The Survival of Zombie Firms: Evidence from the European Sovereign Debt Crisis

Chenyue Lei *

Boston University

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Abstract

Do financial crises feature a productivity-enhancing reallocation where resources are shifted from low-productivity firms to high-productivity firms? To answer this question, I construct a bank lending model with heterogeneous firms and government policies on banks' capital adequacy requirements and bank bailouts. My model demonstrates that these policies can induce under-capitalized banks to roll over loans to otherwise inviable firms ("zombie lending").

Consistent with other model predictions, my empirical results find a significantly reduced exit rate of low-productivity firms during the 2011 European sovereign debt crisis, indicating the survival of "zombie firms". This implies that in the presence of credit misallocation, a financial crisis is not cleansing.

*Email: cylei@bu.edu. Mailing Address: Boston University, Department of Economics, 270 Bay State Rd., Boston, MA 02215.

1 Introduction

An efficient economy should see a productivity-enhancing reallocation where resources are shifted to high-productivity firms and inefficient firms should be scrapped (Schumpeter et al. (1939)). However, recent observations document an increasing prevalence of "zombie firms" in Europe: firms that would typically exit in a competitive market now have an increased survival rate.

In this paper, I formalize a mechanism of how credit misallocation from banks with impaired balance sheets, induced by poorly-designed policies, could result in the promotion of zombie firms. In this partial equilibrium model, firms with idiosyncratic productivity shocks have to rely on bank financing to fund capital and operations. Banks can lend funds to firms or invest in risky assets. The government has four policy instruments: (1) a regulatory capital adequacy ratio, (2) tightness of the regulatory capital requirement, (3) bank bailout decisions, and (4) supervision of injected capital. Banks need to decide whether to roll over their loans if firms have trouble repaying the debt. When banks prolong existing loans to these low-productivity firms, "zombie lending" occurs and zombie firms appear. In my model, zombie lending only happens when banks are either under-capitalized and failing to satisfy the regulatory capital ratio, or insolvent. Banks are more likely to engage in zombie lending when the capital ratio requirement is tight, the bailout capital is not sufficiently large, or bank supervision is not strict enough.

My model derives an implication to motivate empirical strategy to examine zombie firms during a financial crisis. The testable hypothesis is that low-productive firms are less responsive to a financial shock than high-productivity firms on the exit margin.

My paper is organized as follows. Section 2 discusses related literature on the topic. Section 3 describes the theoretical framework. Section 4 derives the model implication about the effect of a financial shock on firm exit. Section 5 outlines an empirical model. Finally, Section 6 concludes.

2 Literature

This paper directly contributes to the literature studying the phenomenon of a particular credit misallocation: zombie lending. A noteworthy paper focuses on the Japanese crisis and demonstrates that large Japanese banks often engaged in sham loan restructurings that kept credit flowing to otherwise insolvent borrowers (Caballero et al., 2008). Since 2008, the focus has been extended beyond Japan to Europe. Credit misallocation increased the failure rate of healthy firms and reduced the failure rate of non-viable firms (e.g., McGowan et al. (2017), Acharya et al. (2017) and Schivardi et al. (2017)). To detect the prevalence of zombie firms, the literature heavily relies on financial ratios that lack solid theoretical foundations. This paper complements this work by providing a structural model to examine whether there are zombie firms in the economy.

To explain the rising prevalence of zombie firms during a crisis, a strand of works (e.g., Acharya et al. (2017), Albertazzi and Marchetti (2010), and Giannetti and Simonov (2013)) point out that misguided policies encourage inefficient lending behavior. Acharya et al. (2017) provides evidence that after bank rescue support (i.e., the Outright Monetary Transaction program), banks regain lending capacity but some still remain weakly capitalized. Most likely driven by risk-shifting incentives, these banks extend loans to weaker firms with pre-existing lending relationships. Other proposed motivations for zombie lending include regulatory pressure to increase their capital ratios and a moral suasion motive (e.g., Blattner et al. (2019), Caballero and Hammour (1991)). Overall, the literature suggests that poorly-designed policy measures aggravate the problems of loan misallocation. Motivated by this empirical evidence, my model highlights how government policies can cause zombie lending. According to the literature (e.g., Caballero et al. (2008), Kwon et al. (2015)), there are various forms of zombie lending. The model described in the paper is able to better elucidate zombie lending scenarios for both solvent and insolvent banks.

This paper also contributes to the theoretical literature on zombie lending and zombie firms (e.g., Bruche and Llobet (2013), Jaskowski (2015), Hu and Varas (2021), Acharya et al. (2021), Faria-e Castro et al. (2023)). Closely related, Bruche and Llobet (2013) proposes a framework to investigate banks' incentives for zombie lending, without the role of the government. Acharya et al. (2021) also has a diabolical sorting where poorly capitalized banks engage in zombie lending. However, my paper formalizes the policies of capital adequacy requirement and the bank bailout.

Finally, this paper is closely related to the literature on recession cleansingness and business dynamism. Since the pioneering work of Schumpeter et al. (1939), economists have been interested in how business cycles affect the allocation of resources. The conventional view of recessions, emphasized in Caballero and Hammour (1991), is based on the assumption that markets select the most productive firms and hence a recession is a time of accelerated productivity-enhancing reallocation. However, the cleansing hypothesis has been challenged by several studies highlighting potential distortions. These studies reveal "sullying" or "scarring" effects of recessions. My paper is in line with previous conclusions that credit frictions may therefore alter the productivity-enhancing effect of recessions Barlevy (2003). The existence of zombie firms imply that the financial crisis is not cleansing.

3 Model

In this section, I develop a simple model with a firm-bank-government nexus. Banks engage in zombie lending due to a motive to gamble for resurrection. Policies aggravate credit distortion.

3.1 Set up

Consider an economy with three dates, $t = 0, 1, 2$. There is no discounting across dates. There is no particular role for consumers.

Banks

There exists a continuum of risk-neutral banks, that operate to maximize the expected value of their equity. Bank liability is exogenously given with face value $D \geq 1$, due to be paid at $t = 1$. Bank assets include corporate loans and risky assets. All banks have a measure of 1 for loans. Each loan has a face value of 1. All banks have a measure a of risky assets which can either be good or bad. Banks face two types of shock: a firm-level idiosyncratic productivity shock ε, which affects firm profitability and the ability of loan repayment; and a bank-level idiosyncratic asset return shock η. Assume η is identically distributed over time, serially independent, and orthogonal to ε. The distribution of η is denoted as $\Psi(\eta)$ with density $\psi(\eta)$. At $t = 0$, banks are ex-ante identical. At $t = 1$, banks learn both shock realizations and can decide whether to roll over the loan.

