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Abstract

This article explores the concept of zombie firms, tracing its theoretical origins and analyzing its implications for economic productivity and resource allocation. We review global standards for identifying zombie firms and advance a theoretical distinction between subsidized-credit, profitability-based, and hybrid definitions. The paper then focuses on five OECD countries as a case study, investigating the incidence of zombie firms and their anatomy. Empirically, we employ linear probability models and dynamic logit models to study the probability of a firm being classified as a zombie at any point in time. We find that firm history, returns on assets, productivity dynamics, and debt accumulation are the most relevant factors in modeling the current state of zombiness. Lastly, we use a Kaplan-Meier estimator to study the survival rates of viable and non-viable firms, and find that zombies are 8–10 p.p. less likely to survive. Our findings underscore the need for definitional harmonization, and point towards the role of management practices that monitor multiple performance indicators to mitigate zombie congestion and its negative impact on market efficiency.

JEL Classification: D24, G32, G33, L25
Keywords: Zombie Firms, ICR, Firm productivity, Financial performance, OECD countries

1 Introduction

The persistence of firms that remain active despite prolonged financial distress has become a central concern in debates on productivity, resource reallocation, and economic dynamism. Commonly labeled *zombie firms*, after the pioneering work of Kane (1987), these businesses are typically characterized by a sustained inability to generate sufficient profits to service their debt, yet they continue operating due to ongoing creditor support, regulatory forbearance, or institutional rigidities. The concept gained prominence in the study of Japan's "lost decade", where the survival of distressed firms was linked to the concept of *evergreen lending* and economic stagnation (Caballero et al., 2008; Hoshi, 2006). The global financial crisis of 2008-2010, the European sovereign debt crisis and, more recently, the COVID-19 pandemic, have raised concerns about *zombification* in advanced economies, particularly in light of extensive public guarantees and liquidity support (Banerjee and Hofmann, 2018; Pelosi et al., 2021).

From a theoretical standpoint, zombie firms challenge the Schumpeterian mechanism of *creative destruction*. In competitive markets, inefficient firms exit, allowing labor and capital to be reallocated towards more productive uses (Schumpeter, 1942). When this process is hindered, resource misallocation may persist, reducing aggregate productivity and dampening long-term growth (Hsieh and Klenow, 2009). Empirical evidence suggests that the presence of zombie firms can crowd out investment possibilities for healthier firms, distort credit markets, and reduce industry-level productivity growth (Caballero et al., 2008; McGowan et al., 2018). Moreover, weak insolvency regimes and consolidated bank–firm relationships might exacerbate the problem by softening budget constraints and delaying the exit of economically non-viable firms (Peek and Rosengren, 2005).

Despite growing interest, there is no universally accepted definition of zombie firms, as identification strategies vary significantly across studies. Some approaches typically rely on subsidized borrowing conditions (Acharya et al., 2019; Caballero et al., 2008; Hoshi, 2006), while profitability-based techniques use financial indicators of firm-level performance (Banerjee and Hofmann, 2018; McGowan et al., 2018; Schivardi et al., 2022). Other approaches combine multiple indicators to distinguish temporarily distressed firms from structurally non-viable ones (Acharya et al., 2019; Favara et al., 2024). The absence of a standardized definition substantially affects the reliability of estimates and cross-country comparability, underscoring the importance of methodological transparency, as argued by Pelosi et al. (2021). Despite recent

efforts in systemic literature review (Antić and Ichev, 2025; Shome and Verma, 2025), there is little research on the degree of comparability of different identification approaches. Hence, the first objective of this article is to synthesize the most widely used methodologies to identify zombie firms, advancing a theoretical distinction between subsidized-credit, profitability-based and hybrid approaches, challenging the validity of their assumptions, and proposing alternative methodologies. Secondly, the research aims to provide some descriptive evidence of the phenomenon in a cross-country setting, a dimension that, to the best of our knowledge, has remained unexplored (Antić and Ichev, 2025; Shome and Verma, 2025). Using ORBIS data for the period 2015-2024, we examine whether different definitions generate substantially different estimates of prevalence, sectoral distribution, and composition of the population of zombies. This comparison is essential to improve cross-country comparability and provide insights for scholarly discussions and policy design, acknowledging that accurate identification is necessary to design effective financial supervision mechanisms, and industrial policies that avoid the inefficient preservation of non-viable firms.

Following the work of McGowan et al. (2018), this research identifies zombies based on the firm's ability to repay its outstanding debt, i.e., its debt-servicing capacity. Empirically, we use a fixed effects linear probability model to study the probability for a firm to be classified as zombie at any point in time. We find evidence of strong persistence of the phenomenon, with past zombies more likely to be trapped in this state. Furthermore, low returns on assets, low productivity, and debt growth are associated with a higher probability of being identified as zombie. These results strongly align with the empirical evidence that zombies are, on average, less productive and kept alive by subsidized lending (Acharya et al., 2020, 2019; Caballero et al., 2008; Favara et al., 2024; Fukuda and Nakamura, 2011). Our findings are robust to a number of alternative specifications. Lastly, we study survival rates of healthy and unhealthy companies using the strategy of Banerjee and Hofmann (2022), who employ the Kaplan and Meier (1958) estimator. We find that zombies have higher observed market-exit rate than non-zombies of roughly 10 percentage points, consistently with previous empirical evidence (Banerjee and Hofmann, 2022; Pelosi et al., 2021).

The remainder of this article proceeds as follows. Section 2 traces the conceptual foundations of zombie firms and advances the theoretical distinction of the most widely used identification criteria. Section 3 presents stylized facts of the phenomenon of zombie firms in the OECD

countries of interest. Section 4 presents data and descriptive statistics, while the empirical specification and the main findings are discussed in Section 5. Section 6 concludes with some final remarks and insights for future research.

2 Defining and Identifying Zombie Firms: A Global Perspective

The concept of *zombie firms* has gained prominence in economic and financial literature due to its implications for productivity, resource misallocation, market and institutional efficiency. Initially associated and developed with Japan's prolonged economic stagnation in the 1990's (Caballero et al., 2008), zombie firms have since been studied in various economies, particularly in the aftermath of the Global Financial Crisis and the Covid-19 pandemic. Identifying these firms remains analytically challenging, as methodologies diverge across countries, data structures, and institutional frameworks. Therefore, the present section aims to propose a structured review of the academic literature and empirical strategies used to define and detect zombie firms. We begin with a historical and definitional overview of the concept of zombie firms and follow with an analysis of key identification criteria, proposing a methodological classification into subsidized credit, profitability-based, and hybrid approaches. Lastly, the section concludes with an overview of global methodological approaches to assess the persistence of distressed companies in economies.

2.1 Theoretical Origins and Conceptual Foundations

The term *zombie* was first introduced in economic analysis by Kane (1987), who used it to describe economically unviable firms that remain in the market due to external support from financial institutions and government subsidies. Such firms should exit the market because of operational inefficiencies, but continue to operate and tie up resources that could be better allocated. Hoshi (2006) adapted the definition to the analysis of the economic behavior of Japanese companies, referring to *"...those firms that make extremely low interest payments given their levels of debt"*. The author emphasized that these firms were not simply unprofitable, but were being actively supported through subsidized loans. Hoshi's conceptual and empirical framework provided the later financial parameters and channels to identify zombie firms.

Caballero et al. (2008) popularized and expanded this concept in their seminal study on Japan's economic stagnation. They formalized the idea of *evergreen lending*, referring to the bank practice of extending or restructuring loans to avoid recognizing losses of unprofitable businesses, disrupting the systematic exit of non-viable firms. Subsequent studies have sought to expand the concept of zombie firms beyond Japan's banking crisis, and develop generalized criteria applicable to multiple economic and institutional contexts. Among others, McGowan et al. (2018) contribute to the literature by examining OECD settings, finding that firms tend to persist in economies characterized by weak insolvency regimes, inefficient banking systems, and limited labor mobility. These structural rigidities hinder an efficient reallocation of resources, suppressing the Schumpeterian process of *creative destruction* (Schumpeter, 1942). Favara et al. (2024) add a U.S. perspective showing that the pandemic-driven recession and its triggers on fiscal and prolonged monetary support led to a rise in zombie firms, especially among companies with easier access to capital markets. In a similar manner, Pelosi et al. (2021) examine the Italian landscape and demonstrate the persistence of zombies in a context of state-backed credit guarantees or bank forbearance, and they suggest that unprofitability alone is an incomplete indicator of the unviability of firms. More recent studies (Albuquerque and Iyer, 2024; Ascani and Nair, 2025) show the need for a multifaceted definition of zombie firms to reduce misclassification errors, and delimit the scope of the phenomenon.

2.2 Empirical Identification Criteria: Subsidized Credit, Profitability-Based and Hybrid Approaches

Despite the most recent efforts in systematic literature review, which also employ bibliometric approaches, the identification of zombie firms remains inherently complex, as these entities exist on a spectrum of financial distress, profitability, and productivity inefficiencies. While the conceptual definition generally indicates businesses that are unprofitable, yet continue to operate in the market due to different forms of support, there exist many operational definitions that are based on several accounting indicators. Recent studies (Antić and Ichev, 2025; Shome and Verma, 2025; Upadhyay and Baag, 2024) converge in identifying multiple criteria to detect zombie firms, including a variety of indicators of profitability, productivity, debt-servicing capacity, risk of default, and access to subsidized credit. The authors strongly emphasize the need to standardize the operational definitions of zombie firms, which would represent a first

step in ensuring a higher degree of comparability in the study of the phenomenon.

After a comprehensive review of the literature on the phenomenon of zombie firms, this section proposes a methodological classification of the most widely used identification approaches into subsidized-credit definitions, profitability-based definitions, and hybrid approaches. This classification is purely theoretical and only aims to group comparable techniques together, discussing the advantages and disadvantages of each approach, and offering nuanced insights on the methodologies to detect the existence of nonviable firms in the market.

2.2.1 Subsidized-Credit Approach

Subsidized-credit definitions follow the seminal work of Caballero et al. (2008), according to which the classification is based on the assessment of whether the firm is receiving subsidized loans. To detect zombie firms, the authors compute the interest rate gap as the difference between the actual interest rate paid by a generic firm i at time t, $r_{i,t}$, and a conservative lower bound of advantageous interest rates, $r^*_{i,t}$. Whether the gap is negative, that is, $r < r^*$, the firm is classified as zombie[1]. The Caballero-Hoshi-Kashyap (CHK) method has shaped the literature on the identification of zombie firms with the prominent role of discounted lending, as in Fukao and Kwon (2006) and in Giannetti and Simonov (2013). A similar approach is also followed by Acharya et al. (2019), who compute the hypothetical interest rate benchmark using the median interest rate paid by public AAA-rated firms. A firm is classified as zombie whether (i) the interest rate gap is negative; (ii) firms are rated BB or lower; and (iii) the same syndicate of banks has already provided a loan to the firm[2].

Subsidized-credit approaches align the conceptual notion of zombies with their operational definitions. If Kane (1987) used the term zombie to define non-viable firms that are kept alive in the market thanks to various forms of support, detecting zombies through the lens of subsidized lending might seem natural, if not tautological. However, the first studies on the matter (Caballero et al., 2008; Hoshi, 2006) have already warned of the data constraints that they face. The authors argue that what they observed about the firms' debt structure was

[1]A second approach developed by Caballero et al. (2008) resorts to an indicator function to define a fuzzy subset of zombie firms, introducing a more robust technique to misclassification of non-zombies.

[2]The intuition behind the third condition is that whether the syndicate composition has remained constant, this entails a situation of credit forbearance or consolidated firm-banks relationship. As argued by Acharya et al. (2019), this condition holds in 95% of the cases.

the type of debt instrument (e.g. short-term loans, long-term loans, bonds, etc.) but not the exact interest rates paid on the obligations. As suggested by McGowan et al. (2018), subsidized-credit definitions require detailed information on the debt composition of each company, making them difficult to implement for all types of businesses. Indeed, publicly quoted firms have the obligation to report their debt structure, while information for small private firms is far less accessible (Banerjee and Hofmann, 2022).

Furthermore, Schivardi et al. (2022) argue that in subsidized-credit definitions, it is difficult to disentangle evergreen lending (i.e., the practice of lending at discounted rates) from low central bank interest rates, which might occur in periods of economic stagnation. Lastly, we suggest that this approach might suffer from a lower degree of comparability in a cross-country context (Andrews et al., 2017). Indeed, countries differ in terms of financial reporting obligations, insolvency regime characteristics, and credit support policies, which would undermine the reliability of results when the same definition is applied to several countries. For example, more stringent insolvency regimes might impose additional requirements on banks to grant credit to borrowers. Given the limitations of these definitions, several other identification techniques have been proposed in the literature.

