry remain undercapitalized, i.e., zombie lending is defined as borrowing of weak firms from weak banks. Banks are classified as undercapitalized according to their total capital ratio as of 2010, i.e., at the onset of the sovereign debt crisis. Specifically, we classify a bank as undercapitalized if its total capital ratio is in the lowest quartile of the distribution at the end of 2010. Consistent with the existing literature, we show that (at the firm level) zombie firms are less likely to exit the market and maintain higher sales growth and debt levels if they borrow from undercapitalized banks, a first indication that zombie lending affects competitive dynamics in these industries.

We construct industry-level innovation measures using patent applications from Orbis, originally sourced from PATSTAT. In particular, following the existing literature (e.g., Bloom *et al.*, 2016), we compute an annual measure of patent stocks for each industry using patent applications and reasonable assumptions about the patent stock decay.

As expected, we do not find that our innovation measures respond immediately in the same year that we observe a high level of zombie lending within an industry. This is because patent filings are typically the outcome of research and development activities carried out in prior years, meaning they lag behind innovation decisions. Supporting this view, we identify a statistically and economically significant *negative* effect of credit misallocation on the number of annual patent applications and the annual growth of the patent stock one to three years later. This effect can be attributed to both a decrease in the entry of new, innovative firms and a reduced innovation rate among existing firms.

The effect is also economically significant. An industry in the top 75th percentile for undercapitalized banks and zombie firms experiences a 19.3 percentage point (p.p.) lower growth rate in its patent stock between 2010 and 2016 compared to an industry in the bottom 25th percentile. In other words, the patent stock growth rate decreases by approximately 3 p.p. per year. Given that the average annual growth rate is 4.5%, this finding suggests that credit misallocation can significantly impact innovation.

Although we classify banks as undercapitalized based on their total capital ratio as of 2010, a concern remains that banks might be weak *because* they are exposed to low-performing firms. However, we present evidence to suggest otherwise. Parallel trend tests show that, prior to 2010, the performance of firms borrowing from weak banks was identical to that of firms borrowing from strong banks. The divergence in trends begins after 2010, coinciding with the onset of the sovereign debt crisis when zombie lending became more widespread.[1]

We then use banks' exposure to the Spanish mortgage and real estate market in 2006,

[1] Acharya *et al.* (2021), for example, demonstrate that banks that remained undercapitalized following the 2008-09 GFC increased zombie lending after 2010.

prior to the financial crisis, as an instrument for bank capitalization in our regressions. This instrument is relevant because the collapse of the Spanish property bubble during the financial crisis led to greater losses for banks that were more heavily exposed to the mortgage market beforehand. The exclusion restriction necessitates that industry innovation activity is correlated with banks' pre-crisis mortgage market exposure only through the impact of weakened bank balance sheets within the industry. We provide a detailed argument in the main body of the paper supporting the plausibility of this condition. Our IV models continue to show a strong negative effect of zombie lending on innovation.

We then explore several cross-sectional dimensions to understand the effect of zombie lending on innovation. First, we investigate whether the effect differs based on the initial level of innovation activity within the sector. Our findings indicate that zombie lending particularly hampers innovation in industries with a high proportion of intangible capital, substantial R&D investments, and those classified as high-tech.

Second, we utilize detailed self-reported data on firms' innovation activities collected through the Community Innovation Survey (CIS), which is conducted by the European Parliament every two years. This survey asks participants about their innovation activities over the preceding two years. To construct granular industry-level innovation measures directly from the raw firm-level data, we accessed the micro-datasets for the 2012 and 2014 survey editions as secure-use files at Eurostat's Center in Luxembourg. The use of CIS data offers two key advantages: i) Not all innovations are patented, and even when they are, patent applications are typically filed only after the innovation is completed. In contrast, the surveys capture innovation activities from the previous two years, regardless of whether the innovation is eventually patented. ii) The CIS survey includes additional questions that allow us to examine the effects across different types of innovation activities. As a result, we gain insights into various forms of innovation (such as process, service, product, or marketing innovation), whether the firm applied for intellectual property rights or licensing, including patent applications, and the amount spent on R&D, both internally and externally.

We confirm that patenting activity is lower in industries with a large share of zombie lending and the effect increases even in 2014 consistent our baseline results. Specifically, we document impaired innovation activities in services and process innovation. Moreover, we show that firms have significantly reduced their IP and licensing activities in industries with a high share of zombie lending. They significantly reduced their R&D expenses, and, importantly, in-house R&D expenses. Overall, the survey evidence suggests that the effect of credit misallocation is not confined to hampering incremental innovation but affects innovation activities in firms' core areas.

We then investigate the channels through which zombie lending might influence innovation. Our main hypothesis is that zombie lending significantly alters the competitive dynamics within the affected industry. Theoretical frameworks suggest that policies favoring unproductive incumbents effectively create barriers to entry and diminish competition (e.g. Aghion *et al.*, 2019; Acemoglu *et al.*, 2018; Caballero *et al.*, 2008). Reduced competition, in turn, can negatively impact the innovation incentives of incumbent firms (e.g. Aghion *et al.*, 2009).

We provide evidence that zombie lending reduces competition in affected industries. In sectors with high levels of zombie lending, entry rates for young, innovative firms significantly decline, while zombie firms themselves are less likely to exit the market. Additionally, we observe a decrease in deflated material costs—used as a proxy for industry output—and an increase in total factor productivity (TFP) dispersion, a widely recognized indicator of resource misallocation (Hsieh and Klenow, 2009). These findings collectively point to a notable decline in industry dynamism as a result of zombie lending.

While these findings support the idea that the decline in innovation activity is linked to reduced competition, the tests do not directly establish this connection. Therefore, in the next step, we further explore the specific mechanisms through which competition might influence innovation. The relationship between competition and innovation is theoretically complex. The Schumpeterian perspective predicts a *negative* relationship, arguing that increased competition diminishes the potential for earning post-innovation rents (Aghion *et al.*, 2015). Conversely, increased competition might enhance firms' incentives to innovate if innovation can be used as a strategy to escape competition and secure higher post-innovation rents (Aghion *et al.*, 2005).

We bring these different theoretical predictions to the data and—following Aghion *et al.* (2005)—divide industries into two groups: (1) "laggard industries," i.e., industries in which the technological gap among firms is large and (2) "neck-and-neck industries," i.e., industries with firms that have similar technological levels. In neck-and-neck industries, firms innovate to escape intense competition today and reap higher post-innovation rents tomorrow. Since increased competition reduces pre-innovation rents more than post-innovation rents in these industries, a positive relationship between competition and innovation is expected (Aghion *et al.*, 2009). Consistent with these theoretical predictions, our findings show that the decline in patenting activity due to zombie lending is concentrated in industries with neck-and-neck competition, while no such effect is observed in laggard industries.

Overall, our results highlight the negative externalities associated with zombie lending, as it diminishes both competition and innovation within the affected industries. Understanding the impact of distorted bank lending incentives on innovation is crucial, given that innovation is a driving force behind economic growth (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1994). Our findings suggest that, although the short-term profitability impact on healthy firms may be limited, zombie lending can have long-lasting consequences by weakening industry dynamics and thereby reducing firms' incentives to innovate.

Related literature. Our paper relates to the literature on the effects of credit misallocation on industry dynamics.[2] Peek and Rosengren (2005) and Caballero *et al.* (2008) show that undercapitalized banks continue lending to zombie firms in Japan, which has negative effects on healthy firms and overall industry dynamics. Acharya *et al.* (2024) document consistent results, i.e., evidence for distorted competition due to zombie lending, for Europe after the GFC. Blattner *et al.* (2023) document that misallocation of capital by undercapitalized banks in Portugal caused a decline in productivity. Schivardi *et al.* (2022) find evidence for zombie lending in Italy even before the GFC and the European sovereign debt crisis, but

[2] There is a related literature that examines the effects of resource misallocation more generally, see, among others, Hsieh and Klenow (2009) for international and Gopinath *et al.* (2017) for European evidence.

argue that there are limited spillover effects on the performance of healthy firms.[3] We add to this literature by explicitly examining how distorted competition caused by zombie lending can impact firms' incentives to innovate—a key driver of economic growth.

We also contribute to the large literature on the determinants of innovation and, specifically, to the literature that examines the link between finance, product market competition, and innovation (see He and Tian, 2018, for a survey of the literature on finance and corporate innovation). There is evidence that a more competitive banking sector can foster innovation by small and private firms (e.g., Bai *et al.*, 2018; Cornaggia *et al.*, 2015; Hombert and Matray, 2017), while effects are mixed for public and less external finance-dependent firms (e.g., Acharya and Xu, 2017; Amore *et al.*, 2013; Cornaggia *et al.*, 2015). In contrast to this literature we do not explicitly focus on the structure of the banking sector but provide evidence that distorted bank lending incentives can affect industry competition among non-financial firms with negative effects on innovation activity.

