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ZOMBIE FIRMS AND PRODUCTIVITY: AN ANALYSIS BASED ON TAX DATA*

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Entreprises zombies et productivité : une analyse fondée sur les données fiscales

Cet article étudie les entreprises zombies en France, c'est-à-dire celles dont les bénéfices sont insuffisants pour couvrir les paiements d'intérêts, sur la période 2009–2023, avec une attention particulière portée à la crise du COVID-19 et à ses conséquences. À partir de données fiscales exhaustives au niveau des entreprises (2009–2023) et de données issues du Country-by-Country Reporting (2016–2023), l'analyse corrige les bénéfices des grandes multinationales à l'aide d'une méthodologie récente issue de la littérature sur l'optimisation fiscale. Les approches traditionnelles surestiment largement la prévalence des zombies parmi ces groupes, la correction réduisant leur part pondérée par l'emploi jusqu'à 10 points de pourcentage.
À l'échelle de l'économie, les entreprises zombies représentent 8 % de l'emploi et 3,7 % des entreprises, avec une prévalence plus faible parmi les PME. Après la pandémie, leur part a temporairement augmenté, culminant à 9 % en 2022. La probabilité de faillite des zombies s'est effondrée en 2020, avant de se redresser progressivement sans retrouver son niveau pré-crise en 2023. Enfin, l'article montre que les secteurs les plus exposés aux entreprises zombies connaissent une moindre entrée de nouvelles firmes et un affaiblissement de la sélection du marché (moins de sorties d'entreprises à faible productivité), avec un effet d'éviction direct limité sur les entreprises saines.

Mots-clés : Entreprises zombies, transfert de bénéfices, productivité agrégée, multinationales, effets de congestion

Codes JEL : G33, H26, O47, F23

Zombie firms and productivity: an analysis based on tax data

This paper studies zombie firms in France, businesses whose profits are insufficient to cover interest payments, over 2009–2023, with particular attention to the COVID-19 period and its aftermath. Using exhaustive firm-level tax data (2009–2023) and Country-by-Country Reporting data (2016–2023), the analysis adjusts profits for large multinationals using a recent methodology from the tax avoidance literature. Traditional approaches significantly overestimate zombie prevalence among these firms, with corrections reducing the employmentweighted share by up to 10 percentage points. Across the full economy, zombie firms account for 8% of employment and 3.7% of firms, with lower prevalence among SMEs. Following the pandemic, the zombie share rose temporarily, peaking at 9% in 2022. The bankruptcy penalty for zombies collapsed in 2020, then began a gradual recovery; as of the period ending in 2023 it had not fully normalized. The paper then examines how the presence of zombie firms affects the economy through misallocation channels—asking whether they impede reallocation among healthy firms and weaken creative destruction. We find that industries with a higher zombie share are associated with reduced firm entry and weaker market selection (fewer exits of low-productivity firms), with limited direct crowding-out of healthy firms.

Keywords: Zombie Firms, Profit Shifting, Aggregate Productivity, Multinational Enterprises, Congestion effects

JEL Code: G33, H26, O47, F23

1 Introduction

The phenomenon of zombie firms—unproductive businesses that continue to operate despite being unable to cover their debt servicing costs—has garnered significant attention over the past decade due to its potential impact on economic productivity and growth. The term gained prominence following the stagnation of the Japanese economy in the 1990s, where the persistence of such firms was first highlighted as a contributing factor to the enduring economic slump (Caballero et al., 2008). Such persistence is often enabled by 'zombie credit,' where banks continue to lend to these unviable firms, typically to avoid recognizing losses on their own balance sheets or due to implicit government guarantees. In the aftermath of the COVID-19 pandemic, aggressive public support measures were implemented across Europe to sustain the productive sectors during unprecedented disruptions. While these interventions were crucial for short-term stability, concerns have emerged about their long-term implications, particularly the risk of "zombification" of the economy and its potential to hamper productivity growth (Bénassy-Quéré, 2021), as these measures could inadvertently mimic the effects of traditional zombie credit by sustaining otherwise non-viable businesses through non-market mechanisms. This paper provides one of the first comprehensive post-crisis assessments of this risk, leveraging exhaustive French tax data up to 2023. My findings reveal a clear, albeit temporary, increase in the employment-weighted share of zombies among mature firms. The share rose by about 1 percentage point, peaking at 9 percent in 2022 before declining back to 8 percent in 2023. Consistent with this transitory rise, the default penalty for zombie firms collapsed in 2020 and remained muted in 2021, when bankruptcies were at historic lows. Yet among the few firms that did fail, zombies were relatively more common than before. The penalty approached pre-crisis levels by 2023.

Despite the importance of understanding zombification, existing research lacks comprehensive evidence, as most studies focus on panels of large private firms (Adalet McGowan et al., 2018; Acharya et al., 2022) or publicly traded companies (Banerjee and Hofmann, 2018), leaving a significant gap in our knowledge regarding small and medium-sized enterprises (SMEs) given their role in the economy. In France, SMEs constitute a crucial part of the economy; in 2021, there were 159,000 SMEs, employing 4.3 million people and generating nearly 23% of the total value added by all firms.[1] This paper addresses this gap by providing one of the first comprehensive analyses of zombie firms in a major economy—France—using exhaustive firm-level tax data from 2009 to 2023, building on prior work such as Hassine and Mathieu (2023).

Leveraging this extensive dataset presents unique challenges, particularly concerning the accurate measurement of firm profitability. Large multinational corporations often engage in profit-shifting activities to minimize tax liabilities, significantly distorting fiscal data. For France, it is estimated that shifted profits constitute approximately 17% of the total corporate profits reported by firms, representing a substantial portion of the economy (Tørsløv et al., 2023). Standard methods of identifying zombie firms, typically applied to consolidated balance sheet data at the global level, do not face the issue of profit-shifting distortions. However, my use of granular fiscal data introduces this challenge, as profits are reported separately for tax purposes. By addressing these distortions through profit-shifting adjustments, my analysis provides a more accurate estimation of zombie firms in France.

To overcome this challenge and address the distortions caused by profit shifting among large multinational firms, this paper uses the novel methodology developed by Guvenen et al. (2022). I adjust firm profits for large French multinationals using Country-by-Country Reporting (CbCR) data from 2016 to 2023. My findings reveal that traditional zombie firm identification methods significantly overestimate the share of zombie firms among French multinationals. After adjusting for profit shifting, the employee-weighted share of zombie firms among French multinationals decreases from 14% to 10% on average, with adjustments as large as 10 percentage points in certain years. Across the entire economy, zombie firms represent approximately 8% of employment among mature French-owned firms, or 3.7% of firms. The lower unweighted figure reflects the relatively small share of zombies among SMEs, consistent with their lower leverage and higher propensity to exit the market.

[1] Les entreprises en France, Édition 2023, INSEE.

I analyze how zombie firms affect productivity through spillover channels, such as congestion effects, where zombie firms may crowd out more productive firms, and the extensive margin, where their presence disrupts the creative-destruction process by affecting firm entry and exit. While zombie firms are found to be less productive than non-zombie firms, I find limited evidence that zombie congestion reduces average growth of healthy firms, but some evidence that higher zombie shares dampen labor reallocation towards more productive firms, with no clear effect on capital reallocation. However, industries with a higher share of zombie firms tend to have lower entry rates of new firms, though the evidence is inconclusive once controlling simultaneously for time and industry fixed effects. These industries also display lower overall bankruptcy rates, consistent with the idea that zombie congestion may weaken market selection for all firms, or be indicative of general suppressed exit dynamics in those industries. As previewed at the outset, this weakening of market discipline was particularly acute during the COVID-19 pandemic, when the individual default penalty for being a zombie temporarily collapsed before rebounding.

This comprehensive analysis contributes to a more nuanced understanding of zombie firms and their economic implications. By using exhaustive tax data and introducing adjustments for profit shifting, I provide valuable insights for policymakers and researchers concerned with productivity growth, fiscal policy, and the health of the corporate sector in the post-pandemic economy. The findings highlight the need to consider the impact of zombie firms on the entry of new firms and the importance of policies that facilitate creative destruction. My results also underscore the importance of efficient bankruptcy processes (Becker and Ivashina, 2021) and strong banking sectors in facilitating the restructuring or exit of unproductive firms, thereby fostering a more dynamic and resilient economy.

Related Literature

This paper contributes to three related strands of the literature.

First, it adds to the extensive research on zombie firms and their effects on productivity and economic dynamics (Caballero et al., 2008; Adalet McGowan et al., 2018; Acharya et al., 2022). In contrast to previous studies focusing on large firms or publicly traded companies, this paper leverages exhaustive firm-level tax data from France (2009-2023) to quantify the share of zombie firms across the entire size distribution, including SMEs. This comprehensive approach and the use of exhaustive data on firm entry and exit provide more precise insights into how zombie prevalence varies by firm size and affects aggregate productivity through congestion effects and firm dynamics (impact on entries and exits). To my knowledge, the current studies on France (Hassine and Mathieu, 2023) do not explicitly adjust for the international dimension of firm-level profit shifting when identifying zombie firms, whereas this paper does so using CbCR-based profit corrections for large multinationals.

Second, this paper contributes to the tax avoidance literature by showing how firm-level profit-shifting adjustments can improve the measurement of multinational corporations' performance and its implications for productivity analysis. It builds on prior work on profit shifting and tax avoidance by multinational corporations (Bilicka, 2019; Tørsløv et al., 2023; Guvenen et al., 2022), and connects these insights to the study of zombie firms. In particular, it relates to research that looks at the specific case of France and how profit shifting affects tax earnings and measurement (Vicard, 2023; Aliprandi et al., forthcoming). Traditional methods of identifying zombie firms may overestimate their prevalence among multinationals due to profit shifting. By using the novel methodology from Guvenen et al. (2022), this paper bridges the gap between studies on tax avoidance and zombie firms. Beyond specifically studying zombie firms, it highlights how firm-specific profit-shifting estimates can be leveraged for a wide variety of analyses that are not possible with only aggregate profit-shifting data.

Third, this paper relates to research on the economic consequences of the COVID-19 pandemic, particularly concerning firm bankruptcies, government interventions, and the possible zombification of the economy (Banerjee and Hofmann, 2018; Gourinchas et al., 2021; Bénassy-Quéré, 2021; France Stratégie, 2021). By analyzing exhaustive data on firm dynamics in France, this study provides empirical evidence on how the pandemic and policy responses have influenced zombification. This informs the policy debate on balancing crisis support with the need to prevent long-term productivity stagnation.

2 Defining Zombie Firms using Fiscal Data

This section outlines the methodology and data sources used to identify zombie firms within the French economy. It details the data I use on French firms (throughout the paper, this term refers to consolidated corporate groups), explains the criteria for classifying zombie firms, and examines the effects of fiscal optimization and profit shifting on these classifications. By addressing data consistency and methodological challenges, the section provides a robust framework for analyzing the prevalence and characteristics of zombie firms.

2.1 Data and Methodology

This study draws on two primary data sources derived by French fiscal authorities: the FARE dataset from INSEE and the French CbCR dataset from DGFiP. Both sources offer rich, detailed data on firm-level activity.

Firm Balance Sheets. The data on French firms, FARE, is provided by the French National Statistics Institute (INSEE). The data covers the period 2009–2023 and is reported at the legal-unit level. Because these are unconsolidated accounts, I use data on firm ownership (LIFI) to consolidate accounts at the group level and to define key variables used in the analysis (see Appendix A.1 for specific details on consolidation and variable construction). The unit of observation in the empirical analysis is therefore the corporate group; for brevity, I refer to these groups as "firms" throughout the paper. Working at the group level rather than at the legal-unit level involves a trade-off. On the one hand, financing decisions, interest payments and profit shifting are determined at the group level, so the ICR-based zombie definition is conceptually closest to a consolidated balance sheet and comparable to the existing zombie literature. On the other hand, this choice blurs the mapping between groups and narrowly defined industries for multi-activity business groups and prevents me from exploiting within-group heterogeneity across legal units. I privilege the group definition because the financing margin is central to the questions in this paper, but this implies that sectoral zombie shares and congestion estimates should be interpreted as approximations to more granular, legal-unit patterns. The variables of interest are interest payments, total debt, assets, value added, EBE, and firm age. I complement the data with employment coming from the *Base Tous Salariés* (BTS) dataset. This is important as firms have specific incentives to underreport their employment in their tax returns, as pointed out by Askenazy et al. (2022). This in turn leads to overestimating firm-level productivity levels. Key operational variables used for the zombie definition and labor productivity measures, such as employees and EBITDA, are summable across a group's legal units. However, this consolidation method presents a known limitation for financial variables like interest payments and debt. Summing these figures across units can lead to double-counting of intra-group liabilities, thereby overestimating the group's true external interest payments. While this represents a limitation to the analysis, a robustness check detailed in Appendix A.3.2 shows that this overestimation has a small and consistent impact on our main zombie firm classification. Evidence from the subset of about 100 large groups with fully consolidated accounts (the *"Entreprises Profilées de Cible 1"*) shows that the lower-bound correction removes about twice the actual intra-group interest and thus roughly halves true interest payments. I therefore keep the simpler consolidation as the baseline and use the corrected series only as a robustness check. I measure productivity at the firm level using deflated labor productivity (per worker). The deflator is the official INSEE Value Added deflator.[2]

In addition, the LIFI dataset has information on the nature of the ultimate owner for each group. This lets me classify firms according to ultimate ownership (*"French Multinationals", "Independent & Franco-French firms", and "Foreign-Owned group"*).

Unit of analysis: corporate groups vs. legal units. The decision to work at the group level rather than the legal-unit level is central for the rest of the paper. From a financing perspective, interest coverage, access to bank

[2] I use the aggregate (economy-wide) value-added deflator for total resident sectors and total industries (base 2020); this has no bearing on results that use within-sector×year relative productivity measures.

credit, and profit-shifting decisions are determined at the level of the consolidated group balance sheet, not at the level of individual legal entities. Using groups as the unit of observation is thus natural for questions about zombie credit and debt-servicing capacity, and it is also the level at which the Guvenen-type profit-shifting correction can be meaningfully implemented. The downside is that sectoral measures—such as industry-level zombie shares or congestion variables used later in Section 4—are constructed by assigning each group to a single main NACE industry. For groups operating multiple legal units across different industries, this compresses their activity into one sector and prevents me from observing within-group reallocation of resources across lines of business. As a result, the sectoral estimates should be read as capturing the exposure of industries to zombie *groups*, rather than a fully granular mapping between establishment-level zombies and narrowly defined product markets.

CbCR. I also use the French CbCR (*"Country-by-Country Reporting"*) dataset, made available by the DGFiP. French multinational firms with above 750 million euros in annual sales have the obligation to report their yearly profits and other characteristics (employees, capital, tax paid, ...) to the French fiscal authority, covering each country in which they are based. This reporting obligation started in 2016, as part of the larger OECD BEPS (*Base Erosion and Profit Shifting*) program. Its stated goal is to better understand the fiscal optimization of large firms, and fight their base erosion behavior. A key advantage of this dataset compared to other similar ones like the OFATS (*Outward Foreign Affiliates Statistics*) database is that it is a fiscal source rather than a survey.[3] As such the response rate is much higher and there are fewer missing values. The quality of the responses is also higher for the same reasons. On average, it comprises the 300 largest French multinationals. These firms, while representing a small fraction (around 4%) of the total number of French MNEs, account for a substantial share (approximately 60%) of their employment. Notably, multinationals falling below the CbCR reporting threshold are not covered by our profit shifting adjustment. However, since significant profit shifting is predominantly a feature of the very largest corporations (Aliprandi et al., forthcoming), the lack of adjustment for these smaller MNEs is expected to have a limited impact on the accuracy of their zombie firm identification, as their reported fiscal profits are likely to be less distorted by such practices.

Note: The CbCR data only exists for the period (2016-2023). For that reason, all profit shifting results pre-2016 are done by estimating the average shifted profits for each firm on the period 2016-2023, and then using that value as the shifted profits when CbCR is missing. I show in Appendix A.3.1 that this assumption is reasonable, though obviously imperfect.

Fiscal vs. Accounting Data. A key distinction in this paper, vital for understanding the analysis of fiscal optimization by large firms in later sections, is the difference between fiscal and accounting data. This paper utilizes the FARE dataset, derived from the annual fiscal declarations that all French firms are required to submit for tax purposes.[4]

Unlike consolidated accounting data commonly provided by publicly traded firms, which report global financial performance, fiscal data in the FARE dataset exclusively reflect firms' French activities. For example, revenues generated by an American subsidiary of Airbus would not be subject to French taxation and, therefore, are not included in the French fiscal declaration. This discrepancy between fiscal and accounting data manifests differently across three types of firms.