2.2.2 Profitability-Based Approach

Profitability-based definitions rely on firm-level accounting indicators of performance and profitability. The most widely used metric is the Interest Coverage Ratio (ICR), computed as Earnings Before Interests and Taxes (EBIT) over total interest payments, which reflects the firm's ability to pay interest on its outstanding debt, commonly defined as *debt-servicing capacity*. The key contribution is represented by the paper of McGowan et al. (2018), where firms are defined as zombies if they have an interest coverage ratio below one for three consecutive years and are over 10 years of age. As argued by the authors, the age restriction is necessary to prevent young and innovative start-ups from being misclassified as zombies. Grounding its recognition on a higher degree of comparability, this approach has been largely used in subsequent works (see, among the others, Andrews et al. (2017) and Costa et al. (2022)). Rodano and Sette (2019) challenge the accuracy of EBIT in the computation of the ICR, and opt for EBITDA[3]. They argue that companies that have invested heavily in a particular year will ex-

[3]Earnings Before Interest, Taxes, Depreciation and Amortization.

perience high depreciation in the subsequent years, resulting in lower EBIT, while EBITDA remains unchanged. This critique is reinforced by Pelosi et al. (2021), who use both EBIT and EBITDA as alternative strategies to identify zombie firms. In their work, the authors classify firms as zombies if their EBIT (EBITDA) is either lower than the interest expenses (ICR<1) or negative for three consecutive years, and the firm is at least 10 years old. More recently, Ascani and Nair (2025) show that EBITDA-based measures deliver more conservative estimates of the zombie phenomenon, as earnings are generally higher when computed through EBITDA rather than EBIT. Building on the ICR as a measure of profitability, two additional approaches are worth mentioning. First, Banerjee and Hofmann (2018) define zombie companies based on a persistent lack of profitability and low stock market valuation. In their work, a firm is classified as zombie whether (i) it has an ICR lower than one, and (ii) its Tobin's Q is below the median value of the sector for (iii) two consecutive years; the second condition replaces the age restriction of McGowan et al. (2018), introducing the requirement that firms must have low future potential profits to be classified as zombies. However, we argue that the approach of Banerjee and Hofmann (2018) suffers of two potential caveats: first, it has low external validity, as the Tobin's Q, calculated as the ratio of asset market value over replacement costs, is available only for listed firms (Favara et al., 2024); second, the two-years frame might increase the probability of misclassifying viable firms under restructuring. The second approach has been developed by Albuquerque and Iyer (2024) and Favara et al. (2024), who classify firms as zombies if: (i) ICR<1, (ii) their leverage is above the median value of the country-industry pair, and (iii) they have negative real sales growth[4] for (iv) at least two consecutive years. Some contributions depart from the use of ICR as an indicator of profitability, relying on Returns on Assets (ROA) and net investments. Among others, Storz et al. (2017) identify zombie firms as those companies that have: (i) ROA<0, (ii) net investments<0, and (iii) debt-servicing capacity, calculated as the ratio of EBITDA over total financial debt, below the threshold of 5%, for (iv) at least two consecutive years. The authors argue that subsidized-credit techniques imply non-trivial definitions of benchmark interest rates in case of non-listed companies, whereas ICR-based definitions contradict the fundamental assumption of Caballero et al. (2008) that zombie firms

[4]The authors argue that sales growth is a reliable predictor of future profitability, as in Whited and Wu (2006).

receive subsidized loans. Schivardi et al. (2022) reinforce this critique using ROA[5] as indicator of profitability, and leverage to measure debt exposure. Accordingly, zombie firms have: (i) the three-year moving average of ROA below the prime rate[6], and (ii) leverage above the threshold of 40%[7].

2.2.3 Hybrid Approach

To address the limitations of single-criterion models, hybrid approaches combine subsidized-credit and profitability-based definitions. Hence, these strategies integrate multiple perspectives in the identification of zombie firms.

One of the first strategies has been developed by Fukuda and Nakamura (2011) and Nakamura and Fukuda (2013), who broaden the CHK method by adding two extensions (hereinafter, FN-CHK). They argue that the original CHK model might misclassify healthy firms as zombies, especially in a context of quantitative easing, and fail to classify non-viable firms as zombies, in cases where evergreen lending occurs at the interest rates prevailing in the market. For the former issue, they introduce a profitability criterion, where those firms that present an EBIT above the prime rate are excluded from the classification, while for the latter, they rely on the evergreen lending criterion, classifying as zombies only highly-leveraged companies, whose borrowings have increased from the previous to the current year. Shen and Chen (2017) have incorporated the evergreen lending criterion from the FN-CHK model and added the condition that firms must have negative annual actual profits for three consecutive years. As argued by the authors, the use of actual profits allows for the exclusion of government subsidies, which are likely to play a major role in balance sheet data of Chinese firms. However, we highlight that this method might lead to different results in countries where state subsidies are less relevant and firms are artificially kept alive mainly through banks' discounted loans.

More recently, Favara et al. (2024) have used a double definition of zombie firms: the first approach incorporates profitability measures such as high debt exposure, limited debt-servicing

[5]ROA is computed either as EBIT or EBITDA over total assets, integrating the contribution of Rodano and Sette (2019) and Pelosi et al. (2021) on the topic.

[6]The prime rate is the three-year moving average interest rate paid by the safest borrowers, i.e., those with an Altman Z-Score of either 1 or 2 out of 9 (Altman et al., 2024).

[7]The threshold corresponds to the median value of leverage for firms that exited the market in the two following years. Some alternative definitions of Schivardi et al. (2022) use 60% as a threshold for leverage.

capacity, and negative sales growth; the second approach follows Acharya et al. (2019) in combining speculative-grade rating and receiving subsidized credit at interest rates below those charged to the safest companies. The authors argue that the two definitions are complementary and allow researchers to reduce mistakes in the detection of non-viable companies.

As hybrid approaches integrate aspects from both subsidized-credit and profitability-based definitions, they are more robust to misclassification errors. Since they employ various definitions of subsidized lending, they are generally in line with the conceptual definition of zombie firms. At the same time, they also employ profitability criteria, identifying firms whose performance is structurally weak. Despite their robustness, hybrid approaches are not exempted from some criticism. Indeed, using articulated definitions inevitably requires accurate balance sheet data and information on the debt structure of the firm. This could, in principle, reduce their validity in cases where accurate data collection is more difficult, forcing the choice of cheaper definitions.

2.3 Cross-Country Methodologies and Institutional Sensitivities

The operationalization of zombie identification varies significantly across countries due to differences in data availability, institutional frameworks, and policy environments. OECD countries have developed detailed financial databases that support micro-level classification based on ICR and other profitability-based definitions (McGowan et al., 2018). Identification that relies on subsidized-credit approaches is possible only with detailed information on the debt composition of the firms, which is more likely to occur for listed companies (Caballero et al., 2008; Hoshi, 2006). Thus, it does not include small and medium-size corporations, which represent the large majority of the European industrial demography (OECD and Eurostat data).

Methodologically, we can identify three broad approaches that have been developed in the literature on cross-country detection of non-viable businesses. The first strategy is based on accounting thresholds, including interest coverage ratio, return on assets, and debt exposure. Although straightforward, this method often lacks robustness across different industries and is vulnerable to earnings management (Banerjee and Hofmann, 2018). As for the latter issue, the authors argue that financial reporting might suffer from arbitrary window dressing when firms artificially alter their balance sheets to meet specific regulatory thresholds.

The second approach involves econometric models with panel data regression and fixed

effect specifications to control for unobserved heterogeneity and firm-specific dynamics. The advantage of longitudinal data lies in their ability to account for firm-level business dynamics, such as transitioning back to healthy status, or exiting the market, both of which trigger a declassification from zombie status (Pelosi et al., 2021). Longitudinal studies thus enable researchers to investigate the determinants of zombification, while exploring corporate dynamics once a firm is initially classified as a zombie. For example, McGowan et al. (2018) use such models to demonstrate the persistence of zombie status and its correlation with cyclical dynamics: employing a three-year window to control for the persistence of financial distress, the main empirical specification includes country-sector-year fixed effects that further control for the potential effects of business cycles. Similarly, Pelosi et al. (2021) compute transition matrices that contain the status over a three-year horizon for each firm in a given year, accounting for demographic dynamics; accordingly, each company can be categorized as healthy, zombie, or out of the market[8]. As one-third of the firms transition back to healthy status, the authors suggest interpreting the identification of zombie firms with caution. The third approach developed by the literature is, by far, the most recent, thereby requiring further validation by future studies. This strategy relies on the application of machine learning classifiers trained on large datasets to detect non-linear interactions and complex patterns among financial, productivity, and institutional variables, thus improving the predictive accuracy of zombie firm identification (Brahmana, 2025; Wang et al., 2025). While promising, this methodology requires access to large and granular databases that contain accurate information on balance sheet and income statement data. This might be inherently complex considering that the coverage and representativeness of most databases remain highly uneven in cross-country contexts.

3 Zombie Firms in OECD Countries: Stylized Facts and Institutional Context

Shome and Verma (2025) argue that a large part of the studies on zombie firms focus on Asian economies rather than Europe. The authors show that the geographical scope of the research is highly skewed, with 78 studies related to Asia, mostly in the context of China (n = 57) and

[8]As indicated by Pelosi et al. (2021), a firm can be out of the market if (i) it has started a bankruptcy procedure, (ii) it is signaled as in liquidation, or (iii) it has been canceled from the Firm Register.

Japan (n = 16), 24 to Europe, and 10 to America. Moreover, they find that only 15 studies out of 132 relate to a multi-country context. Similarly, Antić and Ichev (2025) outline sharp discrepancies in the regional commitment to research, with China and Japan standing out as the most productive countries in terms of both total publications and institutional affiliation of corresponding authors. In their analysis, only a few studies adopt a cross-national perspective, including the seminal works of Acharya et al. (2019) on GIIPS countries, and Banerjee and Hofmann (2018) and McGowan et al. (2018) on OECD economies (Antić and Ichev, 2025). Although European countries represent a unique laboratory for the study of zombie firms due to their institutional framework, bank-oriented financial markets, and rigid labor market regulations (Schivardi et al., 2022), the geographical scope of the research has been limited, highlighting the need for further studies.

Empirical studies converge in identifying some stylized facts about the prevalence of zombie firms. McGowan et al. (2018) show that the share of zombie firms varies significantly between countries, ranging from around 3% in France and Finland, to 6% in Italy and 10% in Spain in 2013. According to their findings, the share of zombie companies has increased in Belgium, Spain, and Italy from 2007 to 2013, while remaining relatively stable in Finland, France, the United Kingdom, South Korea, Sweden, and Slovenia. Furthermore, the authors show that the share of physical capital sunk in zombie firms in 2013 ranges from 19% in Italy to less than 5% in Slovenia, while the share of labor sunk spans from 14% in Belgium to around 5% again in Slovenia.

In this regard, Ascani and Nair (2025) argue that estimates of the prevalence of zombie firms vary according to different identification approaches. The authors use Italian data and argue that EBITDA-based measures deliver more conservative estimates of the incidence of unhealthy companies among total active firms, with shares ranging from 2 to 4 percent. When zombies are identified through EBIT-based measures, the share increases to 4–7 percent. This discrepancy is consistent with the fact that EBITDA adds back depreciation and amortization to EBIT, generally resulting in a higher value.

With regard to the anatomy of economically non-viable firms, Banerjee and Hofmann (2022) show that the mean values of labor productivity and total factor productivity of zombie companies are around half those of their healthy counterparts. Distressed companies also exhibit negative cash flow and interest coverage ratios, and higher book and market leverage relative

to healthy firms, particularly within the top quartiles of the distribution. Furthermore, the authors argue that zombies face a probability to exit the market of around 9 percent, compared to a mere 4 percent for non-zombies. Similarly, Albuquerque and Iyer (2024) argue that non-viable firms tend to invest less, are less productive, less profitable, and face a significantly higher risk of default. Schivardi et al. (2022) use Italian data for the period 2004–2013 and show that GDP growth and the share of zombie firms are negatively correlated. Moreover, the authors argue that the share of zombies that have exited the market because of default and bankruptcy stands at 12.8 percent, compared to 3.3 percent for non-zombie firms, while the proportion of terminated bank-firm relationships is slightly higher for zombies (11 percent against 9 percent). On the topic of lending and support measures, Pelosi et al. (2021) argue that during the Covid-19 pandemic, non-viable firms have been less likely to obtain a grant or to put debt into moratorium, while being more likely to obtain fully guaranteed loans due to being classified as low-quality borrowers.