Banks are supervised by the government. I assume that they have to satisfy two requirements:

1. Solvency: Equity ≥ 0
2. Well-capitalization: $\dfrac{\text{Equity}}{\text{Asset}} \geq \kappa$, where κ is the regulatory capital adequacy ratio

The requirements are held ex-ante. But ex-post, they may be violated depending on shock realizations. These features are different from usual constraints which have to be satisfied all the time. It reflects a degree of regulatory forbearance.

Firms

There exists a continuum of risk-neutral firms in the economy. Firms face idiosyncratic productivity shock ε. The production is completely financed by bank debt of measure 1. At $t = 0$, firms are ex-ante identical. At $t = 1$, firms learn productivity shock. If ε is high, firms can have full loan repayment and stay in the market. Otherwise, firms choose to default without loan repayment and exit if banks stop lending. Firms that make a profit do not keep the fund. Instead, firms distribute the profit back to shareholders and in each period firms are fully debt-financed. I assume productivity ε evolves stochastically, i.e., ε is serially dependent. The distribution of η is denoted as $\Phi(\varepsilon)$ with density $\phi(\varepsilon)$.

For simplicity's sake, I assume firms and banks are one-to-one mappings: a firm can only borrow from one bank and a bank only lends to one firm. This assumption can capture an important characteristic that zombie lending usually occurs among weak banks with weak firms (Acharya et al. 2017). If relaxed, the mechanism still works in general but the correlation would be smaller.

Government

A government supervises banks by looking at their balance sheets. The government ascertains the solvency and capitalization statuses of banks from their reported, or book-value balance sheets. But the government cannot ascertain the market-value of the balance sheet. Thus, a bank can underreport or delay the loan loss while maintaining a seemingly acceptable balance sheet. In this case, the government cannot immediately detect the problem. This results in asymmetric information flow between the government and banks.

In addition to the capital adequacy ratio κ, the government has three main policy instruments:

1. χ, tightness of regulatory capital requirement: if the government can tell from the bank balance sheet that the bank is solvent but that it does not satisfy the minimum capital ratio, then the bank is not allowed to invest in any type of assets and is also subject to a punishment that is a fraction of χ from its equity value.

   χ can be interpreted as the cost to raise the capital in zero time spent. A higher χ suggests to break the rule. This might create a distorted incentive for banks to lie on the balance sheet.

2. λ, bailout decision: when banks have a risk of bankruptcy or a solvency problem, the government must decide whether to bail out banks for liability loss as well as the size of the bailout if so. $\lambda = 0$ means no bailout.

3. (θ, β): if a bailout is implemented, the government needs to monitor the use of injected capital. θ is the effective monitoring ratio, where $0 \leq \theta \leq 1$. If a bank is caught by the government for inappropriate use (i.e., loan extension to zombie firms), then the bank incurs a punishment of β, where $\beta \geq 0$.

Banks take these regulations into consideration when making lending decisions at $t = 1$. I will describe later in detail how government programs affect banks continued lending decisions.

3.2 Timing

t = 0

All banks are ex-ante identical with the liability of face value D, 1 unit of corporate loan, and risky asset a. Assumptions A1 and A2 in Appendix A guarantee that banks have no incentive to deviate from such an asset portfolio.

All firms are ex-ante identical in expected productivity and have the same technology. Every firm borrows 1 unit of corporate loan from the bank for operation. Without loss of generality, I assume that the gross interest rate of the loan in this period is 1. In response to the productivity shock and policies, banks make continued lending and investment decisions. If firms exit from the markets, then they will be replaced by equal-massed identical entrants. An entrant's productivity follows the same distribution $\Phi(\varepsilon)$ and will be revealed later.

t = 1

Each bank realizes its idiosyncratic shock η_1 on asset returns. Each firm realizes its idiosyncratic productivity shock ε_1 and makes loan payment decisions. If firms repay the loan, then the bank's balance sheet looks as Table 1. Alternatively, if firms do not repay the loan, then the balance sheet looks as in Table 2. ε^* is the productivity threshold. When $\varepsilon_1 \geq \varepsilon^*$, firms can make a full loan repayment. Banks cannot observe firms' productivity directly. But from repayment data, banks can tell whether productivity $\varepsilon \geq \varepsilon^*$ or $\varepsilon < \varepsilon^*$. If banks are insolvent, then banks decide whether to roll over the loan of the same measure of 1. Firms that receive the loan will survive and produce. If banks are insolvent, then they may go bankrupt.

Table 1: Bank balance sheet at t = 1, with firm loan repayment

Asset	Liability
1	D
$a\eta_1$	Equity
	$1 + a\eta_1 - D$

t = 2

Firms that receive the loan continue operations. New idiosyncratic productivity ε_2 and risky asset return η_2 are revealed for surviving firm-bank pairs. The interest rate is $R_H < 1$ for high-

Table 2: Bank balance sheet at t = 1, without firm loan repayment

Asset	Liability
$a\eta_1$	D
	Equity
	$a\eta_1 - D$

productive firms ($\varepsilon_1 \geq \varepsilon^*$) and $R_L > 1$ for low-productive firms ($\varepsilon_1 < \varepsilon^*$). The loan measure is still 1. The productivity threshold is now ε_H^* for high-productive firms and ε_L^* for low-productive firms. At the end of t = 2, firms exit if they cannot repay the loan.

3.3 Bank and firm types at t = 1

I divide firms at $t = 1$ into two types by the productivity threshold ε^*. When $\varepsilon_1 \geq \varepsilon^*$, firms can make a full loan repayment. I label these firms as high-productivity firms, type H. When $\varepsilon_1 \geq \varepsilon^*$, firms cannot make a full loan repayment. I label these firms as low-productivity firms, type L.

For convenience, I assume for the support of η. Assumption 1 says that η is bounded below at the value where the bank's capital ratio requirement is satisfied as long as the firm can make a full loan repayment. This assumption guarantees that banks are well-capitalized if they are paired with high-productivity firms.