The literature on the effects of product market competition on innovation highlights that effects can be theoretically ambiguous (see Aghion *et al.*, 2015; Gilbert, 2006; Schmutzler, 2010, for an overview of the literature). Frésard and Valta (2016) document that the response of corporate investment to more intense competition is contingent upon whether firms compete in strategic substitutes or complements. Aghion *et al.* (2005) argue that the effect on innovation depends on the mode of competition. We provide consistent results in the context of zombie lending: credit misallocation by weak banks can distort industry dynamics and affect innovation, however, the effect is concentrated in industries in which firms with a similar technology level compete, i.e., industries with neck-and-neck competition.

[3] The general literature on zombie lending and bank credit misallocation (without a specific focus on industry dynamics) is large, see, among others, Acharya *et al.* (2019, 2021); Bonfim *et al.* (2023); Gamberoni *et al.* (2016); Giannetti and Simonov (2013); Hassan *et al.* (2017). For a recent overview of the literature see Acharya *et al.* (2022).

2 Data

2.1 Sample selection

We obtain information on annual balance sheet and income statement items for all Spanish firms in the Bureau van Dijk (BvD) Orbis database. We construct a sample that is representative for the overall Spanish economy following Kalemli-Ozcan *et al.* (2024). Our analyses focuses on the European debt crisis period, i.e., 2010 to 2016., during which credit misallocation was a substantive issue (see, e.g., Acharya *et al.*, 2019). We exclude utilities and financial industries, i.e., restrict the sample to firms in manufacturing and service sectors [NACE Rev.2 codes 05-82 (excluding 64-66)]. We further focus on unlisted, bank-dependent, firms, and require firms to have non-missing information on total assets, sales, and employment. We remove firms with negative debt and firms with less than three employees. The final sample comprises ∼425,000 unique firms.[4]

Firm-level patent information comes from from the BvD Orbis intellectual property database, which sources information from PATSTAT (beginning in 1978). PATSTAT is maintained by the European Patent Office (EPO) and comprises patent applications with the EPO as well as national patent offices. The dataset provides information on priority, application, and publication dates, application type, publication title as well as information about patent owner(s) (name, bvdidnum, country) and inventor(s) (name, country). Additionally, information on whether the patent was granted and on the cited and citing documents (number, count) is available. We are able to match more than 18,000 firms that have one or more patents since 1978 to the financial data in Orbis described above.

Information on firms' bank relations is from BvD's Amadeus Bankers. The dataset contains the unique firm identifier (bvdidnum) and the name(s) of the banks the firm holds a relationship with. We hand-match bank names to BvD's Bankscope, from which we source detailed information on various bank balance sheet and income statement items. We remove

[4] We relax restrictions when calculating entry rates and innovation measures, as requiring sufficient data coverage would systematically exclude very young firms and entrants. The unrestricted sample comprises more than 900,000 unique firms.

banks that account for a negligible fraction of firm-bank relationships in our sample and are left with 18 banks. These 18 banks have lending relationships with more than 345,000 firms and cover 95% of the firm-bank relations in our sample.

2.2 Zombie lending

Following the seminal work of Caballero *et al.* (2008), the literature broadly defines zombie lending as the extension of credit by under-capitalized banks to non-viable "zombie firms" at subsidized rates.[5] In this section, we describe how we define i) under-capitalized banks and ii) non-viable firms. In the empirical analyses, "zombie lending" is the joint occurrence of a large share of non-viable firms and under-capitalized banks in the same sector.

Under-capitalized banks: We classify banks as under-capitalized if their total capital ratio is in the lowest quartile of the distribution at the end of 2010.[6] Based on this definition, we identify firms that are in lending relationships with under-capitalized banks. Specifically, $LowCap_i$ is an indicator variable equal to one if firm i is in a lending relationship with an under-capitalized bank as of 2010.[7]

Next, we construct an industry-level measure that describes the extent to which sectors are dependent on weak banks. $LowCap_j$ is the fraction of firms in industry j (4-digit NACE code) that borrow from weak banks as of 2010. The distribution of $LowCap_j$, displayed in Table 1 below, shows that the activity of weak banks varies significantly across industries, representing the variation that we are going to exploit in the analyses.

Zombie firms: Distressed firms that would exit the market under normal conditions but continue to operate because of evergreening of credit are commonly referred to as "zombie firms" (Caballero *et al.*, 2008). Different definitions of zombie firms are used in the literature.

[5] Under-capitalized banks have an incentive to avoid writing off existing capital (Caballero *et al.*, 2008), for example, because they have incentives to gamble for resurrection due to debt overhang (Bruche and Llobet, 2014). Banks might become under-capitalized because of myopic policies to bailout bank creditors (Acharya *et al.*, 2022) or because of inefficient resolutions of insolvency (Becker and Ivashina, 2021).

[6] We use the total capital ratio to define bank capitalization as it is consistently reported for all banks in the sample. However, all findings are robust to using the banks' tier-1 capital ratio.

[7] For firms with more than one bank relationship, we require all banks to be under-capitalized.

Most definitions focus on a combination of profitability, debt service capacity, and (future) profit potential (e.g., Caballero *et al.*, 2008; Adalet McGowan *et al.*, 2018; Banerjee and Hofmann, 2018).[8]

Following this literature, we classify firms as zombie firms if: i) return on assets (net income over total assets) is negative, ii) net investment (change in fixed assets) is negative,[9] iii) debt servicing capacity (EBITDA over total debt) is below 5%, iv) and i)-iii) hold for at least two consecutive years. We use a two-year instead of a single-year definition to distinguish between zombie firms and firms that are hit by a temporary negative shock.[10]

Figure 2 shows the fraction of firms in an economy defined as "zombies." We benchmark Spain against as Germany and France, i.e., economies that were less exposed to the European debt crisis. While the zombie share is flat in France and Germany, we see a strong increase in the share of zombie firms in Spain at the beginning of the European debt crisis. This increase in the zombie share parallels the development of the non-performing loan share for Spanish banks (see e.g. OECD, 2017). The subsequent decrease in both zombie share and non-performing loan ratio coincides with the large scale recapitalization of the Spanish banking sector by the European Stability Mechanism (ESM) in 2012 and 2013 (see here for details on the ESM's program time line for Spain).

[8] For a more in depth discussion of the zombie lending literature as well as definitions of zombie firms used in the literature, see the overview article of Acharya *et al.* (2022).

[9] Our firms are privately-held firms and we thus do no have market values to assess future profit potential via Tobin's Q. We include the change in investments over the priors years as a proxy for the ability to generate future profits. Similar definitions have recently been used in a European context by, for example, Acharya *et al.* (2022), Schivardi *et al.* (2022), and Storz *et al.* (2017).

[10] Another criteria often used to identify zombie firms is the comparison of a benchmark interest rate to the loan interest rate paid by a firm to identify "subsidized credit" (e.g., Acharya *et al.*, 2019; Caballero *et al.*, 2008). The information provided by Orbis on liability type, structure, and maturity is insufficient to infer whether firms are charged below market rates. Further, European firms use a substantial amount of trade credit that does not carry any direct interest payment. That is, any ratio using interest expenses from income statements underestimates the actual interest rate paid by firms, leading to an upward bias in the number of firms identified as zombies. However, we explore alternative measures that add criteria to identify subsidized credit (in the spirit of Acharya *et al.*, 2019, 2024) and find qualitatively similar results (untabulated).

2.3 Innovation activity

We compute the total number of patent applications of all firms active in industry j in year t. We use priority numbers and priority dates (i.e., the date of the *first* application for which priority is claimed in accordance with Article 87 EPC) to calculate the total number of patents. This procedure avoids any double counting as the priority right provides the claimant with a time-limited (12 month) right to file a subsequent application in another country for the same invention. Using only application numbers would hence potentially lead to double-counting of patents. Further, the priority date identifies the *earliest* date associated with each patent.

Because of the time-lag between innovation and the time of application, we compute the growth of an industry's patent stock as second measure for innovative activity. Using the methodology outlined in Lach (1995) and Bloom *et al.* (2016) we estimate an industry's patent stock using a perpetual inventory method with a depreciation rate (δ) of 15%, starting in 1978 (i.e., the first year with available PATSTAT information).[11] Specifically, we compute annual industry-level patent stock estimates as

$$PatentStock_{j,t} = Patents_{j,t} + (1 - \delta) \cdot PatentStock_{j,t-1}, \tag{1}$$

where $Patents_{j,t}$ is the total number of patent applications. The patent stock growth rate is defined as the log change in $PatentStock$ between periods. As discussed above, we generally rely on patent *applications* as the more timely measure for firms' innovative activity. However, we also calculate measures using *granted* patents for robustness.[12]

[11] Unlike Bloom *et al.* (2016) we do not weight our measure by employment because of data availability (especially for young firms).

