Passive Ownership and Market Selection: Evidence from U.S. Zombie Companies

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Abstract

Using a panel of U.S. public firms (1990-2024), this study examines how the rise of passive ownership distorts market selection, contributing to the creation and survival of zombie firms. To establish causality, I employ a Granular Instrumental Variable framework (Gabaix and Koijen, 2024) leveraging idiosyncratic liquidity shocks of the "Big Three". I find that an exogenous increase in passive ownership drives a deterioration in structural firm productivity, effectively trapping firms in a state of financial and operational stagnation. This trap is sustained by two distinct mechanisms. First, a governance vacuum: within-firm estimates show that passive capital reduces CEO pay-performance sensitivity, insulating entrenched management and allowing them to pursue a "quiet life" at the expense of efficiency. Second, a credit channel: contrary to traditional evergreening narratives, creditors penalize this lack of internal oversight by demanding higher loan spreads, especially in stable environments where market turbulence cannot substitute for monitoring. Finally, survival analysis reveals that passive capital significantly prolongs ongoing zombie spells.

Keywords: Institutional ownership, Passive investors, Zombie firms, Corporate governance.

JEL Codes: D24, G23, G32, G33, G34, E44, L2

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1 Introduction

Zombie firms are unviable companies that continue to operate despite weak fundamentals, avoiding exit through bankruptcy or acquisition. In the past few decades, the share of zombie firms among publicly quoted companies in advanced economies has increased significantly, rising from about 5% in the late 1980s to approximately 16% by 2023[1]. Concurrently, the persistence of zombie status has intensified, with the probability that a zombie firm remains in that state the following year increasing from 60% to over 80% (Banerjee et al., 2024). In this paper, I examine how the rise of passive institutional ownership contributes to this persistence and affects the market selection process of financially distressed firms.

Addressing the dynamics of zombie firms is crucial because they are often associated with adverse macroeconomic consequences. These include the misallocation of capital and labor (Caballero et al., 2008; Andrews and Petroulakis, 2019), depressed aggregate productivity growth (Adalet McGowan et al., 2018; Banerjee and Hofmann, 2018), and weakened competitive dynamics due to reduced market entry and innovation (Carreira et al., 2022; Acharya et al., 2022).

The rise in zombie firm prevalence has traditionally been linked to both financial and regulatory factors. Weak bank balance sheets and poorly designed insolvency regimes incentivize banks to roll over loans to non-viable firms instead of recognizing losses (Caballero et al., 2008; Andrews and Petroulakis, 2019; Schivardi et al., 2022). Persistently low interest rates have further contributed by lowering debt servicing costs and encouraging loan evergreening (Borio and Hofmann, 2017; Banerjee and Hofmann, 2018). However, recent evidence indicates this dynamic does not universally apply to modern, competitive credit markets. For instance, Favara et al. (2024) demonstrate that U.S. banks do not engage in subsidized zombie lending; instead, irrespective of capital levels, they actively tighten lend-

[1]These figures are based on the definition used by Banerjee and Hofmann (2022). While the literature offers no universally agreed-upon definition of zombie firms, Banerjee and Hofmann (2022) note that the estimates remain broadly consistent across alternative definitions.

ing terms and reduce exposure to financially distressed firms. This divergence highlights a critical gap: if subsidized bank debt is not keeping U.S. zombie firms afloat, another market force must be artificially suppressing their exit.

I propose that this missing force resides in the equity markets, specifically, the unprecedented structural shift toward passive institutional ownership. While the literature has focused primarily on the role of banks and monetary policy in sustaining zombie firms, it has largely overlooked the potential influence of institutional investors through the control rights associated with their equity stakes. The rapid rise of passive investing has further reshaped ownership structures: passive funds now account for the majority of assets under management in U.S. equity funds, managing over 60% more than active funds. These developments raise an important question of whether the composition of institutional ownership shapes zombie dynamics. The relevant mechanism is not shareholders' preference over firm exit, as both active and passive equity holders prefer survival over liquidation given that equity is wiped out in bankruptcy, but whether they can discipline management. Active investors monitor intensively and pressure managers to restructure even under distress. Passive investors cannot apply the same firm-specific pressure: Bebchuk and Hirst (2019) document that the Big Three have on average only 21 investment stewardship personnel covering nearly 18,000 portfolio firms, and index investing creates a free-rider problem whereby the costs of monitoring are borne by the engaging fund while the benefits are shared across all funds tracking the same index. This structural under-resourcing potentially allows entrenched managers to avoid the painful operational decisions needed to either recover or exit.

The effects of institutional ownership on zombie dynamics are theoretically ambiguous. On one hand, large and persistent institutional shareholders can strengthen governance and reduce the likelihood that weak firms survive without restructuring (Velury and Jenkins, 2006; Chung and Zhang, 2011; Bena and Ortiz-Molina, 2013). This governance channel has become increasingly important as creditor discipline has weakened: covenant lite loans, which strip out maintenance covenants, have grown from just over 10% in 2007 to more than 80% of the U.S. leveraged loan market by 2020 (Bräuning et al., 2022), and permissive

EBITDA definitions have further eroded the quality of remaining protections (Ivashina and Vallee, 2020).[2]

On the other hand, in the past two decades financial markets have witnessed the rise of passive institutional investors, which have much lower capacity for monitoring than active institutional investors. The expansion of index funds and ETFs has markedly increased passive ownership, prompting debate over how these investors shape governance and monitoring (Appel et al., 2016; Schmidt and Fahlenbrach, 2017; Appel et al., 2019; Heath et al., 2022; Brav et al., 2024). Adler et al. (2025) show that passive investors are associated with higher borrowing costs because lenders perceive them as weaker monitors and less responsive to firm fundamentals.

Building on these insights, this paper proposes that passive institutional ownership distorts the market selection of distressed firms by fundamentally altering the disciplinary environment for management. When passive investors displace active ones, the governance vacuum they leave behind reduces the pressure on managers to restructure, cut costs, or exit unprofitable operations. For firms already navigating financial distress, this weakened oversight provides the critical friction that traps them in zombie status.

To test this empirically, I exploit exogenous variation in firm-level passive ownership using a Granular Instrumental Variable (GIV) framework (Gabaix and Koijen, 2024). Specifically, I isolate fundamental-blind liquidity shocks stemming from idiosyncratic capital flows of the Big Three asset managers, namely BlackRock, Vanguard, and State Street. I interact these manager-level shocks with firms' lagged ownership weights to generate plausibly exogenous shifts. Using this identification strategy, I document three principal findings that illustrate this market distortion.

First, I establish that passive ownership causally increases zombie incidence and significantly prolongs zombie spells, indicating a delayed market exit.

[2]Shareholder governance operates through monitoring and disciplining management, and is distinct from creditor governance, which operates through loan covenants that grant control rights independently of equity ownership. In the absence of these contractual tripwires, creditor governance cannot reliably substitute for the monitoring vacuum created by passive investors.

Second, I identify a governance channel driving this survival. While the empirical literature regarding passive monitoring remains fiercely debated due to the localized limitations of index-assignment designs (Gormley and Kim, 2025), I utilize a stringent high-dimensional panel fixed-effects design to capture the continuous macroeconomic shift in ownership. This approach confirms that the expansion of passive capital significantly attenuates managerial performance incentives. I further demonstrate that zombie firms with high passive ownership exhibit significantly greater entrenchment. Shielded from removal threats and facing weaker financial incentives, managers face reduced pressure to implement operational improvements or undertake costly restructuring.

Third, I show that this governance distortion transmits directly to firm fundamentals. Specifically, I document a causal decline in productivity, demonstrating that managers, insulated from market discipline, fail to execute necessary efficiency improvements. Compounding this operational decay is a severe credit penalty. Breaking from traditional evergreening narratives where zombies receive artificially cheap debt, I find that lenders accurately price this erosion of oversight and demand higher loan spreads. This aligns perfectly with Adler et al. (2025), who show that high passive ownership directly increases borrowing costs due to weaker monitoring, as well as recent evidence from Favara et al. (2024) demonstrating that U.S. banks charge a risk premium, rather than a subsidy, to distressed firms. I establish a clear boundary condition: this credit penalty is concentrated in stable, low-volatility environments, where external market turbulence cannot substitute for internal monitoring. Ultimately, the joint effect of weaker productivity and higher interest expenses pushes marginal firms below the viability threshold, sustaining those that would otherwise exit in an efficient selection process.

The structure of the paper is as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 provides descriptive statistics. Section 5 presents the identification strategy and estimates the causal effect on zombie status. Section 6 tests the quiet life hypothesis. Section 7 analyzes the persistence of distress using survival analysis. Section 8 concludes.

2 Literature review and contribution

This study contributes to the literature on the drivers of zombie firm prevalence. Existing research identifies two primary explanations for the rise of zombie firms: financial sector weaknesses and monetary policy. Impaired bank balance sheets and inefficient insolvency regimes incentivize lenders to roll over credit to non-viable firms to avoid recognizing losses (Caballero et al., 2008; Andrews and Petroulakis, 2019; Schivardi et al., 2022). Simultaneously, prolonged low interest rates reduce debt-servicing costs and encourage forbearance, enabling underperforming firms to survive (Borio and Hofmann, 2017; Banerjee and Hofmann, 2018, 2022; Acharya et al., 2022). However, recent evidence suggests that these debt-market frictions do not universally explain zombie persistence in modern, competitive credit markets. For instance, Favara et al. (2024) find that U.S. banks do not engage in subsidized evergreening; instead, they actively tighten lending terms and increase spreads for distressed firms. These findings suggest that if credit markets are penalizing rather than subsidizing unproductive firms, another force must be artificially suppressing their market exit. This paper fills this gap by showing that the "lifeline" for these firms has shifted from the debt market to the equity market. I document how the weak monitoring and reduced managerial incentives induced by passive institutional ownership can directly lead to zombie firm status, providing an alternative mechanism for survival that persists even when lenders demand higher risk premiums.

This analysis also connects to the macroeconomic literature on resource allocation. Efficient markets rely on creative destruction to reallocate capital from unproductive to productive uses (Hopenhayn and Rogerson, 1993; Ahearne and Shinada, 2005). Passive ownership interferes with this process by creating a wedge between firm viability and firm survival: even when a firm's fundamentals no longer justify its continued existence, the governance vacuum induced by passive capital insulates managers from the disciplinary pressures that would otherwise force restructuring or exit, allowing unproductive firms to persist and misallocate resources at the expense of more productive competitors.