Recent studies have also provided evidence on the critical role of legal and regulatory contexts in shaping the incidence of zombie firms. For example, weak insolvency regimes and lengthy bankruptcy procedures allow non-viable firms to continue operating despite clear signs of financial distress (Andrews and Petroulakis, 2019). The authors present evidence that improvements in bank health are likely to be associated with a reduction in the share of zombie firms, particularly in areas with more efficient insolvency systems. Similarly, Schivardi et al. (2022) suggest that in areas with a higher concentration of under-capitalized banks, zombie firms face a lower probability of market exit, whereas negative spillovers on healthy firms are negligible. This finding partly challenges a well-established strand of literature which argues that healthy firms suffer from credit misallocation and the crowding out of investment possibilities due to the rising share of unprofitable companies (Acharya et al., 2019; Caballero et al., 2008; Ren et al., 2023).

Therefore, we can conclude that key empirical regularities emerge from the existing literature. In general, consolidated bank-firm relationships (Acharya et al., 2019; Caballero et al., 2008; Pelosi et al., 2021), together with the structural characteristics of insolvency regimes, might amplify the prevalence of zombie firms. This is particularly evident in countries where inefficient bankruptcy and liquidation procedures hinder the Schumpeterian process of creative destruction, obstructing the market exit of economically and financially distressed businesses.

4 Data and Descriptive Statistics

4.1 Data Source

The analysis relies on ORBIS as its primary data source. Developed and distributed by Bureau van Dijk, this database comprises detailed firm-level financial statements, demographic, managerial, and commercial information from approximately 650 million capital companies. Covering small, medium, and large enterprises, these comprehensive data facilitate an in-depth analysis of corporate performance, financial health, and economic status through a rich longitudinal evaluation of entities from selected OECD countries of interest.

Table A1 in the Appendix outlines the sequential steps of the data retrieval strategy. First, companies are selected regardless of their operating status, thereby including active, inactive, and unknown-status companies. Second, the geographical scope is initially restricted to a selected set of European economies: Germany, Spain, France, Italy, Poland, Portugal, Sweden, and the United Kingdom. In line with McGowan et al. (2018), the sample is restricted to non-farm non-financial business sectors (NACE Rev.2 codes 10-83, excluding 64-66). This strategy omits agriculture, forestry and fishing (codes 01–03), the mining industry (codes 05–09), as well as public administrations and related activities, education, cultural and recreational activities, arts, entertainment and membership organizations (codes 84 and above). Furthermore, we restrict the sample to companies that exclusively report unconsolidated accounts (ORBIS Consolidation Code U1), to avoid double-counting of corporate activities, which might be the case if both the consolidated account of the parent-company and the unconsolidated accounts of its subsidiaries coexist in the database (McGowan et al., 2018). Lastly, we limit the selection to companies with a known value of financial expenses, EBITDA, and the number of employees in the latest available fiscal year. This criterion excludes companies with non-available recent financial information, allowing to retain only those observations that are more likely to report the core financial indicators required for their main identification as zombies (Ascani and Nair, 2025; McGowan et al., 2018; Pelosi et al., 2021).

Although the initial selection included eight OECD countries, a preliminary assessment of data quality has highlighted non-negligible issues. First, ORBIS coverage is highly uneven across most countries, potentially resulting in a non-random composition of the population of interest. Moreover, computational constraints posed significantly challenges in managing ex-

ceptionally large and complex datasets. Hence, for the purpose of this preliminary study, only companies from Italy, France, Spain, Germany, and the United Kingdom have been preserved. These five countries represent the five largest economies in Europe in terms of nominal GDP (excluding Russia, for which ORBIS coverage is not assured). Focusing on larger economies increases the number of observations available for each country and improves statistical precision, but it does not eliminate concerns about non-random ORBIS coverage.

The final sample includes data for 1,151,553 capital companies across the five selected countries for the years 2015–2024. This ten-year window enables a comprehensive longitudinal analysis of firms that endured diverse economic challenges. In line with the standard practice of empirical analysis of zombie firms (Albuquerque and Iyer, 2024; Ascani and Nair, 2025; Banerjee and Hofmann, 2022; Pelosi et al., 2021), a decade-long analysis is sufficiently large to observe dynamics of zombification, including potential recovery of previously unhealthy firms, and mapping market exits. In addition, the outbreak of the Covid-19 pandemic at the beginning of 2020 bisects the sample into two symmetric sub-periods, laying the empirical foundations to investigate the effects of the pandemic-induced economic crisis on the population of interest.

The dataset comprises a comprehensive set of balance sheet items enabling the reconstruction of key financial and economic indicators to assess corporate performance in terms of both productivity and profitability[9].

4.2 Data Descriptive

4.2.1 Identifying zombie firms

As noted in Chapter 2.2, the identification of zombie firms is inherently complex for a number of reasons. First, these companies exist on a spectrum of economic and financial distress, and the absence of a universally accepted framework precludes an unequivocal classification (McGowan et al., 2017). Moreover, the identification strategy heavily depends on the availability of balance

[9]Variables representing monetary values were initially retrieved in nominal terms in US dollars and subsequently deflated using macrosector-specific price deflators. To this end, we used data from the Bureau of Economic Analysis of the U.S. Department of Commerce. Specifically, we used chain-type price indexes for gross output by industry, referring to 2017 as the base year. This strategy allowed us to use deflators that refer, respectively, to manufacture (NACE Rev.2 10–39), construction (NACE Rev.2 41–43), and private services (NACE Rev.2 45–83). Ultimately, this choice considers different price variations across macrosectors, which might represent a source of unobserved heterogeneity if not taken into account.

sheet data and indicators of financial performance. Indeed, researchers face a trade-off between the need for granular information and the accessibility or manageability of large datasets. In our case, we do not have access to detailed data regarding the composition of debt for most of the observations. Therefore, this constraint immediately excludes any attempt to implement an approach à la Caballero et al. (2008), which would require accurate data on debt structure and interest expenses.

Focusing solely on profitability-based methodologies, which can be implemented more easily given the set of balance sheet indicators at our disposal, we resort to the approach proposed in the seminal work of McGowan et al. (2018) and extend it by integrating subsequent contributions.

Firms are defined as zombies if they exhibit an interest coverage ratio below one for three consecutive years and are at least 10 years old (McGowan et al., 2018). Incorporating the convincing argument of Rodano and Sette (2019), we calculate the interest coverage ratio using both EBIT and EBITDA. This choice is strategic in ensuring a first comparison of closely related definitions, as is common practice in the most recent literature (see, for example, Ascani and Nair, 2025). Formally:

$$\mathrm{ICR}_{it}^{\mathrm{EBITDA}} = \frac{\mathrm{EBITDA}_{it}}{\mathrm{InterestPayments}_{it}} \tag{1}$$

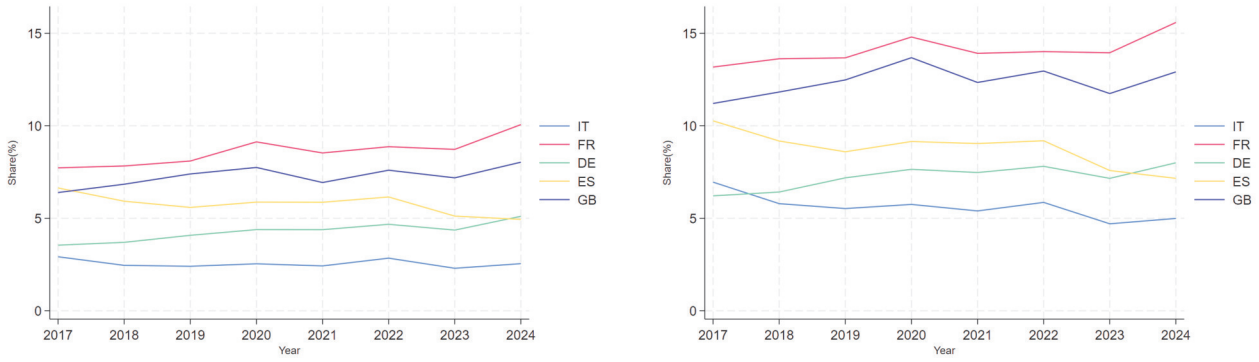
$$\mathrm{Z}_{it}^{\mathrm{EBITDA}} = 1 \text{ if } \begin{cases} \mathrm{ICR}_{it}^{\mathrm{EBITDA}} < 1 \text{ in } \{t-2, t-1, t\} \\ \mathrm{Age} > 10 \end{cases} \tag{2}$$

In the computation of the interest coverage ratio, the denominator is represented by total interest payments (or total financial expenses), which, in our dataset, reports a non-negligible number of missing values. To overcome this issue, following the work of Pelosi et al. (2021), we also classify as zombies those companies where EBITDA (or EBIT) is negative for three consecutive years and have at least 10 years of age. Formally:

$$\mathrm{Z}_{it}^{\mathrm{EBITDA}} = 1 \text{ if } \begin{cases} \mathrm{EBITDA}_{it} < 0 \text{ in } \{t-2, t-1, t\} \\ \mathrm{Age} > 10 \end{cases} \tag{3}$$

This choice enables the inclusion of both firms whose margins are not sufficient to repay their debt, i.e., they have a low debt-servicing capacity (McGowan et al., 2018), and firms experiencing a prolonged condition of negative earnings (Pelosi et al., 2021). Fig. 1 shows the

share of zombie companies among total firms over the period 2017-2024 for the five countries of interest, where ICR is computed with EBITDA in panel (a) and with EBIT in panel (b)[10]. Data for Italy (IT) are strictly comparable to Ascani and Nair (2025) as we meticulously follow the same methodology: similarly, we estimate a share of zombie firms around 2–3% when ICR is calculated through EBITDA, and around 5–6% when calculated through EBIT. Similar results for Italy are also obtained by Pelosi et al. (2021), who report a share of zombies around 3–5% for the period 2017-2019. As shown by Fig. 1, France (FR) and United Kingdom (GB) have the highest share of zombie firms, ranging from 6 to 8% for the former and from 8 to 10% for the latter (10–15% when considering EBIT-based measures in the right panel). Spain (ES) reports a share of around 6% up to 2022, and a significant decline of 1 percentage point in the last two years. Lastly, Germany had a share below 4% in 2017 (around 6% for EBIT) that has slowly increased up to 5% in 2024 (7.5% for EBIT). Estimates for countries different from Italy are less easily comparable due to different identification approaches used in previous studies. We resort to Albuquerque and Iyer (2024), who estimate the share of zombie firms to diverge when considering listed and private firms. The authors find a share of 8–10% among listed companies and 2–4% among private ones for France and United Kingdom for the period 2017-2022. Accordingly, we argue that our estimates might be upwardly biased due to large listed firms being overrepresented for these countries in the ORBIS dataset, as confirmed by the analysis of dimensional classes discussed below in the present section.



(a) EBITDA

(b) EBIT

Figure 1: Share of zombie firms among total firms (%)

[10]Observations for 2015 and 2016 are mechanically unavailable because the zombie identification criteria require a three-year rolling window. Given that our dataset contains information starting from 2015, the first year for which estimates can be computed is 2017.

Beyond the specific definitions used to identify zombie firms, a second dimension of analysis is represented by the shares of capital and employment sunk in zombie firms[11], which might be informative about the fraction of production inputs tied up in unprofitable businesses. Fig. 2 reports data for 2017 and 2024, representing the first and last years for which zombie estimates are available in our analysis. Both EBIT- and EBITDA-based definitions are employed, denoted by light and dark bars, respectively.

Interestingly, Italy in 2017 is the only country where the share of capital sunk in zombie companies is significantly higher than the share of zombies under both definitions. This result suggests that a relatively larger fraction of physical capital is misallocated toward unprofitable and financially distressed companies, in line with studies on the crowding out of investment opportunities for healthy firms (Acharya et al., 2019; Caballero et al., 2008; Ren et al., 2023). These findings for Italy are substantially in line with those of Ascani and Nair (2025), who find an identical pattern for the period 2012–2018. Similarly, Pelosi et al. (2021) estimate that for Italy, in 2019, the incidence of zombie firms was around 3–5% of active firms, 4–10% of total assets, and only 2–4% of active workers.