First, for French firms without foreign subsidiaries, including independent enterprises (*"Entreprises Indépendantes"*) and group-affiliated firms that are purely domestic with no foreign subsidiaries (*"Entreprises Franco-françaises"*), we expect no substantial difference between accounting and fiscal data, as their economic activities are confined to France. Second, for French multinational enterprises (*"Multinationales Françaises"*)—those with a parent company in France and subsidiaries abroad—a divergence emerges, as their foreign activity is not fully captured in

[3] Although CbCR reports are not directly used for tax assessments and the extent of their verification is uncertain, they are a legal obligation for firms. This makes them more reliable than OFATS, though not necessarily exempt from misreporting.

[4] *Formulaire n°2050-LIASSE*: impots.gouv.fr

their French tax filings. Finally, for French subsidiaries of foreign multinational enterprises (*"Multinationales Etrangères"*)—those with a parent company located outside France—this divergence is most pronounced since a significant portion of their economic activity and profits may be attributed to the foreign parent and thus fall outside the scope of French fiscal reporting.[5]

The methodology for maintaining consistent group identifiers over time, which is crucial for tracking firm ownership changes and integrating datasets like CbCR, is detailed in Appendix OA1.

2.2 Zombie firm definition

I follow the standard definition in the literature for zombie firms, as outlined by the OECD (Adalet McGowan et al., 2018). Specifically, a firm is classified as a zombie if its Interest Coverage Ratio ($ICR = \frac{EBE}{Interest\ Payments}$) is below 1 for three consecutive years, and it is at least 10 years old. This captures the idea that a firm is unable to pay its interest payments using its economic profits. Acharya et al. (2022) argue that this definition does not fully capture the misallocation effects of zombie firms, finding that these effects occur when subsidized credit allows non-viable firms to distort competition, thereby depressing investment and employment growth at healthier competitor firms. I nevertheless adopt this simpler measure for clarity and to focus on the impact of tax optimization on zombie classification. More generally, this OECD-style ICR criterion should be read as a parsimonious indicator of persistent difficulty servicing debt rather than as a one-to-one measure of firm "non-viability". The ICR is jointly determined by operating performance and financing choices (debt versus equity, maturity, collateral), so otherwise similar firms can fall on different sides of the zombie threshold depending on how they are funded. In what follows, "zombie" therefore means a mature firm that repeatedly fails to cover interest out of recurring operating surplus given its balance-sheet structure.

This definition presents challenges when applied to French fiscal data due to profit and debt shifting by multinational firms under Base Erosion and Profit Shifting (BEPS) practices. BEPS can distort both EBE and debt levels, leading to artificially low or negative ICR values that misclassify firms as zombies. For example, using a dataset similar to mine for British firms, Bilicka (2019) finds that fiscal data often report exactly zero profits for large multinationals at suspiciously high rates, in contrast to local firms. Similarly, Tørsløv et al. (2023) show that Orbis data significantly underreports multinational profits, excluding those booked in key tax havens like Bermuda or the US. For instance, while Orbis lists Apple's 2016 global profits as \$55.3 billion, it records only \$2.0 billion at the subsidiary level, omitting profits shifted to tax havens.

Given these distortions, zombie classification based on fiscal data requires careful consideration, as these practices can bias the results.

ICR and Firm Size Distribution Figure 1 shows the median Interest Coverage Ratio (ICR) across the firm size distribution for 2019 as an example. Firms are ranked by employment count, and the median ICR is calculated using a rolling window of approximately 1,000 firms. The x-axis represents the logarithm (base 10) of firm size rank, with lower values corresponding to larger firms. The data shows a clear negative correlation: the larger the firms, the lower the median ICR. This highlights two key points, which I explore further in this paper:

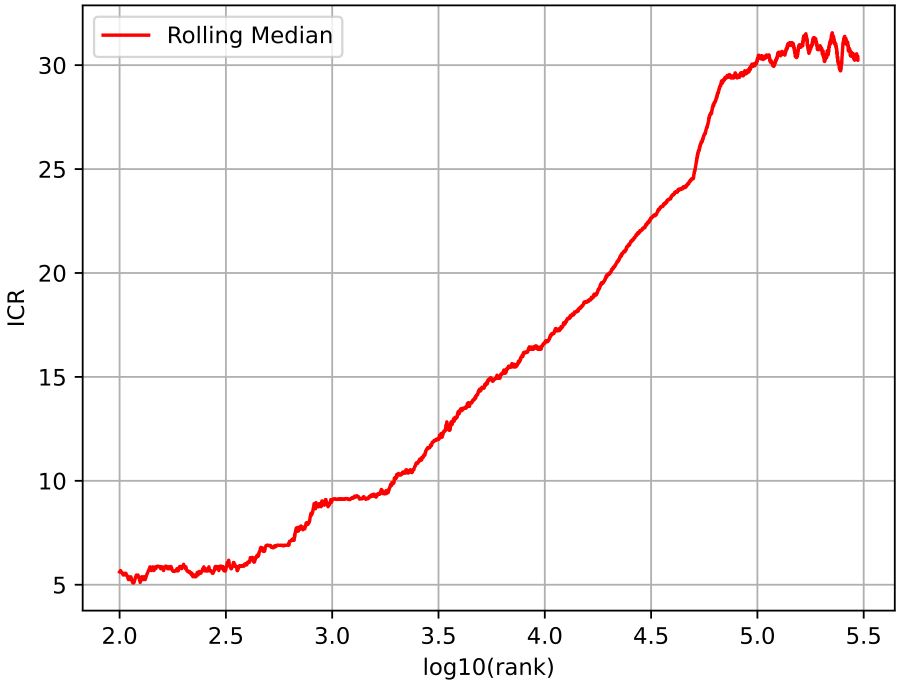
1. On the side of smaller firms, higher ICRs may reflect lower leverage, possibly due to more limited access to funding.

2. For larger firms, lower ICRs could be due to higher debt levels, greater use of debt for tax benefits, or broader tax optimization strategies. Indeed, debt financing generally offers tax advantages through the deductibility of interest payments. This aspect is particularly relevant in France, where the Conseil des Prélèvements

[5] While the distinction is continuous in practice, we follow official INSEE standards and classify firms solely by the location in France or not of the group head (*"siège social"*).

Obligatoires CPO (2023) has noted the specific generosity of interest deduction rules, contributing to a significant bias in favor of debt financing for large enterprises.[6] It could also be due to broader tax optimization strategies.

Figure 1: Median ICR by firm size ranking (2019)



Notes: Based on ICR (not debiased). Firms are ranked by employment, with the x-axis showing the logarithm (base 10) of firm size rank. Median ICR is calculated for each firm using a rolling window of approximately 1,000 firms centered around that firm's rank. Larger firms have lower ranks and lower median ICRs, while smaller firms have higher ranks and higher median ICRs.
Source: FARE, BTS, LIFI. Author's computation.
Sample: Non-financial corporate sector with more than 5 employees, no foreign firms.

The observed distribution hints at the need for a closer examination of ICR classifications for large firms, a focus of the subsequent section. It is important to acknowledge that these patterns reflect that the ICR mechanically embeds leverage and capital intensity: large, asset-heavy firms that own real estate and finance it with debt will, for a given profitability, display lower ICRs than asset-light firms that rely more on equity or renting. In that sense, the zombie indicator is partly shaped by business models and sectoral capital intensity as well as by pure underperformance, and should be interpreted as a measure of financing-sensitive fragility rather than a pure ordering of firm quality.

2.3 Fiscal Optimization and Profit Shifting

I first outline the economic framework for estimating shifted profits and then detail the practical application of this method, specifically using the CbCR data for large French multinationals, while addressing the strong assumptions required for this estimation.

Framework to estimate profit shifting I follow the methodology of Guvenen et al. (2022) to estimate shifted profits. The core idea is that profits in a country should align with its physical presence—measured by capital or labor. Unlike aggregate matching methods (e.g., Tørsløv et al., 2023) this approach uses micro-level CbCR data

[6]The CPO (2023) notes that the difference in the effective average tax rate between an equity-financed investment and a debt-financed investment was around 10 percentage points in 2021 for large French enterprises (p.40).

to estimate shifted profits at the firm level. Because being a zombie firm is precisely a firm-specific condition, I need those firm-specific estimates.

A multinational firm i, operating in multiple countries, has a Cobb-Douglas production function in each country c with technology $A_{i,c}$, labor $L_{i,c}$, and capital $K_{i,c}$. The parameter α represents the elasticity of output with respect to labor, p_c is the price of output in country c, w_c is the wage rate, and r is the cost of capital, assumed to be constant across all countries. The profits of the firm in country c are given by:

$$\Pi_{i,c} = p_c A_{i,c} L_{i,c}^{\alpha} K_{i,c}^{1-\alpha} - w_c L_{i,c} - r K_{i,c}. \tag{1}$$

The key assumption is that the firm has an identical production function and equal markups in all countries where it operates, which implies that profits in any given country are proportional to the firm's capital in that country. Specifically:

$$\Pi_{i,c} \propto K_{i,c}. \tag{2}$$

Aggregating this relationship across all countries gives the firm's global profits:

$$\Pi_{i,\text{World}} = \sum_c \Pi_{i,c}. \tag{3}$$

Using the proportionality between profits and capital, we can express the ratio of profits to capital as (see Online appendix OA2 for the full derivation):

$$\frac{\Pi_{i,c}}{\Pi_{i,\text{World}}} = \frac{K_{i,c}}{K_{i,\text{World}}}. \tag{4}$$

Applying this relationship to $c = \text{France}$, the firm's expected profits in France based on capital allocation are:

$$\Pi_{i,\text{Expected}} = \Pi_{i,\text{World}} \cdot \frac{K_{i,\text{FR}}}{K_{i,\text{World}}}. \tag{5}$$

We observe the profits $\Pi_{i,\text{FR}}$ from the firm's balance sheets. The shifted profits can then be calculated as the difference between the expected profits (based on capital allocation) and the observed profits in France:

$$\Delta\Pi_i = \Pi_{i,\text{Expected}} - \Pi_{i,\text{FR}}. \tag{6}$$

A positive $\Delta\Pi_i$ indicates that the firm has shifted profits outside France, although nothing in this model or in practice restricts shifted profits to being positive. Specific tax incentives or national advantages, for instance, could lead some firms to localize profits in France, resulting in negative profit shifting ($\Delta\Pi_i < 0$).

This method relies on the assumption that the production function is identical across all countries where the firm operates and that profits are proportional to capital allocation. This is a strong assumption, as it implies a common production technology with the same α across countries. Reassuringly, Aliprandi et al. (forthcoming) show that similar results are obtained when reallocating profits using wage bills instead of capital for the same set of French multinationals, suggesting that the assumption of a common α across countries is a reasonable approximation. Formally, if the capital- and wage-bill reallocations coincide, then $K_{i,c}/K_{i,\text{World}} = (w_c L_{i,c})/(wL)_{i,\text{World}}$ for all c, which implies $K_{i,c}/(w_c L_{i,c})$ is constant across countries; with Cobb–Douglas and cost minimization $rK_{i,c}/(w_c L_{i,c}) = (1-\alpha_{i,c})/\alpha_{i,c}$, so with common r this forces $\alpha_{i,c} \equiv \alpha_i$ across countries. Because wage expenses are not reported in the CbCR data, I implement the capital-based allocation. Appendix A.3.1 discusses in greater detail other possible sources of error and robustness checks, including benchmarking against the literature and a haven-only reallocation using the EU list, which yields similar aggregate magnitudes.

Practical Implementation To implement this methodology for the large French Multinationals in my sample, one needs firm-level data on profits, both inside and outside France, as well as country-level inputs (capital and/or labor). The Country-by-Country Reporting (CbCR) data provides these inputs, along with a specific measure of profits: "Profit (Loss) before Income Tax" (in French, *Bénéfice (ou perte) avant impôts*). This CbCR-specific item is conceptually closest to the standard French fiscal measure of *Résultat Courant Avant Impôts*, which is available in the FARE dataset. However, as demonstrated by Delpeuch et al. (2019) who compare these exact two data sources, the measures are not identical due to differences in consolidation scope and accounting standards between CbCR declarations and French fiscal accounts. Crucially, OECD guidance clarified in 2019 (applicable from 2020, though unevenly applied) and reaffirmed in 2024 (mandatory from 2025) specifies that this profit measure should exclude dividends received from other constituent entities within the group. Because implementation in the early years was inconsistent, some residual uncertainty remains in the data.

A critical methodological choice is the choice of the profit measure to apply the Guvenen profit reassignment to, as the model is quite theoretical. In addition, profit shifting can manifest differently depending on the definition of profits used - before or after financial and tax items for instance.

I consider two main issues: (i) the divergence in accounting standards between the CbCR data (IFRS norm) and the FARE dataset (French norm), and (ii) the distinction between pre-tax fiscal profits and economic profits (EBE). Indeed, I use EBE to compute the ICR but I estimate the amount of shifted profits using the CbCR pre-tax fiscal profits, and reassign this amount to the EBE of the relevant French firms. This assumes that profit shifting operates similarly across both profit measures, which is a reasonable simplification as discussed below and detailed in Appendix A.2.1.

Profit shifting typically occurs through three primary mechanisms: transfer pricing, which is the setting of prices for transactions between related entities within a multinational enterprise, the manipulation of intangible assets (such as intellectual property), and debt shifting. Transfer pricing and intangible asset manipulation generally affect both pre-tax profits and EBE similarly, as they involve adjustments to revenues or costs that are recognized early in the accounting process. Hence, estimating shifted profits using pre-tax fiscal data and reassigning them to EBE is justifiable under these two mechanisms. Debt shifting, however, represents a specific challenge as it primarily affects pre-tax profits by increasing interest expenses without directly altering EBE. While I acknowledge this discrepancy, I show in Appendix A.2.1 that debt shifting does not invalidate the zombie firm identification based on the ICR. For that reason, I do not aim to estimate the amount of debt shifting happening at the firm level.

I combine equations 5 and 6 to compute firm-specific profit shifting $\Delta\Pi$. The adjusted ICR, incorporating re-assigned profits, is then calculated as:

$$\text{ICR}_{\text{adjusted}} = \text{ICR} + \frac{\Delta\Pi}{\text{Interest Paid}} \tag{7}$$

where $\Delta\Pi$ represents the re-assigned profits based on CbCR data. The estimated range of aggregate profit shifting (10 to 20 billion euros per year) is consistent with values found in the literature for France, though somewhat lower than the €32–36 billion figures reported by Tørsløv et al. (2023) and Vicard (2023). This is largely due to differences in scope: their estimates include profits shifted by both French and foreign MNEs, while ours focuses exclusively on French-headquartered firms. By contrast, our estimates align more closely with those of Aliprandi et al. (forthcoming), who rely on the same CbCR data and a comparable reallocation method. As detailed in Appendix A.3.1, this places our firm-specific results within the plausible range found in the literature. Furthermore, the aggregate estimates from our baseline model remain broadly consistent under an alternative specification where profit reallocation is restricted only towards known tax havens (see Figure 10). This helps address the concern that the baseline may partly reflect real differences in production or markups across countries.

Furthermore, Table 10 in Appendix A.2 reports descriptive statistics on the estimated shifted profits by industry.

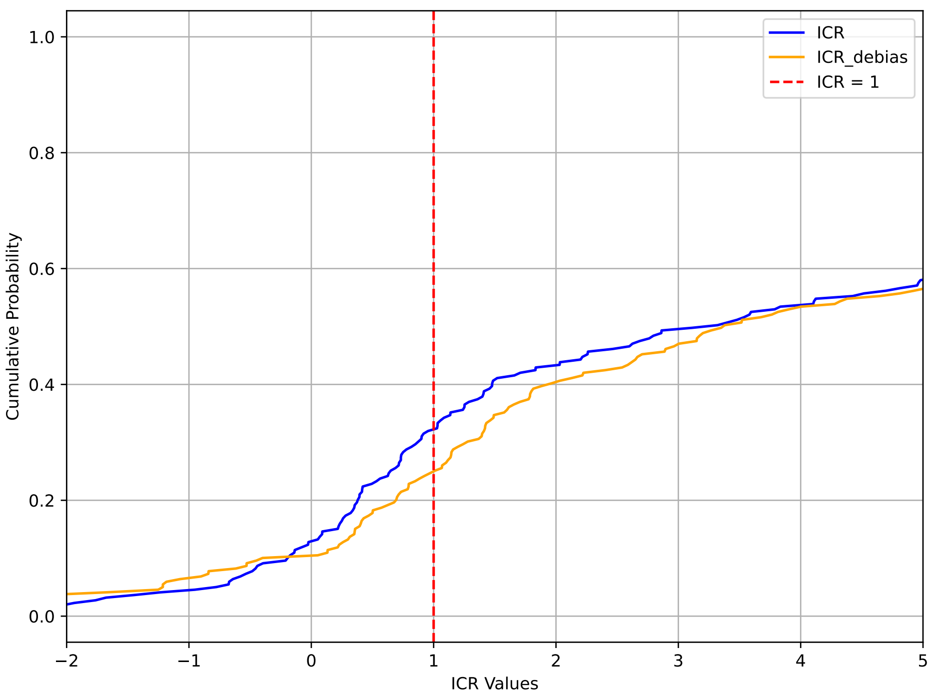
2.4 ICR Estimation

Figure 2 illustrates the impact of debiasing profits on the cumulative distribution function (CDF) of the interest coverage ratio (ICR) among French multinational firms. Using raw fiscal data, I estimate that in 2019, around 30% of these firms were unable to cover their interest payments through economic activity. After debiasing, this share falls to about 22%. The sharpest adjustment occurs near ICR $\approx$ 1. Since EBITDA is measured before interest payments, firms reporting ICR around 1 (prior to debiasing) are typically those with low taxable profits relative to accounting earnings.