[12] Note that we do not use citation-based measures because of our short sample period and the time lag between patent application and citations.

2.4 Descriptive statistics

Panel A of Table 1 shows descriptive statistics by 4-digit NACE industry. Detailed definitions of all industry-level variables can be found in the Online Appendix. On average, industries produce six patent applications per year and have a patent stock (based on applications) of 42 patents. The median (mean) 4-digit NACE industry has a (sales-weighted) zombie share ($ZShare$) of 4% with a standard deviation of 7%. Our $LowCap$ variable indicates that the median and mean industry contains about 20% firms that are associated with only weakly capitalized banks.

The median (mean) 4-digit NACE industry consists of 172 (555) firms. There is substantial variation in industry size with median (mean) sales of 0.99 (3.22) billion euros. We also investigate (market) exit of firms using the definition in Beaver *et al.* (2023), who identify bankrupt firms using the status variable in BvD's Orbis.[13] The mean and median exit rate is about 2% per year.

We then investigate the performance of firms in industries with poorly capitalized banks at the firm-year level following previous literature (e.g., Schivardi *et al.*, 2022). We run the following fixed effects regression at the firm×year-level:

$$y_{i,t} = \beta LowCap_j \times Z_{i,t} + \gamma Z_{i,t} + \delta' \mathbf{X_{i,t-1}} + \alpha_i + \alpha_{j,t} + \varepsilon_{i,t}, \tag{2}$$

where $y_{i,t}$ is the dependent variable, $LowCap_j$ is a continuous variable indicating the degree of under-capitalization for banks active in industry j as of 2010, $Z_{i,t}$ is a dummy equal to one if firm i is identified as a zombie firm in year t, and zero otherwise, $\mathbf{X_{i,t-1}}$ is a vector of lagged firm controls, and α_i and $\alpha_{j,t}$ indicated firm and industry×year fixed effects, respectively.

Panel B shows the results. The dependent variable in column (1) is $Exit$, i.e., an indicator variable equal to one if firm i exits the market in year t. Zombie firms in industries with well

[13] Specifically, a firm i is classified as "exiting" in year t if two conditions are met: (i) it is the last year in which the firm is observed in the sample and (ii) the firm's status is "*Active (insolvency proceedings)*," "*Bankruptcy*," "*Dissolved*," "*Dissolved (demerger)*," "*Dissolved (liquidation)*," "*Dissolved (merger or takeover)*," "*In liquidation*," "*Inactive (no precision)*," "*Dissolved (bankruptcy)*," or "*Dissolved (litigation)*."

capitalized banks are 4 percentage points (p.p.) more likely to exit compared to non-zombie firms. This is consistent with the idea that zombie firms are non-viable. However, the exit probability is significantly lower for zombie firms in industries with a large share of under-capitalized banks. All else equal, a one standard deviation increase in *LowCap* decreases the probability that a zombie firm exists the market by ∼0.6 p.p. This is consistent with negative effects of evergreening on industry competition.

Columns (2) reports results for *Sales Growth*. Zombie firms have weaker sales growth compared to non-zombie firms. Again, however, this effect is muted in industries with a higher share of under-capitalized banks.

Column (3) reports results for firms' *Debt/Asset*. Zombie firms have higher debt levels compared to non-zombie firms, in particular in industries with a higher share of under-capitalized banks. This is consistent with the idea that under-capitalized banks continue to lend to non-performing borrowers.

Finally, we document in column (4) that the average interest rates for zombie compared to non-zombie firms is decreasing in the share of under-capitalized banks in an industry. This is consistent with the notion of subsidized credit. Overall, our results mirror those in prior studies and are consistent with sclerosis due to credit misallocation.

3 Zombie lending and innovation

This section explores the potential long-run negative effects of zombie lending on innovation activity and thus economic growth. The aim of this section is to establish a link between credit misallocation and innovation. We explore channels in detail in Section 4.

We document that zombie lending negatively relates to innovation activity in Section 3.1 and discuss potential threats to identification in Section 3.2. Section 3.3 examines effects in the cross-section of industries and shows that results are stronger in high-tech and high R&D industries. We use data from the Community Innovation Survey in Section 3.4 and show that our results also hold when using innovation measures that including patented and un-patented innovation activities by firms.

3.1 Baseline results

Setup: We examining if zombie lending predicts patent applications zero-, one-, or three-years ahead by estimating the following fixed-effects Poisson model (see Cohn *et al.*, 2022):

$$y_{j,t+h} = \beta LowCap_j \times ZShare_{j,t} + \gamma ZShare_{j,t} + \delta' \mathbf{Z_{j,t-1}} + \alpha_t + \alpha_j + \varepsilon_{j,t+h}, \tag{3}$$

where $y_{j,t+h}$ is the number of patent applications in industry j at time $t+h$, $\mathbf{Z_{j,t-1}}$ is a vector of lagged industry controls, and α_j and α_t are industry and time fixed effects, respectively.

We further analyze innovation activity in the industry cross-section using the industries' patent stock growth, as defined in Section 2.3, as dependent variable. We examine the patent stock growth over the entire sample period, i.e., from 2010 to 2016. While zombie lending peaked in Spain already in 2013 (Figure 2), we find that there is a delayed effect of credit misallocation on innovation activity (see discussion below). We estimate the following cross-sectional model using OLS:

$$\Delta \text{Pat Stock}_j = \alpha + \beta LowCap_j \times ZShare_j + \gamma ZShare_j + \delta LowCap_j + \theta' \mathbf{Z_j} + \varepsilon_j, \tag{4}$$

where ΔPat Stock is the patent stock growth for industry j over the 2010 to 2016 period, $LowCap_j$ is a continuous variable indicating the degree of under-capitalization for banks active in industry j as of 2010, $ZShare_j$ is the sales-weighted share of zombie firms in industry j in 2010, and $\mathbf{Z_j}$ is a vector of industry controls measured in 2010.

Results: Results are reported in Table 2. As there is usually a substantial time-lag between research, product development, and the filing of a patent application, we do not expect to see an immediate effect of zombie lending on patent filings. This is precisely what we find in the data. Contemporaneously (columns 1), we do not find a significant effect of credit misallocation on the number of patent applications. One to three years ahead, however, we observe a statistically and economically significant decline in the number of patent applications in industries with a high share of zombie firms and weak banks with the effect increasing over time.

The results in the industry cross-section confirm that innovation activity is negatively correlated with the presence of zombie firms and weak banks in an industry. Table 2 shows that there is a significantly negative effect of $LowCap \times ZShare$ on industries' patent stock growth over the 2010 to 2016 period. Columns (2) to (4) split the patent stock into innovation activity by different subsets of firms. Column (2) indicates that most of the reduction in innovation activity comes from incumbent firms and not from a reduced entry of innovation active entrants. Columns (3) and (4) show that non-zombies account for most of the reduction in innovation activity relative to zombie firms, indicating negative spillover effects of credit misallocation on the innovation activity of viable firms.

The effect is economically significant. The estimates from column 1 imply that an industry in the highest 75th percentile in terms of weak bank capitalization and weak firm share experiences a 19.3 percentage point (p.p.) lower growth rate in its patent stock over the time period from 2010 to 2016 compared to an industry in the lowest 25th percentile. That is, the patent stock growth rate is reduced by about 3 p.p. per year. Considering that the unconditional average growth rate is 4.5% per year, this result indicates that credit misallocation can have a sizable impact on innovation.

We generally rely on patent *applications* as the more timely measure for firms' innovative activity. Panel B of Table 3 shows the results using *granted* patents when calculating industries' patent stocks. The results are qualitatively similar.

3.2 Instrumental variable results

A lingering concern is the potential endogeneity of bank capitalization and associated reverese causality issues. That is, banks may be weak *because* they are exposed to weak (zombie) firms. If this is the case our results may capture a persistently low performance and associated drop in innovation activity of weak firms. We address this issue in two ways. First, we examine pre-trends using several proxies of the loan portfolio quality of weak and strong banks prior to 2010. Second, we explicitly instrument bank capitalization.