Furthermore, this research advances the debate on passive ownership and corporate governance. While early evidence suggested index funds promote low-cost governance reforms (Appel et al., 2016), subsequent work indicates that passive ownership can weaken oversight (Schmidt and Fahlenbrach, 2017), provide only procedural monitoring (Heath et al., 2022), or engage selectively (Brav et al., 2024). The severity of this governance failure becomes clearer when contrasted with the literature on activist hedge funds, which documents that activist investors exert intensive, performance-sensitive monitoring and can generate substantial improvements in firm value and governance (Brav et al., 2008, 2015). By comparison, passive investors lack both the incentives and the flexibility to intervene in underperforming firms, making their influence fundamentally different from the targeted activism undertaken by hedge funds.

Beyond governance, recent studies explore how passive ownership affects broader economic outcomes. Schmalz and Zame (2024) show that while index funds improve diversification, they raise equity valuations and depress expected returns, reducing aggregate investor welfare. Adler et al. (2025) find that firms with higher passive ownership face higher loan spreads, as lenders perceive weaker monitoring and greater borrower risk. This paper traces the downstream real effects of this financial penalty, showing how higher spreads, combined with weakened managerial discipline, ultimately determine whether distressed firms survive or exit.

Finally, the paper offers a methodological contribution to identifying the causal effects of passive institutional ownership. Prior studies typically exploit exogenous variation from index reconstitutions, particularly around the Russell 1000/2000 cutoff (Appel et al., 2016; Boone and White, 2015; Crane et al., 2016). While powerful, these designs are less practical when few distressed firms lie near the threshold. To capture richer within-firm variation across the entire market, I build on the flow-to-stock literature (Edmans et al., 2012; Dessaint et al., 2019; Wardlaw, 2020) by integrating a Granular Instrumental Variable (GIV) framework (Gabaix and Koijen, 2024). I isolate strictly exogenous liquidity shocks driven by the idiosyncratic capital flows of the Big Three. Interacting these manager-level shocks

with a firm's lagged ownership weights, and explicitly splitting the instrument to capture asymmetric corporate responses to net inflows versus outflows, produces a robust, overidentified firm-level instrument. This provides a cleaner, highly flexible strategy for studying the causal impact of passive ownership on zombie outcomes.

3 Data and variable construction

3.1 Data sources

The empirical analysis draws on multiple data sources to construct a panel of U.S. publicly traded firms with detailed information on institutional ownership, financial conditions, and firm characteristics. The sample spans the period from 1990 to 2024, and is structured at the firm-year level.

Institutional ownership data are obtained from the Thomson Reuters Institutional Holdings 13F Database (S34), which provides quarterly equity holdings of institutional investors managing more than $100 million in assets[3], and the Thomson Reuters Mutual Fund Holdings (S12) Database, used to measure firm-level exposures to individual funds. S12 records stock holdings of individual funds, while the S34 aggregates holdings across entire fund families and includes other 13F filers such as insurance companies and pension funds. Thus, S34 offers broader coverage, whereas S12 provides greater granularity. For these reasons, total institutional ownership and ownership concentration are computed using S34, whereas passive ownership is derived from S12, which allows for a more accurate specification of investor types.

The reliability of institutional ownership measures is further enhanced by incorporating information from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. This

[3]The analysis uses the updated version of the 13F (S34) data provided by WRDS, which addresses significant feed issues and missing observations previously identified in 2019 Q3 and Q4. Following WRDS's review and release of corrected data in 2022, institutional ownership estimates for affected quarters have been patched to restore reliability.

dataset provides comprehensive historical information on mutual fund characteristics, including flows, structure, and asset allocation. To match the CRSP dataset with the Thomson Reuters Mutual Fund Holdings (S12), I use the MFLINKS table from Wharton Research Data Services (WRDS). MFLINKS provides a reliable linking mechanism that maps CRSP mutual fund identifiers to their corresponding S12 identifiers, allowing researchers to merge fund characteristics and holdings precisely over time.

Firm-level accounting and financial statement variables are sourced from the Compustat North America Fundamentals Annual Database. These data are used to construct distress indicators, control variables, and additional firm characteristics. In addition, the monthly CRSP U.S. Stock Database is used to obtain stock market information.

Loan-level information is obtained from Thomson Reuters LPC's Dealscan Database, which provides detailed data on syndicated loan contracts for U.S. firms. Dealscan includes information on facility- and deal-level characteristics such as loan spreads, sizes, maturities, start and end dates, collateral, and borrower identifiers. These data are merged with Compustat using the Chava and Roberts (2008) borrower link file, which allows for precise matching between borrower firms and financial statement information. Loan-level variables are used to capture firms' access to credit markets and to construct the cost of debt measure employed in the analysis, defined as the natural logarithm of the average loan spread across all facilities initiated by the firm in a given fiscal year.

Finally, data on corporate governance provisions and executive compensation incentives are obtained from the Institutional Shareholder Services (ISS) and Coles et al. (2006), respectively. The first dataset tracks governance arrangements and anti-takeover provisions for a large cross-section of U.S. publicly traded firms. I utilize these data to construct the Entrenchment Index (E-Index) following the methodology of Bebchuk et al. (2009). The second dataset contains information on compensation incentives, specifically CEO pay-performance sensitivity, computed as in Core and Guay (2002). Details on data cleaning procedures, variable construction, and sample construction are described in Appendix A.

3.2 Identification of zombie firms

The literature has not yet settled on a single definition of zombie firms (Banerjee et al., 2024). Commonly, they are identified based on characteristics such as current profitability, firm age, and leverage, with persistent unprofitability, older age, and elevated leverage serving as primary indicators.

In my study, I rely on the definition of zombie firm proposed by Adalet McGowan et al. (2018), which is the most widely adopted approach in the empirical literature. According to this definition, a firm is considered a zombie if it is at least ten years old and has maintained an interest coverage ratio (ICR) below one for three consecutive years. This criterion focuses on identifying firms that experience prolonged financial distress without explicitly conditioning on leverage or sales performance. The age restriction serves to distinguish genuinely unviable firms from young, innovative start-ups that may temporarily operate with negative earnings while developing new products or technologies. The three-year persistence window is designed to filter out short-term cyclical fluctuations and capture sustained weakness in firms' ability to service debt.

3.3 Institutional ownership

I compute the total institutional ownership level of a firm as the portion of shares outstanding held by all institutional investors, providing a baseline measure of the extent of institutional involvement in a firm. The main independent variable, *Passive*, is defined as the portion of a firm's outstanding shares held by passive funds. Following Busse and Tong (2012), Iliev and Lowry (2015), and Appel et al. (2016), passive investors are identified by matching fund names in the Thomson Reuters Mutual Fund Holdings (S12) data to the CRSP Survivor Bias Free US Mutual Fund Database using MFLINKS. A fund is classified as passively managed if its name contains an index-related string or if the CRSP database identifies it as an index

fund[4]. All other mutual funds that can be matched to the CRSP mutual fund data are classified as actively managed, and funds that cannot be matched are left unclassified.

3.4 Loan terms

Following Adler et al. (2025), I aggregate individual loan tranches to the deal level by taking the earliest loan start date, the latest maturity date, and summing tranche amounts to compute the total deal size. Loan spreads and maturities are calculated as tranche size-weighted averages. Deals are then aggregated to the firm-year level by weighting each deal by its total size, allowing the construction of a firm-year measure of the cost of debt (*Spread*), defined as the natural logarithm of the average loan spread across all facilities initiated by the firm in a given fiscal year.

3.5 CEOs incentives and management entrenchment

To capture the direct financial alignment between management and shareholders, I incorporate CEO pay-performance sensitivity ΔPPI. Following Coles et al. (2006), who build upon Core and Guay (2002), ΔPPI is computed as the partial derivative of the CEO's equity and option portfolio value with respect to the firm's stock price, measured as the expected dollar change in portfolio wealth for a 1% change in the underlying stock price. This measure quantifies the financial incentives managers have to maximize shareholder value. High delta values indicate strong incentive alignment, whereas low values suggest that executives are financially insulated from poor corporate performance.

To complement these financial incentives and measure the degree of structural managerial insulation from market discipline, I construct the Entrenchment Index (*E-Index*) following the methodology of Bebchuk et al. (2009). The *E-Index* is constructed using data from the Institutional Shareholder Services (ISS) Governance database and focuses on six key

[4]The strings used to identify index funds include: Index, Idx, Indx, Ind_ (where _ indicates a space), Russell, S & P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, and 5000.

governance provisions identified in the literature as the primary drivers of entrenchment and negative firm valuation. These provisions are: (i) *staggered boards*, (ii) *limits to shareholder bylaw amendments*, (iii) *poison pills*, (iv) *golden parachutes*, (v) *supermajority requirements for mergers*, and (vi) *supermajority requirements for charter amendments*. The *E-Index* is calculated as the sum of these binary indicators for each firm-year, yielding a score ranging from 0 to 6, where higher values indicate stronger anti-takeover protections and greater entrenchment.

4 Summary statistics and descriptive evidence

4.1 Sample composition and zombie spells

The final panel consists of 6,493 publicly traded U.S. firms observed between 1990 and 2024, distributed among 90 industries at three-digit-NAICS- level[5]. Among the entire universe of firms, 2,816 companies are eligible for the zombie classification under the baseline Adalet McGowan et al. (2018) definition, as they are at least ten years old. Of the eligible companies, 2,378 never became zombies during the sample period, while 438 experienced at least one zombie spell.

Overall, the dataset contains 28,785 firm-year observations, of which 3,689 (12.96%) are classified as zombie years. This share provides a firm-year estimate of zombie prevalence among publicly listed U.S. companies over the sample period.

In total, the dataset identifies 1,024 zombie spells, defined as consecutive years in which a firm satisfies the zombie criteria. Among these spells, 347 ended with a recovery, meaning that the firm returned to financial viability, and 677 ended with an exit from the Compustat panel. The latter represents firms that disappeared from the dataset while still classified as zombies, which differs from ordinary exits that occur when a firm leaves the panel outside a zombie episode.

[5]Industries with less than ten firms are removed to ensure consistent within-industry variation.

Among the zombie firms exiting the panel, CRSP delisting codes are available for 135 cases. Most (70 %) fall under code 100, indicating that trading stopped for unspecified reasons. The remaining codes primarily reflect distress-related forced delistings, such as insufficient capital or equity (560), failure to meet exchange requirements (550, 551, 552, 561, 584), delinquent filings or unpaid fees (580), and bankruptcy or insolvency (574), with only a small number tied to company-requested deregistration or liquidation.