Assumption 1 (Lower bound of risky asset return) $\min \eta \geq \eta^\star = \frac{1}{a}\left(\frac{D}{1-\kappa} - 1\right)$.

Similarly, I also classify banks at $t = 1$ into two types by the risky asset return threshold $\eta^* = \frac{1}{a}\left(\frac{D}{1-\kappa}\right)$. When $\eta_1 \geq \eta^*$, banks are still well-capitalized without the loan repayment. I label these strong banks as type H. When $\eta_1 < \eta^*$, banks are weakly-capitalized or insolvent if they don't receive the loan repayment. I label these weak banks as type L. Then I can categorize firm-bank pairs into 4 groups: HH (High-type firm and High-type bank), HL (High-type firm and Low-type bank), LH (Low-type firm and High-type bank), and LL (Low-type firm and Low-type bank).

3.4 Firm exit at t = 1

For the HH and HL pairs, firms have positive payoffs and banks are well-capitalized. Banks have the incentive to roll over the loan. No banks or firms will exit the market.

For the LH pair, banks are well-capitalized. Banks can keep the fund as cash, roll over the loan, or invest in risky assets. I make Assumption 2 so that well-capitalized banks with low-productivity firms prefer lending to new firms. Without debt financing, firms in the LH pair will exit.

Assumption 2 (Evolution of productivity) *$\mathbb{E}(\varepsilon_2|\varepsilon_1)$ is increasing in ε_1*

For the LL pair, when D is sufficiently large, the weakest banks with the lowest value of η_1 without loan repayment are solvent. When D is small, some banks become insolvent. This is formalized in Assumption 3.

Assumption 3 (Banks solvency) *If $1 \leq D\frac{\kappa}{1-\kappa}$ (D is large enough), then all banks in LL type are solvent. If $1 > D\frac{\kappa}{1-\kappa}$ (D is sufficiently small), then banks in LL type with small η_1 can be insolvent.*

Suppose banks are solvent, banks need to decide whether to take immediate action to realize the loan loss. If banks take immediate action, then they will face a penalty and lose a fraction χ of the equity value. If banks delay writing off the bad loans, banks take the gamble of the resurrection of these low-productivity firms. Banks will compare the expected equity value and decide whether to roll over the bad loan to otherwise default firms. If so, zombie lending occurs and zombie firms will survive. Zombie generated in the model is among weak banks and weak firms. This is consistent with the findings in Acharya et al. (2017). Proposition 1 states that sufficient conditions for zombie lending occurs when banks are solvent but under-capitalized. When the expected equity value is greater than the equity value net of penalty for failing to satisfy the capital requirement, then banks have the incentive to roll over bad loans. $\mathbb{E}(\eta)$ is the expected value of the risky asset return η. Proposition 1 suggests that a larger value of χ is associated with a larger chance of zombie lending as the inequality is more likely to hold. In this case, there is no role of the government bailout.

Proposition 1 *If*

$$R_L\left[1-\Phi(\varepsilon_L^*|\varepsilon_1 < \varepsilon^*)\right] + (a\eta_1 - 1)\mathbb{E}(\eta) - D \geq (a\eta_1 - D)(1-\chi), \quad \text{with } a\eta_1 \geq \max\{1, D\} \tag{1}$$

then solvent but weakly-capitalized banks in LL type will roll over their bad loans.

Table 3 shows four types of firm-bank pairs. It reports bank lending decisions and firm exit responses for each type .

Corollary 1 *With sufficiently small κ, small χ, and large D, there is no zombie lending at t=1.*

Table 3: Bank and firm types at t=1

Firm type		Bank type: High ($\eta_1 \geq \eta^*$)	Bank type: Low ($\eta_1 < \eta^*$)
	High ($\varepsilon_1 \geq \varepsilon^*$)	banks are well-capitalized, continue lending; firms survive	banks are weakly-capitalized, continue lending; firms survive
	Low ($\varepsilon_1 < \varepsilon^*$)	banks are well-capitalized, but stops lending; firms exit	banks are weakly-capitalized, and maybe insolvent; firms may survive

Depending on the values of the parameters, banks in LL type may not roll over their bad loans. Corollary 1 summarizes the conditions under which no zombie lending exists. When the capital requirement is not tight (a small κ), the punishment for failing to satisfy the requirement is lenient (a small χ), and the economy is booming (a large D), zombie lending will not occur. This illustrates that without the influence of these policies, there is a potential for zombie lending and credit misallocation during economic downturns. These policies contribute to the worsening of the zombie lending problem.

Suppose D is sufficiently small so that banks with small η_1 are insolvent without loan repayment. Then government needs to decide whether to inject capital to bail out otherwise default banks. Proposition 2 describes another type of zombie lending. The government decides to bailout these banks by giving a fund of size λ. Banks should use the credit to pay off the liability; if they do, banks will have an equity value of $\lambda + a\eta_1 - D$. However, banks may have an incentive to distort the use of capital by keeping credit flow to their firms. This incentive increases as banks' lending positions are eased by the bailout capital, but they remain under-capitalized. Proposition 2 suggests that when λ, β, and θ are larger, the inequality is less likely to hold. This means that with a large bailout capital, harsh punishment, and strict bank supervision, zombie lending of the second type (insolvent banks) is less likely to happen.

Proposition 2 *Assume*

$$\lambda \geq D - a\eta_1$$
$$R_L[1 - \Phi(\varepsilon^{**}(\varepsilon_2))] + (\lambda + a\eta_1 - 1)\mathbb{E}(\eta) - D \geq a\eta_1 - \beta$$

If

$$(1-\theta)\left\{R_L[1-\Phi(\varepsilon_L^*|\varepsilon_1<\varepsilon^*))]+(\lambda+a\eta_1-1)\mathbb{E}(\eta)-D\right\}+$$
$$\theta(a\eta_1-\beta)\geq\lambda+a\eta_1-D,$$
$$\text{with } a\eta_1<D \tag{2}$$

then insolvent banks in the LL type will misuse the bailout capital and roll over their bad loans.