(a) 2017 (b) 2024

Figure 2: Share of zombie firms, employment and capital (%)

The comparison of the two panels suggests that the share of zombie firms increased after the Covid-19 pandemic in Germany, France, and the United Kingdom. In contrast, Italy and Spain experienced a modest decline in the share of zombie companies, which might reflect the extensive policy support deployed during the pandemic-driven recession. Indeed, this divergence lines up

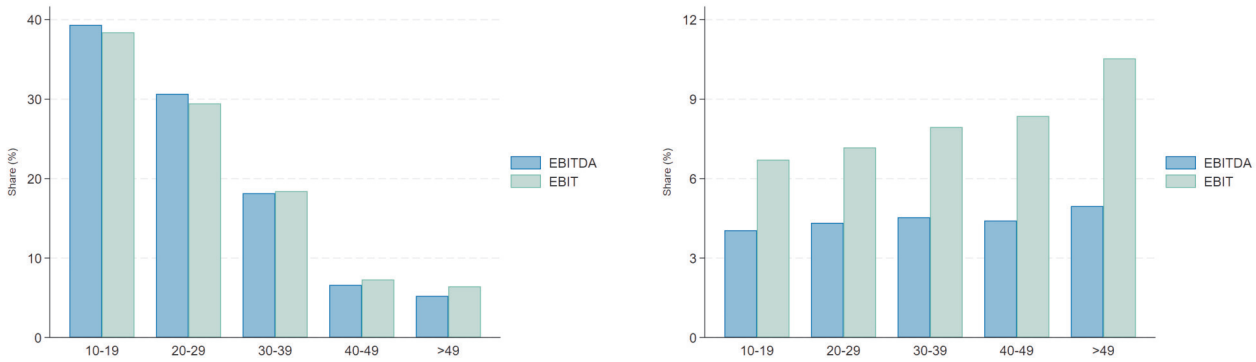
[11]The share of capital is computed as the ratio of physical capital employed in zombie firms over total physical capital, while the share of employment is the same but for the number of employees (Ascani and Nair, 2025).

with cross-country differences in emergency credit guarantees and firm selection mechanisms (McGowan et al., 2018), which however warrants further investigation in future research.

To study the distribution and composition of the zombie population, we analyze it employing different dimensions - specifically age, size, and industry - aiming to offer a comprehensive overview of the phenomenon.

4.2.2 Age

First, following Ascani and Nair (2025), we categorize firms into five age classes[12]. Figure 3 presents aggregate data for all countries over the entire period of analysis. Panel (a) shows, for each age class, the percentage share of zombie firms relative to the total zombie population. Accordingly, more than two-thirds of the population of non-viable companies is composed of firms that are less than 30 years old, whereas older firms exhibit a lower incidence. However, panel (b) reveals that the share of zombies among total active companies within each age category increases with age. This suggests that, in our sample, the many young zombie firms do not weigh much on the total for their age category, while the relative incidence of older zombies tends to be larger (Ascani and Nair, 2025).



(a) (b)

Figure 3: Share of zombies by age class. Panel (a): Share of zombie firms by age class among total zombie firms (%). Panel (b): Share of zombie firms among total firms by age class (%)

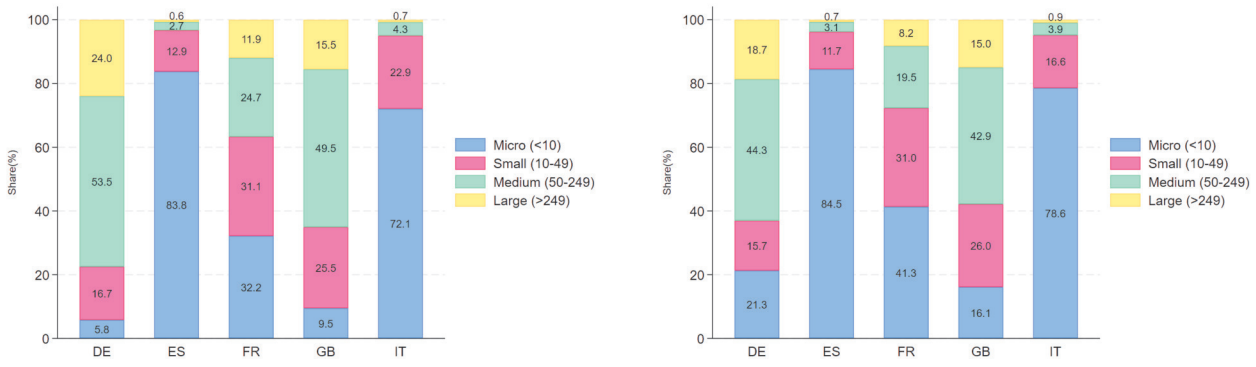
[12]Firms that are less than 10 years old are excluded from the analysis as they cannot assume the status of zombies according to the definitions of McGowan et al. (2018) and Pelosi et al. (2021) used in the main identification approaches.

4.2.3 Size

Secondly, following the standard Eurostat classification, we categorize companies into four size classes based on their number of employees, namely micro (less than 10 employees), small (10–49 employees), medium (50–249 employees), and large (more than 249 employees) firms.

Then, for each country we compute the relative share of each size class within the total zombie population, and report the results in Figure 4, again for the first and last years for which data are available. For this analysis, we only rely on EBITDA-based measures, as they naturally deliver more conservative estimates of the phenomenon, as suggested by the previous figures and confirmed by empirical evidence (Ascani and Nair, 2025; Rodano and Sette, 2019).

The two panels reveal a heterogeneous situation across countries. Spain and Italy report the highest shares of micro-firms within the zombie population, standing at 83.8% and 72.1% in 2017, and 84.5% and 78.6% in 2024, respectively. In both countries, companies with more than 250 employees account for less than 1% of the total number of zombie firms. Differently, Germany and United Kingdom's population of zombies is largely composed by medium and large enterprises, with the former accounting for around half of the total number of firms and the latter ranging between 15 and 24%. France shows a more diversified composition, with large firms accounting for around 12% in 2017 and 8% in 2024. This situation clearly points towards heterogeneous dynamics in selection mechanisms across different countries, with different type of firms more likely to be identified as zombies in certain countries rather than others.



(a) 2017 (b) 2024

Figure 4: Composition of zombie firms by size class (%)

Comparing the two panels, we also note that the relative weight of micro-companies increased in all countries from 2017 to 2024, with growth ranging from 0.7 percentage points in

Spain to 15.5 percentage points in Germany. We argue that this progressive zombification of micro-firms might stem from the uneven effect of the pandemic-driven recession, which potentially exacerbated financial distress for very small businesses (Barrero et al., 2020; Helmersson et al., 2021)[13].

4.2.4 Industry

To further investigate heterogeneity within the phenomenon of zombie firms, we resort to a third dimension of analysis, examining the population of economically nonviable firms across industry classifications. Figure 5 shows the aggregate prevalence of zombie firms by industry, following the two-digit NACE Rev.2 classification[14]. When identification is based on the use of EBITDA, only sector 12 (Manufacture of tobacco products) is characterized by a share of zombies above 15%. When considering EBIT-based measures, six additional sectors report a zombie prevalence above 15%, namely: sector 51 (Air transport), sector 58 (Publishing activities), sector 60 (Programming and broadcasting activities), sector 68 (Real estate activities), sector 70 (Activities of head offices and management consultancy activities), and sector 72 (Scientific research and development). Not surprisingly, these industries are traditionally characterized by a higher concentration of State-Owned Enterprises (SOEs) and/or private companies which are largely subsidized by public authorities, or where governments have ownership stakes. This evidence suggests that zombie firms are more likely to emerge in heavily-subsidized sectors, confirming that government subsidies might support economically non-viable firms even during periods of persistent unprofitability[15], in line with previous empirical evidence (Acharya et al., 2019; Caballero et al., 2008; Fukao and Kwon, 2006; Kane, 1987).

Lastly, we interact sectoral and geographical dimensions in Figures 6 and 7, where sectors are aggregated in manufacture (NACE Rev.2 10-33), construction (NACE Rev.2 41-43) and services (NACE Rev.2 45-82, excluding 64-66). Following this classification, Figure 6 shows the percentage share of zombie companies among total active firms for the five countries of interest

[13] A recent contribution to this debate comes from **?**, who argue that Covid-19 placed a special role on fiscal policies aimed at rescuing companies short of liquidity.

[14] Data are aggregated over the entire sample period and across all countries.

[15] A word of caution is needed when interpreting these results due to the unbalanced number of observations across different sectors. The relative weights (in %) of the sectors are as follows: sector 12, < 0.01; sector 51, 0.03; sector 58, 0.38; sector 60, 0.11; sector 68, 5.17; sector 70, 2.32; sector 72, 0.35.

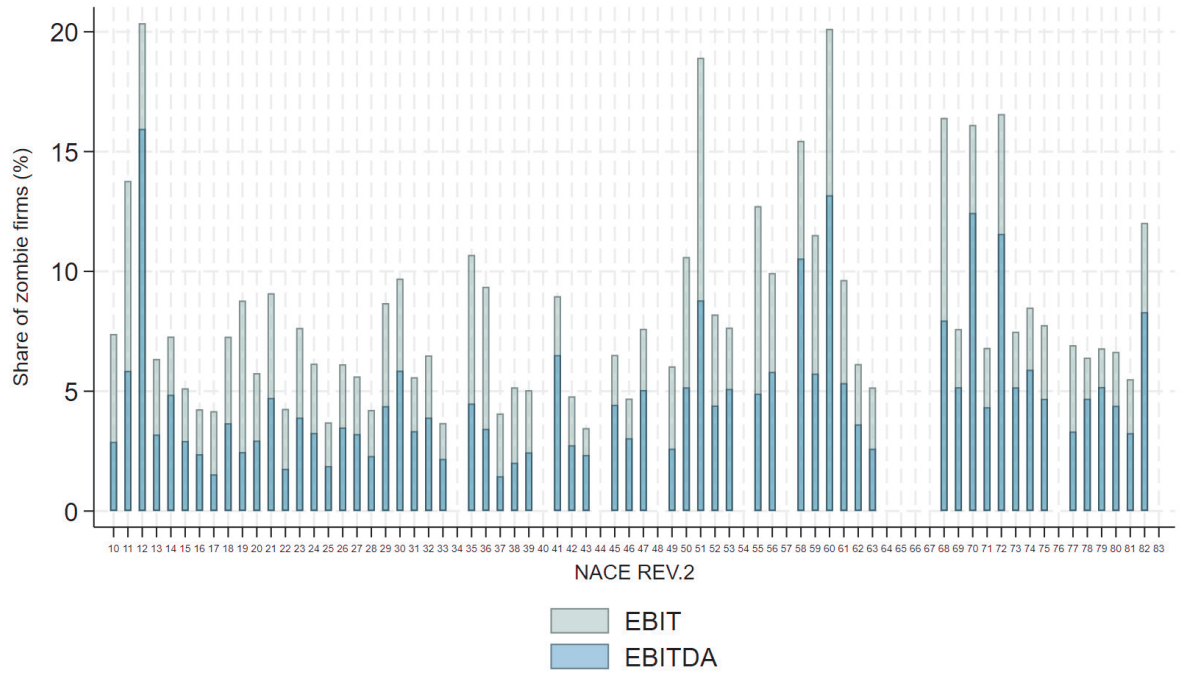
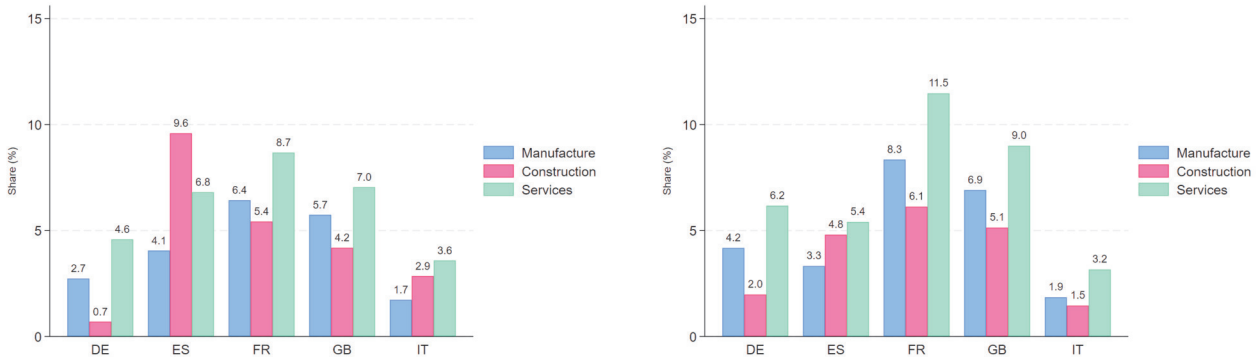


Figure 5: Share of zombie firms among total firms by sector NACE.Rev.2

in 2017 and 2024.[16]. In all countries, with the exception of Spain in 2017, the services sector is characterized by the highest share of unhealthy firms. Within each country, the lowest share is generally found in construction, except for Spain in both years and Italy in 2017.[17]. Fig. 7 shows the composition of the zombie population by macro-sector, comparing 2017 in panel (a) and 2024 in panel (b). Zombies in the service sectors account for around two thirds of the total number of zombie firms, whereas zombies in manufacture and construction sectors split the remaining third heterogeneously across countries. Comparing the two panels, we note that the share of zombie companies in service sectors has generally increased from 2017 to 2024, while remaining steady only in Germany. These results are in line with the hypothesis that service-providing firms have been disproportionally affected by the Covid-19 crisis, as they were more vulnerable to prolonged periods of financial distress, generating insufficient earnings to service their outstanding debt obligations(Barrero et al., 2020).