4.2 Industry distribution of zombie firms

Figures 1 and 2 document the distribution of zombie firms across U.S. industries in 2024, highlighting where financial distress is most concentrated and where it matters most for the overall economy. For each three-digit NAICS industry, I compute (i) the share of firms that meet this definition and (ii) the industry's contribution to the aggregate stock of zombie firms, defined as the number of zombies in the industry divided by the total number of firms in the economy.

Figure 1 ranks industries by their contribution to the aggregate zombie share. This metric reflects both the prevalence of zombies and the economic weight of the sector, capturing which industries account for the largest portion of underperforming firms in the corporate landscape. Chemical manufacturing and electronic-product manufacturing emerge as the dominant contributors, consistent with their large scale, high capital intensity, and greater exposure to credit markets. These sectors combine a non-negligible incidence of zombie firms with a substantial footprint in the overall economy, making them key drivers of aggregate inefficiency.

Figure 2, by contrast, ranks the same industries by their within-industry zombie share, offering a complementary view focused on relative distress rather than aggregate importance. Here, data-processing, broadcasting, and other knowledge-intensive service industries display the highest concentration of zombie firms, despite their smaller overall economic weight. This pattern suggests that financial weakness is not limited to traditional manufacturing but

extends to technology-driven and digital sectors, where firm-entry is frequent, competition is high, and business models are often supported by intangible assets. These industries may therefore harbor a disproportionate number of firms that survive despite weak fundamentals, reflecting either persistent investor support or slower market exit.

The two figures reveal distinct but related dimensions of the zombie phenomenon. Figure 1 highlights which sectors matter most for aggregate resource misallocation, while Figure 2 shows where the problem is most acute in relative terms.

Figure 1: Top 10 industries by contribution to zombies (2024)

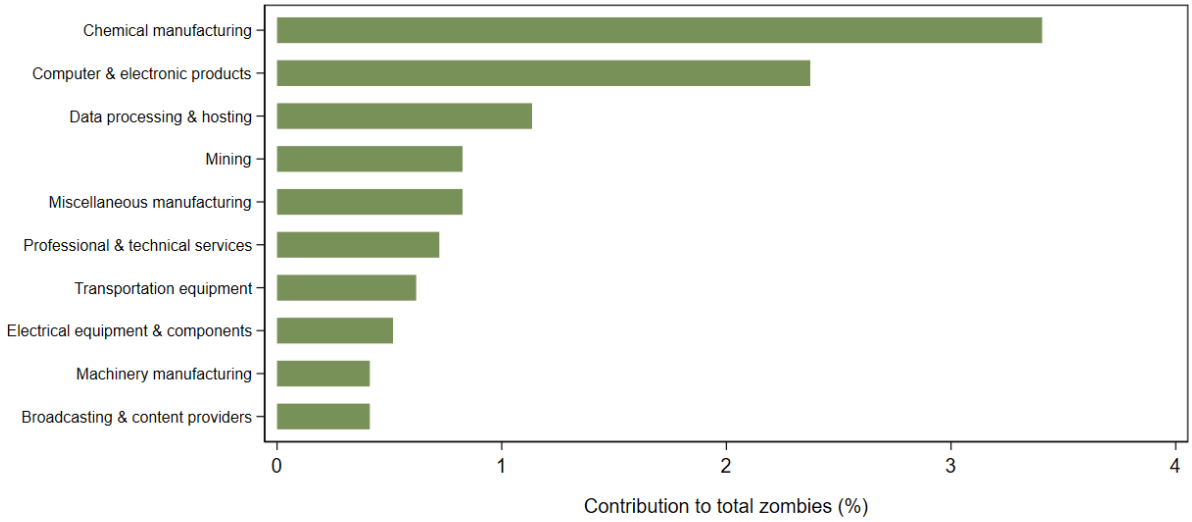
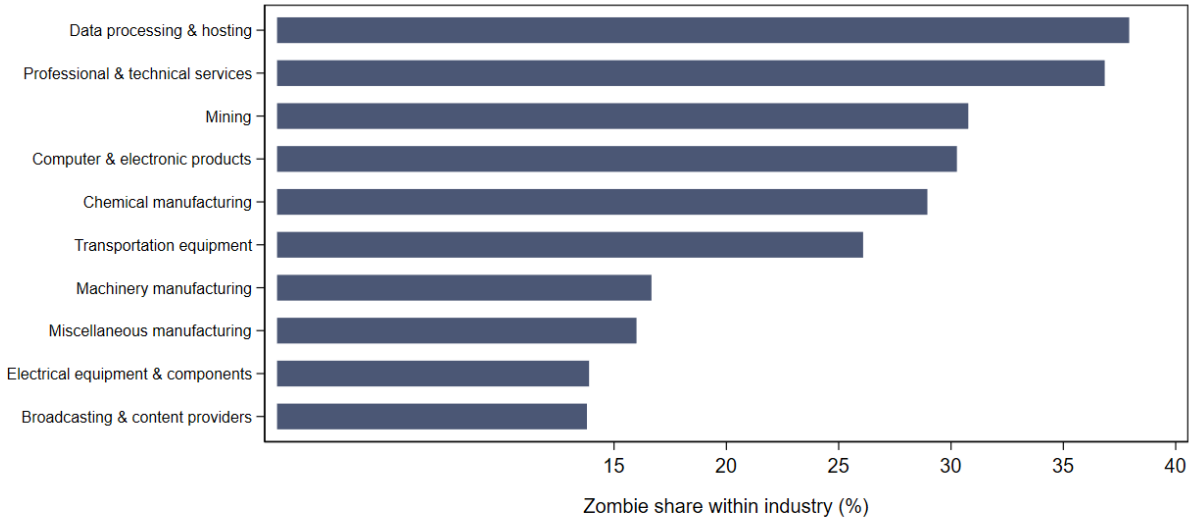


Figure 2: Top 10 industries by within-industry zombie share (2024)



Notes: Figure 1 reports the industries contributing the most to the aggregate stock of zombie firms (share of total zombies). Figure 2 presents the within-industry zombie share (fraction of firms classified as zombies within each sector). In both figures, a firm is considered a zombie following Adalet McGowan et al. (2018) if it is at least ten years old and has maintained an interest coverage ratio below one for three consecutive years.

4.3 Firm characteristics by zombie status

Table 1 summarizes key firm characteristics for zombie and non-zombie firms between 1990 and 2024. Consistent with Banerjee and Hofmann (2022), zombie firms are substantially smaller across virtually all size metrics. On average, they hold a much lighter asset base, about $6.1 billion compared with roughly $14 billion for non-zombies, and generate considerably lower sales revenues. Their operations are also less labor-intensive, as the typical zombie employs only around ten workers, roughly half the employment level observed in healthier firms. This pattern extends to physical capital, where zombies maintain far fewer property, plant, and equipment resources, reflecting both reduced investment capacity and diminished production scale. Their market presence is correspondingly weaker, with zombie firms capturing only about two percent of industry market share, compared with three percent among non-zombies.

Profitability indicators point to even sharper differences. Zombie firms earn an average ROA of just 4%, far below the 14% observed among non-zombies, and their operating income, measured through EBIT, is only about one-third of that generated by healthier firms. At the same time, their book-to-market ratios are markedly higher, indicating lower market valuations relative to fundamentals and signaling investors' limited expectations regarding future performance.

Financial structure further illustrates the challenges faced by distressed firms. Zombies carry slightly more leverage and face significantly more expensive debt financing, with loan spreads averaging 1.97% compared with 1.40% among non-zombie firms. This higher cost of borrowing reinforces the constraints under which these firms operate and reflects lenders' heightened perception of credit risk.

Finally, investment and productivity patterns underscore the broader inefficiencies associated with zombie firms. Their capital expenditures are substantially lower, consistent with reduced growth opportunities and limited access to financing, and their total factor productivity is also weaker, indicating reduced efficiency in converting inputs into output.

Table 1: Firm characteristics by zombie status

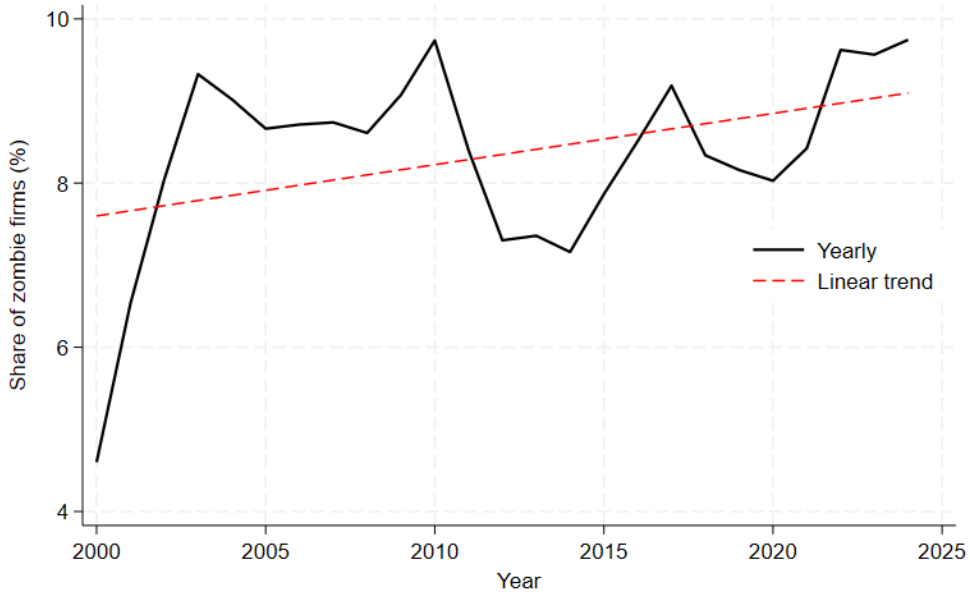
Variable	Non-Zombie Firms	Zombie Firms
Size and Scale		
Assets	13,986.25	6,155.60
Sales	7,426.54	3,146.07
Market Share	0.03	0.02
Employees	22.26	10.34
Property, Plant & Equipment	2,752.97	1,754.64
Profitability		
Return-on-Assets	0.14	0.04
EBIT	800.50	249.22
Book-to-Market	0.62	0.80
Debt and Leverage		
Total Debt	2,155.82	1,163.36
Debt-to-Assets	0.28	0.29
Loan Spread	1.40	1.97
Investment		
CapEx	446.15	265.17
Productivity		
TFP	3.25	3.05
Number of Firms	2,378	438

Notes: The sample covers the period from 1990 to 2024. According to Adalet McGowan et al. (2018), a firm is considered a zombie if it is at least ten years old and has maintained an interest coverage ratio below one for three consecutive years. All financial variables are reported in millions of U.S. dollars.