Pre-trends: To examine potential pre-trends, Figure 3 displays the performance of industries that borrow from weakly capitalized or well capitalized banks. We rank industries based on $LowCap$ as of 2010 and define two groups based on a median split. We plot industry performance over the 2004 to 2016 period. If there were a direct link from industries' poor performance into banks' capitalization, we would expect to see a stronger decrease in performance during the crisis for those industries that are populated with weak banks (defined according to their total capital ratio as of 2010). The upper part of Figure 3 shows industry profitability (sales-weighted ROA), the lower part shows average TFP growth.[14] In both graphs we observe very similar trends prior to and during the global financial crisis, while the paths only start to diverge in 2010 with the beginning of the sovereign debt crisis.

Instrumental variable estimates: Next, in order to address endogeneity concerns more explicitly, we instrument bank capitalization in the innovation regressions with banks' exposure to the Spanish mortgage and real estate market in 2006, i.e., before the onset of the financial crisis. We define the instrument as of 2006 to rule out any reverse causality concerns. We use the average mortgage loans to asset ratio of the banks that populate each industry j to construct an industry-level instrument $MortgExp_{j,2006}$.[15]

The instrument is relevant as the Spanish property bubble collapsed during the financial crisis and banks that were ex-ante more exposed to the mortgage market suffered larger losses. The exclusion restriction requires that industry innovation activity is only correlated with banks' pre-crisis mortgage market exposure through a weakening of the balance sheets

[14] Firm-level TFP is measured using fixed elasticities for labour (2/3) and capital (1/3) (e.g. Caballero *et al.*, 2008; Acharya *et al.*, 2024). Specifically, we estimate TFP as $log(sales) - 2/3\ log(employment) - 1/3\ log(fixed\ assets)$. Our results are robust to the usage of alternative TFP measures proposed in Gopinath *et al.* (2017).

[15] Five banks in the sample are the result of mergers during the 2008-2011 period. For these banks, we collect information from the annual reports of all pre-merger entities to approximate the exposure for the merged entities.

of banks that are active in the industry. This assumption would be violated if there, e.g., is a direct correlation between an industry's mortgage market exposure and the mortgage exposure of banks that are active in the industry. Three pieces of evidence suggest that this is not a significant concern. First, the pre-trend analysis reported above documents that industries with weak banks (as of 2010) did not perform worse that industries with strong banks during the crisis. If there were a correlation between bank and industry mortgage market exposure we would expect industries that borrow from low capitalized banks to under-perform during the financial crisis. Second, there is only a weak correlation between an industry's mortgage exposure and innovation activity (correlation of -0.1 between industry patent stock in 2010 and $MortgExp_{j,2006}$). For instance, the construction sector and real estate markets exhibit little overall innovation activities. Third, our results are robust to excluding industries with a high direct mortgage market exposure (e.g. construction).

First stage: The instrumental variable estimates are reported in Table 4. We estimate the following first stage model:

$$LowCap_j = \alpha + \beta MortgExp_{j,2006} + \gamma' \mathbf{Z_j} + \varepsilon_j, \tag{5}$$

where $\mathbf{Z_j}$ is a vector of lagged industry controls measured in 2010. Column (1) of Table 4 shows the first stage results. The fraction of under-capitalized banks in an industry is higher when banks in that industry had a higher ratio of mortgage loans to total assets in 2006. The F-statistic is 84, i.e., the instrument is not weak.

Second stage: Columns (2) to (4) of Table 4 report second stage results. Similar to Table 3, our results suggest that zombie lending has an adverse effect on innovation in an industry. The patent stock declines significantly over the 2010 to 2016 period.

3.3 Heterogeneity

Next, we explore whether the effect varies with the ex-ante level of innovation activity in the sector. We would expect effects to be stronger for industries in which firms innovate to maintain a competitive advantage of their peers. For this purpose, we employ three proxies for the level of innovation activity, namely capital intensity, R&D expenses, and a high-technology classification.

1. *Capital Intensity* is defined as the average share of tangible fixed assets to total assets over the five years prior to the start of our sample period. We classify industries with below (above) median *Capital Intensity* as low (high) capital intensive. Low capital intensive industries according to this definition have a higher share of intangible assets, i.e., typically exhibit higher innovation activity.

2. *R&D Expenses* is the average fraction of R&D expenses to total sales over the five years prior to the start of our sample period. As we do not observe R&D expenses for our sample of small, bank-dependent, firms, we classify industries using Compustat data for U.S. firms.[16] We classify an industry as a low (high) R&D industry based on a median split.

3. Finally, we classify industries as *Low or High Technology* industries based on the definition by EUROSTAT.

Results are reported in Table 5. As expected, capital misallocation reduces innovative activity particularly in industries that have higher share of intangible capital (column 1), high R&D intensity (column 4), and in high-technology industries (column 6).

3.4 Evidence from the Community Innovation Survey

In the analysis so far we use patent applications to proxy for industry innovation activity. While patents are an objective and widely available measure of innovation activity, not all innovations are patented and, if an innovation is patented, the application is only filed after the innovation is completed. In this section we provide further evidence using data from

[16] Similar to the Rajan and Zingales (1998) external finance dependence measure, the idea is that R&D intensity is a sector-specific characteristic, i.e., we can use U.S. data to to identify the R&D intensity of Spanish sectors.

the Community Innovation Survey (CIS), which is part of the EU science and technology statistics and the main data source for measuring innovation in Europe.[17] The surveys asks firms about innovation activities irrespective of whether the innovation is (later) patented or not. The survey further allows to break down innovation activities by type.

While the micro-dataset provides firm-level information, anonymization rules prevent us from matching firm-level data directly to the CIS micro-datasets. In line with our main analyses, we aggregate firm-level responses contained in CIS on an industry level and supplement the data with information on zombie lending and bank capitalization. CIS asks firms "yes or no" questions, which we encode as indicator variables. We calculate sales-weighted averages at the 4-digit industry level.

The firms sampled by CIS (∼30k firms per survey round) are representative and, on an industry level, account for ∼64% of total industry sales, on average. We rely on the latest available survey vintages comprising data for 2010-2014.[18]

Results: The results are reported in Table 6. The dependent variable in columns (1) and (2) is the fraction of firms that report *any* innovation activities (irrespective of whether the innovation is later patented) in industry j in the 2012 or 2014 survey, respectively. Firms in industries with a high zombie share and weakly capitalized banks, are less likely to report that they engaged in any innovation activities. Consistent with our previous results, the effect is stronger in the 2014 compared to the 2012 survey. We distinguish between different types of innovation in columns (3) to (6). The strongest (negative) effect is observed for service and process innovation.

In Panel B of Table 6, we report results using survey answers to questions related to patenting activities and R&D spending. The dependent variable in column (1) and (2) is the fraction of firms in the industry that indicate that they applied for an intellectual property (IP) right (including licences) or a patent, respectively. We find that firms in industries with

[17] The biennial surveys are executed by national statistical offices according to an EU framework and are collected and harmonised by Eurostat. The survey is conducted at the enterprise level. We accessed the confidential micro-datasets as secure use files at Eurostat's SAFE Center in Luxembourg.

[18] Data is made available to researchers only with a significant time lag.

a high share of zombie lending ($LowCap \times ZShare$) are significantly less likely to report that they applied for a patent or an IP right compared to industries with a lower degree of zombie lending.

Finally, we examine firm R&D spending in thousands of € in columns (3) to (6). Specifically, we define the log total R&D-related expenses across all firms in the industry. Results indicate significantly lower R&D expenses for firms in industries with a high share of zombie lending. Columns (5) and (6) distinguish between in-house and external R&D expenses. The effects is somewhat stronger for in-house expenses, however, the difference between the coefficients is small.

Overall, the survey evidence is consistent with our earlier results on patent applications and patent stock. Importantly, it shows that results are not specific to using patent applications as a measure for innovation activities. A high degree of zombie lending is negatively correlated with innovation also using proxies that are independent of whether the innovation is (later) patented or not.

4 Why does zombie lending affect innovation?

After having established that innovation activities decline in industries with a large degree of zombie lending we now aim at exploring the underlying channels. We start with a discussion of the theory and then proceed to test the theoretical predictions to shed light on the mechanism that links credit misallocation to innovation activities.

4.1 Theory

A recent body of theoretical literature considers the role of "subsidies" to incumbent firms, which may distort competition. While these models differ in the specific nature of the "subsidies," they share the underlying notion that resources are not allocated to the most efficient use, i.e., are informative for the discussion on potential effects of credit misallocation.

For instance, Caballero *et al.* (2008) model the effects of distorted bank lending incentives to unproductive incumbent firms, i.e., zombie lending. Acemoglu *et al.* (2018) more generally analyze the effects of providing (untargeted) subsidies to incumbents. Aghion *et al.* (2019) analyze the effect of better credit access on productivity under binding credit constraints for incumbent firms. The models provide the following common predictions on the effects of capital misallocation on industry dynamics.