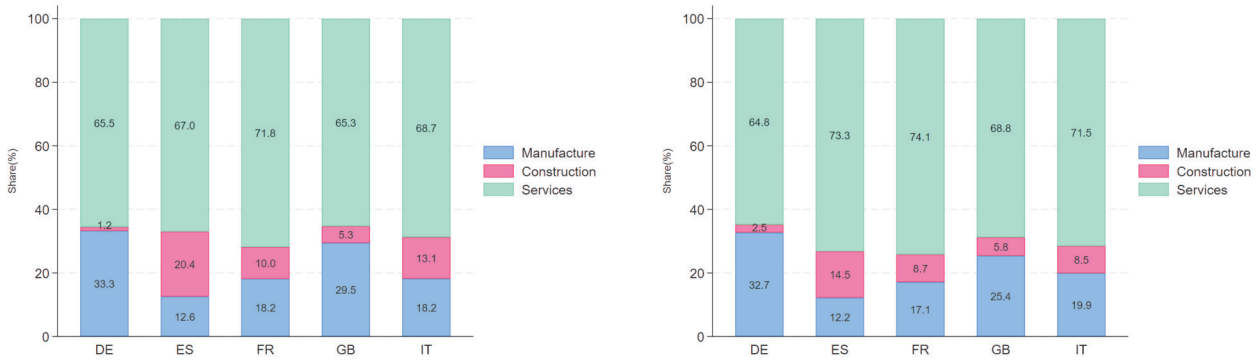
[16]Zombies are identified using exclusively the EBITDA-based specification.

[17]The sharp decrease for the construction sector in Italy might be linked to the approval of government subsidies for dwelling renovations – Bonus Facciate and Superbonus 110% – from 2021 onwards, which might have helped previously unprofitable firms to become healthier (Accetturo et al., 2025).



(a) 2017 (b) 2024

Figure 6: Share of zombie firms among total firms by macro-sectors (%)



(a) 2017 (b) 2024

Figure 7: Composition of zombie firms by macro-sectors (%)

4.2.5 Anatomy of zombie firms

To conclude the present section, we examine the anatomy of zombie firms following the methodology adopted by Banerjee and Hofmann (2022). In their study, the authors compare healthy and unhealthy companies across a broad range of different balance-sheet and performance indicators. To do so, they split the population into zombies and non-zombies and calculate mean, median, and quartile values for each of the two groups.

We apply a similar methodology and report the results in Table 1, comparing the mean and median values for zombie (Z) and non-zombie (NZ) firms using exclusively the EBITDA-based classification. To ensure that our findings are not distorted by the outbreak of the COVID-19 pandemic, the same statistics are also reported for the 2017-–2019 period, which predates the introduction of containment and lockdown measures that may have artificially reduced sales

and limited labor and capital mobility (Barrero et al., 2020; Goolsbee and Syverson, 2021).

First, we observe that, on average, zombie firms are smaller in terms of both total assets and number of employees. This finding corroborates the descriptive evidence presented in Figure 4, which showed that SMEs constitute a large share of the zombie population. While the discrepancy between mean and median values is negligible for total assets, this is not true for the number of employed workers. This divergence further reveals that the employment distribution is highly skewed, with many micro and small enterprises living in a situation of prolonged financial distress.

In line with the findings of Banerjee and Hofmann (2022), we also find that unhealthy firms exhibit a lower share of intangible investments of less than one percentage point over the entire sample period, and roughly two percentage points for the years 2017–2019.

Distressed companies report substantially lower, and in many cases negative, earnings and interest coverage ratios, which is inherently true when considering that these indicators are part of the identification approach themselves. It is also worth noting that returns on assets and interest coverage ratios tend to be less negative before the outbreak of the pandemic, suggesting that the Covid-19 crisis has worsened the distress of already unprofitable firms.

Lastly, zombie firms are investigated in terms of economic performance. In line with the evidence of Banerjee and Hofmann (2022) and Albuquerque and Iyer (2024), our findings indicate that zombie companies are less dynamic than their healthy counterparts, exhibiting substantially lower employment growth rates over the sample period. As documented in the literature (Acharya et al., 2019; Banerjee and Hofmann, 2022; Caballero et al., 2008), zombie firms are also found to be less productive, both in terms of labor productivity (LP) and total factor productivity (TFP)[18].

Taken together, these descriptive statistics provide some insightful evidence on the effectiveness of the identification strategy implemented in this analysis. Indeed, detecting zombie firms through their inability to service outstanding debt correctly identifies companies whose performance is lower in terms of economic growth, productivity, and capacity to generate sufficient

[18]Labor productivity is defined as the nominal productivity of labor, computed as real value added per worker. TFP represents the level of total factor productivity estimated using the semi-parametric estimator proposed by Levinsohn and Petrin (2003), where capital is instrumented with the lagged value of investments in intermediate inputs, under the assumption that the productivity process follows a Markov specification. All underlying monetary values are expressed in real terms using appropriate deflators for each year of the analysis.

Table 1: Summary statistics by zombie status

	2017-2024				2017-2019			
	Mean		Median		Mean		Median	
	Z	NZ	Z	NZ	Z	NZ	Z	NZ
ln Tot Assets	14.63	14.80	14.54	14.69	14.76	14.89	14.70	14.79
Nr. of Employees	16.80	20.56	3	7	16.68	21.31	4	8
Share Intangible (%)	8.30	9.05	0	0.12	7.11	8.90	0	0.15
Leverage (%)	10.82	9.89	4.85	5.60	10.75	11.33	4.83	6.89
ROA	-9.41	5.73	-5.96	3.63	-8.16	5.22	-5.13	3.13
EBITDA	-34427.1	413834.1	-25710.5	80300.8	-26362.8	421378.6	-24021.5	84355.6
ICR	-36.11	151.32	-6.75	11.56	-31.00	152.16	-5.66	10.62
Age	24.42	23.80	22	22	23.64	23.04	21	21
Debt Growth (%)	90.21	87.14	-3.74	-3.78	91.54	81.84	-1.13	-0.05
Sales Growth (%)	8.50	6.58	-3.60	0.08	13.08	9.04	-0.37	2.18
Emp. Growth (%)	1.45	5.11	0	0	2.46	5.84	0	0
ln LP	7.97	10.65	9.96	10.73	9.13	10.79	10.12	10.80
ln TFP	-3.10	-1.11	-1.60	-1.17	-2.30	-1.14	-1.53	-1.24

Note: This table reports mean and median values of selected variables by zombie status. All differences in means are significant at the 1% significance level based on a two-sample t-test with unequal variances. Values are expressed in percentage when indicated. Variables are calculated as follows: Share Intangible (%) as the percentage ratio of intangible assets over total fixed assets; Leverage as the ratio of total debt over total assets; ICR as the ratio of EBITDA over financial expenses. Growth variables are defined as follows: $((X_t - X_{t-1})/X_{t-1}) \cdot 100\%$ with X being respectively: total debt, sales, number of workers. All variables are trimmed at the 1^{st} and 99^{th} percentiles.

earnings from sales.

5 Empirical Methodology and Results

Using a symmetric two-part structure, we discuss the empirical methodology used in the analysis and the results for the sample of interest. Section 5.1.1 outlines longitudinal specifications that include firm and year fixed effects, thereby restricting the sample only to switchers, i.e. those observations that change status at least once during the period of analysis. Section 5.1.2 extends the analysis to the entire population of interest, incorporating observations that are either never or always classified as zombies. For this purpose, firm fixed effects are substituted with country-sector-year fixed effects. Symmetrically, Sections 5.2.1 and 5.2.2 show the results of the analysis.

5.1 Empirical Methodology

5.1.1 Sample of Switchers

To examine the probability of a firm i being classified as a zombie at any point in time t ($Z_{i,t} = 1$), we first employ a Linear Probability Model (henceforth LPM) with individual and time fixed effects:

$$Z_{i,t} = \theta_1 Z_{i,t-1} + \theta_2 Z_{i,t-2} + \gamma \mathbf{X}_{i,t-1} + \delta_i + \lambda_t + \varepsilon_{i,t} \tag{4}$$

where $Z_{i,t-1}$ and $Z_{i,t-2}$ denote the one- and two-period lagged values of zombie status, respectively, in order to control for the persistence of the phenomenon. The model includes a vector of controls, $\mathbf{X}_{i,t-1}$, which comprises the logarithm of total assets as a proxy for size, return on assets (ROA), leverage, the logarithm of total factor productivity (TFP), and a dummy variable D^{debt} that equals 1 if the firm's debt increased between $t-2$ and $t-1$, and 0 otherwise. To address endogeneity concerns - given that zombie firms are more likely, by definition, to generate low or negative earnings - all explanatory variables enter the specification in their lagged forms.

We then incorporate firm fixed effects in δ_i to capture unobserved time-invariant heterogeneity, such as managerial practices and market positioning, which are likely to influence firm structural productivity and profitability. By construction, these individual fixed effects absorb all those variables that do not have within-unit variation; consequently, observations for firms that never change status are dropped from the estimation. Since always zombies and never zombies exert no within-firm variance, the estimation is strictly restricted to the sample of switchers, i.e., those firms that change status at least once in the period of analysis. Furthermore, we include time fixed effects in λ_t to control for common shocks at the aggregate level. Given that the analysis spans the 2015—2024 period, there might be some exogenous macroeconomic shocks which affect all firms simultaneously, including, for example, the Covid-19 pandemic and the subsequent economic crisis.

The choice of covariates comprised in $\mathbf{X}$ aims to control for variables that have been included by the literature as key predictors of zombification. Consequently, the model employs return on assets (ROA) as an indicator of financial performance, integrating the arguments of Storz et al. (2017) and Schivardi et al. (2022), who use ROA to measure profitability and to identify zombie firms. We expect a negative coefficient for ROA, as higher financial returns should

mechanically reduce the probability of a firm being identified as a zombie. Similarly, the equation includes leverage among the covariates, which is used by the same authors as a proxy for the risk of default of a firm. Therefore, higher debt exposure is expected to correlate with a higher probability of zombie status (Albuquerque and Iyer, 2024; Favara et al., 2024; Schivardi et al., 2022). To further check for the role of debt dynamics, we introduce the dummy variable D^{debt} to capture whether total debt increased in the prior year, testing the hypothesis that debt accumulation might signal financial distress (Brahmana, 2025). Finally, we include total factor productivity (TFP) to test the standard theoretical assumption that low productivity levels are associated with the status of economically unviable firms (Caballero et al., 2008; Costa et al., 2022; Fukao and Kwon, 2006; Hsieh and Klenow, 2009; Kane, 1987).