This echoes findings in Bilicka (2019), which documents "bunching" at zero taxable profits among UK subsidiaries of multinationals, despite positive accounting profits—a pattern not seen in domestic firms. While I do not identify bunching per se, the concentration of the adjustment around ICR $\approx$ 1 appears consistent with the idea that profit-shifting is most visible at this margin.

Not all firms engage in such behavior—regulatory constraints and enforcement risks limit the scope for shifting (Ferrari et al., 2022)—but among those that do, the ICR $\approx$ 1 region appears to be a focal point.

Figure 2: CDF of ICR and debiased ICR for French multinational firms (2019)



Notes: This graph shows the CDF (cumulative distribution function) of ICR for French Multinationals using the normal ICR measure ("ICR" in blue) and the debiased ICR ("ICR_debias" in orange) using the profit shifting estimates. The vertical line is at the ICR = 1 threshold which is used to identify zombie firms. The graph is truncated for low and high values of ICR on the x-axis to focus on the range around 1.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

3 Zombie Firms in France: Prevalence and Characteristics

Having made this adjustment for large French Multinationals, I now present the actual zombie firm estimations. The final dataset comprises all firms in the non-financial, commercial sector in France with more than 5 employees. Except for the descriptive statistics in 3.1, all the statistics are among the sample of mature French firms (10 years or older; results are robust to this cutoff, see Figure 11 in the appendix). Industry is defined using the NACE 2-digit codes. Each year, the dataset includes approximately 300 000 firms, accounting for 75% of employees but 90% of value added within the non-financial commercial sectors included in the analysis. This enhances the credibility of subsequent estimations of zombie firm prevalence and their spillover effects.

3.1 Descriptive statistics

Table 1 reports summary statistics across firm categories. On average, zombie firms are older and larger, consistent with the idea that their continued operation is supported by long-standing relationships with banks. Beyond these static balance sheet characteristics shown in the table, a key dynamic feature of zombie firms is their high degree of persistence; if a firm is a zombie, it has an 81% probability of remaining a zombie the following year, a statistic that is stable through time.

Table 1: Balance sheet characteristics, by firm category

	Non Zombie	Zombies	Not Mature	Foreign Firms
Book Leverage (%)	13.63	23.21	18.76	9.59
Labor Productivity (100k€/emp.)	0.52	0.36	0.38	0.75
Profitability (%)	3.78	-4.79	3.76	2.61
Assets (k€)	812.52	1,143.77	379.12	5,712.22
Age	21	26	5	23
Avg. Firms per Year	171,791	5,686	98,134	10,078

Notes: The table reports median values of accounting variables. Foreign Firms are firms with a non-French ultimate owner, Not Mature are firms less than 10 years old, Zombies and Non Zombies are classified using the OECD definition. Labor productivity is deflated using the VA deflator from INSEE, Profitability is defined as EBIT over sales, age is in years. Avg. Firms per Year shows the average number of firms per year.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees, 2011–2022.

Foreign firms are included in Table 1 to illustrate that their financial characteristics differ systematically from comparable domestic firms. To investigate this point more systematically, Table 2 focuses on the universe of group-affiliated firms—both French and foreign—and reports results from regressions of key firm-level financial variables on an indicator for foreign ownership, controlling for industry and firm size.

To avoid circularity, I do not compare firms on the ICR directly (our outcome of interest), but instead examine the unadjusted values of its components: EBE (the numerator) and interest expenses (via leverage and cost of debt, i.e., the denominator). This approach highlights that both elements of the ICR can be distorted for foreign firms in ways that are not easily corrected using French fiscal data alone.

The results in Table 2 confirm that, relative to the reference category of purely domestic French groups, both foreign-owned and French multinational groups exhibit financial patterns consistent with tax optimization. Foreign-owned groups have significantly lower profitability and slightly lower leverage than domestic French groups, which is consistent with shifting profits out of France and localizing debt in their home jurisdictions. In contrast, French multinational groups also exhibit lower profitability but significantly higher leverage, a pattern in line with shifting profits out while shifting debt *into* France.

While both types of multinational groups show signs of these distortions, the critical distinction for this paper's methodology lies in our ability to correct for them. For French multinational groups, we rely on CbCR data to adjust for these distortions. This correction, however, is not possible for foreign-owned groups as equivalent data is not available. This explains why we exclude foreign-owned groups from the core sample.

Table 2: Differences in financial characteristics: foreign vs. French firms

	Profitability (1)	MarginRate (2)	Leverage (3)	CostDebt (4)
Ref. group: Domestic non-MNE	-	-	-	-
Foreign MNE	-0.898***	-1.583***	-0.140	0.947***
	(0.233)	(0.263)	(0.479)	(0.149)
French MNE	-0.967***	-2.302***	1.027*	0.691***
	(0.305)	(0.447)	(0.521)	(0.079)
Assets	0.204***	1.639***	1.234***	-0.023
	(0.069)	(0.170)	(0.215)	(0.022)
age	-0.023***	-0.087***	-0.086***	0.002*
	(0.003)	(0.010)	(0.017)	(0.001)
NACE	x	x	x	x
year	x	x	x	x
Observations	824277	824277	824277	824277
S.E. type	by: NACE	by: NACE	by: NACE	by: NACE
R^2	0.089	0.093	0.127	0.069
R^2 Within	0.006	0.024	0.015	0.003

Significance levels: $*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$. Format of coefficient cell: Coefficient (Std. Error)

Notes: This table reports coefficient estimates from regressions of firm-level financial characteristics on ownership indicators for foreign (Foreign MNE) and French multinationals (French MNE). The omitted group is French group-affiliated firms that are not multinationals. All regressions control for year, industry (NACE), and firm size (log assets). *Profitability* is defined as EBIT over sales; *MarginRate* is EBIT over value added; *Leverage* is debt divided by assets; and *CostDebt* is the effective interest rate, calculated as interest expenses divided by debt. Standard errors are clustered by 2-digit NACE sector.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial multinational firms, 2011–2022.

3.2 Impact of profit shifting on French multinationals

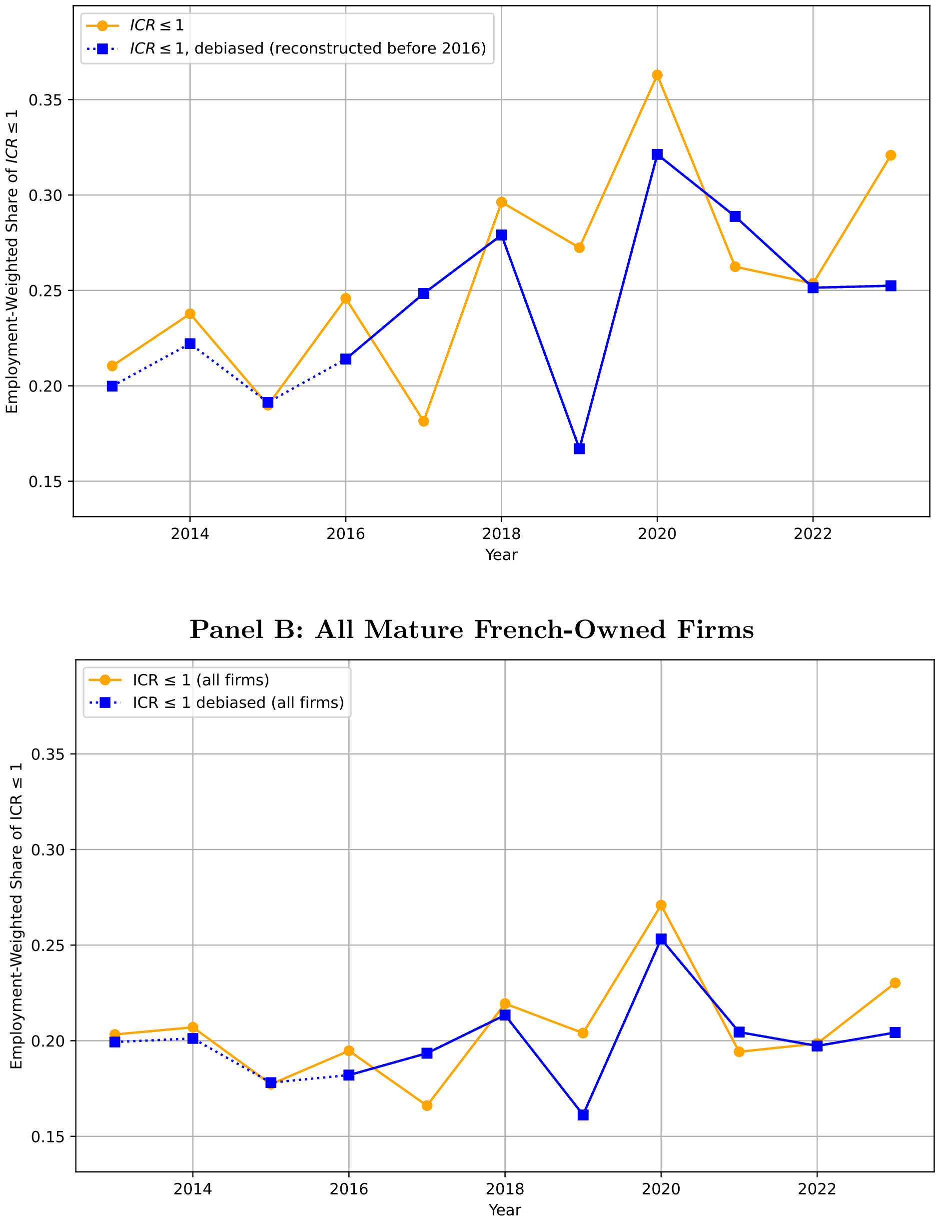
Figure 3 (Panel A) shows how ICR debiasing generally reduces the percentage of French multinational firms with an ICR of 1 or less. For example, in 2020, this percentage drops by over 4 points after debiasing, showing the importance of the adjustment. The correction is particularly pronounced in 2019, a year of high profits for large French groups, so that reallocating shifted profits back to France mechanically moves several of those firms from just below to just above the ICR ≤ 1 threshold. In a few years, by contrast, the debiasing slightly increases the share of firms with ICR ≤ 1: this reflects cases where the Guvenen-type allocation implies negative shifted profits, i.e. profits being reallocated *into* France, as illustrated by the False Healthy group in Table 3.

Panel B then applies the exact same one-year ICR ≤ 1 indicator to the full population of mature French-owned firms. This provides the direct bridge to the next subsection, where the analysis is tightened to the three-year ICR < 1 criterion defining zombie firms.

Figure 3: Employment-weighted share of firms with ICR ≤ 1

Panel A: French Multinationals

Panel B: All Mature French-Owned Firms



Notes: This figure illustrates the share of firms with ICR ≤ 1 using the debiased and non-debiased ICR. The orange line corresponds to the normal ICR, and the blue line corresponds to the debiased ICR. The blue line is dotted before 2016, as shifted profits are imputed for this period.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
*Sample: **Panel A** — Non-financial French multinationals with more than 5 employees and more than 10 years of age, excluding foreign-owned firms. **Panel B** — Non-financial mature French-owned firms with more than 5 employees and more than 10 years of age.*

3.2.1 Profile of reclassified 'false-zombies'

It is natural to examine the characteristics of these reclassified firms. Table 3 shows descriptive statistics for the set of firms present in the CbCR dataset. I separate them into four groups: Healthy firms, Zombie firms, False Zombies (firms reclassified as non-zombies), and False Healthy firms (firms reclassified as non-healthy). False Zombies showcase a significant amount of profit shifting and are on average larger than other firms. This is consistent with the evidence that profit shifting is concentrated among the largest, most sophisticated firms. For instance, using the same dataset, Aliprandi et al. (forthcoming) find that most profit shifting happens among the largest firms. It should be noted that profits can also be shifted into France, potentially influenced by specific national incentives such as France's tonnage tax regime for shipping companies ('taxe au tonnage'). The negative median 'ProfitShifted' for the False Healthy group observed in Table 3 could reflect such inward shifting for some entities, distinct from the broader outward-shifting trend of profit shifting. To further explore these patterns, I compute each firm's share of capital located in France (France K share). Firms with a larger capital presence in France are more likely to exhibit lower estimated profit shifting in absolute value and are therefore less likely to be reclassified in either direction. The higher France K share observed for Healthy and Zombie firms is consistent with this, and they indeed show low estimated shifted profits.

Table 3: Characteristics for CbCR firms by zombie and reclassification status

	Zombies	False Zombies	False Healthy	Healthy Firms
Book Leverage (%)	37.90	35.59	22.41	23.38
Labor Productivity (100k€/emp.)	0.69	0.75	0.88	0.87
Assets (k€)	3,521,291.41	4,240,826.93	1,164,484.06	1,389,886.43
Profit Shifted (k€)	2.07	82,251.36	-64,802.00	0.00
Profitability (%)	-1.24	-0.70	2.75	3.14
ICR	-0.09	0.08	1.87	4.75
ICR Debiased	-0.32	1.36	-2.25	4.75
Avg. Firms per Year	22.00	24.00	19.00	240.00
France K. Share	0.40	0.24	0.22	0.60
Share of Total Employment (%)	2.19	3.34	1.48	29.23

Notes: The table reports the median values of accounting variables in France for firms appearing in CbCR. Zombies are classified using the OECD definition. A firm is a False Zombie if it is reclassified as Non Zombie using our method. Healthy firms are all other firms. Leverage is debt divided by assets; productivity is deflated labor productivity (INSEE VA deflator); assets are book assets; Profit Shifted estimated with the Guvenen method. *Profitability* is defined as EBIT over sales. France K Share is the ratio of French capital to world capital. Share of Total Employment is the average share of employment among all French mature firms in our sample. Avg. Firms per Year shows the average number of firms per year.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial multinationals present in the CbCR dataset, 2011–2022.