Without loss of generality, assume Equation 1 in Proposition 1 holds for all solvent banks and Equation 2 in Proposition 2 holds for all insolvent banks in the LL type. Therefore, all firms in the LL type will not exit the market. In this case, the aggregate productivity of the economy can be expressed as

$$A=\underbrace{\mathbb{E}(\varepsilon|\varepsilon\geq\varepsilon^*)[1-\Phi(\varepsilon^*)]}_{\text{HH and HL types}}+\underbrace{\mathbb{E}(\varepsilon)\Phi(\varepsilon^*)[1-\Psi(\eta^*)]}_{\text{LH type}}+\underbrace{\mathbb{E}(\varepsilon|\varepsilon<\varepsilon^*)\Phi(\varepsilon^*)\Psi(\eta^*)}_{\text{LL type}}$$

In the absence of the punishment policy χ, solvent banks in the LL type may still have the incentive to roll over their bad loans, summarized in Proposition 3.

Proposition 3 *In the absence of the policy χ, if*

$$R_L\left[1-\Phi(\varepsilon_L^*|\varepsilon_1<\varepsilon^*)\right]+(a\eta_1-1)\mathbb{E}(\eta)-D\geq(a\eta_1-D),\ \text{with } a\eta_1\geq 1$$

then solvent but weakly-capitalized banks in LL type will roll over their bad loans.
Without loss of generality, there exists $\eta^\star\geq\eta^*$ such that for all $\eta_1<\eta^\star$, the inequality holds.

Compared to Proposition 1, the inequality in Proposition 3 is less likely to hold without a factor of $(1-\chi)$. Therefore zombie lending is induced by both banks' own motives and the policy of capital ratio requirement. I label this case as the "efficient economy". Then the efficient economy's productivity is

$$\begin{aligned}A^\star=&\underbrace{\mathbb{E}(\varepsilon|\varepsilon\geq\varepsilon^*)[1-\Phi(\varepsilon^*)]}_{\text{HH and HL type s}}+\underbrace{\mathbb{E}(\varepsilon)\Phi(\varepsilon^*)[1-\Psi(\eta^*)]}_{\text{LH type}}\\&+\underbrace{\mathbb{E}(\varepsilon|\varepsilon<\varepsilon^*)\Phi(\varepsilon^*)\Psi(\eta^\star)+\mathbb{E}(\varepsilon)\Phi(\varepsilon^*)[\Psi(\eta^*)-\Psi(\eta^\star)]}_{\text{LL type}}\end{aligned}$$

Then

$$A^\star-A=\Phi(\varepsilon^*)[\Psi(\eta^*)-\Psi(\eta^\star)][\mathbb{E}(\varepsilon)-\mathbb{E}(\varepsilon|\varepsilon<\varepsilon^*)]$$

Since $\mathbb{E}(\varepsilon|\varepsilon > \varepsilon^*) \geq \mathbb{E}(\varepsilon) \geq \mathbb{E}(\varepsilon|\varepsilon < \varepsilon^*)$, therefore $A^\star \geq A$, the efficient economy has higher aggregate productivity.

4 Model Implications: Effect of A Financial Shock

Suppose there is an exogenous financial shock on firms at t=2 such that the productivity threshold for loan repayment increases from $\varepsilon_H^*, \varepsilon_L^*$ to $\varepsilon_H^{**}, \varepsilon_L^{**}$ respectively. Similarly, a larger R_L increases $\eta^\star$ to $\eta^{\star\star}$. η^* does not depend on R_L or R_H, so it stays the same.

Proposition 4 *Without a financial shock, the exit rate of high-productivity firms is:*

$$Pr(Exit|\varepsilon_1 \geq \varepsilon^*) = \Phi(\varepsilon_H^*)$$

The exit rate of low-productivity firms is:

$$Pr(Exit|\varepsilon_1 < \varepsilon^*) = \begin{cases} 1 - \Psi(\eta^\star) + \Phi(\varepsilon_L^*)\Psi(\eta^\star), & \textit{efficient} \\ 1 - \Psi(\eta^*) + \Phi(\varepsilon_L^*)\Psi(\eta^*), & \textit{zombie} \end{cases}$$

The change in the exit rate in response to a financial shock is:

$$\Delta Pr(Exit|\varepsilon_1 \geq \varepsilon^*) = \Phi(\varepsilon_H^{**}) - \Phi(\varepsilon_H^*)$$
$$\Delta Pr(Exit|\varepsilon_1 < \varepsilon^*) = \begin{cases} \Phi(\varepsilon_L^{**})\Psi(\eta^{\star\star}) - \Phi(\varepsilon_L^*)\Psi(\eta^\star) - [\Psi(\eta^{\star\star}) - \Psi(\eta^\star)], & \textit{efficient} \\ [\Phi(\varepsilon_L^{**}) - \Phi(\varepsilon_L^*)]\Psi(\eta^*), & \textit{zombie} \end{cases}$$

Proposition 4 summarizes the effect of financial shock on exit rates for productive and unproductive firms. It shows that first, high-productivity firms have a lower exit rate than low-productivity firms since $\varepsilon_H^* < \varepsilon_L^*$. Second, the exit rate of low-productivity firms is higher in the efficient economy than in the zombie lending economy. Third, a financial shock is associated with an increase in the firm exit rate for both types of firms.

Corollary 2 *With reasonable parameter values,*

$$\Delta Pr(Exit|\varepsilon_1 \geq \varepsilon^*) \begin{cases} < \Delta Pr(Exit|\varepsilon_1 < \varepsilon^*), & \textit{efficient} \\ > \Delta Pr(Exit|\varepsilon_1 < \varepsilon^*), & \textit{zombie} \end{cases}$$

Corollary 2 states another implication of Proposition 4 that in response to a financial shock, the increase in exit rate for high-productivity firms can be smaller than the increase for low-productivity firms if zombie lending exists, which I can test empirically. Appendix A illustrates a numerical example.