To address the well-known limitations of a Linear Probability Model (Wooldridge, 2010, 2016), we also employ a dynamic logit specification. In equation (5), the probability of a firm being classified as a zombie at time t, $\Pr(Z_{i,t} = 1)$, is modeled as a logistic function that depends on the same set of covariates previously defined:

$$\Pr(Z_{i,t} = 1) = \Lambda \left(\theta_1 Z_{i,t-1} + \theta_2 Z_{i,t-2} + \gamma \mathbf{X}_{i,t-1} + \lambda_t + \alpha_i\right) \tag{5}$$

where $Z_{i,t-1}$ and $Z_{i,t-2}$ denote the one-and two-period lagged values of Z_i, respectively; $\mathbf{X}_{i,t-1}$ is the vector of controls as previously defined, and λ_t represents time fixed effects captured via annual indicator variables. Lastly, α_i accounts for firm fixed effects, which, as noted above, condition the estimation on the sub-sample of switchers.

5.1.2 Total Population

Over a relatively short estimation horizon, the fraction of switchers typically represents only a minor share of the total population. Indeed, it is likely that a firm never enters the status of zombie, and there exist some firms that were classified as zombies in the initial year of the analysis and do not change status until the end of the sample period. In order to incorporate the entire population under study, we replace the firm fixed effects of equation (4) with country-sector-year fixed effects, specifying the model as follows:

$$Z_{i,t} = \theta_1 Z_{i,t-1} + \theta_2 Z_{i,t-2} + \gamma \mathbf{X}_{i,t-1} + \delta_{cst} + \varepsilon_{i,t} \tag{6}$$

where δ_{cst} captures unobserved heterogeneity at the country-sector-time level. The under-

lying assumption is that firms operating within the same industry and located in the same country share, at least partially, common structural characteristics and macroeconomic shocks. This choice is rooted both in the descriptive evidence provided in Section 4.2 that highlights remarkable differences in zombie prevalence across geographical and industrial dimensions, and in previous empirical studies (McGowan et al., 2018), which use country-sector-year fixed effects across several specifications.

Ensuring methodological consistency presents a distinct econometric challenge. Indeed, a dynamic logit specification with firm fixed effects, as the one implemented in equation (5), mechanically restricts the estimation only to the sub-sample of switchers. To overcome this limitation and include the entire population, one could, in principle, use a random effects dynamic logit model, assuming that firm-specific unobserved heterogeneity is uncorrelated with the regressors, i.e., $\text{Cov}(\alpha_i, \mathbf{X}_{i,t}) = 0$.

This orthogonality assumption is highly unlikely to hold empirically, as unobserved firm-level heterogeneity is systematically correlated with the explanatory variables. For instance, the empirical literature widely documents that better managerial practices are often strongly correlated with both higher levels of productivity and higher return on assets (Bloom and Van Reenen, 2007). Another source of unobserved heterogeneity consists of the market structure in which the firm is operating, which generally influences structural productivity (Aghion et al., 2005; Syverson, 2004).

To address this limitation, we resort to the approach proposed by Mundlak (1978) and further developed in subsequent studies by Bell and Jones (2015) and Wooldridge (2005, 2019). This framework, widely known as the Mundlak correction, decomposes the firm-specific unobserved heterogeneity into two distinct components:

$$\alpha_i = \pi \overline{\mathbf{X}}_i + \mu_i \tag{7}$$

where $\overline{\mathbf{X}}_i$ denotes the vector of within-firm longitudinal averages of the explanatory variables. This term introduces a formal correction into the random effects logit model, as the mean values of the explanatory variables capture the unobserved heterogeneity at the firm level. To illustrate this logic through our previous example, if firm i possesses superior managerial quality than firm j, and given that better managers are associated with increased profitability, $\overline{\text{ROA}_i}$ is expected to be systematically higher than $\overline{\text{ROA}_j}$.

By construction, the residual error component, μ_i, is now orthogonal to the explanatory vari-

ables, such that $\text{Cov}(\mu_i, \mathbf{X}_{i,t}) = 0$. Therefore, equation (8) estimates a random effects dynamic logit specification incorporating the Mundlak correction, where $\Lambda(\cdot)$ denotes the cumulative logistic distribution function.

$$\Pr(Z_{i,t} = 1) = \Lambda\left(\theta_1 Z_{i,t-1} + \theta_2 Z_{i,t-2} + \gamma \mathbf{X}_{i,t-1} + \lambda_t + \pi \overline{\mathbf{X}}_i + \mu_i\right) \tag{8}$$

5.2 Results

5.2.1 Sample of Switchers

Table 2 reports the empirical estimates of the Linear Probability Model with firm fixed effects outlined in equation (4). Columns (1) and (2) incorporate the one-year and two-year lagged values of $\text{Z}_{i,t}$, respectively, whereas column (3) includes both lags simultaneously. Looking at the adjusted R^2, the model reported in column (3) emerges as our preferred specification.

Within the sample of switchers, companies that were classified as zombies at time $t-1$ exhibit an approximately 23 percentage points higher probability of being classified as zombies also in time t, indicating a moderate effect of status persistence. Conversely, if a company was classified as zombie at time $t-2$ ($\text{Z}_{i,t-2} = 1$), but recovered in the following year ($\text{Z}_{i,t-1} = 0$), its probability of being a zombie at time t decreases by around 13 percentage points. This result underscores the moderate role of firm recovery within the sample of switchers: once an enterprise exits the condition of zombiness, the likelihood of relapsing into the zombie state is significantly diminished.

The estimated coefficients of the control variables seem to align with our theoretical expectations. Specifically, firm size at time $t-1$ - proxied by the logarithm of total assets - exhibits a negative correlation with probability of being classified as a zombie at time t. This result corroborates the preliminary insights from the descriptive analysis, suggesting that smaller businesses might be more vulnerable to entering financial distress.

The return on assets (ROA) also exhibits a negative correlation with the probability of being classified as a zombie. As ROA is reported as a percentage, we find that for a firm that increases its return on assets by 10 percentage points at $t-1$, its probability of being identified as zombie in the following year drops by 1.2 percentage points. The interpretation for total factor productivity (TFP) requires careful consideration due to its log-transformed nature: we estimate that a 10% increase in productivity at time $t-1$ is associated to a

Table 2: Results of Linear Probability Model

	(1)	(2)	(3)
Z_{t-1}	0.2415***	—	0.2314***
	(0.0032)		(0.0039)
Z_{t-2}	—	-0.0766***	-0.1273***
		(0.0032)	(0.0028)
ln Tot Assets$_{t-1}$	-0.0025***	-0.0061***	-0.0039***
	(0.0008)	(0.0010)	(0.0009)
ROA$_{t-1}$	-0.0013***	-0.0015***	-0.0012***
	(0.0000)	(0.0000)	(0.0000)
Leverage$_{t-1}$	0.0000*	0.0000*	0.000
	(0.000)	(0.000)	(0.000)
ln TFP$_{t-1}$	-0.0021***	-0.0023***	-0.0018***
	(0.0001)	(0.0001)	(0.0001)
D_{t-1}^{debt}	-0.0005**	-0.0007***	-0.0006**
	(0.0002)	(0.0002)	(0.0002)
Constant	0.0640***	0.1291***	0.0897***
	(0.0119)	(0.0158)	(0.0140)
No. Obs.	1,356,205	1,092,665	1,092,665
Adj. R^2	0.549	0.539	0.561
Fixed Effects	i,t	i,t	i,t

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

lower probability of being identified as a zombie at time t of approximately 0.02 percentage points. Debt exhibits a negative sign, which is a counterintuitive result compared to our ex-ante expectations. Indeed, this seems to contradict our hypothesis that debt accumulation signals financial distress. However, the literature on credit rationing argues that in a context of imperfect information, banks prefer to lend exclusively to borrowers who are more likely to repay their debt (Stiglitz and Weiss, 1981). Hence, firms experiencing structural distress might be less likely to obtain new credit from banks and other financial intermediaries. Therefore, a more granular analysis should take into account the composition of the firm's debt, to assess whether these companies receive subsidized lending, as theorized by Caballero et al. (2008).

To verify whether the baseline findings also hold across distinct institutional contexts, we estimate our preferred specification separately for each country and report the results in Table

A2 in the Appendix. We find clear evidence of cross-country heterogeneity, which might be driven by differences in the leniency of national insolvency regimes (McGowan et al., 2018).

To complement this preliminary analysis, we estimate our preferred specification separately also for each macro-sector, and report the results in Table A3 in the Appendix. In general, the estimates reveal no substantial variations in terms of state persistence, recovery, return on assets, and productivity.

We perform several robustness checks to verify whether the baseline findings hold when employing alternative control variables in equation (4). First, we replace total factor productivity with the nominal labor productivity, estimating a significant negative effect in almost all specifications. Furthermore, the results also hold when total factor productivity is estimated via the Olley and Pakes (1992) methodology, suggesting that productivity remains a crucial variable to look at when studying the dynamics of zombification. Comparable estimates are also obtained when the logarithm of total assets is replaced with the logarithm of the number of employees as an alternative proxy for size. Lastly, to check that our results are not distorted by sectors with high concentration of zombies, we estimate the baseline equation by excluding those sectors with an aggregate zombie incidence above 10%[19]. The resulting estimates are strictly comparable to the baseline findings, providing robust evidence of the persistence of this phenomenon even when filtering out sectors with a higher presence of unprofitable companies.

To further address endogeneity concerns, we perform equation (4) using the two-year lagged values for each explanatory variable contained in vector $\mathbf{X}$, and report the results in Tables A4 and A5 in the Appendix, for countries and macro-sectors, respectively. Overall, our baseline findings are robust to this alternative lag structure, yielding strictly comparable estimates for most variables. Lastly, we test methodological consistency using a dynamic logit model with firm fixed effects, as explained in Section 5.1.1. Results are shown in Table A6 in the Appendix and reveal similar conclusions.

5.2.2 Total Population

Since switchers constitute only a small fraction of the total population, this justifies the need to extend the analysis to the entire population for which zombie identification has been possible.

[19]Namely, we exclude: sector 12 (Manufacture of tobacco products), sector 58 (Publishing activities), sector 60 (Programming and broadcasting activities), sector 70 (Activities of head offices and management consultancy activities), sector 72 (Scientific Research and Development).

We estimate equation (6) on the full sample and report the results in Table 3. By analogy with Table 2, columns (1) and (2) include only Z_{t-1} and Z_{t-2}, respectively, while column (3) includes both values.

Interestingly, the pattern of persistence changes substantially compared to the previous specifications. Once we include the full sample of observations in the analysis, companies identified as zombies in $t-1$ are approximately 64 percentage points more likely to be zombies in t. When instead Z_{t-2} is included as the sole regressor, firms that were zombies two years prior are 44 percentage points more likely to be zombies today. When both Z_{t-1} and Z_{t-2} are included simultaneously, the former captures a large part of the total effect, as last year's zombies display a roughly 60 percentage point higher probability of remaining unhealthy. The substantially higher coefficient observed for Z_{t-1} compared to that obtained in the sample of switchers (around 23 percentage points) carries a distinct economic interpretation: while the switchers specification only captures transitory dynamics - conditioning the estimation on companies that change status during the total sample period - the full-population specification predominantly reflects structural persistence. Therefore, the magnitude of the coefficient is mainly driven by the effect of permanently distressed firms who enter the analysis already in a zombie state and remain trapped in that condition[20].

Furthermore, the two-year lagged value of the zombie status (Z_{t-2}) now contributes positively, standing approximately at 6 percentage points in column (3), while in Section 5.2.1 it exhibited a negative coefficient. This discrepancy carries a significant economic implication, as the two coefficients reflect different underlying mechanisms: within the sample of switchers, Z_{t-2} primarily reflects the impact of recovery, suggesting that companies that exit the zombie state are less likely to transition back into a distressed condition. Differently, when the entire population is accounted for, Z_{t-2} reflects the structural persistence of the many companies that are permanently zombies in the analysis: the longer the persistence in the zombie status, the

[20]The large coefficient on Z_{t-1} should be interpreted as evidence of strong predictive persistence rather than causal state dependence. This magnitude is consistent with the results obtained for transition matrices in Chapter 6, which show that most zombie firms remain zombies in the following year, while only a very small fraction of healthy firms enter zombie status. Moreover, since zombie status is defined over a three-year accounting window, consecutive zombie indicators partly overlap by construction. The estimated persistence therefore combines genuine economic persistence in financial distress with mechanical persistence induced by the classification rule.

higher the probability of remaining trapped in that condition, corroborating the hypothesis that the majority of these under-performing companies operate in a state of structural economic and financial distress.