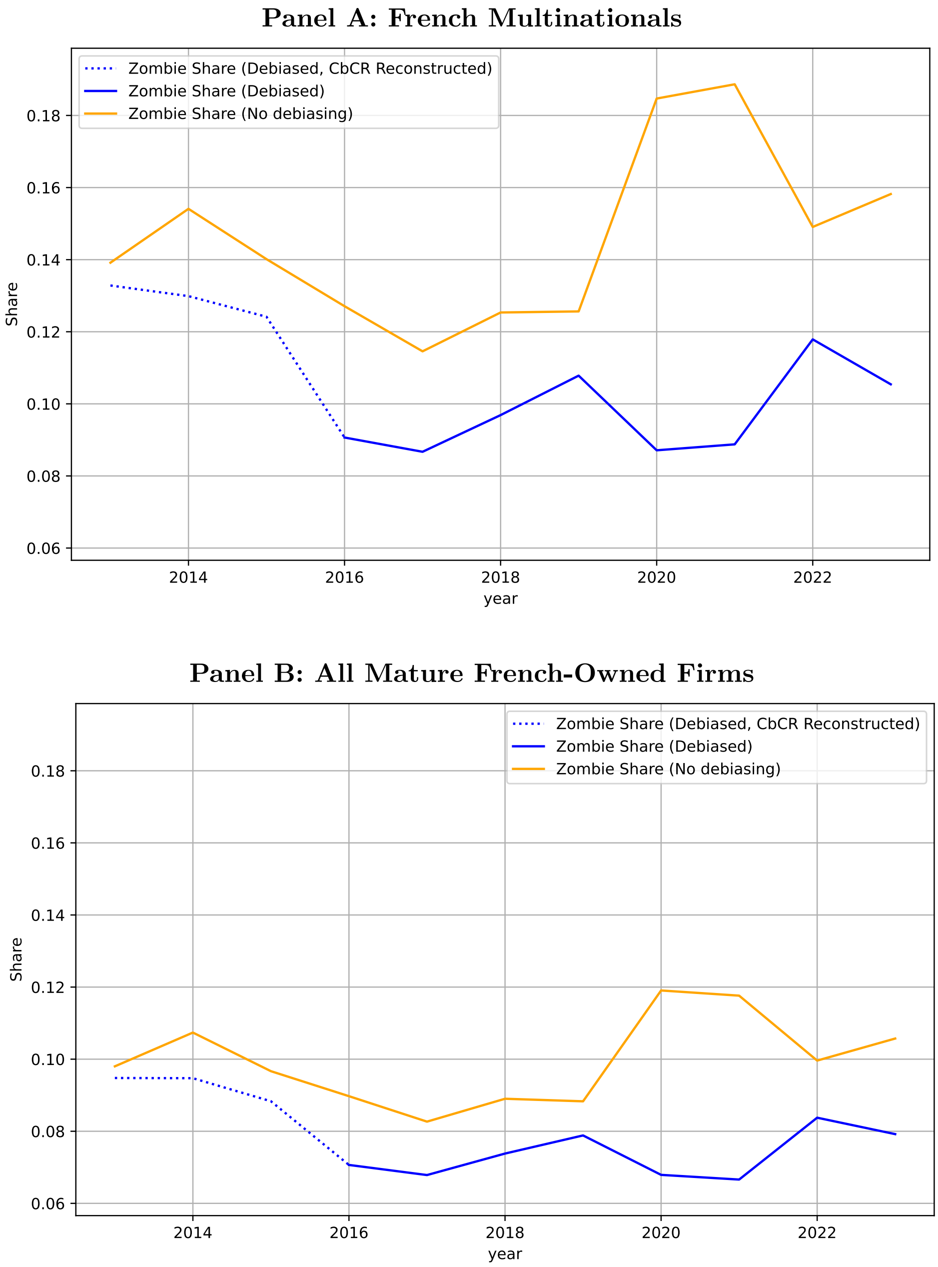
3.3 Zombie Firm Share

Building on the one-year ICR ≤ 1 indicator shown for all firms in Panel B of Figure 3, I now apply the full zombie definition, which requires having an ICR < 1 for three consecutive years. On average in France over the period from 2012 to 2023, zombie firms represent approximately 8% of employment for my sample of mature French-owned firms (Figure 4). Compared to the estimates found in the literature for France, these are in the same range. For instance, Adalet McGowan et al. (2018) find a 6% share of zombie firms in France in 2013. In contrast, Banerjee and Hofmann (2022) find higher percentages (more than 12%). This can be explained because their sample consists of publicly traded firms, and thus much larger on average. As pointed out before, larger firms are more prone to being zombies, even after accounting for profit shifting. It is also worth noting that this 8% estimate is broadly robust to the method of consolidating intra-group interest payments; a sensitivity analysis detailed in Appendix A.3.2 (Figure 12), using a more conservative lower-bound for these payments, indicates that our primary estimate might slightly overstate the zombie share by approximately 1 to 1.5 percentage points, though the overall dynamics and trends remain consistent. Because this alternative understates true external interest payments, we do not use it as a baseline.

For French multinationals (Panel A), the profit-shifting adjustment generally reduces the share of zombie firms (by approximately 4 percentage points on average), with this effect being substantially stronger during the 2016–2023 period, for which I have complete CbCR data and where the adjustment reaches up to 10%, but the dynamics of this adjustment in 2019 and 2020 warrant specific attention. As shown in Figure 4, the debiased zombie share (blue line) drops in 2020, a trend that diverges sharply from both the non-debiased series (orange line) and the one-year ICR measure (Figure 3), which spike due to the pandemic. This counter-intuitive decline illustrates the inertia inherent in the three-year consecutive criterion. To be classified as a zombie in 2020, a firm requires an ICR < 1 in 2018, 2019, and 2020. As discussed in Section 3.2, our profit-shifting correction is particularly pronounced in 2019—a year of high profitability—mechanically pushing the ICR of several large firms above 1 for that specific year. This "cure" in 2019 breaks the three-year chain, thereby disqualifying these firms from zombie status in 2020 despite the subsequent deterioration in their financial health. By contrast, in the non-debiased series these firms remain with ICR < 1 in 2019, so they stay classified as zombies and the Covid shock appears as an increase in the zombie share rather than a decline.

See Figure 13 for shares by firm ownership type.

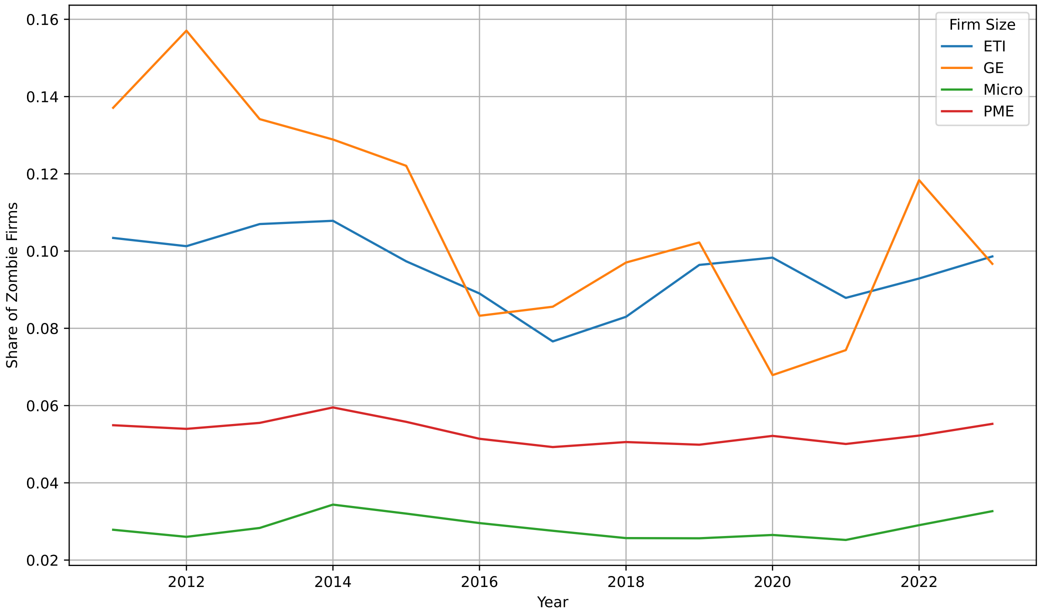
Figure 4: Employment weighted share of zombie firms in France



Notes: This graph illustrates the employment-weighted share of zombie firms in France (blue). The results without applying the profit-shifting debiasing strategy are shown in orange. The blue line is dotted before 2016, as shifted profits are imputed for this period.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: ***Panel A*** *— Non-financial French multinationals with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.* ***Panel B*** *— Non-financial mature French-owned firms with more than 5 employees and more than 10 years of age.*

Zombie shares along the firm size distribution. A key advantage of the data is the ability to have all firms, not only the largest or publicly traded firms that the firm-level datasets used to study zombie firms usually use. I document that small and micro firms, as defined by firms with under 250 employees (SMEs) and under 10 employees (Micro) have a small propensity of being defined as zombies, as shown in Figure 5. This is not surprising, as small firms might find it hard to access debt. On average, they are less levered and have a higher propensity to go bankrupt. As pointed out in the literature, this makes them less likely to receive zombie credit.

Figure 5: Proportion of zombie firms by firm size.



Notes: This graph illustrates the labor-weighted share of zombie firms in France by firm size.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

Interest Rate Dynamics and the Post-COVID Period The 2010-2020 decade was characterized by a secular decline in interest rates, a fact that significantly influenced macroeconomic conditions. To illustrate how this decline may have affected the prevalence of zombie firms, I perform an exploratory analysis by computing an alternative Interest Coverage Ratio (ICR) under a hypothetical scenario where interest rates remained at their initial levels, in 2012. For this exercise, I assume that firms' debt financing choices are unchanged, that is debt levels remain as observed, but I vary only the interest rate paid on that debt. Specifically, I set the hypothetical cost of debt to the median value in 2012, which is 4%. This simplifying assumption likely leads to an overestimate: in reality, firms may have taken on more debt precisely because rates declined. If interest rates had remained high, leverage would likely have been lower, implying fewer zombies than our counterfactual suggests.

The actual ICR is defined as:

$$\text{ICR} = \frac{\text{EBE}}{\text{Interest Payments}} = \frac{\text{EBE}}{\text{Debt}} \times \frac{\text{Debt}}{\text{Interest Payments}} = \frac{\text{EBE}}{\text{Debt}} \times \frac{1}{\text{Cost of Debt}}$$

Under the hypothetical scenario with constant interest rates, the ICR becomes:

$$\text{ICR}_{\text{Hypothetical}} = \frac{\text{EBE}}{\text{Debt}} \times \frac{1}{\text{Cost of Debt}_{\text{Hypothetical}}}$$

This can be expressed in terms of the actual ICR:

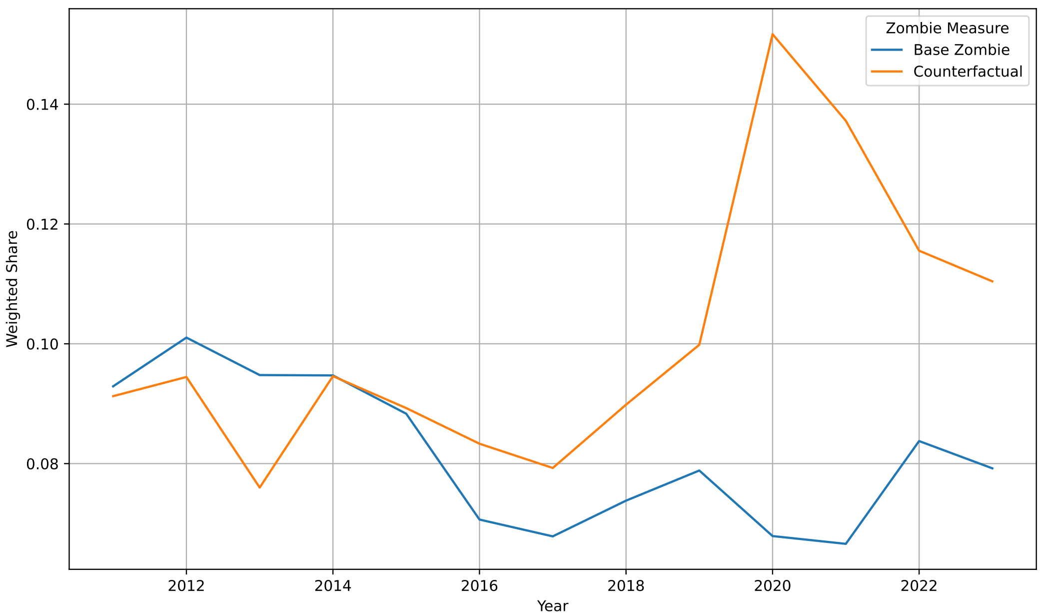
$$\text{ICR}_{\text{Hypothetical}} = \text{ICR} \times \frac{\text{Cost of Debt}}{\text{Cost of Debt}_{\text{Hypothetical}}}$$

Using this alternative ICR, Figure 6 shows that, had interest rates remained at 4%, the share of zombie firms would have been higher throughout the decade, and would have risen sharply from 2019 onward.

Overall, this suggests that lower interest rates could in fact partially explain the observed decrease in zombie firms, as reduced interest payments improve firms' ICRs (assuming that economic profits relative to debt levels remain unchanged). Given the standard definition of zombie firms—those with an ICR below 1 for three consecutive years—even modest ICR improvements from lower financing costs can mechanically reduce the aggregate share of such firms.

Note. An alternative reading of this counterfactual is as a stress-test or a measure of firms' latent vulnerability: at each date t, it approximates the additional share of firms that would become zombies if borrowing costs suddenly rose to 4%. Because firms roll over debt progressively and zombie status requires three consecutive years with ICR < 1, this exercise tends to overstate fragility—the adjustment would not occur instantly but only gradually and firms would probably lower their debt. Still, the gap between the actual and counterfactual measures is informative: before COVID it was modest, around 1–2 percentage points, but during the pandemic it widened to nearly 7 percentage points, highlighting the latent vulnerability in the corporate sector. In parallel, the post-COVID period is also marked by a persistently higher share of low-profit firms than before the pandemic, which suggests that weak profitability, even in an environment of low interest rates that mechanically boost ICRs, sustains a larger pool of vulnerable firms.

Figure 6: Proportion of Zombie Firms Under Actual and Hypothetical Interest Rates



Notes: Counterfactuals based on alternative interest rate scenarios.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

The COVID-19 crisis in 2020 caused significant disruptions for firms in France, resulting in substantial declines in activity and profitability. At the same time, extensive public support measures were implemented. It is important to consider the potential impact of these measures on our zombie firm identification and the actual shares of zombies. Between 2020 and 2022, the French state mobilized approximately €250 billion in business support, of which four instruments accounted for almost the entire envelope: State-Guaranteed Loans (PGE, €143 bn), the Solidarity Fund (€41 bn), short-time work subsidies (€22 bn), and social contribution exemptions/deferrals (€8.5 bn) (Cour des Comptes, 2023). For interpretation, we distinguish two channels: an *accounting/measurement* channel (effects on recorded costs that then impact our EBE or Interest Payments measurement that may affect identification) and a *real* channel, where thanks to the public support measures, some firms that would otherwise not be classified as zombies are classified as zombies because they would have gone bankrupt. The main types of measures are as follows:

- *i) PGE (State-Guaranteed Loans):* Although firm debt increased, firms continue to service these loans, often at market interest rates, so the Interest Coverage Ratio (ICR) is not artificially improved.

- *ii) Social contribution relief:* Reduces recorded labor costs which might have temporarily raised EBE, but it mainly targeted micro-firms (Cour des Comptes, 2023, p. 14), which rarely classify as zombies in our data (Figure 5).

- *iii) Solidarity Fund* and *iv) short-time work subsidies:* These measures enter as extraordinary income or offset labor costs, potentially increasing EBE. However, their distorting effect on our aggregate zombie share is estimated to be small, because payments were often capped and concentrated in specific sectors like hospitality and among very small firms.

Taken together, this tells us that there is limited risk that Covid-specific accounting rules bias our estimates. We now turn to the real (economic) impact. Because of its size and broad eligibility, the main support measure of interest is the PGE. In practice, its principal effect was to prevent exit. This has two implications: **(A)** it may have kept otherwise viable but temporarily unprofitable firms alive; such firms might then be *classified as zombies* in our data even though they are arguably healthy (*temporary misclassification*). **(B)** it may have kept structurally unprofitable firms alive; these are *actual zombies* that we correctly classify, and lower bankruptcies then mechanically *raise* the observed zombie share. Our three-year window alleviates concern **(A)**—a truly profitable business that tapped the PGE is unlikely to show ICR < 1 for three consecutive years—but it does not rule it out. In particular, transitory distress among otherwise viable PGE users could *partly* account for the 2022 spike in zombies when the pandemic was not fully over. By contrast, depressed bankruptcy rates in 2020–2021 make **(B)** plausibly important. Because our definition requires three consecutive years with ICR < 1, these survival dynamics show up with a lag, contributing to the 2022 increase as an accumulation of already-zombie firms that don't exit the economy thanks to loans. Figure 3—which shows an approximate doubling of firms with ICR < 1—is consistent with both **(A)** and **(B)**. Without loan-level data on PGE take-ups, it is not possible to decide on the most important mechanism.

Sectoral heterogeneity. There is significant heterogeneity in zombie shares across industries, ranging from about 3% in Food & Beverages to nearly 19% in Mining and Utilities. Following Bernstein et al. (2019), I group NACE industries into (i) capital-intensive tradables (manufacturing and extractive industries), (ii) knowledge-intensive services, and (iii) low-sunk-cost non-tradables.[7] Tradables such as Transport Manufacturing or Mining exhibit the highest zombie shares (15–20%), consistent with large fixed-asset bases and high reallocation frictions. Non-tradables like Retail or Accommodation average around 8–10%, while services, including Professional Services, fall in between at roughly 6–11%. These sectoral patterns correspond to the employment-weighted zombie shares calculated over the A17 classification. See Table 4 for details.

[7] Adapted to the French NACE classification: non-tradables = Wholesale/Retail (GZ) and Accommodation & Food (IZ); services = Construction (FZ), Transport/Storage (HZ), Information/Communication (JZ), Professional Services (MN); tradables = Manufacturing (C1, C3–C5) and Mining/Utilities (DE). The logic follows Bernstein et al. (2019): non-tradables hinge on local footfall, services rely on local knowledge spillovers, and tradables serve non-local demand.