First, subsidies to incumbents lead to sclerosis, i.e., the preservation or expansion of low-type incumbent firms that otherwise would have exited the market. Caballero *et al.* (2008) highlight this effect in a model of zombie lending, where banks directly choose to protect incumbent firms from a negative shock that would otherwise have led to their default. Acemoglu *et al.* (2018) and Aghion *et al.* (2019) provide evidence that relaxing credit constraints or providing direct subsidies to incumbents particularly benefits less efficient firms and helps them remain longer on the market. In our setting, this translates to the prediction that a misallocation of resources from weak banks in favour of low type firms should result in lower exit rates of these firms. This is confirmed by our evidence reported in Table 1.

Second, the resulting market congestion discourages the entry of new, more productive, firms. That is, a larger degree of distortions, such as continued lending by weak banks to unproductive firms, can deter entry with potential adverse effects on incumbents' incentives. The corresponding prediction on our setting is that industries with a larger degree of distorted lending incentives, i.e., industries with a larger share of low-type firms that are supported by weak banks, should exhibit lower overall entry rates.

This discussion highlights that capital misallocation in favour of low-type incumbent firms can result in a de facto market entry barrier with potentially adverse effects on incumbent firms' incentives. There is a large theoretical literature on firm dynamics and growth that analyzes the link between competition and innovation. While most empirical studies point to a positive correlation between innovation activity and product market competition, the effect of competition on innovation—absent of any resource misallocation effects—is theoretically ambiguous and depends, e.g., on whether competition occurs pre- or post-innovation (see

Aghion *et al.*, 2015; Gilbert, 2006; Schmutzler, 2010, for an overview of the literature).

The traditional "Schumpeterian" view emphasizes the importance of monopoly rents to create incentives for innovation, i.e., predicts a negative relationship between (*ex post*) competition and innovation. On the other hand, the pressure put on firms by (*ex ante*) competition may induce them to exert innovative effort. For instance, in Arrow (1962) a monopolist enjoys (high) profits even absent of innovation and hence trades off the benefit of innovating with the negative effects on the existing technology ("replacement effect"). In competitive markets, in contrast, normal profits are low and hence the relative returns to innovation high, if the innovator has property rights ex post (e.g., through patent protection).

In an attempt to reconcile the general implication of the Schumpeterian growth model (lower competition leading to more innovation) and empirical findings that more competition leads to more innovation, Aghion *et al.* (2005) provide theoretical and empirical evidence for an inverted U-sharped relationship. One the one hand, increased competition reduces pre-innovation rents more than post-innovation rents, for firms that compete in industries with similar technological level (i.e., in neck-and-neck industries). Innovation in these industries helps firms to escape competition and benefit from the high post-innovation rents. On the other hand, if the technological gap among firms is large (i.e., in laggard industries), post-innovation rents are decreased more by competition, leading to less innovation. The later being in line with the classical Schumpeterian growth models.[19]

This discussion highlights that capital misallocation can impede industry competition. This in turn can affect innovation activities of both zombie and non-zombie firms in the sector. The effect, however, might depend on the mode of competition. A decrease in competition would discourage incumbents from innovating in particular in neck-and-neck industries. We test these predictions in the next section.

[19] Aghion *et al.* (2009) test this prediction in the U.K. by exploiting variation in entry conditions cause by policy reforms. Results indicate that the threat of (technologically advanced) entrepreneurs differently affects incumbents incentives to innovate depending their distance to the technological frontier. Incumbents that are close to the frontier (i.e., neck-and-neck) boost their productivity and innovation to escape competition and survive entry, while incumbents that a far away from the technological frontier (i.e., laggard industries) experience a strong reduction in the expected rents from R&D, discouraging productivity and innovation growth.

4.2 Empirical results

In a first step, we examine effects of zombie lending on competition at the industry-level. While zombie firms are less likely to exit industries with a high share of under-capitalized banks (cf. Table 1), spillover effects are likely on both non-zombie firms in these industries as well as entrepreneurs who want to enter the market. We estimate the following model at the industry×year level:

$$y_{j,t} = \beta LowCap_j \times ZShare_{j,t} + \gamma ZShare_{j,t} + \delta' \mathbf{Z_{i,t-1}} + a_j + a_t + \varepsilon_{j,t}, \tag{6}$$

All variables are defined above.

The results are reported in Table 7. Column (1) shows that industries populated with a high share of zombie firms *and* undercapitalized banks have significantly lower entry rates. This is consistent with the conjecture that the protection of low-performing incumbents deters entrepreneurs from entering markets. Results are similar using sales-weighted entry rates (untabulated). Column (2) shows results for industry-level exit rates. The coefficient on the interaction term $LowCap \times ZShare$ is positive but significantly smaller that then entry effect and only borderline statistically significant. That is, while zombie firms are less likely to exit affected industries, see Table 1, the net exit effect is small and even mildly positive at the industry level as the presence of zombie firms exerts pressure on the remaining incumbents. Both the entry and the exit effects, however, indicate that competitive dynamics decrease, i.e., industries become more concentrated.

Next, we analyze productivity dispersion among firms. TFP dispersion is a common measure of resource misallocation (see e.g., Martin, 2008; Schivardi *et al.*, 2022). The results in column (3) indicate that zombie lending is indeed associated with an increase in TFP dispersion in $t + 1$, highlighting the link between zombie lending and misallocation.[20]

Finally, we investigate product-market consequences of misallocation. Column (4) shows that the growth of (deflated) material costs, a proxy for industry output, is lower in industries

[20] The effect on TFP dispersion appears not to be contemporaneous but materializes one to two years ahead.

populated with a large share of zombie firms and weak banks.[21] Together with the result that entry rates decline, this suggests a reduction in competition in industries with a larger degree of credit misallocation.

Effect by mode of competition: As highlighted in Section 4.1, the effect of competition on innovation is complex and depends on many factors including the type of competition. Aghion *et al.* (2005, 2009) argue that incumbents' incentives to innovate are positively affected by (increased) entry and competition in neck-and-neck industries, i.e., industries in which firms compete on a similar technological level, while their incentive to innovate are negatively affected in laggard industries, i.e., industries with a large technological gap among firms.

Relating these findings to our setting, where the interplay of zombie firms and weak banks lowers competition and entry, we expect to find two things. First, with respect to laggard industries we do not expect a change in innovation output as the threat to post-innovation rents is reduced. Second, reducing competition in neck-and-neck industries alleviates the pressure on pre-innovation rents and makes post-innovation rents relatively less attractive, while a decrease in competition would discourage incumbents from innovating.

To test these hypotheses, we follow Aghion *et al.* (2005) and identify neck-and-neck and laggard industries based on industry differences in total factor productivity (TFP). First, we compute the technological gap on the firm level by identifying the frontier firm—the firm with the largest TFP—within each industry j as of 2010, calculate the difference to all other firms in the same industry, and scale it with the frontier's TFP, i.e.,[22]

$$\textit{Technological Gap}_{i,2010} = \frac{\text{Max } TFP_{j,2010} - TFP_{i,2010}}{\text{Max } TFP_{j,2010}}. \tag{7}$$

[21] A reduction in competition is associated with a reduction production quantity in standard competition models. Granular information on firms' sales *quantities* is, however, not available as firms only report total revenue, i.e., quantity × price. Similarly, material costs capture both a change in production quantity and potential changes in the price of input factors. By deflating material costs, i.e., filtering out variation that arises because of a change in input costs, this measure aims at isolating material costs changes due to changes in production quantities.

[22] See footnote 14 for details on TFP estimation at the firm level.

We then compute the sales-weighted average of *Technological* $Gap_{i,2010}$ for each industry, where a low (high) value corresponds the small (large) technological gap, indicating neck-and-neck (laggard) industries. We split industries based on the median value of the industry-level technological gap in 2010 and run separate regressions for each of the two groups.

Results are reported in Table 8, columns (1) and (2). Consistent with our hypotheses, we find no statistically significant impact of misallocation for laggard firms, supporting the conjecture that firms in these industries do not react (significantly) to a decrease in competition. Neck-and-Neck industries on the other hand show a sizable negative and statistically significant effect on innovation. This can be explained by a decrease in entry threat, documented above, which in turn makes pre-innovation rents become relatively more attractive, discouraging incumbent firms from innovating.