Looking at the other control variables, the estimated coefficients confirm both our theoretical predictions and the previous findings. The coefficient for ROA is slightly larger than in the baseline specification: an increase of 10 percentage points in the return on assets at time $t-1$ reduces the probability of being classified as a zombie at time t by around 1.5 percentage points. Similarly, a 10% increase in TFP at time $t-1$ results in a lower probability of approximately 0.03 percentage points. Finally, debt accumulation exhibits a statistically significant negative coefficient, corroborating our previous hypothesis of credit rationing (Stiglitz and Weiss, 1981) even in large samples.

Table 3: Results of Linear Probability Model

	(1)	(2)	(3)
Z_{t-1}	0.6372***	—	0.5986***
	(0.0026)		(0.0031)
Z_{t-2}	—	0.4389***	0.0595***
		(0.0035)	(0.0024)
ln Tot Assets$_{t-1}$	0.0007***	0.0008***	0.0007***
	(0.0001)	(0.0001)	(0.0001)
ROA$_{t-1}$	-0.0015***	-0.0027***	-0.0015***
	(0.0000)	(0.0000)	(0.0000)
Leverage$_{t-1}$	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
ln TFP$_{t-1}$	-0.0035***	-0.0061***	-0.0034***
	(0.0001)	(0.0001)	(0.0001)
D_{t-1}^{debt}	-0.0013***	-0.0017***	-0.0011***
	(0.0002)	(0.0003)	(0.0002)
Constant	0.0031**	0.0091***	0.0029*
	(0.0015)	(0.0023)	(0.0016)
No. Obs.	1,415,469	1,149,824	1,149,824
Adj. R^2	0.469	0.288	0.467
Fixed Effects	cst	cst	cst

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As in the previous section, we test the robustness of our findings using alternative definitions of productivity, employing different proxies for size, and excluding sectors with a zombie incidence above 10% from the analysis. We also replicate the previous exercise by replacing the one-year lags of the control variables with their two-year lagged values. Overall, the estimates do not show any meaningful changes, confirming that our findings are robust to a variety of alternative specifications.

Following the arguments of Section 5.1.2, methodological consistency is tested through a random effects dynamic logit model with a Mundlak (1978) correction. Under the assumption that the firm-specific time-averages of the control variables, $\overline{\mathbf{X}}_i$, capture the unobserved individual heterogeneity, and that residuals μ_i are orthogonal to the explanatory variables, we estimate equation (8) on the full sample. Results are reported in Table A7 in the Appendix. Although the magnitude of the estimates is not directly interpretable in economic terms[21], the signs of the coefficients generally confirm the direction of the previous findings.

5.3 Zombie Survival

To study the temporal trajectories of survival rates across viable and non-viable firms, we follow Banerjee and Hofmann (2022) in implementing the nonparametric estimator proposed by Kaplan and Meier (1958). This methodology provides an empirical estimate of the survival function $S(t)$, which models the probability that a given firm survives after time t. For a sample with observed failure times $t_1, ..., t_k$, where k is the number of distinct failure times observed, the Kaplan-Meier estimator at any time t is given by:

$$\hat{S}(t) = \prod_{i|t_i \leq t} \left[1 - \frac{d_i}{n_i}\right] \tag{9}$$

where t_i represents the duration of the observation, d_i is the number of failures occurring at time t_i, and n_i is the number of firms at risk at time t_i (Cleves, 2008).

In Stata, this survival framework is set up through the command `stset`, which requires a duration variable and an indicator function that equals 1 whether the firm has failed (i.e., it has exited the market), and 0 otherwise[22]. While the duration variable can be easily reconstructed

[21] Due to computational constraints, marginal effects represent heavy calculations for very large datasets. However, one could resort to a manual computation of the average marginal effects using the properties of the logistic function.

[22] The full specification of the command is: `stset duration, failure(failed==1)`

using the consecutive years in which a firm is present in the sample, the failure indicator requires precise and time-consistent information on the status of the firm for each year (Cleves, 2008; Dickman and Coviello, 2015).

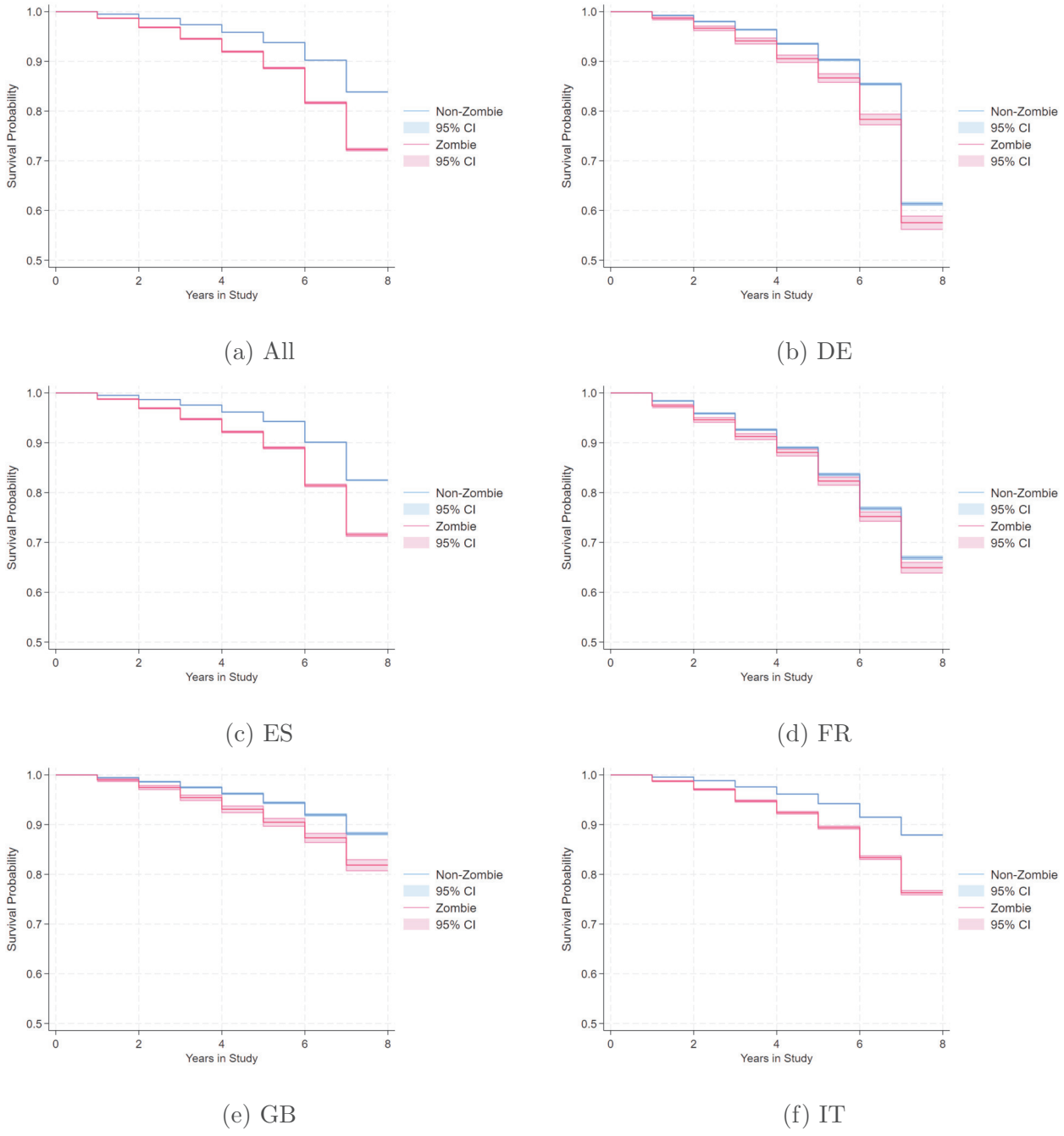
Since explicit administrative data on firm liquidations and bankruptcies are unavailable, we proxy market exit using the final year of observed financial data for each firm. Specifically, we assume that firms whose final observation occurs prior to 2024 have exited the market earlier than the end of the period of analysis. We acknowledge the fact that this approach cannot perfectly disentangle true corporate failure (i.e., insolvency or bankruptcy) from administrative attrition, such as firms simply ceasing to report information or idiosyncratic drops in ORBIS coverage. Because of this limitation, our estimates should be interpreted as a lower bound of the true survival probability, as this proxy likely overestimates the actual number of failures. However, under the assumption that, for sufficiently large samples, zombie and non-zombie firms are equally susceptible to reporting omissions or coverage drops, any observed divergence in survival trajectories must be driven by underlying differences in failure risk between the two groups. Therefore, under this assumption, the framework enables the comparison of survival rates of zombie firms relative to their healthy counterparts.

Fig. 8 compares the estimated Kaplan-Meier survival curves for zombie and non-zombie firms. Throughout the duration analysis, zombie firms are identified using the baseline classification approach described in the previous sections[23].

Panel 8(a) presents the survival estimates pooled across all countries in the sample. The graph is a stepwise function that plots, for each year, the survival probability of the two groups. A comparison between the two curves suggests that zombie companies exhibit a significantly lower survival probability compared to their healthy counterparts, with a gap that widens over the survival horizon. At the end of the sample period, approximately 72% of zombies survived, compared to approximately 84% of healthy firms. Furthermore, we also note that the confidence intervals around the two estimated functions remain strictly non-overlapping throughout the entire horizon.

To evaluate the robustness of these findings even in smaller samples, the survival analysis is

[23]The graph also plots the corresponding 95% confidence intervals. To compute these intervals, the asymptotic variance of $\ln\left[-\ln \hat{S}(t)\right]$ is used (Kalbfleisch and Prentice, 2002). The confidence bounds are then $\hat{S}(t)\exp\left(\pm z_{\alpha/2}\ \hat{\sigma}(t)\right)$, where $z_{\alpha/2}$ represents the $(1-\alpha/2)$ quantile of the standard normal distribution (Cleves, 2008).



(a) All (b) DE

(c) ES (d) FR

(e) GB (f) IT

Figure 8: Survival rate of zombie and non-zombie firms

conducted separately for each country, and the results are reported in Panels 8(b)-8(f). Panel (b) reveals volatile estimates for Germany, a pattern likely driven by reporting irregularities and an unbalanced ORBIS coverage, especially in the final years of the analysis. Spain and Italy (panels (c) and (f), respectively) display consistent trajectories; in both countries, the survival rate of zombie firms is approximately 10 percentage points lower than that of healthy companies. Panel (d) reveals a different scenario for France, where the survival curve for

zombie firms lies roughly 2 percentage points lower than the one for healthy firms in each point in time. Lastly, panel (e) shows that the United Kingdom exhibits a survival gap of around 5 percentage points in the final years of the analysis. Notably, zombie firms in the UK exhibit a higher cumulative survival rate (82%) compared to the one observed in the entire sample (72%) [24]. Together, these findings suggest that around one fourth of the companies identified as zombies exit the market, compared to less than one fifth of healthy ones. These estimates are in line with the evidence documented by Pelosi et al. (2021), who find that one third of zombies exit the market, while the exit rate is one fifth among non-zombies. Furthermore, Banerjee and Hofmann (2022) estimate that approximately 25% of the total zombies have exited the market, corroborating the plausibility of our empirical estimates. Overall, these results appear consistent with the literature and support the use of the last available year as a reliable proxy for a firm's observed exit.

6 Conclusion

This paper contributes to the growing literature on the phenomenon of zombie firms, offering preliminary evidence from five OECD countries. First, it proposes a comprehensive classification of main identification approaches used in the literature. We categorize zombie definitions in three approaches, respectively: subsidized credit, profitability-based, and hybrid approaches, discussing advantages and empirical challenges of each identification technique. Using ORBIS data for more than 1 million capital companies from Italy, France, Spain, Germany, and UK, we present some descriptive evidence for the period 2015-2024. Using the approach of McGowan et al. (2018), we identify firms as zombies based on their (in)capacity to generate sufficient earnings to repay their debt. We find a heterogeneous situation across countries, both in terms of prevalence and composition of the population of non-viable firms. On average, zombie companies report a lower share of intangible investments, lower capital intensity, and negative returns on assets and interest coverage ratios. Moreover, they are less productive and less dynamic, as they report lower employment and sales growth.