Table 4: Average Zombie Shares by Sector (2011–2022)

A17	ShortName	Zombie Labor Share	Fixed Cost	Sunk Cost Mean
GZ	Wholesale Retail	0.08	Non Tradable	0.09
IZ	Accommodation Food	0.10	Non Tradable	
FZ	Construction	0.05	Services	0.07
HZ	Transport Storage	0.06	Services	
JZ	Information Communication	0.06	Services	
MN	Professional Services	0.11	Services	
C1	Food Beverage Mfg	0.03	Tradable	0.11
C3	Electronics Machinery Mfg	0.07	Tradable	
C4	Transport Mfg	0.18	Tradable	
C5	Other Mfg	0.06	Tradable	
DE	Mining Utilities	0.19	Tradable	

Notes: 'Sunk Cost Mean' is the group average across sectors in each Fixed Cost category. Horizontal lines separate groups. Tradable = high sunk cost, Services = medium, Non-tradable = low. Source: FARE, CbCR, BTS, LIFI. Sample: Non-financial firms with > 5 employees and > 10 years, excluding foreign-owned firms.

4 Zombie Firms and Macroeconomic Spillovers

The potential macroeconomic impact of zombie firms is not solely driven by their lower productivity levels but also by their effects on aggregate resource allocation, as the zombie literature has emphasized. Through which channels do zombie firms affect aggregate productivity and resource allocation? To explore this, I present a standard accounting decomposition for labor productivity and labor productivity growth rate. It starts with an exact decomposition of aggregate labor productivity as a labor-weighted average of firm-specific productivities:

$$LaborProd_t = \sum_i s_{i,t} LaborProd_{i,t} \tag{8}$$

where $s_{i,t} = \frac{L_{i,t}}{L_t}$ is the labor share of firm i (L_t, the total labor) and $LaborProd_{i,t}$ its labor productivity defined as deflated value added per worker.

Differentiation with regard to time of equation (8) leads to the following approximation which is exact up to a second order term:

$$\begin{aligned}\Delta\text{LaborProd} = &\sum_i s_i \Delta\text{LaborProd}_i + \sum_i \text{LaborProd}_i \Delta s_i \\ &+ \sum_{j\in\text{Entry}_t} s_j \text{LaborProd}_j - \sum_{k\in\text{Exit}_{t-1}} s_k \text{LaborProd}_k\end{aligned} \tag{9}$$

Here, the summations over i refer to continuing firms, i.e., those active in both periods $t-1$ and t. Entry_t and Exit_{t-1} denote the sets of firms entering and exiting the economy between $t-1$ and t, respectively.

Decomposing further by zombie status (noting that entrants cannot be zombies by definition), we obtain the following characterization of aggregate productivity growth:

$$\begin{aligned}\Delta\text{LaborProd} = &\underbrace{\sum_{i\in Z} s_i \Delta\text{LaborProd}_i + \sum_{i\in Z} \text{LaborProd}_i \Delta s_i}_{\text{i) Low Prod. Growth (Zombies)}} \\ &+ \underbrace{\sum_{i\in NZ} s_i \Delta\text{LaborProd}_i + \sum_{i\in NZ} \text{LaborProd}_i \Delta s_i}_{\text{ii) Congestion effect (Non-Zombies)}} \\ &+ \underbrace{\sum_{j\in\text{Entry}} s_j \text{LaborProd}_j - \sum_{k\in\text{Exit, NZ}} s_k \text{LaborProd}_k - \sum_{k\in\text{Exit, Z}} s_k \text{LaborProd}_k}_{\text{iii) and iv) Creative destruction}}\end{aligned} \tag{10}$$

This decomposition highlights four distinct margins through which zombie firms can negatively influence productivity growth: i) a **direct productivity drag**, as zombie firms are inherently less productive and may also exhibit lower productivity growth; ii) **congestion effects at the intensive margin**, which weaken the reallocation of labor and capital toward more productive firms and suppress the growth of healthy competitors; and iii) and iv) **impaired creative destruction at the extensive margin**, where the same market congestion reduces firm exit and deters the entry of new firms. These congestion channels, covering both intensive and extensive margins, were first emphasized by Caballero et al. (2008). In the following sections, I test each of these mechanisms.

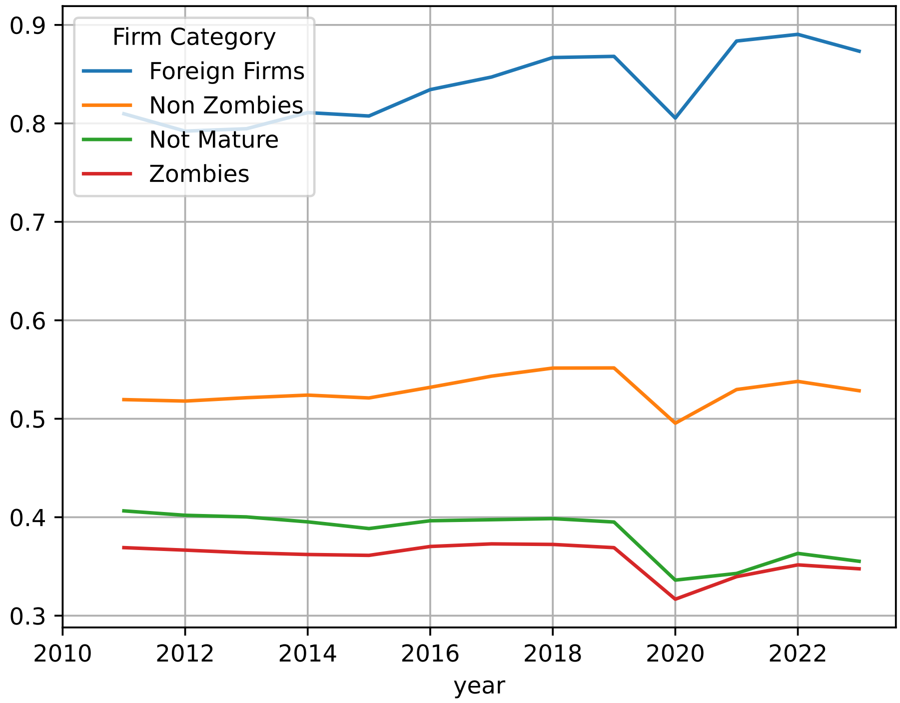
Because the unit of observation is the corporate group, all sector-level variables used below (zombie shares, entry and exit rates, etc.) are constructed by assigning each group to a single 2-digit NACE sector based on its dominant activity. For diversified groups this compresses heterogeneity across legal units and may attenuate sectoral congestion patterns.

4.1 Lower Productivity & Productivity Growth of zombie firms

Zombie firms directly lower overall productivity because they are less productive than other firms. This result is partly due to how zombie firms are defined, but it is still important to highlight. Figure 7 shows that, on average, zombie firms are visibly less productive than non-zombie firms, with median productivity levels approximately 30% lower. This result is robust to controlling for Industry × Time fixed effects (slightly larger difference, around 35% lower productivity), and similar when looking at capital productivity.

In addition, zombie firms also exhibit significantly lower productivity growth. In a regression of firm-level labor-productivity growth on a zombie indicator with NACE × year fixed effects, the zombie coefficient is -0.007^{***} (s.e. 0.002), i.e. about 0.7 percentage point lower growth. Relative to the average growth rate of non-zombies (around 1%), this corresponds to roughly 70% of their mean growth rate. Full results are reported in Appendix Table 12.

Figure 7: Median productivity level by firm type



Notes: This graph illustrates labor productivity by ultimate firm ownership. Productivity is measured as deflated labor productivity (value added per worker) expressed in 100,000 euros, using the VA deflator from INSEE.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees.

4.2 Congestion Impact of Zombie firms

At the intensive margin, I look at how non-zombie firms are impacted by the presence of zombie firms.

Impact on healthy firms. I use the standard specification introduced by Caballero et al. (2008), where $Y_{i,t}$ is either firm-specific labor or capital growth, in percentage points, NotZombie is a dummy for non-zombie firms, and ZombieShare is the share of zombies in the firm's industry j at time t. The term $FE_{j,t}$ denotes industry-by-year fixed effects (2-digit NACE × year).

$$Y_{i,t} = \beta_1 NotZombie_{i,t} + \beta_2 ZombieShare_{j,t} * NotZombie_{i,t} + FE_{j,t} \tag{11}$$

The coefficient of interest is β_2, which measures how non-zombie firms in industries with high shares of zombies have lower growth. It is expected to be negative if this congestion occurs. The regression results in Table 5 show mixed evidence. While the interaction of non-zombie status with zombie labor share (`NotZombie` $\times$ `ZombieLaborShare`) is negative (-0.017), it is not statistically significant, providing weak support for a congestion effect on labor growth. The interaction with zombie capital share is also not significant.

Table 5: Non Zombie congestion

	Labor Growth (1)	Assets Growth (2)
NotZombie	0.068***	0.098***
	(0.002)	(0.003)
NotZombie × ZombieLaborShare	-0.017	
	(0.017)	
NotZombie × ZombieCapitalShare		-0.005
		(0.015)
Employees	0.062***	
	(0.001)	
Assets		0.051***
		(0.001)
age	-0.001***	-0.001***
	(0.000)	(0.000)
NACE × Year	x	x
Observations	2074974	2074974
S.E. type	by: NACExYear	by: NACExYear
R^2	0.034	0.050
R^2 Within	0.024	0.029

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Format of coefficient cell: Coefficient (Std. Error)

Notes: Labor Growth and Assets Growth are measured in percentage points. NotZombie is a dummy variable indicating whether the firm is not a zombie. ZombieLaborShare and ZombieCapitalShare represent the share of zombie firms in the industry by labor and capital, respectively. Assets is the total log assets of the firm, Employees is the log employee count. Age is the firm's age in years. NACExYear includes 2-digit NACE industry-year fixed effects. Standard errors are clustered by 2-digit NACE industry-year.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

Reallocation. I then estimate the efficacy of labor and capital reallocation towards more productive firms. For a firm i, in industry j, I define the productivity deviation $ProdDeviation_{i,t-1} := Productivity_{i,t-1} - MeanProductivity_{j,t-1}$ which measures how productive a firm is relative to its industry average. $Y_{i,t}$ is either firm-specific labor or capital growth, in percentage points.

$$Y_{i,t} = \beta_1 ProdDeviation_{i,t-1} + \beta_2 ZombieShare_{j,t-1} * ProdDeviation_{i,t-1} + FE_{j,t} \tag{12}$$

This regression measures the efficacy of factor reallocation towards more productive firms through the coefficient β_1 on $ProdDeviation_{i,t-1}$. The β_2 coefficient on the interaction term $ZombieShare_{j,t-1} * ProdDeviation_{i,t-1}$ measures how zombie firms impact this reallocation. Table 6 shows that for labor growth (1), more productive firms experience higher growth ($\beta_1 = 0.067^{***}$), as expected. However, for asset growth (2), more productive firms show lower growth ($\beta_1 = -0.015^{***}$). Regarding the impact of zombie firms (β_2), a higher zombie labor share significantly dampens labor reallocation towards more productive firms (interaction coefficient of -0.081^{***}). Conversely, the zombie capital share does not show a significant impact on capital reallocation (interaction coefficient of 0.010). Thus, the results indicate a negative spillover for labor reallocation but not conclusively for capital.

Table 6: Factor Reallocation Regression

	Labor Growth (1)	Assets Growth (2)
ProdDeviation_L1	0.067***	-0.015***
	(0.003)	(0.003)
ProdDeviation_L1 × ZombieLaborShare	-0.081***	
	(0.025)	
ProdDeviation_L1 × ZombieCapitalShare		0.010
		(0.009)
Employees	0.059***	
	(0.001)	
Assets		0.053***
		(0.002)
age	-0.001***	-0.001***
	(0.000)	(0.000)
NACE × Year	x	x
Observations	2074974	2074974
S.E. type	by: NACExYear	by: NACExYear
R^2	0.041	0.043
R^2 Within	0.032	0.021

Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Format of coefficient cell: Coefficient (Std. Error)
Notes: Labor Growth and Assets Growth are measured in percentage points. ProdDeviation_L1 is the lagged deviation of a firm's productivity from the industry mean. ZombieLaborShare and ZombieCapitalShare represent the share of zombie firms in the industry by labor and capital, respectively. Assets is the total log assets of the firm, Employees is the log employee count. Age is the firm's age in years. NACExYear includes 2-digit NACE industry-year fixed effects. Standard errors are clustered by 2-digit NACE industry-year.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

4.3 Bankruptcy & Firm entry

Finally, I look at the impact zombie firms have on the extensive margin of firms by looking at how they impact firm entry and exit. As pointed out by Acharya et al. (2024), zombie credit should theoretically lead to both fewer new firms and lower default rates.

Bankruptcy Rates. I use official data on firm bankruptcies for the whole universe of French firms (BODACC data, see Appendix A.1 for details on the definition). It provides at the SIREN level whether or not a firm has undergone a bankruptcy for any given year, starting in 2009. I aggregate those to get group bankruptcy dummies, which are equal to 1 if more than 50% of its legal units undergo a bankruptcy that year (weighted by employee count). A key advantage of this dataset is that it is firm-specific, and not sectoral averages as are commonly used. This allows me to look at the firm-specific impact of zombification, and default probabilities for zombies.

An additional advantage is that BODACC records all official bankruptcies in France, making it the authoritative source used in official statistics. While some firms disappear from the data each year without appearing in BODACC, those exits are heterogeneous — ranging from small firms in distress that never entered a court procedure to cases of mergers, acquisitions, or voluntary dissolutions of otherwise healthy firms. By focusing on BODACC, we capture only court-registered bankruptcies, which provides a much clearer and cleaner measure of genuine financial failure.

To investigate the impact of zombie firms, we estimate a series of logistic regression models of bankruptcy probability. We use two-year forward bankruptcy rates, meaning a firm is considered bankrupt if it fails within the following two years. Figure 9 shows the average bankruptcy rates by firm type across our sample. The general form of our logistic model for firm i in industry j at time t is:

$$\begin{aligned}\text{Logit}(\text{P}(\text{Bankrupt}_{i,t} = 1)) = \beta_1\,\text{Zombie}_{i,t} + \beta_2\,\text{Productivity}_{i,t} + \beta_3\,\text{ZombieShare}_{j,t} \\ + \text{Interactions} + \delta\,\text{Controls}_{i,t} + \text{FE}_t\end{aligned} \tag{13}$$

where $\text{Productivity}_{i,t}$ is measured either with sector-specific quantiles ($ProdQt$) or as a continuous deviation from the industry mean ($ProdDeviation$). The specific interaction terms and variables included vary across specifications, as detailed in Table 7. The table reports the average marginal effects (AME) derived from these models, and tells a two-part story about how zombification affects firm exit.

First, we examine how the bankruptcy penalty for a firm's *own* zombie status is conditioned by its productivity (Columns 1-2). Column (1) establishes the baseline: being classified as a zombie is associated with an increase in the probability of bankruptcy by a significant 6 percentage points. As expected, firms in lower productivity quantiles are also more likely to fail. Column (2) introduces interaction terms to test for heterogeneous effects (no baseline). Here, the coefficient on `Zombie`$\times$`ProdQt=5` (0.10) directly represents the penalty for a zombie in the highest productivity quintile—a 10 percentage point increase in bankruptcy risk. The significant negative interaction terms (e.g., -0.06 for `ProdQt=1`) reveal that this penalty is substantially attenuated for the least productive firms. This implies that the bankruptcy penalty for being a zombie is most severe for firms that are otherwise highly productive, for whom the inability to service debt is a particularly strong negative signal.

Second, to draw a direct parallel with our factor reallocation analysis (Table 6), we test how industry-level zombie congestion impairs the overall market selection process (Columns 3–4). For this, we switch from productivity quantiles to the continuous `ProdDeviation` measure. Column (3) confirms that having a higher productivity deviation from the industry mean reduces bankruptcy risk. Column (4) presents the key specification mirroring our reallocation regression. The negative coefficient on `ZombieLaborShare` is consistent with the idea that industries with many zombies exhibit fewer bankruptcies on average. Crucially, the positive and significant coefficient on the interaction term, `ProdDeviationxZombieLaborShare` (0.10), provides the direct link to our findings on the intensive margin. This interaction captures the congestion mechanism: in industries with many zombies, the sensitivity of exit risk to productivity is weakened. Intuitively, when credit and market shares remain tied up in low-productivity incumbents, competitive pressure and financial discipline are reduced, so even marginal non-zombie firms become less likely to shrink or exit for a given productivity level. Consistent with this mechanism, zombie credit can keep otherwise-exiting firms alive ("blocked-exit" channel, Acharya et al. (2024)), thereby reducing bankruptcies and weakening selection. Two sector-level features can reinforce this pattern: (i) weaker insolvency enforcement—see Becker and Ivashina (2021)—which coincides with both higher zombie shares and fewer formal bankruptcies; and (ii) contamination at the margin, whereby firms not classified as zombies still benefit from zombie credit and face lower near-term default risk. While our estimates are not causal, the results align with these mechanisms that both suppress exits and generate the observed congestion effect.