Table 8, columns (3) and (4), confirm our previous results that the effect is driven by a reduction in innovation activity of incumbent and non-zombie firms in the presence of zombie lending

5 Conclusion

Our study provides novel insights into how zombie lending influences product market competition and, by extension, corporate innovation. Through our empirical analysis of the Spanish economy during the post-Global Financial Crisis period, we find that zombie lending—whereby undercapitalized banks continue to support non-viable firms—has a detrimental effect on innovation activities across industries. Specifically, our findings reveal a substantial decline in patent applications and a depletion of patent stock, particularly in high-technology and R&D-intensive sectors. These results are robust across various measures of innovation, including unpatented innovation activities captured through survey data.

The mechanism behind this decline in innovation is primarily driven by the distortion of competitive dynamics. Zombie lending effectively creates barriers to entry for young, innovative firms, while also enabling zombie firms to remain in the market, thereby reducing competitive pressure on incumbent firms. This reduced competition is especially harmful in "neck-and-neck" industries, where firms typically engage in innovation to escape competition and secure future rents. Our findings suggest that, in such environments, the presence of zombie firms diminishes the incentives for other firms to innovate, leading to a stagnation in industry dynamism.

From a policy perspective, our study underscores the importance of addressing the issue of zombie lending to foster a healthy competitive environment that is beneficial for corporate innovation. Policymakers should consider the long-term negative externalities of maintaining non-viable firms in the market, as these can lead to a significant slowdown in technological advancement and economic growth. Effective measures to recapitalize weak banks and encourage the exit of non-viable firms could help restore competitive pressures and revitalize innovation, ultimately contributing to more robust and sustainable economic recovery and growth.

This analysis provides valuable lessons not only for Spain but also for other economies facing similar challenges, particularly in the context of ongoing economic uncertainties and the potential rise of zombie firms in the wake of crises such as the COVID-19 pandemic. Addressing the root causes of zombie lending could be a crucial step in preventing long-term economic stagnation and fostering a more dynamic and innovative economic environment.

Figure 2: Development of zombie share by country

This figure shows the time trend in the $ZShare$ over our sample period from 2010 to 2016 for France, Germany, and Spain. See the main text for details on the "Zombie Firm" classification.

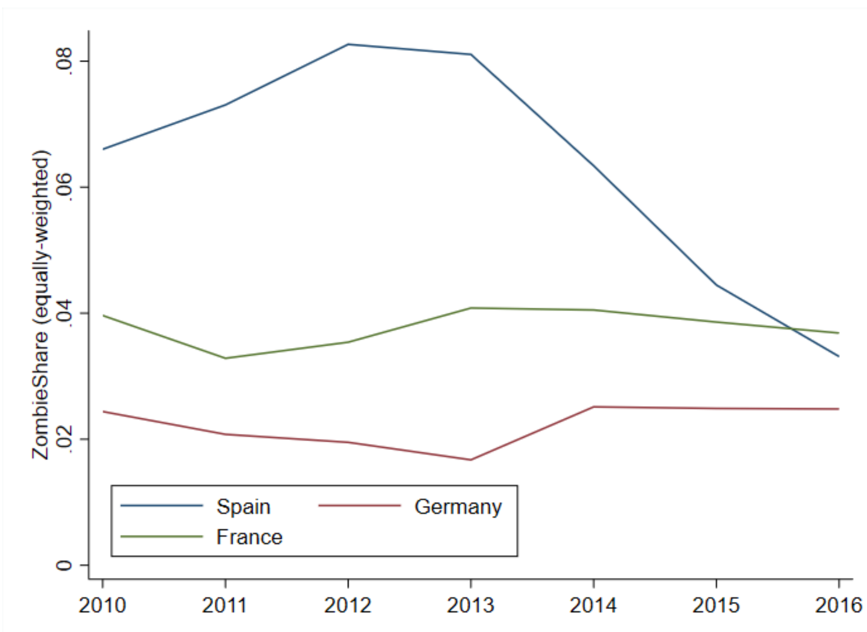

Figure 3: Link between firm and bank performance

This figure shows the development of profitability (ROA) and productivity (TFP) for industries with firms dependent on well or weakly capitalized banks. See main text for details on the sample split and profitability and productivity definitions.

Table 1: Descriptive statistics and firm performance

Panel A presents the distribution of various industry characteristics at the industry × year level. The sample period is 2010 to 2016. The underlying sample contains more than 425,000 unique firms that are aggregated to 470 different 4-digit NACE industries. Detailed definitions of all variables can be found in Table A1. Panel B shows results for regressions relating proxies for zombie lending to firm performance at the firm × year level. $Z_{i,t}$ is a dummy that equals one if firm i is classified as a zombie firm in year t, and zero otherwise. $LowCap_j$ is the fraction firms in industry j that have a lending relationship with a weakly capitalized bank as of 2010. *Exit* is a dummy variable equal to one if firm i exits the market in year t, and zero otherwise. Δ *Sales* is the (log) change in sales for firm i from year $t-1$ to year t. *Debt/Assets* is defined as as long-term liabilities plus current liabilities minus trade credit, scaled by total assets. *Interest Exp./IB Debt* is defined as interest expenses scaled by total interest bearing debt. Firm controls include: *ROA*, *Leverage*, *Sales Growth*, *(log) Assets*, and *Age*. All control variables are lagged by one period. Firm and year fixed effects are included when indicated. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Standard errors clustered on the industry-level are reported in parentheses.

Panel A. Descriptive statistics (industry × year level)

	Mean	S.D.	5pct	50pct	95pct	N
Patenting activity:						
Patent Applications	6.43	20.14	0.00	1.00	27.00	3,136
Patent Stock	41.92	109.08	0.12	9.76	179.64	3,136
Zombie lending:						
ZShare	0.04	0.07	0.00	0.02	0.17	3,283
LowCap	0.20	0.09	0.06	0.20	0.33	3,283
Other industry characteristics:						
# Firms	554.97	1257.96	11.00	172.00	2260.00	3,283
Sales (EURm)	3215.44	6259.60	55.04	993.95	13735.27	3,283
Exit Rate	0.02	0.02	0.00	0.02	0.06	3,283
Entry Rate	0.05	0.03	0.00	0.04	0.10	3,283
Δ TFP	0.03	0.11	-0.10	0.03	0.18	3,283
TFP Dispersion	1.00	0.41	0.51	0.91	1.87	2,130
Deflated Material Cost (EURm)	1828.40	4414.40	15.47	423.24	7862.97	3,283

Panel B: Firm performance and zombie lending (firm × year level)

	(1)	(2)	(3)	(4)
	$\text{Exit}_{i,t}$	$\Delta\text{Sales}_{i,t}$	Debt/ $\text{Assets}_{i,t}$	Interest Exp. / IB Debt $_{i,t}$
LowCap_j x $\text{Z}_{i,t}$	-0.08***	0.13**	0.20***	-0.01**
	-0.03	-0.06	-0.05	0.00
$\text{Z}_{i,t}$	0.04***	-0.13***	0.02*	0.00
	-0.01	-0.01	-0.01	0.00
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1515732	1515732	1515732	1515732

Table 2: Baseline results

This table shows results for poisson regressions relating proxies for zombie lending to innovation activity at the industry × year level. *LowCap*$_j$ is the fraction firms in industry j that have a lending relationship with a weakly capitalized bank as of 2010. Banks are classified as weakly capitalized if their total capital ratio is in the lowest quartile of the distribution at the end of 2010. *ZShare*$_{j,t}$ is the sales-weighted share of zombie firms in industry j in year t. *Patent Applications*$_{j,t}$ is the number of patent applications in industry j in year t. Industry and year fixed effects are included when indicated. Industry controls include: *(log) Sales*, *Fixed Assets/Assets* as well as interactions between the controls and *ZShare*$_{j,t}$ and *LowCap*$_j$. All control variables are lagged by one period. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are clustered at the industry-level are in parentheses.

	(1) Patent Applications$_{j,t}$	(2) Patent Applications$_{j,t+1}$	(3) Patent Applications$_{j,t+3}$
LowCap$_j$ x ZShare$_{j,t}$	4.16	-11.17**	-20.00***
	(5.30)	(5.01)	(5.48)
ZShare$_{j,t}$	3.10	1.50	5.54
	(5.99)	(5.94)	(5.80)
Industry Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	2,765	2,737	2,256

Table 3: Patent stock growth

This table shows results for regressions relating proxies for zombie lending to innovation activity in the industry cross section. $LowCap_j$ is the fraction firms in industry j that have a lending relationship with a weakly capitalized bank as of 2010. Banks are classified as weakly capitalized if their total capital ratio is in the lowest quartile of the distribution at the end of 2010. $ZShare_j$ is the sales-weighted share of zombie firms in industry j in 2010. $\Delta Patent\ Stock_{j,2010-16}$ is the patent stock growth for industry j over the 2010 to 2016 period. Details on the calculation of an industry's patent stock are given in the main text. Panel B mirrors Panel A but uses only granted patents in the calculation of an industry's patent stock. Industry controls are the same as in Table 2, all measured as of 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are in parentheses.