5 Empirical Work

5.1 Regression specifications

As discussed in Section 3, a financial shock is associated with reduced exit response of low-productivity firms when banks are engaged in zombie lending. Motivated by the model implication, I run the following regression:

$$\begin{aligned} Y_{jt} = {} & \beta_1 \text{Productivity}_{j,t-1} + \beta_2 \left(\text{Productivity}_{j,t-1} \times \text{FinancialShock}_{jt}\right) \\ & + \beta_3 \text{FinancialShock}_{jt} + \text{Controls}_{jt-1} + \text{FE} + \varepsilon_{jt} \end{aligned} \tag{3}$$

where j is firm, t is the time, and Y_{jt} is the outcome variable of interest (e.g., exit, investment rate, and new debt issuance). $\text{FinancialShock}_{jt}$ is the firm-specific financial shock and is constructed as follows: I first compute the firm-level interest rate as the ratio of interest payment and total debt. Then I use German short-term interest rates as risk-free rates and take the difference between the firm-level interest rate and the risk-free rate. I use the firm-level interest rate spread to proxy the financial shock. If a firm has a small financial shock, it would typically find it not hard for external financing with respect to loan approval, cost of financing, loan term, etc. So a smaller interest rate can somewhat embody a more minor financial shock that a particular firm confronts. $\text{Productivity}_{j,t-1}$ is the lagged value of firm-level total factor productivity (TFP). I estimate the production function and obtain the TFP using the method described in Appendix C. I consider various measures of productivity. Controls_{jt} includes lagged firm controls and fixed effects. Specifically, I control the firm size and growth potential using total fixed assets (in logarithm) and sales growth rates. FE includes industry-year fixed effects, country fixed effects, and firms' age group fixed effects.

As the financial shock hits, the change in firm exit rate can be expressed as:

$$\begin{aligned} \Delta \Pr(\text{Exit}) &= \beta_2 (\text{Productivity} \times \Delta \text{FinancialShock}) + \beta_3 \Delta \text{FinancialShock} \\ &= \Delta \text{FinancialShock} \times (\beta_3 + \beta_2 \text{Productivity}) \end{aligned}$$

The differential impact on firm exit across productivity levels corresponds to the interaction term between the financial shock and productivity. The parameter of interest is the coefficient for the interaction term β_2. If the estimate is negative, then it suggests that with a larger financial shock, the rise in exit probability is higher for low-productivity firms. In contrast, if the coefficient estimate is positive, then low-productivity firms are less responsive to a larger financial shock in the exit margin. The reduced responsiveness of unproductive firms indicates that the "cleansing" effects of a crisis are smaller. As for other parameters, I expect $\beta_1 > 0$, which indicates that higher productivity is associated with fewer exits, more investment, and more new debt issuance. I expect $\beta_3 < 0$ as a negative financial shock increases the likelihood of the firm exit and decreases firm investment and financing activities.

The OLS estimation using the firm-level interest rate spread suffers the reverse causality bias. Financially weak firms with a bad reputation would be more likely to be charged a higher loan rate. To address the endogeneity concern, I instrument the interest rate spread with the average interest rate of all the other firms in the same industry, year, and country. The relevance restriction is satisfied as the leave-it-out average interest rate spread is highly correlated to firm-specific interest rates. For example, if a country is severely hit by a crisis, the interest rates of all firms in the country would have a similar magnitude.

5.2 Data

I combine a rich dataset of firm-level financial information and country-level aggregate performance from 2010 to 2014. This is a period of the European sovereign debt crisis. My base dataset is the AMADEUS. The dataset contains financial statement data for public and private companies in Europe. It also provides information on firm entry and exit. Earlier works that use the dataset find a reasonably close match (e.g. **?**) to those from census data by comparing aggregate employment. But there are still some issues in the AMADEUS. I describe the dataset and related concerns in detail in Appendix B.1. I adopt a cleaning procedure similar to **?**. But different from them, I did not impute employment for the firms. I describe the data cleaning procedure in Appendix B.2.

5.3 Results

Table 4 reports the regression results. Columns (1) to (3) correspond to the outcome variable of firm exit response, new debt issuance, and investment rate.

In Column (1), the interaction between productivity and interest rate spread returns a significantly positive coefficient value. As expected, the estimated coefficient of productivity is negative and the estimated coefficient of financial shock is positive. As predicted from Section 3, low-productivity firms have a reduced exit response to a financial shock. While a larger financial shock can result in a higher exit rate for both productive and unproductive firms, the impact on high-productivity firms is larger. The estimation results suggest that the financial shock does not induce a productivity-enhancing reallocation, which means that there is a survival of zombie firms.

With the estimates in hand, I can compute marginal effects. When the interest rate spread increases from 25 to 75 percentile, the exit probability for a typical high-productivity (at 75%-

tile) firm will increase by 0.079; the exit rate for a typical low-productivity (at 25%-tile) firm will increase by 0.056. When the interest rate spread increases from 1 standard deviation below the mean to 1 standard deviation above the mean, the exit probability for a typical high-productivity (1 standard deviation above the mean) firm will increase by 0.057; the exit rate for a typical low-productivity (1 standard deviation below the mean) firm will increase 0.139. The economic magnitude is considerable.

Table 4: Firm-level response to financial shock

	(1) Exit	(2) ΔLeverage	(3) Investment rate
FinancialShock	0.0245***	-0.424***	-0.112***
	(0.000670)	(0.0244)	(0.0332)
Productivity × FinancialShock	0.0104***	-0.0328	-0.0988***
	(0.000449)	(0.0190)	(0.0220)
Productivity	-0.0291***	0.0904*	0.525***
	(0.000872)	(0.0400)	(0.0432)
Controls	✓	✓	✓
R^2	0.505	.	0.005
N	2987507	1999750	1961710

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Errors are clustered at firm level.

For the response to new debt issuance and investment rates, the results are similar. Columns (2) and (3) show that high-productivity firms issue more new debt and invest more. When hit by a financial shock, firms take less debt and invest less. The interaction term has a negative coefficient estimate, suggesting in response to a negative shock, the decrease in new debt issuance and investment from high-productivity is larger than those of low-productivity firms. The results demonstrate that a financial crisis has larger negative effects on productive firms in both investment and financing activities.

5.4 Robustness

In the baseline estimation model, I adopt the continuous productivity measure and use the interest rate spread to proxy the financial shock. Here I consider several robustness checks of the estimation method.

Discrete productivity measure

The baseline specification uses the TFP estimate directly. In robustness, I consider the discrete productivity measure, a dummy variable of different values for each tertile group. Based on firm TFP estimates, I divide firms into three productivity groups: low, middle, and high according to the 25% and 75% threshold.