Remark. This analysis reveals a clear parallel between the intensive margin of factor reallocation (Table 6) and the extensive margin of firm exit. A bankruptcy is the limiting case of our intensive-margin analysis: a –100% growth rate in employment and capital, i.e. complete firm exit. Our findings show that the congestion created by zombie firms impairs less the intensive margin (by slowing the growth of surviving firms) than the extensive margin (by preventing the market-driven exit of unproductive firms).

Table 7: Bankruptcy Probability Logit Model

	Dependent variable: Bankruptcy			
	(1)	(2)	(3)	(4)
$zombie\_1$	0.06***		0.07***	
	(0.00)		(0.00)	
$ProdQt = 1$	0.07***	0.07***		
	(0.00)	(0.00)		
$ProdQt = 2$	0.04***	0.05***		
	(0.00)	(0.00)		
$ProdQt = 3$	0.03***	0.03***		
	(0.00)	(0.00)		
$ProdQt = 4$	0.01***	0.02***		
	(0.00)	(0.00)		
$(ProdQt = 1)$x$zombie_1$		0.05***		
		(0.00)		
$(ProdQt = 2)$x$zombie_1$		0.06***		
		(0.00)		
$(ProdQt = 3)$x$zombie_1$		0.07***		
		(0.00)		
$(ProdQt = 4)$x$zombie_1$		0.08***		
		(0.00)		
$(ProdQt = 5)$x$zombie_1$		0.10***		
		(0.00)		
$ZombieLaborShare$	-0.03***	-0.03***	-0.05***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
$ProdDeviation$			-0.04***	-0.05***
			(0.00)	(0.00)
$ProdDeviation$x$ZombieLaborShare$				0.10***
				(0.02)
Year FE	Yes	Yes	Yes	Yes
Observations	2991535	2991535	2991535	2991535
Pseudo R^2	0.10	0.11	0.07	0.05

Notes: The dependent variable is a dummy indicating whether the firm went bankrupt within two years. $zombie\_1$ is a dummy variable indicating if the firm is classified as a zombie. $ProdQt$ denotes sector-specific labor productivity quantiles, with $ProdQt = 5$ as the reference category. $ZombieLaborShare$ represents the share of zombie labor in the firm's industry. Interactions between $ProdQt$ and $ZombieShare$ capture the effect of zombie labor share on firms within specific productivity quantiles. Year fixed effects are included as specified. The values reported are the average marginal effect. Standard errors are reported in parentheses.
Source: FARE, CbCR, BTS, LIFI, BODACC. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

To assess potential changes in the efficacy of market selection mechanisms over time—particularly following the Covid pandemic—I estimate a model with year-specific effects for zombie status. Specifically, I re-estimate equation (13), specification (1), including an interaction between zombie status and each year, so that the zombie effect is $\beta_{Z,t}$. Panel A of Figure 8 reports the logit coefficients (log-odds units). Panel B reports the corresponding average marginal effects (AMEs) in probability units.

For each year t, the AME is computed *within the year-t sample only* by evaluating, for every observation, predicted bankruptcy probabilities under $Z = 1$ versus $Z = 0$ (where Z indicates zombie status that year), holding other covariates at their observed values, and averaging the difference. Restricting to the year-t sample avoids impossible cross-year counterfactuals and composition effects.

A useful approximation links the two metrics:

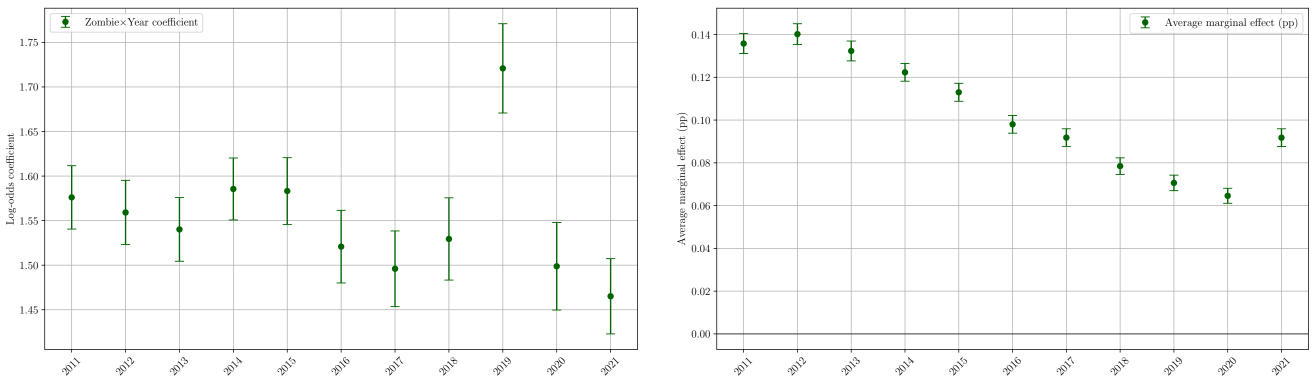
$$\text{AME}_t \;=\; p_{1t} - p_{0t} \;\approx\; \beta_{Z,t}\, p_{0t}\,(1 - p_{0t}) \;\approx\; \beta_{Z,t}\, p_{0t},$$

where p_{0t} and p_{1t} denote, within year t, the average predicted bankruptcy probabilities for otherwise identical non-zombies and zombies.[8] For example, in 2018 the estimates imply that, for otherwise similar firms, zombie status raises the two-year bankruptcy probability from about 5% for non-zombies to about 13% for zombies (an 8 percentage-point gap).

This explains why the 2019 value for the AME is low while the coefficient spikes: baseline bankruptcy rates were near their minimum (Appendix Figure 9), so strong relative selection translated into a small absolute gap. The AME reaches its minimum in 2020. After 2020, the AME rises in 2021 but remains below its pre-Covid average, indicating limited post-Covid cleansing in absolute terms despite some rebound in relative selection.

Interpreting the time profile, recall that year-t coefficients reflect two-year-forward bankruptcies measured over $[t, t+2)$—for example, the 2018 coefficient reflects bankruptcies realized through 2020. For the 2019 coefficient, capturing bankruptcies realized over 2019–2021, baseline bankruptcy risk in that period was near its minimum (Appendix Figure 9), so a large log-odds effect maps into a small AME. The AME reaches its trough in 2020—consistent with the collapse in bankruptcies during the pandemic, plausibly due to Covid-era support measures—and then rebounds in 2021 but remains below early-decade levels (roughly back to its 2017 level). For the 2018–2020 coefficients (capturing bankruptcies over 2018–2022), the depressed AMEs reflect both strong relative selection and unusually low failure rates during the pandemic period, likely influenced by Covid-era support measures.

Figure 8: Zombie status and bankruptcy by year



(a) Logit coefficients.

(b) Average marginal effects (AMEs).

Panel A: Logit coefficients for zombie×year ($\beta_{Z,t}$).
Panel B: AMEs (risk differences in pp.) for zombie×year.
Reading note: A year-t coefficient corresponds to bankruptcies realized over $[t, t+2)$ (e.g., the 2019 coefficient reflects failures recorded between 2019 and 2021, i.e. includes the whole early Covid period). Panel A reports log-odds effects; Panel B reports AMEs, i.e. absolute percentage-point differences in two-year bankruptcy risk between otherwise similar zombies and non-zombies. For instance, in 2018 the AME of about 0.08 means that zombie status raises the two-year bankruptcy probability from roughly 5% for non-zombies to 13% for zombies.
Source: FARE, CbCR, BTS, LIFI, BODACC. Author's computation.
Sample: Non-financial firms with ≥ 5 employees and ≥ 10 years of age, excluding foreign-owned firms.

Firm Entry Rates. To examine a potential decline in firm entry at the sector level, I measure new firm entry as the unweighted share of new firms in an industry, defined as the number of firms less than five years old divided by the total number of firms in the industry. This share captures entry intensity while remaining robust to changes in the legal framework for micro-enterprises during the period of interest.

By definition, new firms cannot be classified as zombies because they do not meet the maturity criterion of being more than ten years old. Therefore, I employ the following industry-level specification inspired by Acharya et al. (2022), with industry and time fixed effects:

$$\text{FirmEntry}_{j,t} = \beta \cdot \text{ZombieShare}_{j,t-1} + \text{FE}_j + \text{FE}_t \tag{14}$$

[8] When baseline risk is low ($p_{0t} \ll 1$), $\beta_{Z,t} \approx \log\left(\frac{p_{1t}}{p_{0t}}\right)$, so $\beta_{Z,t}$ is naturally interpreted as a relative change (log-odds ratio), whereas the AME captures an absolute change (percentage-point gap).

where $\text{FirmEntry}_{j,t}$ is the firm entry rate in industry j at time t, $\text{ZombieShare}_{j,t-1}$ is the share of zombie firms in the same industry in the previous period, and FE_j and FE_t represent industry and time fixed effects, respectively.

Table 8 presents the results: industries with a higher share of zombie firms exhibit lower entry rates of new firms, a result that remains robust to the inclusion of time and industry fixed effects. However, in the most stringent specification with both time and industry fixed effects, the estimated coefficient is almost zero. Because of the limited sample, it is unclear if this is due to an absence of relationship, or lack of statistical power. Overall, the evidence suggests that industries with higher zombie shares tend to have fewer firm entries, though we cannot conclude whether changes in zombie shares within industries are contemporaneously associated with changes in new firm entry, which would be a cleaner test of congestion effects.

Table 8: Impact of Zombie Firms on New Firm Entry

	Young Firm Count Share			
	(1)	(2)	(3)	(4)
ZombieLaborShare	-0.024***	-0.032*	-0.013	-0.001
	(0.008)	(0.018)	(0.008)	(0.017)
year FE	-	-	x	x
NACE FE	-	x	-	x
Observations	634	634	634	634
S.E. type	iid	by: NACE	by: year	by: year
R^2	0.014	0.071	0.330	0.387
R^2 Within	-	0.010	0.006	0.000

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Format of coefficient cell: Coefficient (Std. Error)

Notes: Young Firm Count Share is the number of firms less than five years old divided by the total number of firms in the industry. Fixed effects include NACE industry fixed effects and year fixed effects, as specified. Standard errors are reported in parentheses and are either independent and identically distributed (iid) or clustered by NACE or year, as indicated. Observations correspond to industry-level data.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

5 Conclusion

In this paper, I examined the impact of profit shifting on the identification of zombie firms and their effect on aggregate productivity in France. Utilizing exhaustive firm-level tax data from 2009 to 2023 and incorporating Country-by-Country Reporting (CbCR) data from 2016 to 2023, I adjusted firm profits for potential profit shifting using a novel methodology from the tax avoidance literature. This adjustment addressed the distortions in fiscal data that can lead to overestimations of zombie firms among French multinationals.

My findings indicate that traditional methods significantly overestimate the prevalence of zombie firms when applied to unadjusted fiscal data. After accounting for profit shifting, the estimated share of zombie firms among French multinationals decreases from 14% to 10% on average, with adjustments as large as 10 percentage points in certain years (the correction is symmetric at the firm level and can occasionally move some groups from non-zombie to zombie status, but its net effect on aggregate zombie shares is always negative). Across the entire economy, zombie firms represent approximately 8% of employment among mature French-owned firms, aligning with previous studies. Analyzing the macroeconomic impact of zombie firms on productivity growth, I found that while zombie firms are less productive, older, and larger on average, there is limited evidence of significant congestion effects on healthy firms but some evidence that higher zombie shares dampen labor reallocation towards more productive firms. However, industries with a higher share of zombie firms experience lower entry rates of new firms, suggesting that the presence of zombie firms may hinder the creative destruction process by reducing firm entry, although once controlling for industry and year fixed effects, this relationship is not statistically significant.

Crucially, by extending the analysis through 2023, these findings offer timely insights into the debate on post-COVID-19 zombification. The employment-weighted zombie share peaks at 9% in 2022 and declines to 8% in 2023. Turning to bankruptcies, two facts stand out. First, zombies remain more likely to fail than otherwise similar firms, and that relative disadvantage strengthened again after the pandemic. Second, because overall bankruptcies fell to unusually low levels during the support period, the percentage-point gap in failure rates between zombies and healthy firms also shrank and—despite a rebound in 2021–2022—stayed below its pre-COVID level by 2023. In short, selection tightened mainly in relative terms, not in absolute numbers, implying a muted post-COVID cleansing and helping explain the temporary rise and only modest subsequent easing in zombification.

The concept of market cleansing, however, must be interpreted with caution. The economic impact of firm failure is not uniform across sectors. While the exit of unproductive firms can be a sign of a healthy market, it can also cause lasting damage in sectors with high sunk costs. As argued by Bernstein et al. (2019), liquidation in such industries may not lead to creative destruction, but rather to a loss of valuable local assets and knowledge. My results align with this view: I find that zombie firms are more concentrated in high-sunk-cost tradable sectors and less common in services and non-tradables, where exit barriers are lower. This sectoral heterogeneity has direct policy implications, suggesting that insolvency regimes and crisis support measures should be carefully tailored to account for the different costs of liquidation versus continuation across industries.

Nevertheless, this analysis has limitations that open avenues for future research. A central challenge lies in the structural complexity of multinational enterprises: their layered ownership networks and cross-border operations complicate any attempt to localize profits accurately. Our methodology addresses this by assuming a proportional relationship between profits and capital allocation across countries. While this provides a tractable adjustment mechanism, it likely oversimplifies heterogeneous tax strategies and operational structures. Additionally, the CbCR data is available only for large multinationals with annual sales exceeding €750 million (covering approximately 60% of French MNE employment). While our profit-shifting adjustment is therefore not applied to smaller MNEs, the concentration of significant profit shifting among the very largest firms (Aliprandi et al., forthcoming), as discussed earlier, suggests that the bias from this limitation on the overall zombie estimates is likely modest.

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A Appendix

A.1 Dataset construction

Balance sheet Consolidation. The balance sheet dataset (FARE) is structured at the legal unit (UL) level, requiring the consolidation of variables to derive group-level data. Specific steps for the consolidation process and assumptions are detailed in the bullet points below, where applicable.

The main variables used in our analysis include:

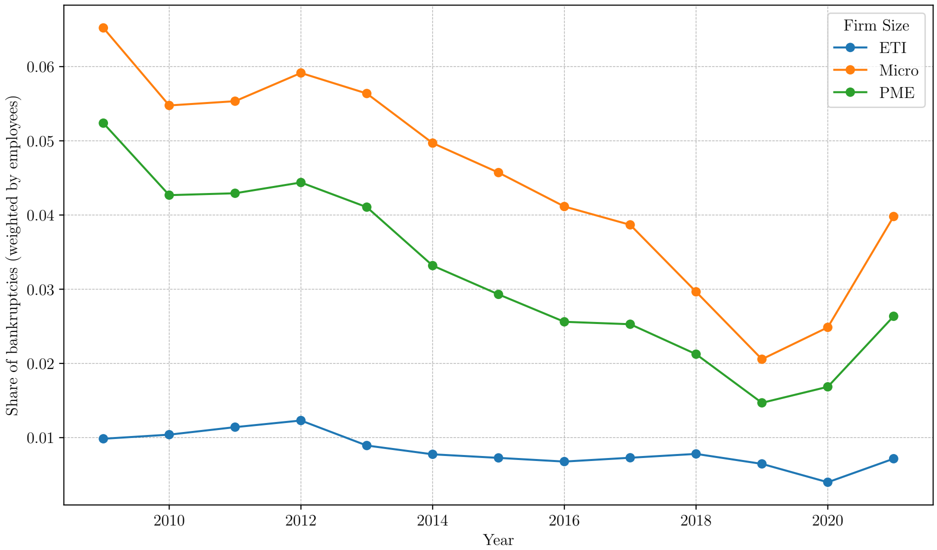
- Firm-level employment (BTS). I prefer using the BTS variable rather than the FARE version because employment is more accurate.
- EBITDA (corresponding to the French *"EBE"*)
- Value Added (*"Valeur ajoutée"*)
- Assets. (*"Total Actif Net"*)
- Age. Defined as the maximum age among the legal units.
- Interest Payments (*"Intérêts et charges assimilées"*). Sum of interest payments among all legal units. This leads to an overestimation of interest payments for groups with significant intra-group debt.
- Debt (*"Emprunts et dettes assimilées"*). Sum of debt among all legal units. This leads to an overestimation of debt for groups with significant intra-group debt.
- Cost-of-debt $= \frac{\text{Interest Payments}}{\text{Debt}}$. Assuming intra-group debt is priced under an arm's length principle—i.e., at the same rate as external debt r—and letting $\text{Debt} = \text{Debt}^{\text{ext}} + \text{Debt}^{\text{intra}}$ and similarly for interest payments, we have:
$$\frac{\text{Interest Payments}^{\text{ext}} + \text{Interest Payments}^{\text{intra}}}{\text{Debt}^{\text{ext}} + \text{Debt}^{\text{intra}}} = \frac{r \cdot \text{Debt}^{\text{ext}} + r \cdot \text{Debt}^{\text{intra}}}{\text{Debt}^{\text{ext}} + \text{Debt}^{\text{intra}}} = r,$$
it is an unbiased estimate of the true cost of debt.