Panel A. All patents

	(1)	(2)	(3)	(4)
Sample:	All firms	Incumbents	Zombies	Non-Zombies
	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$
LowCap$_j$ x ZShare$_j$	-17.19***	-16.13***	-6.66	-12.38*
	(5.99)	(5.80)	(6.82)	(6.72)
ZShare$_j$	1.14	1.64	7.35	1.01
	(5.90)	(6.02)	(6.90)	(6.31)
LowCap$_j$	4.05	5.07*	0.77	3.19
	(3.17)	(2.83)	(5.14)	(3.09)
Industry Controls	Yes	Yes	Yes	Yes
Observations	443	442	321	428

Panel B. Granted patents

	(1)	(2)	(3)	(4)
Sample:	All firms	Incumbents	Zombies	Non-Zombies
	ΔGranted Patent Stock$_{j,2010-16}$	ΔGranted Patent Stock$_{j,2010-16}$	ΔGranted Patent Stock$_{j,2010-16}$	ΔGranted Patent Stock$_{j,2010-16}$
LowCap$_j$ x ZShare$_j$	-13.21**	-13.84***	-9.20	-10.34*
	(5.17)	(4.69)	(6.39)	(5.35)
ZShare$_j$	-2.34	-2.33	7.92	-4.03
	(6.26)	(5.87)	(5.70)	(5.52)
LowCap$_j$	0.74	1.97	0.17	0.22
	(3.03)	(2.73)	(4.99)	(2.90)
Industry Controls	Yes	Yes	Yes	Yes
Observations	441	440	320	426

Table 4: Instrumental variable results

This table shows results for instrumental variable regressions relating proxies for zombie lending to innovation activity at the industry level. First-stage results are reported in column 1. The dependent variable in columns 2 to 4 is Δ*Patent Stock*$_{j,2010-16}$, i.e., the patent stock growth for industry j in 2010. *LowCap*$_j$ is the fraction firms in industry j that have a lending relationship with a weakly capitalized bank as of 2010. *LowCap*$_j$ is instrumented by *MortgExp*$_{j,2006}$, which is defined as the average mortgage loans to asset ratio as of 2006 of the banks that have lending relationships with firms in industry j. *ZShare*$_j$ is the sales-weighted share of zombie firms in industry j in 2010. Industry controls are the same as in Table 2, all measured as of 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are in parentheses.

	1st Stage			
	(1)	(2)	(3)	(4)
Sample:		All firms	Incumbents	Non-zombies
	LowCap$_j$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$
MortgExp$_{j,2006}$	1.17**			
	(0.293)			
Instr.(LowCap$_j$) x ZShare$_j$		-30.78**	-35.87***	-26.15**
		(12.81)	(13.54)	(14.89)
ZShare$_j$		6.20	7.45	3.74
		(7.22)	(7.07)	(6.16)
Instr.(LowCap$_j$)		2.04**	1.60	1.30
		(1.01)	(1.02)	(0.99)
Industry Controls	Yes	Yes	Yes	Yes
F-statistic	83.83			
Observations	443	443	442	428
Adj. R^2	0.90			

Table 5: Cross-sectional heterogeneity

This table shows the result of cross-sectional regressions, splitting industries into subsamples based on the median i) capital intensity, ii) R&D expenses, and iii) technology-/knowledge-intensity. *Capital Intensity* is defined as the average ratio of tangible fixed assets to total assets in industry j as of 2006. *R&D expenses* is defined as R&D expenses scaled by total sales using data on U.S. firms that operate in the analogous industry classification as industry j. *Technology-intensity* classifies industries into high/low tech sectors as defined by EUROSTAT. $LowCap_j$ is the fraction firms in industry j that have a lending relationship with a weakly capitalized bank as of 2010. $ZShare_j$ is the sales-weighted share of zombie firms in industry j in the year 2010. Industry controls are the same as in Table 2, all measured as of 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital Intensity		R&D Expenses		Technology	
Subsample:	Low	High	Low	High	Low	High
	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$	ΔPatent Stock$_{j,2010-16}$
LowCap$_j$ x ZShare$_j$	-26.40**	-10.56	-2.75	-20.482***	-9.390	-26.902*
	(10.20)	(6.49)	(8.86)	(7.66)	(5.80)	(12.79)
ZShare$_j$	9.91	-3.92	-5.78	10.13	0.68	4.59
	(12.85)	(6.71)	(8.17)	(11.86)	(6.08)	(19.10)
LowCap$_j$	1.02	0.62	-0.13	1.20	0.51	1.20**
	(0.56)	(0.46)	(0.73)	(0.45)	(0.47)	(0.57)
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	215	233	168	216	317	131

Table 6: Survey evidence

This table shows results for regressions relating proxies for zombie lending to innovation activity at the industry level using data from the Community Innovation Survey (CIS). The dependent variables in Panel A are continuous variables ranging between 0 and 1, calculated based on firm-level responses to questions on innovation activities. Specifically, firms indicate whether they engaged in any innovation activities in the previous 2 years. We take the sales-weighted average response across all firms in industry j for each survey vintage. Columns 1 and 2 report results for overall innovation activities; columns 3 to 6 distinguish between product, service, process, and marketing innovation activities. Panel B examines effects on patenting activity and R&D expenditures. Firms indicate whether they applied for an interlectual property (IP) right or license (column 1) or a patent (column 2). We take the sales-weighted average response across all firms in industry j for each survey vintage. Columns 3 to 6 examine firm R&D expeditures. Specifically, we calculate the sum of R&D expenses (in '000 EUR) across all firms in industry j for each survey vintage. Columns 5 and 6 further distinguish between investment in "in house" and "external" R&D. Industry controls are the same as in Table 2, all measured as of 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are in parentheses.

Panel A. Overall innovation activity

	(1)	(2)	(3)	(4)	(5)	(6)
			Innovation type			
	All	All	Product	Service	Process	Marketing
Survey vintage:	2012	2014	2014	2014	2014	2014
LowCap_j x ZShare_j	-6.94*	-7.11**	-5.15	-10.34***	-6.64*	1.28
	(3.90)	(3.43)	(4.34)	(3.31)	(3.65)	(3.39)
ZShare_j	3.71	0.89	2.29	7.78***	3.29	4.91
	(4.24)	(4.00)	(5.10)	(2.91)	(4.04)	(3.32)
LowCap_j	4.69	4.31	4.32	3.43	4.34	2.73
	(2.87)	(3.00)	(3.32)	(3.31)	(3.34)	(3.21)
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353	353	353	353	353	353

Panel B. Patent applications and R&D spending

	(1)	(2)	(3)	(4)	(5)	(6)
	IP Right or Lic. Application	Patent Application	ln(R&D Exp.)	ln(R&D Exp.)	ln(R&D Exp. In House)	ln(R&D Exp. External)
Survey vintage:	2014	2014	2012	2014	2014	2014
LowCap_j x ZShare_j	-4.41***	-2.31*	-94.45*	-112.06**	-182.21**	-116.50
	(1.29)	(1.19)	(54.57)	(45.95)	(81.87)	(97.14)
ZShare_j	3.59**	1.72	-2.61	89.98**	64.53	126.44
	(1.81)	(1.42)	(46.35)	(35.25)	(62.99)	(96.21)
LowCap_j	1.49	1.54*	44.86	64.19*	125.66***	182.68
	(1.20)	(0.89)	(30.26)	(35.90)	(44.55)	(74.78)
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	314	314	353	353	353	353

Table 7: Channel: industry competition (I/II)

This table shows results for regressions relating proxies for zombie lending to industry competition at the industry × year level. *LowCap*$_j$ is the fraction firms in industry j that have a lending relationship with a weakly capitalized bank as of 2010. *ZShare*$_{j,t}$ is the sales-weighted share of zombie firms in industry j in year t. *Entry Rate* is the share of firms that report positive sales in industry j in year t for the first time (within five years of incorporation). *Exit Rate* is the share of firms that exit industry j in year t. *TFP Disp* is the standard deviation of industry j's *TFP*. See main text for details on the calculation of industry total factor productivity. Δ *Deflated Material Cost* is the log change in deflated material cost for industry j. Industry controls, lagged by one period, are the same as in Table 2. Industry and year fixed effects are included when indicated. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are in parentheses.