Empirically, we employ a Linear Probability Model to study the probability of a firm being classified as a zombie at any point in time. We find that firm's past history, returns on assets,

[24] The Log-Rank tests have p-values < 0.001 for each country, confirming that the differences are statistically significant

and productivity are significant in modeling the current status of the firm. We estimate that an increase in returns on assets of 10 p.p. is associated to a 1.2 p.p. drop in the probability of being a zombie the following year. Similarly a 10% increase in total factor productivity is associated to a lower probability of around 0.02 p.p. These findings are robust to different definitions of productivity and to several sample exclusions. We also employ a dynamic logit model with to test methodological consistency and find comparable results. Lastly, we use the Kaplan and Meier (1958) estimator to study the survival rates of zombies and non-zombies. We find that one fourth of zombies exit the market, compared to less than one fifth of healthy firms. Under the assumption that administrative attrition are equally distributed among the two groups, this divergence is likely due to a different survival probability for the two groups.

This preliminary studies carries relevant implications for policymakers and academics who want to study the prevalence of the phenomenon and its economic impact across countries and sectors. First, the paper underscores the importance of adopting a common definition of zombie firms, identifying unprofitable businesses that structurally lie in a situation of economic and financial distress. Secondly, it points towards the role of debt growth, and productivity and profitability dynamics, as crucial factors to identify firms more likely to become zombies one day. Therefore, managers and policymakers should cautiously monitor the financial and economic performance of businesses, integrating information from multiple accounting indicators. This should allow, in principle, to differentiate between situations of temporary distress and situations of structurally low productivity and financial fragility. Ultimately, management practices that implement monitoring systems of the performance of the firm should prevent zombie congestion and reduce its negative implications for the entire economy.

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Appendix

Table A1: Search Strategy

Step	Definition	Step result	Search result
Status	Active companies, inactive companies, unknown situation	635,282,973	635,282,973
NUTS1 Classification	Germany, Spain, France, Italy, Poland, Portugal, Sweden, United Kingdom	68,386,654	68,379,745
NACE Rev.2 (two digits)	NACE Rev.2 codes 10-83, excluding 64-66	343,093,417	46,325,070
Consolidation Code	U1 (Only unconsolidated account available)	50,879,249	15,020,146
Financial Expenses	All companies with a non-missing value in last available year	17,348,827	3,043,791
EBITDA	All companies with a non-missing value in last available year	9,320,334	2,589,903
Number of employees	All companies with a non-missing value in last available year	133,464,818	1,573,702
Final sample			1,573,702
Selection due to computational power	Italy, France, Germany, Spain, United Kingdom	1,151,553	1,151,553
Final sample			1,151,553

Note: Financial searches exclude companies with no recent financial data and public authorities, states and governments. Data have been exported from ORBIS. Software version: 381. Data update: March, 13th, 2026. Update number: 381007. Export date: March, 16th, 2026. Step result reports the number of observations satisfying each individual search criterion when considered separately in ORBIS. Search result reports the cumulative number of firms remaining after sequentially applying the criterion together with all previous restrictions.

Table A2: Results of Linear Probability Model by country

	(1) All	(2) IT	(3) FR	(4) DE	(5) GB	(6) ES
Z_{t-1}	0.2314***	0.2314***	0.2564***	0.1398***	0.2940***	0.2257***
	(0.0039)	(0.0072)	(0.0162)	(0.0279)	(0.0171)	(0.0050)
Z_{t-2}	-0.1273***	-0.1325***	-0.1140***	-0.1279***	-0.1088***	-0.1281***
	(0.0028)	(0.0052)	(0.0122)	(0.0192)	(0.0121)	(0.0037)
$\ln$ Tot Assets$_{t-1}$	-0.0039***	-0.0035***	-0.0097	-0.0016	-0.0065	-0.0041***
	(0.0009)	(0.0012)	(0.0062)	(0.0049)	(0.0049)	(0.0015)
ROA_{t-1}	-0.0012***	-0.0009***	-0.0022***	-0.0011***	-0.0016***	-0.0012***
	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0001)	(0.0000)
Leverage$_{t-1}$	0.0000	-0.0000	-0.0000	0.0003*	0.0003***	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
$\ln$ TFP$_{t-1}$	-0.0018***	-0.0021***	-0.0007	0.0010	-0.0011*	-0.0019***
	(0.0001)	(0.0002)	(0.0008)	(0.0008)	(0.0006)	(0.0002)
D_{t-1}^{debt}	-0.0006**	-0.0003	-0.0023	-0.0024**	-0.0004	-0.0010**
	(0.0002)	(0.0003)	(0.0017)	(0.0011)	(0.0016)	(0.0004)
Constant	0.0897***	0.0734***	0.2233**	0.0602	0.1595*	0.0956***
	(0.0140)	(0.0188)	(0.1016)	(0.0864)	(0.0873)	(0.0220)
No. Obs.	1,092,665	475,660	36,147	40,588	38,125	502,145
Adj. R^2	0.561	0.537	0.661	0.673	0.604	0.549
Fixed Effects	i,t	i,t	i,t	i,t	i,t	i,t

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Results of Linear Probability Model by macro-sector

	(1) All	(2) Manufacture	(3) Construction	(4) Service
Z_{t-1}	0.2314***	0.2267***	0.2143***	0.2362***
	(0.0039)	(0.0080)	(0.0107)	(0.0048)
Z_{t-2}	-0.1273***	-0.1344***	-0.1205***	-0.1265***
	(0.0028)	(0.0059)	(0.0073)	(0.0035)
$\ln$ Tot Assets$_{t-1}$	-0.0039***	-0.0078***	0.0016	-0.0044***
	(0.0009)	(0.0018)	(0.0020)	(0.0013)
ROA$_{t-1}$	-0.0012***	-0.0013***	-0.0008***	-0.0012***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Leverage$_{t-1}$	0.0000	0.0001	0.0000	0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0000)
$\ln$ TFP$_{t-1}$	-0.0018***	-0.0023***	-0.0022***	-0.0016***
	(0.0001)	(0.0003)	(0.0004)	(0.0002)
D_{t-1}^{debt}	-0.0006**	-0.0002	-0.0001	-0.0011***
	(0.0002)	(0.0004)	(0.0007)	(0.0003)
Constant	0.0897***	0.1446***	0.0028	0.1019***
	(0.0140)	(0.0285)	(0.0304)	(0.0191)
No. Obs.	1,092,665	323,874	142,924	625,867
Adj. R^2	0.561	0.514	0.545	0.578
Fixed Effects	i,t	i,t	i,t	i,t

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Results of Linear Probability Model with two-year lags by country

	(1) All	(2) IT	(3) FR	(4) DE	(5) GB	(6) ES
Z_{t-1}	0.2350***	0.2342***	0.2673***	0.1382***	0.2828***	0.2306***
	(0.0039)	(0.0072)	(0.0164)	(0.0271)	(0.0170)	(0.0051)
Z_{t-2}	-0.1457***	-0.1484***	-0.1422***	-0.1470***	-0.1291***	-0.1471***
	(0.0029)	(0.0053)	(0.0125)	(0.0193)	(0.0126)	(0.0037)
$\ln$ Tot Assets$_{t-2}$	0.0052***	0.0028**	0.0093	0.0084*	-0.0010	0.0072***
	(0.0009)	(0.0012)	(0.0060)	(0.0050)	(0.0053)	(0.0015)
ROA_{t-2}	-0.0015***	-0.0011***	-0.0028***	-0.0013***	-0.0020***	-0.0017***
	(0.0000)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0000)
Leverage$_{t-2}$	-0.0000*	-0.0000	0.0000	-0.0001	-0.0000	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
$\ln$ TFP$_{t-2}$	-0.0023***	-0.0028***	-0.0006	-0.0010	-0.0016**	-0.0022***
	(0.0001)	(0.0002)	(0.0007)	(0.0009)	(0.0007)	(0.0002)
D_{t-2}^{debt}	0.0003	0.0001	0.0016	0.0001	0.0037**	0.0009*
	(0.0003)	(0.0003)	(0.0017)	(0.0010)	(0.0016)	(0.0004)
Constant	-0.0488***	-0.0242	-0.0825	-0.1146	0.0692	-0.0686***
	(0.0139)	(0.0183)	(0.0982)	(0.0887)	(0.0942)	(0.0217)
No. Obs.	1,076,944	467,749	36,229	41,115	38,077	493,774
Adj. R^2	0.563	0.535	0.667	0.688	0.599	0.552
Fixed Effects	i,t	i,t	i,t	i,t	i,t	i,t

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Results of Linear Probability Model with two-year lags by macro-sector

	(1) All	(2) Manufacture	(3) Construction	(4) Service
Z_{t-1}	0.2350***	0.2261***	0.2210***	0.2409***
	(0.0039)	(0.0081)	(0.0107)	(0.0049)
Z_{t-2}	-0.1457***	-0.1527***	-0.1378***	-0.1452***
	(0.0029)	(0.0060)	(0.0075)	(0.0036)
$\ln$ Tot Assets$_{t-2}$	0.0052***	0.0011	0.0076***	0.0058***
	(0.0009)	(0.0017)	(0.0021)	(0.0012)
ROA$_{t-2}$	-0.0015***	-0.0018***	-0.0013***	-0.0015***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Leverage$_{t-2}$	-0.0000*	-0.0001**	-0.0002**	-0.0000*
	(0.0000)	(0.0001)	(0.0001)	(0.0000)
$\ln$ TFP$_{t-2}$	-0.0023***	-0.0022***	-0.0028***	-0.0022***
	(0.0001)	(0.0003)	(0.0004)	(0.0002)
D_{t-2}^{debt}	0.0003	-0.0000	0.0013*	0.0005
	(0.0003)	(0.0004)	(0.0007)	(0.0003)
Constant	-0.0488***	0.0089	-0.0844***	-0.0537***
	(0.0139)	(0.0269)	(0.0313)	(0.0189)
No. Obs.	1,076,944	320,241	139,965	616,738
Adj. R^2	0.563	0.517	0.548	0.580
Fixed Effects	i,t	i,t	i,t	i,t

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Results of fixed-effects Logit Model

	(1) Log-Odds	(2) Marginal Effects
Z_{t-1}	0.9939***	0.0465*
	(0.0241)	(0.0253)
	[0.9467 ; 1.0410]	[-0.0031 ; 0.0961]
Z_{t-2}	-1.0087***	-0.0472*
	(0.0314)	(0.0258)
	[-1.0702 ; -0.9473]	[-0.0977 ; 0.0034]
$\ln$ Tot Assets$_{t-1}$	0.1877***	0.0088***
	(0.0462)	(0.0026)
	[0.0971 ; 0.2782]	[0.0036 ; 0.0139]
ROA$_{t-1}$	-0.0545***	-0.0025*
	(0.0012)	(0.0014)
	[-0.0569 ; -0.0521]	[-0.0052 ; 0.0001]
Leverage$_{t-1}$	0.0005	0.0000
	(0.0003)	(0.0000)
	[-0.0001 ; 0.0011]	[-0.0000 ; 0.0001]
$\ln$ TFP$_{t-1}$	-0.0045**	-0.0002
	(0.0018)	(0.0001)
	[-0.0080 ; -0.0009]	[-0.0005 ; 0.0001]
D_{t-1}^{debt}	-0.0133	-0.0006
	(0.0204)	(0.0010)
	[-0.0533 ; 0.0266]	[-0.0026 ; 0.0013]
No. Obs.	60,027	60,027
No. Groups	12,780	12,780
Individual FE	YES	YES

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The model also includes year dummies, which are not showed in the table.

Table A7: Random effects logit model with Mundlak correction

	(1) All		(1 - cont.ed) All
Z_{t-1}	3.8867***		
	(0.0264)		
Z_{t-2}	0.2449***		
	(0.0309)		
ln Tot Assets$_{t-1}$	0.2643***	$\overline{\text{ln Tot Assets}}$	-0.1380***
	(0.0366)		(0.0370)
ROA$_{t-1}$	-0.0456***	$\overline{\text{ROA}}$	-0.1359***
	(0.0010)		(0.0024)
Leverage$_{t-1}$	-0.0054***	$\overline{\text{Leverage}}$	0.000
	(0.0005)		(0.0000)
ln TFP$_{t-1}$	0.0008	$\overline{\text{ln TFP}}$	-0.0936***
	(0.0021)		(0.0042)
D_{t-1}^{debt}	0.0400**	$\overline{D}^{debt}$	-0.3027***
	(0.0183)		(0.0514)
Constant	-6.544***	ln σ_u^2	-0.2974***
	(0.0863)		(0.0428)
No. Obs.	1,149,845		
No. Groups	306,447		
Random Effects	YES		

Note: Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dummies for each year are not showed in the table.