Firm bankruptcy (BODACC). I obtain the data on firm bankruptcy from the official BODACC (*"Bulletin officiel des annonces civiles et commerciales"*) website[9]. Bankruptcies are defined following the official Banque de France definition, which classifies bankruptcies as firms undergoing either liquidation (*"Procédure de liquidation judiciaire"*) or reorganization (*"Redressement judiciaire"*). The BODACC data also serves as the underlying microdata for the official bankruptcy statistics for France, which are compiled and published by the Banque de France. It is organized at the 'SIREN' level (legal unit). To analyze bankruptcies at the group level, I consolidate legal unit bankruptcies using the following procedure: for any given year, a group is classified as undergoing bankruptcy if more than 50% of its legal units, weighted by employee count, are undergoing bankruptcy procedures. This threshold ensures that group-level bankruptcies reflect significant financial distress across the group, rather than isolated cases of unit-level restructuring. This is important because large groups often allow some legal units to declare bankruptcy even when the group itself remains solvent. We use the same criteria to define the type of bankruptcy: if more than 50% of the group's employees are in legal units undergoing liquidation, the group is said to be undergoing liquidation, and redressement otherwise.

Figure 9 shows descriptive statistics of bankruptcies by firm type.

[9]The BODACC website can be accessed at: `https://www.bodacc.fr`

Figure 9: Bankruptcy Shares by Firm Size



Notes: The figure shows, by firm size and year, the employee-weighted share of firms that went bankrupt within the next two years.
Reading note: The 2019 value for PMEs indicates that roughly 1.5 % of PMEs went bankrupt between 2019 (inclusive) and 2021.
Source: FARE, CbCR, BTS, LIFI, BODACC. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

A.2 Profit Shifting: explanations and robustness checks

A.2.1 Assumptions for Profit Shifting Estimation

Estimating profit shifting relies on a simplified model of firm profits within a country. In practice, calculating profits is more complex due to varying profit measures and accounting standards. This means that different profit measures will lead to different profit shifting estimates. Therefore, it is essential to explicitly state the underlying assumption used in Equation 7: that shifted profits are the same whether measured by EBE or pre-tax profits.

The main concerns stem from:

1. Accounting differences between CbCR (which follows the IFRS rules) and FARE (French norms).

2. The different measures used to define profits (pre-tax profits in CbCR vs. EBE in FARE).

These issues are extensively discussed in Delpeuch et al. (2019). A key difference between their work and mine is that I am only interested in the shifted profits estimations, and not the levels of profits.

My core assumption is that the profit shifting estimated for pre-tax profits (**Résultat Courant Avant Impôts**) applies equally to EBE. This implies that the components accounting for the difference between these two profit measures are either unaffected by profit shifting or contribute negligibly to it.

Following the accounting standards in France as described in Bach et al. (2019), Table 9 illustrates the exact steps to reconcile EBE—the profit measure used in my main analysis to define the Interest Coverage Ratio (ICR)—with **Résultat Courant Avant Impôts** (pre-tax profits).

The exact adjustment between EBE and pre-tax profits can be written as:

$$\text{EBE} = \text{Pre-tax Profits} + Adj. \tag{15}$$

where:

Table 9: Passage De L'EBE Au RCAI

EBE
- Dotations aux amortissements et aux provisions *(GA + GB)*
+ Résultat Financier *(GV)*
+ Bénéfice Attribué *(GH)*
- Perte Supportée *(GI)*
= Résultat Courant Avant Impôts *(GW)*

$$\begin{aligned} Adj. = &\underbrace{\text{Depreciation}}_{\text{Investment}} + \underbrace{\text{Financial Result}}_{\text{Financial}} \\ &+ \underbrace{\text{Attributed Profit} - \text{Supported Loss}}_{\text{Miscellaneous}} \end{aligned} \tag{16}$$

I use the notation Δ to represent shifted profits. Specifically, for any variable X, $\Delta X = \bar{X} - X$, where $\bar{X}$ denotes the value of X in the absence of profit shifting.

My hypothesis is that the adjusted Interest Coverage Ratio (ICR) is given by:

$$\text{ICR}_{\text{adjusted}} = \text{ICR} + \frac{\Delta\text{Profits}}{\text{Interest Paid}} \tag{17}$$

which relies on the assumption that:

$$\Delta\text{Profits} = \Delta\text{EBE} \tag{18}$$

This comes from assuming that profit shifting does not significantly affect the components of Adj., ie:

$$\Delta\text{Depreciation and Provisions} + \Delta\text{Financial Result} + \Delta\text{Miscellaneous} \approx 0 \tag{19}$$

Here, ΔDepreciation and Provisions, ΔFinancial Result, and ΔMiscellaneous represent the profit shifting occurring through those specific components. I assume that any profit shifting through these components is negligible or that their combined effect is zero.

This assumption is consistent with evidence in the tax literature on Base Erosion and Profit Shifting (BEPS), as summarized by Vicard (2023). The OECD identifies the main mechanisms used by firms to shift profits as:

1. Transfer Pricing
2. Intellectual Property Transfers (intangibles)
3. Debt Shifting

The first two mechanisms, transfer pricing and intellectual property transfers, primarily affect the balance sheet through direct costs early in the accounting process and are therefore directly accounted for. Debt shifting, however, poses a greater challenge, as it reduces pre-tax profits without affecting EBE.

Debt Shifting and the ICR In this paragraph, I consider the effect of *pure* debt shifting—excluding transfer pricing and intangible-related channels (i.e., $\Delta = 0$ for other forms of shifting)—on the ICR. Debt shifting involves increasing interest expenses by borrowing from subsidiaries in low-tax jurisdictions, thereby reducing taxable profits in high-tax jurisdictions. To clarify the effect of debt shifting on the Interest Coverage Ratio (ICR), consider the following analysis:

- The firm increases its interest expenses by an amount $\Delta\text{Interest} > 0$
- Since EBE is calculated before interest expenses, it remains unaffected:

$$\Delta\text{EBE} = 0$$

- The firm's pre-tax profits decrease by the additional interest expenses, so the amount of profits shifted out is:

$$\Delta\text{Profits} = \Delta\text{Interest}$$

Therefore, the assumption $\Delta\text{Profits} = \Delta\text{EBE}$ is invalid in the context of debt shifting. But I will now show that this error compensates when considering the zombie criteria on ICR as I do in the main analysis, and so can be forgotten.

In adjusting the ICR, I (incorrectly) assume that $\Delta\text{EBE} = \Delta\text{Profits}$, leading me to adjust EBE by adding $\Delta\text{Profits}$:

$$\text{Adjusted EBE} = \text{EBE} + \Delta\text{Profits} = \text{EBE} + \Delta\text{Interest}$$

The interest paid increases due to debt shifting:

$$\text{Interest Paid} = \overline{\text{Interest Paid}} + \Delta\text{Interest}$$

where $\overline{\text{Interest Paid}}$ represents the counterfactual interest expenses without debt shifting. The adjusted ICR is then:

$$\text{ICR}_{\text{adjusted}} = \frac{\text{EBE} + \Delta\text{Interest}}{\overline{\text{Interest Paid}} + \Delta\text{Interest}}$$

The "real" ICR, using the counterfactual interest paid (without debt shifting), is:

$$\overline{\text{ICR}} = \frac{\text{EBE}}{\overline{\text{Interest Paid}}}$$

I now show that the condition $\mathbf{ICR_{adjusted}} \leq 1$ **is equivalent to** $\overline{\mathbf{ICR}} \leq 1$.

$$\text{ICR}_{\text{adjusted}} = \frac{\text{EBE} + \Delta\text{Interest}}{\overline{\text{Interest Paid}} + \Delta\text{Interest}} \leq 1$$

$$\iff \text{EBE} + \Delta\text{Interest} \leq \overline{\text{Interest Paid}} + \Delta\text{Interest}$$

$$\iff \text{EBE} \leq \overline{\text{Interest Paid}}$$

$$\iff \frac{\text{EBE}}{\overline{\text{Interest Paid}}} \leq 1$$

$$\iff \overline{\text{ICR}} \leq 1$$

Conclusion Despite the assumption $\Delta\text{Profits} = \Delta\text{EBE}$ being invalid in the case of debt shifting, the condition for the adjusted ICR being less than or equal to one is equivalent to the condition using the counterfactual ICR without debt shifting:

$$\text{ICR}_{\text{adjusted}} \leq 1 \quad \iff \quad \overline{\text{ICR}} \leq 1$$

Therefore, without having to explicitly estimate debt shifting, my zombie estimation remains valid even when debt shifting happens.

A.3 Robustness checks for main analysis

A.3.1 Profit Shifting Estimation

Comparison with Existing Literature. Before turning to the main robustness exercise, I compare my results with those in the literature. The average value for profit shifted in my estimates (10 to 20 billion euros) is consistent with previous findings, although estimates vary based on the data and methods employed. For instance, Tørsløv et al. (2023) estimate that €32 billion in profits were shifted out of France in 2015; however, their figure is derived from macroeconomic data and includes profits shifted by both French and foreign multinationals operating in France, making it not directly comparable to our focus on French MNEs. Using a different approach based on firm-level Foreign Direct Investment (FDI) data, Vicard (2023) finds that profit shifting created an upward bias on France's net FDI income balance corresponding to total missing before-tax profits of €36 billion in 2015; this total includes both French MNEs and foreign MNEs' French affiliates. But restricting to French MNEs only implies roughly €22bn before tax. This slightly larger total possibly reflects the broader coverage of the Banque de France FDI survey, which has a low reporting threshold (direct affiliates with equity or acquisition cost above €5m).

The estimates from Aliprandi et al. (forthcoming) are particularly relevant as they use the same CbCR data source as this study. Focusing specifically on large French multinationals in 2017 and 2018, they find that €23 billion in profits are shifted out for tax reasons and show that this result remains stable when using either capital- or labor-based reallocation methods. Collectively, these studies provide a range of estimates that validate the plausibility of our findings.

Industry-level descriptive statistics. Table 10 reports descriptive statistics on the estimated shifted profits by industry. For each A17 sector, it shows the average level of shifted profits over 2016–2023, as well as the ratio of shifted to reported profits (EBE).

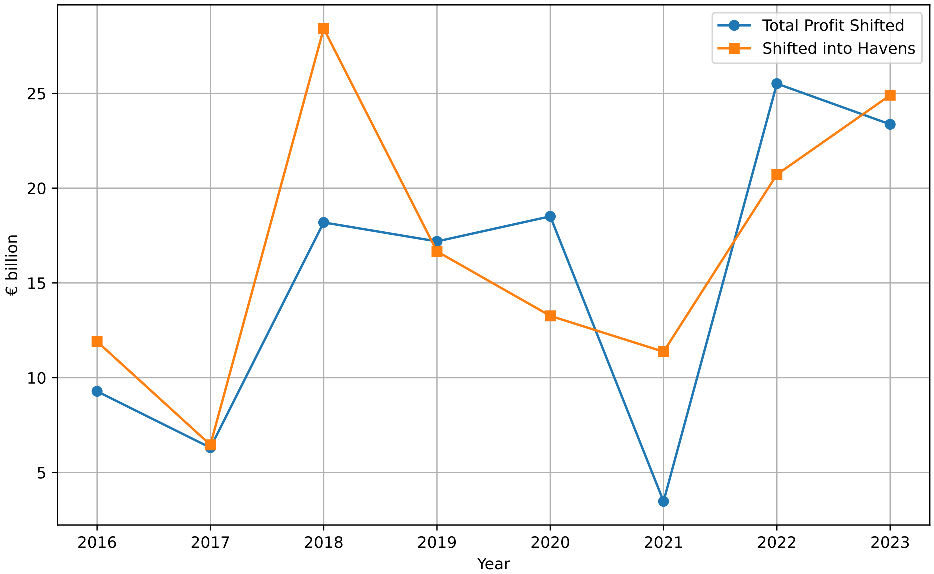
Table 10: Average Shifted Profits by Sector (2016-2023)

	A17	ShortName	ProfitShifted (Million)	EBE (Million)	Ratio
0	C1	Food Beverage Mfg	504	2954	0.17
1	C3	Electronics Machinery Mfg	1181	2207	0.54
2	C4	Transport Mfg	-833	6168	-0.14
3	C5	Other Mfg	3173	11388	0.28
4	DE	Mining Utilities	104	14846	0.01
5	FZ	Construction	-1564	8727	-0.18
6	GZ	Wholesale Retail	-100	7777	-0.01
7	HZ	Transport Storage	1517	11653	0.13
8	IZ	Accommodation Food	795	103	7.68
9	JZ	Information Communication	-375	11419	-0.03
10	MN	Professional Services	632	3342	0.19

Notes: This table reports average shifted profits by A17 industry over 2016-2023 ProfitShifted is estimated using the capital reallocation method developed by Guvenen et al (2022) Ratio is the ratio of shifted profits with sectoral EBE
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms French owned multinationals present in the CbCR dataset.

Tax Haven Robustness. Figure 10 presents both my baseline aggregate profit shifting estimates and a key robustness check. In this robustness exercise, I restrict the analysis to affiliates located in tax havens as defined by the official EU list, and estimate the profit shifted toward these jurisdictions using the capital reallocation method. The aggregate estimates are generally consistent with the baseline, though some variation arises across years. Tax havens typically have little capital and payroll but report high profits—the standard BEPS pattern. By forcing all reallocated profits to land only in these jurisdictions, I reduce the concern that the adjustment is capturing genuine technology or markup differences in non-haven countries. The stability of the results under this restriction suggests that the measured profit shifting is largely concentrated in havens rather than reflecting real production differences elsewhere.

Figure 10: Aggregate Profit Shifting



Notes: This graph shows the aggregate profit shifting estimation for French multinationals using a proportional reallocation procedure based on capital. "Total Profit Shifted" (blue) uses the full sample of affiliates, while "Shifted into Havens" (orange) restricts the reallocation to affiliates in tax havens only and is multiplied by –1 to ensure comparability—a negative value indicates profit shifted into a tax haven. Tax havens are defined according to the official EU list.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial multinationals in CbCR dataset, excluding foreign-owned firms.

Year-to-year robustness For the years before 2016, the CbCR data is not available and for that reason for each firm, I impute shifted profits using the average shifted profits estimated during the period in which CbCR is available. This is obviously a strong assumption, as firms' profit shifting behavior can depend on the firms' profit levels, as well as the tax environments. To address these issues, I look at the stability of profit-shifting estimates by regressing firm-specific profit-shifting estimates on year dummy variables (regression (1)), and on lagged profit shifting (2). Both regressions have firm fixed effects. We see that profit shifting is well explained by firm fixed effects ($R2 \approx 0.4$ in both specifications). Adding the lagged shifted profits does not increase that $R2$ much. This implies that shifted profits are volatile year to year, around a stable average value for each firm. This suggests that using the firm-specific average for the pre-2016 period is a reasonable approach, as it captures the stable component of profit shifting, even if it cannot account for the substantial year-to-year fluctuations.