	(1) Entry Rate$_{j,t}$	(2) Exit Rate$_{j,t}$	(3) TFP Disp$_{j,t+1}$	(4) Δ Deflated Material Cost$_{j,t}$
LowCap$_j$ x ZShare$_{j,t}$	-0.20***	0.10*	0.85***	-0.88**
	(0.05)	(0.06)	(0.21)	(0.38)
ZShare$_{j,t}$	-0.27**	-0.19*	-0.87*	0.34
	(0.13)	(0.10)	(0.46)	(1.27)
Industry Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,283	3,283	2,814	3,283

Table 8: Channel: industry competition (II/II)

This table shows the result of cross-sectional regressions, splitting industries into subsamples based on the median industry technological gap. *Technological gap* is defined following Aghion *et al.* (2005). Within each industry-year, we compute the firm-level gap as Technological $\text{Gap}_{i,t} = (\text{Max } TFP_{j,t} - TFP_{i,t})/\text{Max } TFP_{j,t}$, where Max $TFP_{j,t}$ is the maximum TFP across all firms in industry j in year t. See main text for details on the TFP calculation. We then aggregate Technological $\text{Gap}_{i,t}$ to the industry-year level by taking a sales-weighted average across all firms. We use the average Technological Gap by industry across the sample period to classify industries into "Neck-and-neck" industries (low gap) and "Laggard" industries (high gap). Industry controls are the same as in Table 2, all measured as of 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Robust standard errors are in parentheses.

	(1)	(2)	(3)	(4)
Sample:	All Firms		Incumbents	Non-zombies
Subsample:	Neck-and-Neck	Laggard	Neck-and-Neck	Neck-and-Neck
	ΔPatent $\text{Stock}_{j,2010-16}$	ΔPatent $\text{Stock}_{j,2010-16}$	ΔPatent $\text{Stock}_{j,2010-16}$	ΔPatent $\text{Stock}_{j,2010-16}$
LowCap_j x ZShare_j	-21.90**	-9.44	-22.09*	-27.08*
	(10.48)	(7.78)	(12.59)	(14.60)
ZShare_j	3.90	-12.21	-0.37	0.06
	(8.24)	(8.75)	(8.47)	(7.86)
LowCap_j	0.64	10.84	3.35	2.36
	(3.90)	(6.68)	(3.92)	(4.28)
Industry Controls	Yes	Yes	Yes	Yes
Observations	215	233	210	201

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Appendix

Table A1: Variable Definition - Firm-level

Variable	Definition
Dependent Variables	
$Debt_{i,t}/Assets_{it}$	$\frac{Long\text{-}TermLiabilities_{i,t}+Current\ Liabilities_{i,t}-Trade\ Credit_{i,t}}{Total\ Assets_{i,t}}$
$Exit_{i,t}$	Dummy variable equal to one if: (i) it is the the last year in which we observe the firm in our sample and (ii) the firm's status is one of the following: "*Active (insolvency proceedings)*", "*Bankruptcy*", "*Dissolved*", "*Dissolved (demerger)*", "*Dissolved (liquidation)*", "*Dissolved (merger or take-over)*", "*In liquidation*", "*Inactive (no precision)*", "*Dissolved (bankruptcy)*", "*Dissolved (litigation)*"
$Interest\ Exp_{i,t}/IB\ Debt_{i,t}$	$\frac{Interest\ Expense_{i,t}}{Interest\text{-}bearing\ Debt_{i,t}}$
$\Delta Sales_{i,t}$	$ln(Sales_{i,t}) - ln(Sales_{i,t-1})$
Key Explanatory Variables	
$LowCap_j$ x $Z_{i,t}$	Interaction of continuous variable $LowCap_j$ and dummy variable $Z_{i,t}$
$Z_{i,t}$	Negative ROA AND negative net investments (measured as the log-change in fixed assets) AND debt servicing capacity (measured EBITDA over total debt) is lower than 5%, for at least two consecutive years
Control Variables	
$Age_{i,t}$	Natural logarithm of firm age, computed as the difference between the current year and the year of incorporation
$Leverage_{it}$	$\frac{Total\ Liabilities_{i,t}}{Total\ Assets_{i,t}}$
$ROA_{i,t}$	$\frac{Net\ Income_{i,t}}{Total\ Assets_{i,t}}$
$Total\ Assets_{i,t}$	Natural logarithm of total assets
$\Delta Sales_{i,t}$	$ln(Sales_{i,t}) - ln(Sales_{i,t-1})$
Other Variables	
$Technological\ Gap_i$	$\frac{\text{Max}TFP_j - TFP_i}{\text{Max}TFP_j}$ (as of 2010)
TFP_i	$log(Sales) - \frac{2}{3}log(Employment) - \frac{1}{3}log(Fixed\ Assets)$
$Weak\ Bank_i$	Minimum capitalization dummy (i.e. bank is in lowest quartile of total capital ratio distribution as of 2010) across all banks a firm is associated with

Table A2: Variable Definition - Industry-level

Variable	Definition
Dependent Variables	
$Entry\ Rate_{j,t}$	Share of firms that report positive sales in industry j and year t for the first time within five years of incorporation
$Exit\ Rate_{j,t}$	Share of firms with $Exit_{i,t}$ equal to one relative to the total number firms in industry j in year t
$Innovation\ Activity_{j,t}$	Sales weighted-average of firms that engaged in any innovation activities within the previous 2 years in industry j in year t. We furthermore distinguish between product, service, process and marketing innovation activity based on Community Innovation Survey
$Patent\ Applications_{j,t}$	Number of patent applications in industry j and year t
$R\&D\ Exp_{j,t}$	Sum of R&D expenses accross all firms that operate in industry j in year t. We furthermore distinguish between investment in "in house" and "external" R&D
$TFP\ Disp_{j,t}$	Standard deviation of $TFP_{i,t}$ among all firms i in industry j and year t, where $TFP_{i,t}$ is computed as $ln(Sales_{i,t}) - \frac{2}{3}ln(Number\ of\ Employees_{i,t}) - \frac{1}{3}ln(Fixed\ Assets_{i,t})$
$\Delta Deflated\ Material\ Cost_{j,t}$	$ln\left(\frac{Material\ Cost_{i,t}}{\sum_{i=1}^{n} Producer\ Price\ Index_{i,t}}\right) - ln\left(\frac{Material\ Cost_{i,t-1}}{\sum_{i=1}^{n} Producer\ Price\ Index_{i,t-1}}\right)$ for all firms i in industry j and year t
$\Delta Granted\ Patent\ Stock_{j}$	$ln(Granted\ Patent\ Stock_{j,t}) - ln(Granted\ Patent\ Stock_{j,t-1})$, with δ being a depreciation rate of 15%
$\Delta Patent\ Stock_{j,t}$	$ln(Patent\ Stock_{j,t}) - ln(Patent\ Stock_{j,t-1})$, with δ being a depreciation rate of 15%
$\Delta Sales_{j,t}$	$ln\left(\sum_{i=1}^{n} Sales_{i,t}\right) - ln\left(\sum_{i=1}^{n} Sales_{i,t-1}\right)$ for all firms i in industry j and year t
Key Explanatory Variables	
$LowCap_j$	Average of $WeakBank_i$ across all firms i in industry j as of 2010
$LowCap_j$ x $ZShare_{j,t}$	Interaction of continuous variable $LowCap_j$ and continuous variable $ZShare_{j,t}$
$ZShare_{j,t}$	Sales-weighted share of $Z_{i,t}$ in industry j and year t
Instrumental Variables	
$MortgExp_j$	Average mortgage loans to asset ratio as of 2006 of banks that are in lending relationships with firms in industry j
Control Variables	
$Fixed\ Assets/Assets_{j,t}$	$\frac{\sum_{i=1}^{n} Fixed\ Assets_{i,t}}{\sum_{i=1}^{n} Sales_{i,t}}$ for all firms i in industry j and year t
$Sales_{j,t}$	$ln\left(\sum_{i=1}^{n} Sales_{i,t}\right)$ for all firms i active in industry j and year t
Other Variables	
$Capital\ Intensity_{j,t}$	$\frac{\sum_{i=1}^{n} Tangible\ Fixed\ Assets_{j,t}}{\sum_{i=1}^{n} Sales_{i,t}}$ for all firms i in industry j and year t
$Patent\ Stock_{j,t}$	$Patents_{j,t} + (1-\delta) \cdot Patent\ Stock_{j,t-1}$ for all firms i active in industry j and year t
$ROA_{j,t}$	$\frac{Net\ Income_{i,t}}{Total\ Assets_{i,t}}$
$Technology\text{-}intensity_{j,t}$	Dummy variable which classifies industries into high/low tech sectors as defined by EUROSTAT
$\#Firms_{j,t}$	Number of firms in industry j in year t
$\Delta TFP_{j,t}$	$ln(\varnothing TFP_{j,t}) - ln(\varnothing TFP_{j,t-1})$