4.4 Time-series patterns of zombie prevalence

Figure 3 plots the share of publicly listed zombie firms in the United States from 2000 to 2024. Consistently with Favara et al. (2024), the data reveal a steady upward trend in the prevalence of zombies, rising from around 4-5% in the 2000s to roughly 10% by 2024. The linear trend, shown by the dashed red line, indicates a persistent increase over time, with cyclical spikes that coincide with major downturns, such as the early-2000s recession, the global financial crisis of 2008, and the COVID-19 period. Despite partial recoveries following these shocks, the overall trajectory remains positive, suggesting that each successive cycle leaves behind a higher baseline level of zombie firms.

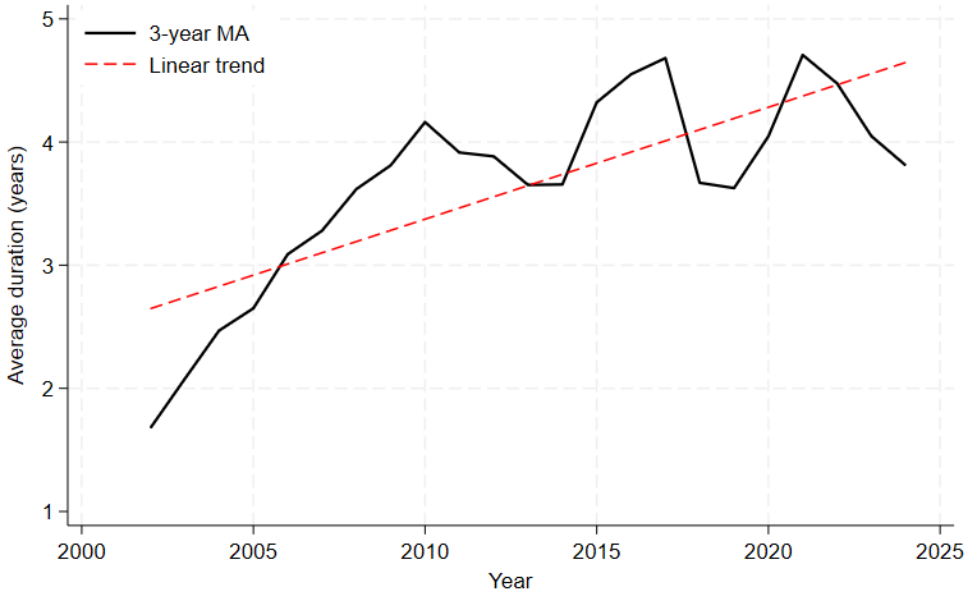
Figure 3: Share of public zombie firms



Notes: The figure plots the annual share of zombie firms, computed as the number of zombie firms divided by the total number of listed firms in each year (2000–2024). According to Adalet McGowan et al. (2018), a firm is considered a zombie if it is at least ten years old and has maintained an interest coverage ratio below one for three consecutive years.

Figure 4 shows the average duration of zombie spells among publicly listed U.S. firms from 2000 to 2024. The average spell length exhibits a clear upward trend, rising from about two years in the 2000s to nearly four years by the early 2020s. The three-year moving average (black line) smooths cyclical fluctuations, while the linear trend (red dashed line) highlights a gradual increase in persistence. This pattern suggests that once firms become zombies, they remain in that state for longer periods, indicating a weakening of exit discipline and prolonged financial distress over time. This trend is consistent with Banerjee and Hofmann (2022), who show that the probability of a zombie firm remaining in that state the following year increased from about 60% in the late 1980s to over 80% by 2023.

Figure 4: Zombie spell duration

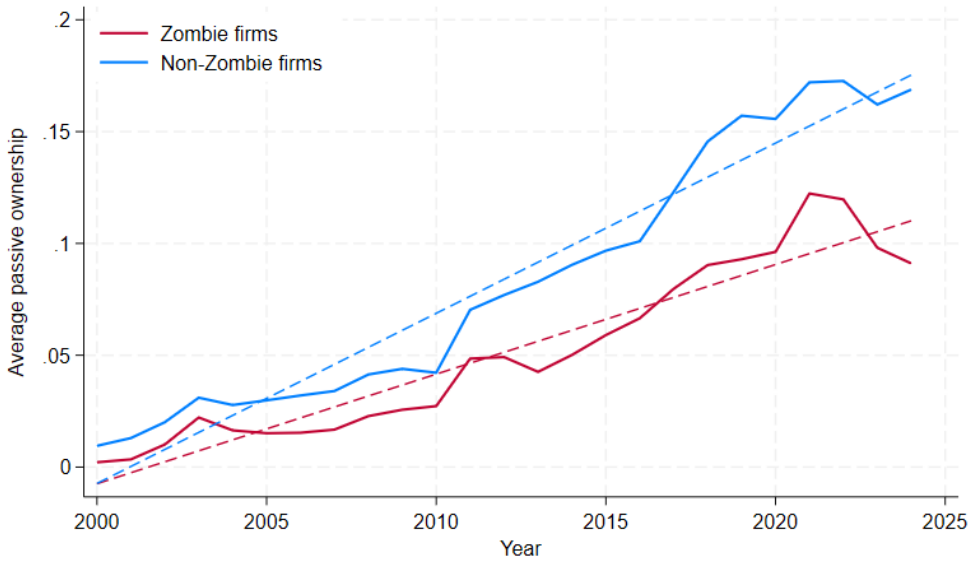


Notes: The figure reports the average duration of zombie spells, computed by identifying consecutive years of zombie status for each firm and averaging spell lengths by year (2000–2024). According to Adalet McGowan et al. (2018), a firm is considered a zombie if it is at least ten years old and has maintained an interest coverage ratio below one for three consecutive years.

4.5 Evolution of passive ownership in zombie and non-zombie firms

Figure 5 compares the evolution of average passive institutional ownership for zombie and non-zombie firms. The data reveal a secular upward trend for both groups, reflecting the structural shift toward index investing in U.S. equity markets. Notably, after 2010, a divergence emerges where non-zombie firms exhibit higher passive ownership ($\approx 17\%$) than zombie firms ($\approx 10\%$), consistent with index funds allocating capital based on market capitalization. As healthy firms grow and distress firms shrink, passive funds mechanically allocate a larger share of capital to the former. However, the rising passive stake in distressed firms remains economically significant; the fact that passive investors now hold a critical block of equity suggests a weakening of monitoring incentives and exit discipline, potentially distorting market selection.

Figure 5: Passive ownership trends



Notes: The figure plots the yearly average share of passive ownership among zombie and non-zombie firms between 1995 and 2024. According to Adalet McGowan et al. (2018), a firm is considered a zombie if it is at least ten years old and has maintained an interest coverage ratio below one for three consecutive years.

4.6 Descriptive regression evidence

Before turning to causal analysis, I first examine the within-firm association between passive ownership and zombie status using standard OLS regression:

$$Zombie_{i,t} = \beta_0 + \beta_1 \, Passive_{i,t} + \Gamma X'_{i,t-1} + \alpha_i + \delta_{s,t} + \epsilon_{i,t} \tag{1}$$

The specification includes lagged firm-level controls commonly associated with zombie status (Favara et al., 2024; Banerjee et al., 2024), alongside firm and industry-by-year fixed effects to account for unobserved heterogeneity across firms and common macroeconomic shocks.

Table 2 reports these descriptive OLS estimates. Control variables exhibit the expected signs. Larger and more profitable firms are less likely to be zombies, while higher leverage increases distress risk. *Liquidity*, measured by the current ratio, reduces the likelihood of zombie status, whereas tangibility increases it, consistent with lower flexibility associated with fixed assets. The *Book-to-Market* ratio is positive but statistically insignificant.

The passive ownership coefficient is negative and statistically significant at the 1% level, indicating that firms with greater passive ownership are, on average, less likely to be classified as zombies.

This negative association highlights a profound selection effect driven by index construction rules. Because major indices enforce strict profitability requirements and utilize market-cap weighting, the declining equity values of distressed firms mechanically reduce their index allocations. Consequently, passive capital naturally concentrates in fundamentally stronger enterprises, leaving zombie firms with structurally lower, yet still economically consequential, passive ownership. Hence, a naive OLS analysis might mistakenly interpret this mechanical selection effect as a causal governance benefit of passive ownership. This stark contrast with the positive causal effect identified in the subsequent Instrumental Variable (IV) analysis underscores the necessity of isolating exogenous, fundamental-blind variation to disentangle index selection rules from the true governance impact of passive investors.

Table 2: LPM regression of zombie status on passive ownership

	$\boldsymbol{Zombie}_{i,t}$	
	Coefficient	**Std. Error**
$\boldsymbol{Passive}_{i,t}$	**-0.274*** **	**(0.097)**
$Size_{t-1}$	-0.080***	(0.011)
$Return\text{-}on\text{-}Assets_{t-1}$	-0.890***	(0.073)
$Leverage_{t-1}$	0.111***	(0.034)
$Liquidity_{t-1}$	-0.020***	(0.005)
$Fixed\ Assets_{t-1}$	-0.027	(0.067)
$Book\text{-}to\text{-}Market_{t-1}$	0.059***	(0.014)
$External\ Dependence_{t-1}$	0.002***	(0.001)
$Constant$	0.835***	(0.095)
Observations	16,058	
R^2	0.694	
Firm fixed effects	Yes	
Industry-by-year fixed effects	Yes	

Notes: The table reports OLS estimates of the association between passive ownership and zombie status. According to Adalet McGowan et al. (2018), a firm is considered a zombie if it is at least ten years old and has maintained an interest coverage ratio below one for three consecutive years. Standard errors are clustered at the firm-level. Stars denote significance at 10%, 5%, and 1%.