Table 5: Firm-level response to financial shock, with discrete productivity measure

	(1) Exit	(2) ΔLeverage	(3) Investment rate
FinancialShock	0.00502***	-0.368***	-0.141***
	(0.00103)	(0.0351)	(0.0303)
Low Productivity × FinancialShock	-	-	-
Medium Productivity × FinancialShock	0.0230***	-0.0395	0.104
	(0.000936)	(0.0307)	(0.0709)
High Productivity × FinancialShock	0.0315***	-0.131***	-0.0980***
	(0.00100)	(0.0369)	(0.0290)
Low Productivity	-	-	-
Medium Productivity	-0.0751***	0.185**	0.110
	(0.00186)	(0.0650)	(0.118)
High Productivity	-0.0912***	0.365***	1.095***
	(0.00196)	(0.0767)	(0.0620)
Controls	✓	✓	✓
R^2	0.506	.	0.005
N	2987507	1999750	1961710

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fixed effects include country, and year x industry group effects.

Errors are clustered at firm level.

Table 5 reports the regression estimation results. The results are qualitatively similar to the estimates with the continuous measure. The interaction between productivity and interest rate spread returns a coefficient of positive value, significant and increasing in magnitude when productivity rises.

Alternative financial shock measures

The baseline specification exploits the computed firm-specific interest rate spread to proxy the financial shock. In a robustness check, I consider other proxies: government bond spreads and a crisis dummy.

Government bond yields are retrieved from **?** and International Monetary Fund (IMF) International Financial Statistics (IFS) database. The OECD provides 10-year government bond yields percent per annum. The long-term government bond yield in IFS refers to one or more series representing yields to maturity of government bonds or other bonds that would indicate longer term rates. The crisis dummy equals 1 if (i) the year is between 2010 and 2012, and (ii) the country is Portugal, Italy, Ireland, Greece, or Spain (PIIGS). The table is not shown here but the results are robust with these aggregate measures.

Selected countries

Since different countries have different reporting requirements of firm information, I conduct a robustness check for a selected of economies. Following **?**, I restrict my sample to four countries: France, Italy, Spain, and Sweden. I repeat the above regressions for the reduced sample. I find that in general, the results do not change significantly.

6 Conclusion

In this paper, I construct an analytical bank lending model to investigate firm dynamics, in particular the exit decision, in response to a financial shock. I show that government policies (i.e., tight capital adequacy requirements) can lead weakly-capitalized banks to not disclose the true market value of assets on the balance sheet. Instead, they continue lending to otherwise insolvent firms. The continued financing keeps low-productivity firms surviving in the economy, dragging down aggregate productivity.

The model predictions suggest that it is possible to detect whether zombie firms exist in the economy using an estimation framework. If there is zombie lending, then an increase in financial shock leads to a smaller change in exit likelihood for low-productivity firms than for high-productivity firms, which indicates the survival of zombie firms. Although the empirical analysis is not a direct test of zombie lending, it provides a new method to examine the credit misallocation and selection from relative exit responses without ex-ante identifying zombie firms.

My paper demonstrates that rescue policies during a financial crisis might be ineffective and even counterproductive. These policy measures can ease banking lending positions but do not fully recover the bank from the shock, and they may incentivize banks to conduct zombie lending and under-report loan loss. Therefore, my paper argues for well-designed policies that could prevent banks' high risk-taking behaviors.

References

Acharya, V. V., Eisert, T., Eufinger, C., and Hirsch, C. W. (2017). Whatever it takes: The real effects of unconventional monetary policy.

Acharya, V. V., Lenzu, S., and Wang, O. (2021). Zombie lending and policy traps. Technical report, National Bureau of Economic Research.

Albertazzi, U. and Marchetti, D. J. (2010). Credit supply, flight to quality and evergreening: an analysis of bank-firm relationships after lehman. *Bank of Italy Temi di Discussione (Working Paper) No*, 756.

Barlevy, G. (2003). Credit market frictions and the allocation of resources over the business cycle. *Journal of monetary Economics*, 50(8):1795–1818.

Blattner, L., Farinha, L., and Rebelo, F. (2019). When losses turn into loans: The cost of undercapitalized banks.

Bruche, M. and Llobet, G. (2013). Preventing zombie lending. *The Review of Financial Studies*, 27(3):923–956.

Caballero, R. J. and Hammour, M. L. (1991). The cleansing effect of recessions. Technical report, National Bureau of Economic Research.

Caballero, R. J., Hoshi, T., and Kashyap, A. K. (2008). Zombie lending and depressed restructuring in japan. *American Economic Review*, 98(5):1943–77.

Faria-e Castro, M., Paul, P., and Sánchez, J. M. (2023). Evergreening.

Giannetti, M. and Simonov, A. (2013). On the real effects of bank bailouts: Micro evidence from japan. *American Economic Journal: Macroeconomics*, 5(1):135–67.

Hu, Y. and Varas, F. (2021). A theory of zombie lending. *The Journal of Finance*, 76(4):1813–1867.

Jaskowski, M. (2015). Should zombie lending always be prevented? *International Review of Economics & Finance*, 40:191–203.

Kwon, H. U., Narita, F., and Narita, M. (2015). Resource reallocation and zombie lending in japan in the 1990s. *Review of Economic Dynamics*, 18(4):709–732.

McGowan, M. A., Andrews, D., and Millot, V. (2017). The walking dead?

Schivardi, F., Sette, E., and Tabellini, G. (2017). Credit misallocation during the european financial crisis.

Schumpeter, J. A. et al. (1939). *Business cycles*, volume 1. McGraw-Hill New York.

A Model

Assumption A1 (Banks capital adequacy at t = 0)

$$1-\Phi(\varepsilon^*)+a\mathbb{E}(\eta)\geq \frac{D}{1-\kappa}$$

where ε^* is the threshold productivity for firms to repay the loan; $\Phi(\varepsilon)$ is the CDF of firm productivity; $\mathbb{E}(\eta)$ is the expected return of risky asset investment.

Under Assumption A1, banks satisfy the capital adequacy ratio requirement ex-ante at t=0.

Assumption A2

$$1-\Phi(\varepsilon^*)-\mathbb{E}(\eta)\geq 0$$

Under Assumption A2, banks have the incentive to supply a measure 1 of loan to firms, rather than invest all funds in the risky assets.