Table 11: Stability of profit shifted estimation

	ProfitShifted	
	(1)	(2)
ProfitShifted_L1		-0.134
		(0.228)
Firm FE	x	x
Year Dummies	Yes	No
Observations	1979	1569
S.E. type	by: Firm	by: Firm
R^2	0.383	0.400
R^2 Within	0.003	0.015

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

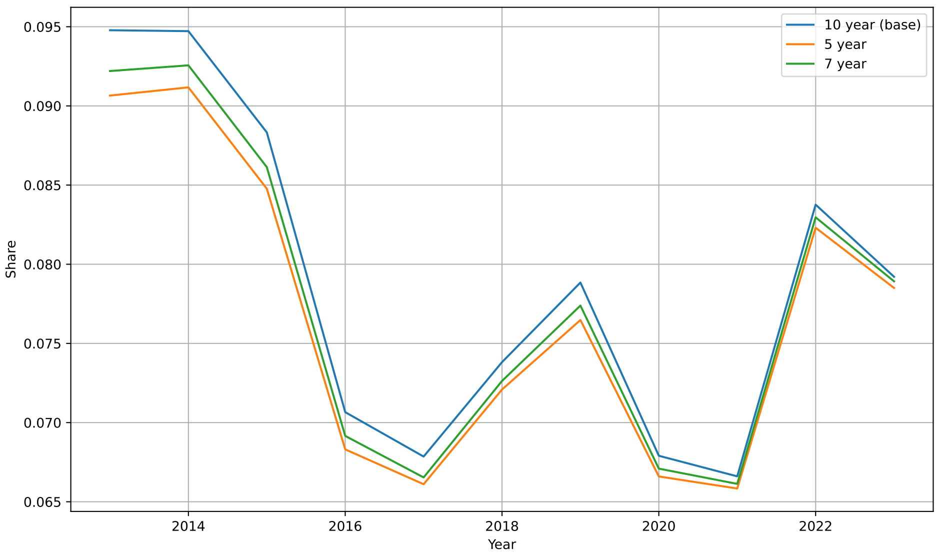
Notes: ProfitShifted is estimated using the capital reallocation method developed by Guvenen et al (2022). Specification (1) is with year dummy variables. The R2 within should thus be interpreted as the residual variance explained by the year dummies, controlling for firm fixed effects.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms French owned multinationals present in the CbCR dataset.

A.3.2 Zombie Criteria Definition

Because the main point of my paper is to showcase the impact the de-biasing procedure has on zombie firm estimation using fiscal data, I follow the most basic OECD definition for zombie firms. Below are some robustness checks regarding that definition.

Maturity criteria. Using a 5, 7 or 10 year criteria for defining zombie firms does not change significantly the estimated shares of zombies (Figure 11).

Figure 11: Maturity Criteria Robustness



Notes: The figure compares zombie shares using alternative definitions for age to define mature firms
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees, excluding foreign-owned firms.

As pointed out in the main text, young firms and small firms have low leverage levels because they find it difficult to access external funds. This in turn means they are unlikely to be zombies.

Intra-group Interest Payment Consolidation As highlighted in the main analysis, consolidating interest payments at the group level leads to an overestimation. Specifically, at the firm level, interest payments consist of both external and intra-group debt:

$$\text{Interest Payments} = Int_{extern} + Int_{intern}.$$

Thus, at the group level G:

$$\sum_G \text{Interest Payments} = \sum_G Int_{extern} + \underbrace{\sum_G Int_{intern}}_{\text{intra-group flows counted as if external}}.$$

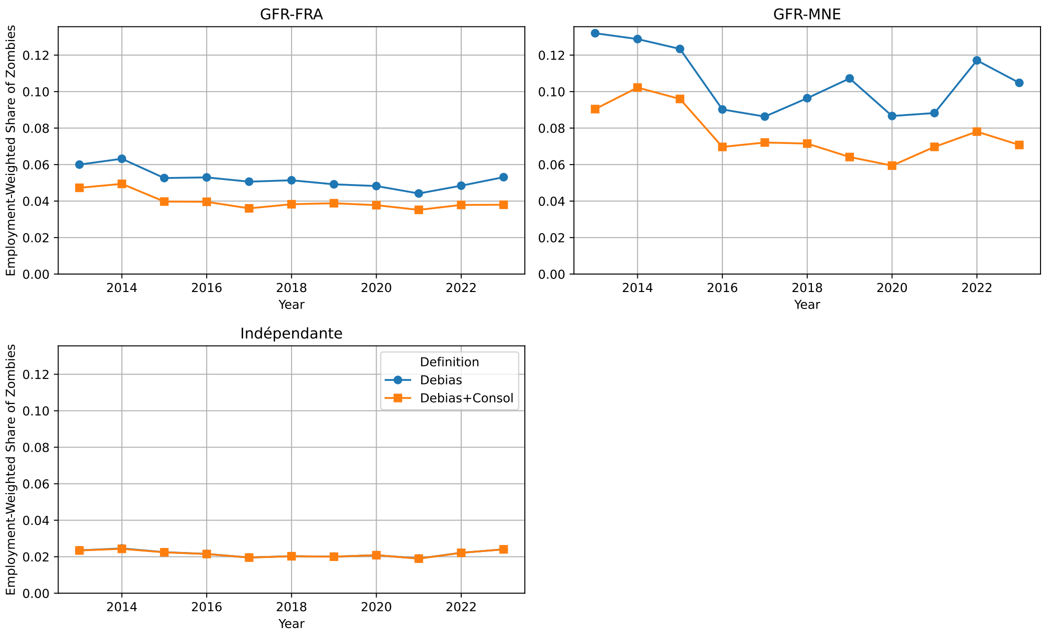
In practice, intra-group interest expenses are compensated by the corresponding intra-group interest revenues recorded on the lender side. Hence, they should not be included in consolidated interest payments. To address this, we use the variable GL (*"Autres intérêts et produits assimilés"*) from the income statement, which measures financial income from interest received — both from intra-group lending and from firms outside the group. Subtracting $\sum_G GL$ therefore offsets the upward bias created by intra-group flows, yielding a lower-bound estimate of the group's true interest burden.

Figure 12 shows that under this assumption the employment-weighted share of zombies is about 9%, roughly 1.5 percentage points below the baseline.

Evidence from fully consolidated balance sheets for a small subset of firms[10] shows that subtracting the entire GL variable leads to underestimating interest payments by roughly half (i.e., removing twice the actual intra-group interest).

Overall, this indicates that the main analysis slightly overestimates the zombie firm share, but the error remains within 1 percentage point. In addition, the dynamics of zombie shares are the same using both estimates.

Figure 12: Robustness Check: Intra-group Debt



Notes: The figure shows the labor-weighted share of zombie firms using a lower-bound correction for intra-group interest, compared to our baseline estimates
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

[10]For these approximately 100 firms (*"Entreprises Profilées de cible 1"*), INSEE hand-collects consolidated balance sheets. I can then test the interest payment consolidation method.

Online Appendix

OA1 Maintaining Consistent Group Identifiers Over Time

Tracking firm ownership over time is complicated by two key issues. First, business groups are inherently dynamic entities: their composition can change frequently due to acquisitions, divestitures, or reorganizations. Second, the identifiers used to represent them (I use the tête de groupe SIREN, or "group head") are unstable and may change across years. These problems are especially acute in the LIFI data, where INSEE introduced major methodological changes in 2012. The identifiers were only stabilized between 2012 and 2015, making it difficult to track groups consistently. For instance, the Airbus Group was known as EADS until 2014; without a robust methodology, these would appear as different groups, preventing us from tracking Airbus across the entire sample.

To address this issue, I define two groups as identical if they share a significant overlap in their constituent firms across two consecutive years. Specifically, for two groups, each identified by a different group head SIREN in year 1 and year 2, I examine the firms (legal units) linked to each group head. If the total size of the firms they have in common—measured by the number of employees—is greater than 50% of the group's total size (calculated as the maximum total size of the group in year 1 or year 2), I consider the two groups to be the same. This approach ensures the continuity of group identifiers despite methodological shifts in the LIFI data, allowing consistent tracking of firm groups over time.

The Country-by-Country Reporting (CbCR) dataset is structured at the group-head SIREN level and contains consolidated variables for the entire multinational group. While this typically aligns with LIFI group definitions, some LIFI groups encompass multiple CbCR declarations. In such cases, I aggregate CbCR variables at the LIFI group level to ensure consistency.

OA2 Deriving profit shifting formula.

A multinational firm i operates in country c with a Cobb-Douglas production function:

$$Y_{i,c} = A_{i,c} L_{i,c}^{\alpha} K_{i,c}^{1-\alpha},$$

where $A_{i,c}$ is total factor productivity, $L_{i,c}$ is labor input, $K_{i,c}$ is capital input, and α is the labor elasticity. The firm's profit is:

$$\Pi_{i,c} = p_c Y_{i,c} - w_c L_{i,c} - r_c K_{i,c},$$

where p_c is the output price, w_c the wage, and r_c the capital rental rate.

The firm optimizes $L_{i,c}$ and $K_{i,c}$ to maximize $\Pi_{i,c}$. The first-order conditions yield:

$$p_c A_{i,c} \alpha L_{i,c}^{\alpha-1} K_{i,c}^{1-\alpha} = w_c, \quad p_c A_{i,c}(1-\alpha) L_{i,c}^{\alpha} K_{i,c}^{-\alpha} = r_c.$$

Dividing these conditions gives the capital-labor ratio:

$$\frac{K_{i,c}}{L_{i,c}} = \frac{(1-\alpha) w_c}{\alpha r_c}.$$

Substituting this into the production function and simplifying, total cost is expressed as:

$$TC_{i,c} = w_c L_{i,c} + r_c K_{i,c} = \frac{w_c L_{i,c}}{\alpha}.$$

With a markup μ_c over marginal cost, prices are $p_c = \mu_c \cdot MC_c$, where:

$$MC_c = \frac{1}{A_{i,c}} \left(\frac{w_c}{\alpha}\right)^{\alpha} \left(\frac{r_c}{1-\alpha}\right)^{1-\alpha}.$$

Revenue is then $R_{i,c} = \mu_c \cdot TC_{i,c}$, and profits are:

$$\Pi_{i,c} = R_{i,c} - TC_{i,c} = (\mu_c - 1)TC_{i,c}.$$

Using $TC_{i,c} = \frac{r_c K_{i,c}}{1-\alpha}$, we have:

$$\Pi_{i,c} = (\mu_c - 1)\frac{r_c K_{i,c}}{1-\alpha}.$$

Generalizing across countries, profits are proportional to capital employed:

$$\Pi_{i,c} = \gamma_c K_{i,c}, \quad \text{where } \gamma_c = (\mu_c - 1)\frac{r_c}{1-\alpha}.$$

Assume equal markups $\mu_c = \mu$ and rental rates $r_c = r$ across countries, so $\gamma_c = \gamma$ is constant. Total worldwide profits are:

$$\Pi_{i,\text{World}} = \sum_c \Pi_{i,c} = \gamma \sum_c K_{i,c} = \gamma K_{i,\text{World}}.$$

Thus, the profit ratio is:

$$\frac{\Pi_{i,\text{FR}}}{\Pi_{i,\text{World}}} = \frac{\gamma K_{i,\text{FR}}}{\gamma K_{i,\text{World}}} = \frac{K_{i,\text{FR}}}{K_{i,\text{World}}}.$$

OA3 Additional regression tables for Section 4

Table 12: Productivity Growth

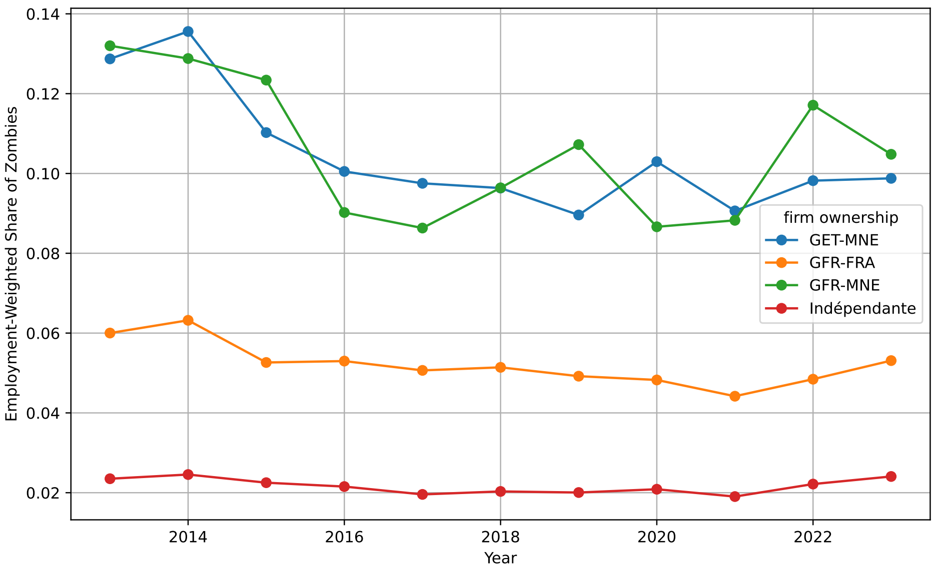
	dProd (1)
zombie_1	-0.007*** (0.002)
NACE × Year	x
Observations	1950454
S.E. type	by: NACExYear
R^2	0.011
R^2 Within	0.000

Significance levels: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01. Format of coefficient cell: Coefficient (Std. Error)

Notes: *dProd* is labor productivity growth. *zombie_1* is the zombie firm indicator. NACExYear includes 2-digit NACE industry-year fixed effects. Standard errors are clustered by 2-digit NACE industry-year.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, excluding foreign-owned firms.

OA4 Additional Graphs & Heterogeneities

Figure 13: Share of zombies by firm ownership type



Notes: The figure shows zombie shares within each firm ownership type.
Source: FARE, CbCR, BTS, LIFI. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age. After profit shifting correction, except for GET-MNE

OA5 Bankruptcy Rates by Bankruptcy Type.

As pointed out in the main analysis, the economic interpretation of bankruptcy events depends critically on whether the firm continues operations ('redressement') or ceases them ('liquidation'). To examine if this distinction interacts with our regression specification in Equation 13, we restrict the sample to bankrupt firms and estimate a logit model with liquidation as the dependent variable.

Formally, let X denote the vector of covariates. Using Bayes' rule, we have:

$$P(\text{Liquidation}|X) = P(\text{Liquidation}|X, \text{Bankruptcy}) \cdot P(\text{Bankruptcy}|X).$$

Thus, a regressor significantly predicting bankruptcy but insignificant in the liquidation regression suggests it affects bankruptcy occurrence but not the type. The results are in Table 13. We see that zombies are more likely to undergo liquidation, but the coefficient is not economically significant, increasing the probability that a bankruptcy is a liquidation only slightly (a few percentage points). We also reproduce the known fact that larger and more productive firms are more likely to undergo redressement, while less productive firms undergo liquidation more often (Despierre et al., 2018).

Table 13: Bankruptcy Type Logit Model

	Dependent variable: Liquidation			
	(1)	(2)	(3)	(4)
$zombie\_1$	0.02***	0.13***	0.02***	0.02***
	(0.01)	(0.03)	(0.01)	(0.01)
$ProdQt = 1$	0.03***	0.04***		
	(0.01)	(0.01)		
$ProdQt = 2$	-0.04***	-0.03***		
	(0.01)	(0.01)		
$ProdQt = 3$	-0.05***	-0.05***		
	(0.01)	(0.01)		
$ProdQt = 4$	-0.05***	-0.04***		
	(0.01)	(0.01)		
$ProdQt = 1)\text{x}zombie\_1$		-0.14***		
		(0.03)		
$ProdQt = 2)\text{x}zombie\_1$		-0.09***		
		(0.03)		
$ProdQt = 3)\text{x}zombie\_1$		-0.08***		
		(0.03)		
$ProdQt = 4)\text{x}zombie\_1$		-0.07**		
		(0.03)		
$ZombieLaborShare$	0.08**	0.08**	0.08**	
	(0.03)	(0.03)	(0.04)	
$ProdDeviation$			-0.03**	-0.04
			(0.01)	(0.02)
$ProdDeviation\text{x}ZombieLaborShare$				0.08
				(0.12)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	118692	118692	118692	118692
Pseudo R^2	0.02	0.02	0.02	0.02

Notes: The dependent variable is a dummy indicating whether the bankruptcy outcome was liquidation (as opposed to redressement). $zombie\_1$ is a dummy variable indicating if the firm is classified as a zombie. $ProdQt$ denotes sector-specific labor productivity quantiles, with $ProdQt = 5$ as the reference category. $ZombieShare$ represents the share of zombie labor in the firm's industry. Interactions between $ProdQt$ and $ZombieShare$ capture the effect of zombie labor share on firms within specific productivity quantiles. Firm controls include age (firm age in years) and log_eff (log of the number of employees). Year fixed effects are included as specified. The values reported are the average marginal effects. Standard errors are reported in parentheses.
Source: FARE, CbCR, BTS, LIFI, BODACC. Author's computation.
Sample: Non-financial firms with more than 5 employees and more than 10 years of age, that went through a bankruptcy between 2011–2023, excluding foreign-owned firms.

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