5 Addressing endogeneity

5.1 Exogenous variation from passive fund flows

To identify the causal effect of passive institutional ownership on zombie dynamics, I consider using plausibly exogenous shocks to passive fund allocations. The most widely adopted instruments in the literature exploit mechanical index rebalancing. Specifically, prior studies have used changes in passive ownership induced by Russell 1000/2000 reconstitutions (Appel et al., 2016; Ben-David et al., 2018; Glossner, 2019; Coles et al. 2022). This event causes large shifts in passive holdings as index-tracking funds adjust their portfolios to reflect index membership. While this approach offers a powerful source of identification, it is not without controversy. As emphasized in recent work (e.g., Wei and Young, 2020; Appel et al., 2020), estimation methodologies vary widely, and their application has often led to conflicting findings. The validity of the design depends critically on the empirical specification and the treatment of confounding factors. In light of these challenges, the strengths and weaknesses of the index rebalancing approach must be weighed carefully.

A further limitation of the Russell 1000/2000 design in my context concerns the availability of firms around the index cutoff. The identification strategy relies on firms located near the reconstitution threshold, yet the number of zombie firms within this narrow range is likely to be very small. Since my analysis focuses specifically on the dynamics of financially distressed and zombie firms, the lack of sufficient treated and control observations at the cutoff would severely constrain statistical power and prevent credible inference. Additionally, because the dependent variable is constructed over a three-year period, potential consecutive annual index reclassifications present a significant challenge. Firms near the cutoff are highly susceptible to switching between the indices from year to year, which would disrupt the consistency of the passive ownership treatment and severely confound the ability to isolate and measure persistent governance effects over the zombie spell.[6]

[6] I attempted to use the Russell 1000/2000 IV strategy following the post-2007 methodology of Appel et al. (2019). Using a bandwidth of 500 firms around the cutoff, the sample size dropped to roughly 900

As a robust identification strategy, I exploit variation in passive ownership arising from the idiosyncratic capital flows of the three largest asset managers: BlackRock, Vanguard, and State Street. This approach builds on the Granular Instrumental Variable framework proposed by Gabaix and Koijen (2024) and the broader literature linking mutual fund flows to stock price pressure (Edmans et al., 2012; Dessaint et al., 2019; Wardlaw, 2020). The core theoretical intuition of the granular framework is that in highly concentrated markets, idiosyncratic shocks to the absolute largest entities do not average out to zero. Instead, these granular shocks are so massive that they directly drive aggregate market outcomes.

Driven by extreme economies of scale, the index fund industry has evolved into a natural oligopoly where the Big Three completely dominate the passive sector, collectively managing over 90% of all assets in passive U.S. equity funds (Fichtner et al., 2017) and controlling roughly 80% of the broader ETF market (Baines and Hager, 2023). Given this unprecedented scale, when these managers experience unexpected investor inflows or redemptions, they must mechanically purchase or sell quantities of shares to strictly replicate their underlying indices. Because these capital allocations are driven purely by index rules, they occur independently of any individual firm fundamentals or performance metrics. The shocks are generated at the aggregate manager level and apply systematically across the portfolio.

Recent literature, such as Zhang (2024), utilizes the granular instrumental variable framework across the entire universe of institutional investors to identify aggregate equity demand shocks. While acknowledging this broad application, my framework differs by targeting passive indexers exclusively to isolate the corporate governance channel. To construct the instrument, I first isolate the idiosyncratic component of manager flows by filtering out predictable characteristics and aggregate macroeconomic sentiment. I then compute the predicted change in ownership by interacting these isolated manager shocks with their respective lagged ownership weights in each specific firm. Finally, to accommodate asymmetric

observations, and diagnostics revealed a weak first stage, rendering the IV estimates unreliable. This was driven by sample selection bias resulting from the complex sample construction required to identify zombie firms (as detailed in Appendix A2).

corporate responses to capital moving in versus out, I explicitly split this measure into distinct positive and negative vectors. Unlike index rebalancing designs, this granular approach avoids structural correlations with market capitalization and provides a highly flexible and purely mechanical source of exogenous variation in passive investment.

The instrument is constructed using a granular flow-to-stock methodology. First, I compute the actual family flow rate for each asset manager:

$$\text{Flow}\%_{f,t} = \frac{\text{Sales}_{f,t} - \text{Redemptions}_{f,t}}{\text{TNA}_{f,t-1}} \tag{2}$$

I calculate this measure directly by aggregating actual reported monthly sales and redemptions over the year, rather than estimating it through changes in total net assets. While estimating flows from TNA is common, it introduces severe measurement error by mathematically assuming all capital is deployed at the exact end of the reporting period (Li and Zheng, 2025). Because investors dynamically deploy capital throughout the year, those mid-year flows experience compound market returns before the year-end TNA snapshot. Consequently, estimating annual flows from TNA changes mechanically scoops up these intra-year capital gains and misclassifies them as fresh inflows, fundamentally confounding true exogenous investor liquidity demand with stock market performance. Furthermore, I explicitly exclude dividend reinvestments from the flow rate calculation because they represent internal capital distributions rather than true external demand shocks from investors.

Second, I extract the idiosyncratic shock from the Big Three family flows by partialling out predictable characteristics and aggregate time trends:

$$Flow\%_{f,t} = \gamma_0 + \gamma_1 Return_{f,t-1} + \gamma_2 Age_{f,t-1} + \gamma_3 Size_{f,t-1} + \delta_t + u_{f,t} \tag{3}$$

I select these specific controls because past performance, fund maturity, and scale are the primary fundamental drivers of mutual fund flows identified in the literature (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Investors reliably chase past returns, while

fund age and fund size dictate the growth trajectory and capacity constraints of the asset manager. The time fixed effects capture aggregate macroeconomic sentiment and broad market cycles. By stripping away these predictable components, the residual isolates the strictly unpredictable idiosyncratic liquidity shock.

Third, I map these family level shocks to the firm level by multiplying the idiosyncratic shock by the lagged ownership share:

$$Z_{i,t} = \sum_{f \in \text{Big 3}} (S_{i,f,t-1} \times u_{f,t}) \tag{4}$$

Here, $u_{f,t}$ denotes the unpredictable idiosyncratic flow shock of passive fund family f in year t, and $S_{i,f,t-1}$ is the lagged ownership share of family f in firm i. To accommodate asymmetric corporate responses to capital moving in versus out, I split this measure into distinct positive and negative vectors. Specifically, $Z^{+}_{i,t}$ captures net inflows where the shock is positive, and $Z^{-}_{i,t}$ captures net outflows where the shock is negative.

The shift component, $u_{f,t}$, is plausibly exogenous to any individual firm's fundamentals or outcomes, as these liquidity shocks are generated at the aggregate family level and apply systematically across the portfolio. In contrast, the share component, $S_{i,f,t-1}$, may be partially endogenous, since funds may overweight firms with certain characteristics. However, the identification remains valid under the assumption that the exogenous shift is uncorrelated with the share weighted potential outcomes. That is, in this context, the validity of the instrument requires that idiosyncratic flows are not systematically related to the average future distress outcomes of the firms that those funds held prior to the flow shock. In other words, unexpected liquidity shocks experienced by passive funds should not be driven by expectations about whether their portfolio firms are likely to enter or exit zombie status.

5.2 Empirical strategy

The predicted change in passive institutional ownership caused by the idiosyncratic flows is obtained by estimating the following first stage regression:

$$\Delta Passive_{i,t} = \gamma_0 + \gamma_1 Z^{+}_{i,t} + \gamma_2 Z^{-}_{i,t} + \Gamma X'_{i,t-1} + \alpha_i + \delta_{s,t} + \nu_{i,t} \tag{5}$$

Here, $\Delta\text{Passive}_{i,t}$ denotes the change in the passive ownership share of firm i between the prior year and year t. The specification includes both the positive shock vector $Z^{+}_{i,t}$ and the negative shock vector $Z^{-}_{i,t}$ as separate instruments to properly model the asymmetric market clearing behaviors of firms during passive inflows versus outflows. The term $X'_{i,t-1}$ represents the vector of lagged firm level controls. To ensure the instruments isolate purely exogenous variation, I saturate the model with stringent fixed effects. The parameter α_i absorbs time invariant unobserved firm heterogeneity while the parameter $\delta_{s,t}$ captures industry-by-year fixed effects, which control for aggregate macroeconomic cycles, industry specific credit crunches or booms, and time varying distress trends that could otherwise confound the results. Finally, $\nu_{i,t}$ is the idiosyncratic error term.

The effect of passive ownership on zombie status is then estimated in the second stage using the predicted values from equation (2):

$$Zombie_{i,t} = \beta_0 + \beta_1 \, \Delta\widehat{Passive}_{i,t} + \Gamma X'_{i,t-1} + \alpha_i + \delta_{s,t} + \epsilon_{i,t} \tag{6}$$

In this equation, $\Delta\widehat{Passive}_{i,t}$ is the fitted value generated from the first stage. The primary coefficient of interest is β_1. Because the specification utilizes two distinct continuous instruments, the two stage least squares estimator does not identify a single homogeneous effect. Instead, β_1 identifies a weighted average of Local Average Treatment Effects (LATE). Specifically, it captures the weighted average of the individual complier effects across the subpopulation of firms induced to alter their passive ownership concentration by the granular liquidity shocks, that is, idiosyncratic fund outflows and fund inflows.

5.3 Results

Table 3 reports the two stage least squares estimates. Column 1 presents the first stage regression, which captures the mechanical relationship between idiosyncratic fund flows and the firm level change in passive ownership. The results reveal a powerful and highly asymmetric corporate response to liquidity shocks.

First, consider the negative shock vector (Z^-). The estimated coefficient is positive (0.0016) and statistically significant at the 1% level. Because this variable perfectly isolates net mutual fund outflows, a more severe economic outflow corresponds to a negative shift in the instrument's distribution. Consequently, multiplying a negative shock by this positive coefficient yields a net decrease in passive ownership. Since the instrument is standardized, the economic magnitude is precise: a one standard deviation exogenous outflow shock from the Big Three mechanically drives a roughly 0.16% decrease in a firm's passive ownership. The economic intuition is straightforward: when massive passive funds experience investor redemptions, index rules force them to blindly liquidate portfolio shares. This directly reduces the numerator of the ownership fraction, leading to a proportional decline in the overall passive ownership share.