A numerical example

Suppose $\kappa = 0.1, a = 2, D = 1.1$. η is uniformly distributed over $[0,1]$. So $\mathbb{E}(\eta) = 0.5$ and $\Psi(\eta) = \eta$. Assume $\Phi(\varepsilon^*) = 0.15$. Assume for low-productivity firms, $\Phi(\varepsilon_L^*|\varepsilon_1 < \varepsilon^*) = 0.2, \Phi(\varepsilon_L^{**}|\varepsilon_1 < \varepsilon^*) = 0.22, R_L = 1.2, R_L' = 1.21$. Assume for high-productivity firms, $\Phi(\varepsilon_L^*|\varepsilon_1 \geq \varepsilon^*) = 0.1, \Phi(\varepsilon_L^{**}|\varepsilon_1 \geq \varepsilon^*) = 0.12$
Therefore Assumption A1 and A2 are satisfied:

$$\begin{aligned}1-\Phi(\varepsilon^*)+a\mathbb{E}(\eta) &= 1-0.15+2\times 0.5 = 1.85\\ &> \frac{D}{1-\kappa}=\frac{1.1}{0.9}=1.22\\ 1-\Phi(\varepsilon^*)-\mathbb{E}(\eta) &= 1-0.15-0.5=0.35>0\end{aligned}$$

Solve $\eta^* = \frac{1}{a}\left(\frac{D}{1-k}\right) = 0.61$. $\min\eta = \frac{1}{a}\left(\frac{D}{1-k}-1\right) = 0.11$.
Then

$$\begin{aligned}\eta^\star &= \frac{R_L[1-\Phi(\varepsilon_L^*|\varepsilon_1<\varepsilon^*)]-\mathbb{E}(\eta)}{a[1-\mathbb{E}(\eta)]} = 0.46 \in (\min\eta, \eta^*)\\ \eta^{\star\star} &= \frac{R_L'[1-\Phi(\varepsilon_L^{**}|\varepsilon_1<\varepsilon^*)]-\mathbb{E}(\eta)}{a[1-\mathbb{E}(\eta)]} = 0.46 \in (\min\eta, \eta^*) = 0.4438\end{aligned}$$

$$\Delta Pr(\text{Exit}|\varepsilon_1 \geq \varepsilon^*) = \Phi(\varepsilon_H^{**}) - \Phi(\varepsilon_H^*) = 0.02$$

$$\Delta Pr(\text{Exit}|\varepsilon_1 < \varepsilon^*) \begin{cases} = \Phi(\varepsilon_L^{**}|\varepsilon_1 < \varepsilon^*)\Psi(\eta^{\star\star}) - \Phi(\varepsilon_L^*|\varepsilon_1 < \varepsilon^*)\Psi(\eta^\star) \\ \quad -[\Psi(\eta^{\star\star}) - \Psi(\eta^\star)] = 0.0225, \text{ efficient} \\ = [\Phi(\varepsilon_L^{**}|\varepsilon_1 < \varepsilon^*) - \Phi(\varepsilon_L^*|\varepsilon_1 < \varepsilon^*)]\Psi(\eta^*) = 0.0122, \text{ zombie} \end{cases}$$

This example illustrates that

$$\Delta Pr(\text{Exit}|\varepsilon_1 \geq \varepsilon^*) < \Delta Pr(\text{Exit}|\varepsilon_1 < \varepsilon^*), \text{ efficient}$$
$$\Delta Pr(\text{Exit}|\varepsilon_1 \geq \varepsilon^*) > \Delta Pr(\text{Exit}|\varepsilon_1 < \varepsilon^*), \text{ zombie}$$

B Data

B.1 Data source

The firm-level data I use is the AMADEUS. It's compiled by the Bureau van Dijk Electronic Publishing (BvD), a private-sector organization that seeks to compile accounting information on companies from all over the world. AMADEUS is one of the BvD products that contains financials, stock prices, and ownership information for approximately 19 million public and private companies in 44 European countries. It also provides information such as region, date of the corporation, last year available, industry, and an indicator of whether a firm is quoted. Amadeus data comes entirely from regulatory filings of local governments. In addition, to including large listed firms, like the Compustat, it also contains private small companies. The data set has names, industries, addresses, and financial accounting information from detailed harmonized balance sheets, income statements, and profit and loss accounts of ïňĄrms. It includes variables such as industry codes, employment, sales, capital, profits, and value-added.

AMADEUS classifies firms into different size categories: very large, large, medium-sized, and small. Companies on Amadeus are considered to be very large when they match at least one of the following conditions:

(a) Operating Revenue $\geq$ 100 million EUR (130 million USD)

(b) Total assets $\geq$ 200 million EUR (260 million USD)

(c) Employees $\geq$ 1,000

(d) Listed

Companies on Amadeus are considered to be large when they match at least one of the following conditions:

(a) Operating Revenue $\geq$ 10 million EUR (13 million USD)

(b) Total assets $\geq$ 20 million EUR (26 million USD)

(c) Employees $\geq$ 150

(d) Not Very Large

Companies on Amadeus are considered to be medium-sized when they match at least one of the following conditions:

(a) Operating Revenue $\geq$ 1 million EUR (1.3 million USD)

(b) Total assets $\geq$ 2 million EUR (2.6 million USD)

(c) Employees $\geq$ 15

(d) Not Very Large or Large

Companies on Amadeus are considered to be small when they are not included in another category.

Since registration of some form of company accounts is a legal requirement of all incorporated firms under EU law, the list of names should be the population. **?** the data is reasonably comprehensive. For example, when comparing aggregate employment in the ORBIS populations to those from census data, we usually find a reasonably close match (e.g. Kalemli-Ozcan et al, 2015; **?**).

However, there are some concerns about the AMADEUS. A well-known problem in the dataset is that BvD has a policy by which ïňĄrms that do not report during a certain period are automatically deleted from their later vintage products, creating an artiïňĄcial survival bias in the sample. Moreover, employment is sometimes a voluntary item for smaller firms. **?** proposes one way to address these problems and maximize the coverage of firms and variables. They suggest accessing data in historical disks and using the AMADEUS and ORBIS (another BvD product) together. But due to the limited access to historical disks, the dataset I use here is still attained from the Wharton Research Data Service WRDS website. Considering the above concerns, I adopt a data-cleaning procedure and examine the validity of the sampling frame.

B.2 Data cleaning procedure

I delete firms when the consolidation variable `CONSOL` equals to C2, which refers to the consolidated statement with an unconsolidated companion. I delete all firms in the financial, government sectors, and non-classifiable which correspond to three-digit US SIC industry codes

[600, 700) and [900, 999]. Checking the variable `LSTATUS` in the data, I drop firms that are classified as "Inactive", "Dissolved", "In liquidation", and "Bankruptcy". Then I restrict the sample to firms to have positive employment, positive total assets, non-negative liabilities, and non-negative sales.