Second, consider the positive shock vector (Z^+). The estimated coefficient is negative (-0.0015) and statistically significant at the 1% level (p=0.010). Because this variable perfectly isolates net mutual fund inflows, a more severe economic inflow corresponds to a positive shift in the instrument's distribution. Multiplying this positive shock by a negative coefficient reveals that unexpected platform inflows also result in a net decrease in passive ownership. Quantifying, a one standard deviation increase in exogenous capital inflows from the Big Three is associated with a 0.15% drop in a firm's passive ownership. While seemingly counterintuitive, this dynamic perfectly aligns with recent empirical evidence by Sammon and Shim (2024), who document that firms act as the primary liquidity providers when index funds are net buyers. Driven by the inelastic demand and resulting price pressure from passive inflows, firms opportunistically act as marginal arbitrageurs in their own eq-

uity, heavily issuing new shares to raise cheap capital. Consequently, this aggressive share issuance inflates the denominator (total shares outstanding), ultimately reducing the overall percentage of passive ownership.
The effects of idiosyncratic passive liquidity inflows on firms' equity issuance activity are reported in Table B1 in Appendix B.

Finally, the granular instruments prove to be robust and strictly valid. The Kleibergen-Paap rk Wald F-statistic is 13.79, comfortably exceeding the traditional Stock-Yogo rule-of-thumb threshold of 10. More importantly, the Anderson-Rubin Wald test yields a highly significant p-value of 0.008, addressing any residual weak instrument concerns. Because the Anderson-Rubin test is fully robust to weak identification, this confirms that the endogenous regressor remains significant in the main equation. Furthermore, because the model is overidentified by utilizing two separate instruments for a single endogenous regressor, I report the Hansen J-statistic to test the overidentifying restrictions. The test yields a p-value of 0.532. This statistically insignificant result confirms that the instruments are valid, correctly excluded from the second-stage equation, and successfully identifying the same variance-weighted local average treatment effect (LATE).

Column 2 of Table 3 presents the second stage estimates, which isolate the causal effect of passive ownership on the probability of entering into and remaining in zombie status. The coefficient on the instrumented change in passive ownership is positive and highly statistically significant at the 5% level (5.034). It is key to note the mechanical timing of the dependent variable. Because a firm is formally classified as a zombie in year t only after enduring its third consecutive year of severe financial distress, this causal estimate specifically captures the effect on firms that are already highly vulnerable. It demonstrates how the proliferation of passive capital acts on firms entering or navigating a prolonged distress cycle, effectively providing the final friction that traps them into formal zombie status.

To properly interpret this coefficient, we must follow the mechanical chain established in the first stage. Because the empirical design utilizes two distinct continuous instruments,

this point estimate does not represent a single homogeneous effect. Instead, it identifies a weighted average of LATE. Specifically, it blends the causal effect across two distinct complier groups: firms whose passive ownership fraction decreases mechanically due to massive fund outflows, and firms whose passive ownership decreases via aggressive equity dilution following massive fund inflows. Because both the negative liquidity shock and the positive liquidity shock independently reduce passive concentration, the overall second stage coefficient averages the distress outcomes of these two distinct corporate responses, with econometric weights strictly proportional to the strength of each instrument in the first stage. Ultimately, this blended effect captures how an exogenous reduction in passive capital directly lowers the likelihood of a firm becoming a zombie. Naturally, interpreting this continuous relationship in the opposite direction validates the core hypothesis that an exogenous expansion of passive ownership strictly elevates zombie risk.

The magnitude of this causal effect is severe. The coefficient indicates that a 1% increase in the change in passive ownership results in an absolute 5% increase in the probability of a firm falling into zombie status. To properly contextualize this penalty, we compare it to the baseline prevalence of distress. The unconditional average rate of zombie firms across the entire sample is 12.96%. Therefore, an absolute increase of 5% translates to a massive 38% relative increase in the baseline probability of distress.

Table 3: 2SLS estimates of zombie status on passive ownership

	(1) First Stage	(2) Second Stage
	$\Delta Passive_{i,t}$	$Zombie_{i,t}$
$Z^{+}_{i,t}$ (Positive Shock)	-0.0015**	
	(0.001)	
$Z^{-}_{i,t}$ (Negative Shock)	0.0016***	
	(0.001)	
$\Delta \widehat{Passive}_{i,t}$		5.033**
		(1.988)
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-by-year fixed effects	Yes	Yes
Observations	14,478	14,478
Kleibergen-Paap F-statistic	13.79	
Anderson-Rubin Test p-value	0.008	
Sargan-Hansen J-statistic p-value	0.532	

Notes: This table reports the two stage least squares estimates of the effect of passive ownership on the probability of a firm being classified as a zombie. Column 1 reports the first stage regression of the change in passive ownership on the positive and negative granular instrumental variables. Column 2 reports the second stage regression predicting zombie status. All specifications include the baseline firm level controls. Firm fixed effects and industry-by-year fixed effects are included to absorb unobserved heterogeneity and aggregate macroeconomic shocks. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.4 Discussion

Relevance. The first requirement for instrument validity is that the instruments must be strongly correlated with the endogenous regressor, which in this case is the change in passive ownership. The positive and negative granular instrumental variables satisfy this condition by design. They aggregate the idiosyncratic liquidity shocks experienced by the Big Three families, weighted by each manager's lagged ownership share in the firm. Because these massive passive families are strictly bound to replicate their underlying indices, sudden investor inflows or redemptions mechanically force them to scale their positions across all constituent firms. As established in the first stage analysis, this generates a powerful and asymmetric impact on a firm's passive ownership concentration. Negative liquidity shocks directly drain the numerator by forcing portfolio liquidations, while positive liquidity shocks trigger aggressive corporate share issuance that drastically dilutes the denominator.

Empirically, the diagnostic tests confirm the strength of this identification strategy. The Kleibergen-Paap F-statistic reaches 13.79, satisfying the standard relevance threshold of 10. To rule out any residual weak instrument pathologies, I also report the Anderson-Rubin Wald test. Because this test provides uniformly valid inference robust to weak identification, it mitigates the risk of size distortions typical of standard IV estimators. Yielding a p-value of 0.008, the test formally rejects the null hypothesis that the endogenous regressor's coefficient is zero, ensuring the subsequent estimates are statistically robust and driven entirely by exogenous variation in passive capital.

Overidentifying restrictions. Because the empirical model employs two distinct instrumental variables (the positive and negative granular liquidity shocks) to instrument for a single endogenous regressor (the change in passive ownership), the system is formally overidentified. This structural overidentification permits an empirical evaluation of the joint validity of the instruments. Specifically, I utilize the Sargan-Hansen J-statistic to formally test the null hypothesis that the instruments are uncorrelated with the structural error term and are therefore correctly excluded from the second stage equation. As reported in the

baseline results, the Sargan-Hansen J-statistic yields a p-value of 0.532. This highly insignificant result indicates that we cannot reject the null hypothesis of instrument validity. Econometrically, this confirms that the split positive and negative liquidity vectors are mutually consistent, identifying the exact same weighted LATE of passive ownership on the probability of corporate distress. This formal test provides strong empirical confidence that the granular shocks satisfy the strict exclusion restriction required for valid causal inference.

Conditional Independence. To interpret the instrumental variable estimates as causal, the identification strategy relies on the independence assumption (or as good as random assignment). This condition requires that, conditional on the set of included covariates, the instruments are uncorrelated with the firm's unobserved latent factors. Formally, let $\epsilon_{i,t}$ denote the unobserved error term in the second stage equation, which captures latent factors affecting zombie risk (for example, management quality, soft information, or unobserved constraints). The identification assumption is:

$$\text{Cov}(Z^{+}_{i,t}, \epsilon_{i,t} \mid X'_{i,t-1}, \alpha_i, \delta_{s,t}) = 0 \quad \text{and} \quad \text{Cov}(Z^{-}_{i,t}, \epsilon_{i,t} \mid X'_{i,t-1}, \alpha_i, \delta_{s,t}) = 0 \tag{7}$$

where $Z^{+}_{i,t}$ and $Z^{-}_{i,t}$ represent the positive and negative granular instrumental variables, $X'_{i,t-1}$ represents the vector of time varying lagged firm controls, α_i denotes firm fixed effects, and $\delta_{s,t}$ denotes industry-by-year fixed effects.

The primary econometric threat to this assumption is the concern that the instruments might be mechanically correlated with the baseline passive ownership share, which is not randomly assigned. To formally establish that this is not the case, we first evaluate the statistical properties of the idiosyncratic shocks. The extracted liquidity shocks have a mean of strictly zero ($E[u_{f,t}] = 0$) by construction, as they are derived as the residuals from the OLS flow regression. Furthermore, the liquidity shock at time t is entirely independent of the firm's lagged passive ownership share ($E[u_{f,t} \mid S_{i,f,t-1}] = 0$). This independence is robustly supported by the unidirectional flow of time. A random aggregate liquidity shock today

cannot possibly influence the historical capitalization table of a firm from the previous year. Conversely, a massive asset manager like Vanguard does not receive aggregate multi million dollar retail inflows simply because of one specific constituent firm in the portfolio last year.

Given these two properties, the expected value of the instrument over time is exactly zero for every single firm, regardless of whether their baseline passive share is 2% or 20%:

$$E[Z_{i,t}] = E[S_{i,f,t-1} \times u_{f,t}] = E[S_{i,f,t-1}] \times E[u_{f,t}] = E[S_{i,f,t-1}] \times 0 = 0 \tag{8}$$

Consequently, we can formally prove that the covariance between the granular instrument and the lagged baseline share is strictly zero:

$$\text{Cov}(Z_{i,t}, S_{i,f,t-1}) = E[Z_{i,t} \times S_{i,f,t-1}] - E[Z_{i,t}] \times E[S_{i,f,t-1}] \tag{9}$$

Substituting the zero expected value of the instrument yields:

$$\text{Cov}(Z_{i,t}, S_{i,f,t-1}) = E[(S_{i,f,t-1} \times u_{f,t}) \times S_{i,f,t-1}] - 0 \tag{10}$$

$$\text{Cov}(Z_{i,t}, S_{i,f,t-1}) = E[S^2_{i,f,t-1} \times u_{f,t}] = E[S^2_{i,f,t-1}] \times E[u_{f,t}] = 0 \tag{11}$$

Therefore, the instrument possesses strictly zero mechanical correlation with the baseline share. It captures solely the random variance of the aggregate shocks over time. However, while the expected value and covariance are zero, the variance of the instrument is entirely driven by the exogenous shock variance scaled by the squared baseline share:

$$\text{Var}(Z_{i,t}) = E[S^2_{i,f,t-1}] \times \text{Var}(u_{f,t}) \tag{12}$$

Because this mathematical property scales the variance with the baseline share, the intensity of the treatment could still theoretically correlate with firm fundamentals. Passive funds allocate capital by tracking indices that often screen for size, profitability, or valuation criteria.

To ensure this treatment intensity does not merely proxy for fundamentally stronger firms that are inherently less likely to become zombies, the conditional independence assumption is satisfied by employing a rigorous empirical saturation of controls.

I address observable financial health by controlling for a rich set of firm fundamentals, including *Size*, *Return-on-Assets*, *Leverage*, *Liquidity*, *Fixed Assets*, and *Book-to-Market*. All firm-level controls are lagged by one period to mitigate concerns of simultaneity bias. I also control for the financial *External Dependence*, a key variable related to corporate zombie status (Banerjee and Hofmann, 2018). Furthermore, the inclusion of firm fixed effects (α_i) absorbs time invariant unobserved quality (such as corporate culture or brand reputation), which effectively partials out the baseline structural level of passive ownership for every firm. Simultaneously, industry-by-year fixed effects ($\delta_{s,t}$) absorb aggregate sectoral shocks that might correlate with broader market cycles.

Conditional on this complete set of covariates and fixed effects, the remaining variation in the instruments is driven solely by the strictly unpredictable idiosyncratic liquidity shocks of the Big Three asset managers. Because these shocks are generated at the aggregate manager level and apply uniformly across broad portfolios driven solely by mechanical index replication, they are plausibly orthogonal to the idiosyncratic unobserved distress risk ($\epsilon_{i,t}$) of any individual firm, fully satisfying the conditional independence assumption.

As an additional robustness check, I evaluate the strict exogeneity of the granular instruments with respect to observable measures of pre-existing firm financial distress. Table C1 in Appendix C presents a predictability test regressing the positive and negative granular liquidity shocks on the firm's standardized lagged Altman Z-score. The results reveal an expected mechanical asymmetry inherent to passive index rules. While historical firm health has no predictive power over positive platform inflows, which are allocated proportionally regardless of fundamentals, severe financial distress does significantly predict negative outflow shocks. This correlation captures a well-documented institutional feature of passive investing, wherein distressed firms suffer market-capitalization degradation and subsequent mechanical down-weighting or index deletion, forcing passive funds to liquidate shares. How-

ever, while statistically significant, the economic magnitude and explanatory power of this relationship are mathematically negligible. A severe, one standard deviation deterioration in a firm's financial health corresponds to merely a 0.033 standard deviation shift in the mutual fund outflow. More importantly, the within-firm R^2 indicates that prior financial distress explains only 0.09% of the variation in the negative shock. This confirms that over 99.9% of the variation in the instrument is driven by strictly exogenous, idiosyncratic capital flows at the platform level, rather than firm-specific capital flight. To formally ensure this minor mechanical selling does not violate the exclusion restriction, Table C2 re-estimates the primary Two-Stage Least Squares (2SLS) model by explicitly incorporating the lagged Altman Z-score into the control vector. To prevent multicollinearity, the baseline covariates that mathematically comprise the Z-score (profitability, leverage, and liquidity) are removed, retaining only orthogonal controls such as firm size, asset tangibility, and external financial dependence. Under this strict conditional independence framework, the causal effect of passive ownership on zombification remains economically large and statistically robust, confirming that the granular shocks do not spuriously proxy for pre-existing distress dynamics.

A natural alternative to this approach would be to directly control for the lagged dependent variable, specifically the firm's zombie status at $t-1$, to capture pre-existing distress. However, zombification is a highly persistent state, introducing a lagged dependent variable into a panel with firm fixed effects introduces severe dynamic panel bias, commonly known as Nickell bias (Nickell, 1981). Because the within-group transformation mean-centers the data to absorb unobserved time-invariant firm characteristics, the transformed lagged dependent variable becomes mathematically correlated with the transformed error term. This dynamics would artificially attenuates the coefficients of interest. Therefore, utilizing the continuous lagged Altman Z-score is the econometrically preferred strategy. It rigorously isolates the firm's pre-existing financial health and bankruptcy trajectory without triggering the structural contamination inherent to dynamic panel estimation.

Exclusion Restriction. The exclusion restriction condition requires that the instruments affect firm outcomes only through the channel of passive ownership and have no direct effect on zombie status. This implies that the coefficients for the granular instruments are zero in the structural equation:

$$Zombie_{i,t} = \beta_1 \Delta Passive_{i,t} + \beta_2 Z^{+}_{i,t-1} + \beta_3 Z^{-}_{i,t-1} + \theta X'_{i,t-1} + \epsilon_{i,t} \tag{13}$$

where $\beta_2 = \beta_3 = 0$. In this context, the exclusion restriction is highly plausible due to the mechanical nature of passive indexation. Idiosyncratic liquidity shocks to the Big Three are generated by millions of retail investors reallocating capital across retirement accounts or broad savings vehicles. These aggregate flows are often driven by exogenous structural shifts, such as a major corporation switching its 401k provider to Vanguard or a fund family triggering a wave of inflows by aggressively decreasing its management fees to gain market share. Such events are products of intense competition within the asset management industry or individual household liquidity needs, rather than the specific financial health or distress trajectory of any single portfolio firm.

One potential challenge to this restriction is the possibility that aggregate inflows trigger contemporaneous price pressure. If stock price movements directly alter a firm's financial health by easing borrowing constraints, the instrument could theoretically affect zombie status through a valuation channel. However, this does not constitute a violation of the exclusion restriction for two reasons. First, as documented by Sammon and Shim (2024), the price pressure exerted by passive inflows is the exact catalyst that triggers the corporate response of aggressive share issuance. Therefore, the price change is an inseparable component of the mechanism that leads to the change in the passive ownership fraction. It is the functional intermediary that forces the denominator of the ownership share to expand, rather than an independent alternative pathway.

Second, the definition of a corporate zombie used in this study relies on the interest coverage ratio, which is a fundamental accounting measure based on operating income and

interest expenses. These metrics are not directly mechanically determined by secondary market stock price fluctuations. While a higher stock price might eventually allow for cheaper refinancing, this process is slow and unlikely to immediately reverse a three year distress trajectory. By controlling for lagged firm fundamentals, market valuation metrics, and fixed effects, I ensure that any potential correlation with market cycles is fully absorbed. This leaves the idiosyncratic manager shocks as a purely exogenous exclusion that affects the firm exclusively through the mechanical shift in its passive ownership concentration.

6 The quiet life hypothesis

6.1 Managerial incentives and entrenchment

The preceding instrumental variable analysis confirms a robust causal link between the proliferation of passive ownership and the probability of corporate zombie status. To move beyond this statistical relationship and uncover the underlying economic mechanism, I now examine the role of firm management. The central hypothesis is that the shift in passive ownership fundamentally alters the disciplinary environment for executives, insulating them from performance-based consequences. In this state, managers may succumb to the "quiet life" hypothesis (Bertrand and Mullainathan, 2003), avoiding the personal and reputational costs of difficult corporate decisions, such as closing inefficient plants or liquidating assets. For a firm already navigating financial distress, this lack of incentive essentially facilitates its survival as a zombie.

A primary channel through which this altered discipline manifests is the deterioration of executive compensation structures. While active monitors typically push for high pay-performance sensitivity to force aggressive restructuring during downturns, the impact of passive indexers remains heavily debated. Because standard localized index-threshold designs (Heath et al., 2022) cannot reliably capture the aggregate displacement of active funds (Gormley and Kim, 2025), capturing this governance shift requires evaluating the continuous macroeconomic transition toward passive capital.

However, while the GIV framework successfully identifies the immediate real effects of passive ownership on operational survival, it is structurally unsuited for evaluating these sticky executive compensation contracts. Liquidity shocks generate extreme, short-term price pressure and volatility, which mechanically distort the annual calculation of equity-based pay-performance sensitivity (ΔPPI) independent of actual board governance decisions.

Therefore, to isolate the underlying governance channel without the confounding mechanical price effects of short-term liquidity shocks, I test whether increased passive own-

ership leads to a reduction in pay-performance sensitivity using a high-dimensional panel fixed-effects design. I estimate this relationship as follows:

$$\Delta PPI_{i,t+1} = \beta_0 + \beta_1 \Delta Passive_{i,t} + \Gamma X'_{i,t-1} + \alpha_i + \lambda_{s,t} + \epsilon_{i,t} \tag{14}$$

Table 4 isolates the within-firm effect of passive ownership on the change in pay-performance sensitivity (ΔPPI). The coefficient on the change in passive ownership is negative and statistically significant at the 5% level (-0.710). In terms of economic magnitude, a 10 percentage point expansion of passive capital drives a 7.1% reduction in the sensitivity of executive compensation to stock returns, directly evidencing a breakdown in internal governance.

Table 4: OLS estimates of pay-performance sensitivity on passive ownership

	$\Delta PPI_{i,t+1}$	
	Coefficient	**Std. Error**
$\Delta Passive_{i,t}$	**-0.710****	**(0.301)**
Controls	Yes	
Observations	10,877	
R^2	0.80	
Firm fixed effects	Yes	
Industry-by-year fixed effects	Yes	

Notes: This table reports the panel fixed-effects (OLS) estimates of the impact of the change in passive ownership on the subsequent change in executive pay-performance sensitivity ΔPPI (in log). All specifications include the baseline firm-level controls. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Building on the observed decline in executive incentives, I now investigate the physical and structural insulation of management through corporate governance provisions. This entrenchment directly complements the reduction in incentives by providing managers with the structural security necessary to pursue a non confrontational corporate strategy.

Unlike active investors, passive funds are severely limited in their ability to discipline management through exit, as the mandate to minimize tracking error makes it mechanically costly to divest from underperforming index constituents (Heath et al., 2022). Furthermore, their low-cost business model and massive portfolio sizes leave stewardship teams structurally under-resourced to engage in deep, firm-specific monitoring (Bebchuk and Hirst, 2019). This dual absence of exit and voice creates a soft governance environment. Insulated from active oversight, managers are free to maintain entrenching provisions that block external intervention, ultimately extending the duration of the zombie spell.

To investigate this mechanism, I examine the differences in the Entrenchment Index (E-Index) between zombie firms with high and low passive ownership. Following Bebchuk et al. (2009), the E-Index is a governance metric identifying six key provisions that drive the negative correlation between governance and valuation: *Staggered boards*, *Limits to shareholder bylaw amendments*, *Poison pills*, *Golden parachutes*, *Supermajority requirements for mergers*, and *Supermajority requirements for charter amendments*. A higher E-Index, calculated as the sum of these binary provisions (0 to 6), indicates a higher degree of insulation from market discipline.