To conduct firm-level analysis, I construct the following variables:

(a) firm exit rate: using the AMADEUS variables `LASTYEAR`

(b) leverage: defined as the ratio of total debt and total assets

(c) sales growth rate:

(d) employment growth rate: using **?** formula

Other works using AMADEUS may use a firm's legal status to construct the exit variable. They label a firm exits if its status changes from "active" to "inactive". However, in my sample, firms' legal status does not change over time so I cannot exploit exit information from the variable `LSTATUS`. I also construct dummy variables for age groups and industry groups.

$$\text{InvestmentRate}_{jt} = \frac{\text{Investment}_{jt}}{\text{Capital}_{jt-1}}$$

$$\text{NewDebtIssuance}_{jt} = \Delta\text{Leverage}_t = \frac{\text{Debt}_t - \text{Debt}_{t-1}}{\text{Asset}_{t-1}}$$

I trim out observations of $\text{NewDebtIssuance}_{jt}$ below 1 and above 99 percentiles. Variables of TFPR, ΔLeverage, investment rates, and firm controls are all standardized.

B.3 Data summary

Table A1 provides information about the coverage of AMADEUS. The dataset is rich enough to have about 11 million observations each year. Most are private companies. In terms of firm size, over half of the firms are small in terms of employees, total assets, and operating revenue. And less than 1% firms are very large [1]. From 2010 to 2014, the share of small firms increases slightly while the percentage of very large firms are almost constant. The skewness of firm size suggests that the sample is likely to be representative of underlying firm distribution. Table A2 presents simple summary statistics from the cleaned sampling panel. Most variation of the panel is due to the cross-country heterogeneity.

[1] I use the AMADEUS-defined company size variable `compcate`. See Appendix **??** for details.

Table A1: Firm coverage of AMADEUS

Year	Num. of observations	Quoted firm	Companies (%)	
			Small	Very large
2010	11,193,472	5,659	61.4	0.336
2011	11,735,884	5,839	63.5	0.332
2012	12,228,851	5,924	71.5	0.333
2013	12,860,547	5,885	75.0	0.322
2014	12,071,159	5,937	78.6	0.336

Table A2: Firm level variables: summary statistics

	Mean	Median	Std.	Top 5%	Botton 5%
Leverage	0.747	0.615	1.158	1.593	0.009
R&D intensity	7.836	0.020	315.750	0.283	0
Sales growth	-0.165	0.014	1.293	0.692	-1.212
Employment growth rate	0.033	0	0.367	0.667	-0.5

C Production function estimation

I estimate firm-level productivity (TFPR), assuming that firm's output is given by a Cobb-Douglas production function:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{4}$$

where Y_{it} is firm value added, A_{it} is physical productivity, L_{it} is labor input and K_{it} is capital input. β_l and β_k are the output elasticity of labor and capital respectively. Labor input is measured as the costs of employees or the number of employees. Capital input is measured as the book value of fixed tangible assets. I deflate these nominal values by the industrial producer price index from the Eurostat and the IMF International Financial Statistics database. The estimation method I use is primarily based on **?** (OP), **?** (LP), **?** (WRDG), and **?** (ACF). Essentially, TFPR is constructed as the residuals from a Cobb-Douglas production function with capital and labor.

Specifically, I estimate the production function in logarithm:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{5}$$

where y_{it}, l_{it}, k_{it}, ω_{it} are the corresponding logarithm of Y_{it}, L_{it}, K_{it} and A_{it} , described in the text. ε_{it} is a production shock that is not observable by the firm before making their input decisions at time t.

The value-added variable uses `VA` from the AMADEUS. Assume that the capital stock is predetermined. So current period capital stock is the lagged value of tangible fixed assets `TFAS`. For labor input, I consider both the costs of employees `STAF`, and the headcount `EMPL`. The former may help adjust for differences in the quality of workers across firms. Following the literature of **?** and **?**, I construct proxy variables for productivity. The proxy variable is an investment in OP and intermediate inputs in LP. Investment is computed as the gross investment level, which equals the difference of capital stocks, adjusted with depreciation `DEPR`. I use material costs `MATE` as the intermediate inputs variable.

Since **?** uses the control function approach to address the endogeneity concern, follow-up works such as **?**, **?**, **?**, **?** and **?** improve the estimation procedure. I use the Stata command `prodest` developed by **?** to estimate the productivity using **?**. I also provide estimation results using the ordinary least square (OLS), fixed effects (FE), LP and ACF in Table A3. There are also different Stata programs, in addition to `prodest`. For example, **?** develop `levpet` **?** write a command `opreg`. But compared to these available user-written commands, `prodest`.

Estimation results of production function output elasticities are reported in Table A3. Panel 1 uses the number of employees as labor inputs and Panel 2 uses the costs of employees instead. Column (1) reports the results of an OLS linear regression of log output - value added - on free and state variables. In Column (2) I add country, industry, and year fixed effects. Column (3) to (5) uses Stata's command `prodest` using the approach of LP, WRDG, and ACF respectively. I use a third-degree polynomial approximation and also account for the firm exit. Given the endogeneity concern in the original OP method, I do not report estimates using the method.

From Table A3 we can see that the output elasticities estimates are similar across different approaches. The estimates of β_l are higher than 2/3 on average. The sum of β_l and β_k is smaller than 1, implying a decreasing return to scale production function at the aggregate level. I cross-check the estimation results with **?**. Using a similar dataset, they instead estimate the production function by country and industry. But their mean and median value of the estimates is similar to my results.

Table A3: Production function output elasticities

	OLS	FE	LP	WRDG	ACF
Panel 1: Number of employees					
Labor elasticity (β_l)	0.852	0.873	0.684	0.708	0.815
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	
Capital elasticity (β_k)	0.165	0.142	0.085	0.082	0.160
	(0.0003)	(0.0002)	(0.0007)	(0.0008)	
Panel 2: Costs of employees					
Labor elasticity (β_l)	0.751	0.715	0.688	0.724	0.783
	(0.0002)	(0.0005)	(0.0002)	(0.0001)	(0.0006)
Capital elasticity (β_k)	0.136	0.140	0.090	0.084	0.079
	(0.0004)	(0.0002)	(0.0003)	(0.0004)	(0.0007)

Standard errors in parentheses

Pooled over all countries and industries