Table 5 presents a univariate comparison of these provisions across zombie firms with low versus high levels of passive ownership. The comparison illustrates that zombies with high passive ownership are significantly more entrenched than their low passive counterparts. The E-Index score for the high passive group is 2.750, compared to 2.141 for the low passive group, representing a statistically significant difference of 0.609. This higher score is primarily driven by specific provisions that shield executives from shareholder pressure. Notably, high passive firms show a prevalence of *Golden Parachutes* at 87% compared to 66% in low passive firms. Furthermore, *Supermajority* requirements are present in 90% of high passive zombies,

whereas they appear in only 38.2% of low passive zombies. A notable exception is the *Poison Pill*, which is significantly less common in firms with high passive ownership (5% versus 33%). This finding is consistent with the evidence in Appel et al. (2016), who document that large passive investors successfully use their influential voting power to reduce explicit takeover defenses like poison pills.

However, this reduction in poison pills does not necessarily imply a more disciplined managerial environment. While passive funds may oppose explicit pills to satisfy broad governance standards or proxy advisor recommendations, this single element does not offset the entrenchment power granted by other E-Index components. The massive surge in supermajority requirements and golden parachutes in the high passive group effectively compensates for the absence of a poison pill, creating a more subtle but equally powerful layer of structural insulation. By protecting the tenure of inefficient executives, this entrenchment facilitates the survival of zombie firms, which ultimately leads to performance deterioration and a higher cost of debt as creditors price in the increased agency risk.

Table 5: Univariate differences in entrenchment components

Governance Provision	**Low Passive** ($N = 34$)	**High Passive** ($N = 58$)	**Difference** *(High - Low)*	**t-stat**
E-Index	2.141	2.750	0.609**	(2.15)
Classified Board	0.386	0.326	-0.06	(-0.84)
Poison Pill	0.331	0.050	-0.281***	(-3.96)
Golden Parachute	0.660	0.872	0.212**	(2.77)
Supermajority Requirements	0.382	0.900	0.518***	(6.58)
Limits to Amend Bylaws	0.176	0.304	0.128	(1.35)
Limits to Amend Charter	0.206	0.302	0.096	(0.80)

Notes: This table compares the prevalence of specific governance provisions between zombie firms with low and high passive ownership concentration. The E-Index measures the degree of managerial entrenchment. Stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6.2 Productivity deterioration and the cost of debt

The governance vacuum documented above, characterized by weakened managerial incentives and entrenched corporate structures, should ultimately manifest in the firm's operational performance. Shielded from removal threats and facing weaker financial incentives, managers face reduced pressure to implement the rigorous technological and organizational improvements required to maintain high productivity. To causally identify this effect, I return to the GIV framework, which isolates exogenous variation in passive ownership free from the mechanical price distortions that made it unsuitable for evaluating compensation contracts.

I estimate the causal effect of passive ownership on firm total factor productivity (TFP), measured by (Ω) with the following second-stage instrumental variable specification:

$$\Omega_{i,t} = \beta_0 + \beta_1 \Delta \widehat{Passive}_{i,t} + \Gamma X'_{i,t-1} + \alpha_i + \lambda s, t + \epsilon_{i,t} \tag{15}$$

where $\Omega_{i,t}$ represents the TFP of firm i in year t, estimated using the control function approach of Ackerberg et al. (2015). $\Delta \widehat{Passive}_{i,t}$ represents the instrumented change in the passive ownership fraction of firm i between years t and $t-1$. $X'_{i,t-1}$ is a vector of lagged firm-level control variables. α_i and $\lambda_{s,t}$ denote firm and industry-by-year fixed effects, respectively. By holding constant the firm's historical characteristics and financial structure, any observed decline in TFP can be causally attributed to the governance changes induced by the exogenous liquidity shocks.

The empirical results in Table 6 link the governance vacuum of passive ownership to a decline in structural productivity. The first-stage instruments remain exceptionally strong (F-statistic of 34.65) and strictly valid (Hansen p-value of 0.426). Specifically, this robust F-statistic comfortably surpasses stringent weak-instrument thresholds, guaranteeing that idiosyncratic fund flows reliably identify endogenous shifts in passive capital.

Column 2 isolates the causal effect of passive ownership on operational efficiency. The second-stage coefficient is negative and statistically significant at the 5% level (-4.010). Because the Ackerberg et al. (2015) methodology estimates Total Factor Productivity (Ω) in natural logarithms, this coefficient represents a semi-elasticity. Economically, a 1 percentage point exogenous increase in passive ownership causes a structural decrease in Ω of 0.0410 log points, which translates to an approximate 4% decline in the firm's actual physical productivity. As managers become entrenched and their compensation becomes insulated from performance, the lack of disciplinary pressure leads to severe operational inefficiencies. Rather than pursuing the difficult restructuring decisions needed to restore efficiency, managers default to the quiet life. This chronic 4% erosion in actual productivity destroys the firm's cash-generating capacity and operational fundamentals over time, effectively trapping distressed firms in the low-productivity state that defines zombie status and facilitating their persistence.

Table 6: 2SLS estimates of TFP on passive ownership

	(1) First Stage $\Delta Passive_{i,t}$	**(2) Second Stage** $\Omega_{i,t}$
$Z^{+}_{i,t}$ (Positive Shock)	-0.003***	
	(0.001)	
$Z^{-}_{i,t}$ (Negative Shock)	0.002***	
	(0.001)	
$\Delta \widehat{Passive}_{i,t}$		-4.010**
		(2.012)
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-by-year fixed effects	Yes	Yes
Observations	20,118	20,118
Kleibergen-Paap F-statistic	34.65	
Sargan-Hansen P-value	0.426	

Notes: This table reports the two-stage least squares estimates of the effect of passive ownership on structural firm productivity. Column 1 reports the first-stage regression of the change in passive ownership on the positive and negative granular instrumental variables. Column 2 reports the second-stage regression predicting productivity (Ω), estimated using the Ackerberg et al. (2015) methodology. All specifications include the baseline firm-level controls. Firm fixed effects and industry-by-year fixed effects are included to absorb unobserved time-invariant heterogeneity and aggregate macroeconomic shocks. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The final component of the governance breakdown involves the credit channel. I hypothesize that passive ownership raises the cost of debt, which directly increases the probability that a firm's ICR falls below the critical zombie threshold. This mechanism is motivated by recent evidence from Adler et al. (2025), who demonstrate that lenders respond to the monitoring gap created by passive capital by demanding higher risk premiums. Because banks perceive high passive ownership as a signal of diminished monitoring, they elevate the cost of private screening and tighten lending standards.

I further explore the boundary conditions of the quiet life hypothesis by interacting passive ownership with firm stock return volatility. According to this hypothesis, managers in poorly governed firms do not necessarily engage in aggressive empire-building, but rather prefer to avoid cognitively and emotionally difficult decisions, such as closing inefficient plants or initiating painful restructurings. As Bertrand and Mullainathan (2003) suggest, managers can only successfully entrench themselves and enjoy the quiet life in stable, predictable environments where they can maintain the status quo without facing immediate bankruptcy. Highly volatile environments, conversely, subject managers to intense market discipline and heightened bank scrutiny that supersedes the passive governance vacuum. Therefore, the credit penalty imposed by lenders should be concentrated precisely in low-volatility firms where the quiet life is actually viable and the risk of zombification is most acute.
To formally evaluate this mechanism, I estimate the conditional effect of passive ownership on the effective cost of debt using the following panel regression specification:

$$Spread_{i,t+1} = \beta_0 + \beta_1 Passive_{i,t} + \beta_2 Vol_{i,t} + \beta_3 (Passive_{i,t} \times Vol_{i,t}) + \Gamma X'_{i,t-1} + \alpha_i + \lambda_{s,t} + \epsilon_{i,t} \tag{16}$$

where $Spread_{i,t+1}$ is the firm-year average loan spread (in log), constructed from Thomson Reuters LPC's DealScan Database. The model includes lagged firm controls and institutional ownership level, firm fixed effects, and industry-by-year fixed effects to isolate the conditional impact of the passive monitoring gap on credit pricing.

Table 7 reports the conditional estimates of the implied interest rate on passive ownership and firm volatility. Consistent with the monitoring gap framework of Adler et al. (2025), I find that passive ownership imposes a severe financial penalty on borrowing firms. The main effect of passive ownership is highly positive and significant (0.727, $p < 0.05$), confirming that creditors actively penalize the lack of shareholder oversight by demanding higher risk premiums.

The negative interaction term (-1.580) reveals a crucial boundary condition: this penalty is concentrated in stable, low volatility environments. This supports a substitution effect between internal monitoring and market discipline, aligning closely with Qiu and Yu (2009), who demonstrate that creditors only price the agency costs of managerial entrenchment into the cost of debt when market forces fail to provide an alternative disciplinary mechanism. In high volatility firms, the inherent turbulence of the market forces managers to stay alert and prompts banks to maintain intense monitoring regimes, rendering the passive equity governance vacuum largely irrelevant. Conversely, in stable, low volatility firms, the shift to passive ownership creates a severe monitoring gap that managers can exploit to enjoy the quiet life. Lenders identify these stable but unmonitored environments as the primary breeding ground for zombie firms, proactively repricing debt to reflect the increased risk of prolonged stagnation.

Table 7: OLS estimates of spread on passive ownership with volatility interaction

	$\boldsymbol{Spread}_{i,t+1}$	
	Coefficient	**Std. Error**
$\boldsymbol{Passive}_{i,t}$	**0.727****	**(0.326)**
$Volatility_{i,t}$	0.292***	(0.047)
$\boldsymbol{Passive}_{i,t} \times \boldsymbol{Volatility}_{i,t}$	**-1.580*****	**(0.530)**
Controls	Yes	
Observations	12,209	
R^2	0.82	
Firm fixed effects	Yes	
Industry-by-year fixed effects	Yes	

Notes: The table reports OLS estimates of the conditional association between passive ownership, firm volatility, and the cost of debt. Standard errors are clustered at the firm level and reported in parentheses. Stars denote significance at 10%, 5%, and 1%.

7 Passive ownership and market selection

What about the duration of zombie spells? If entrenchment insulates managers from market discipline, blocking both internal restructuring and external acquisition, then zombie firms experiencing an influx of passive ownership should remain in distress longer than their peers. To test this, I estimate Cox proportional-hazard models (Cox, 1972) for the duration of zombie spells, in a spirit similar to Banerjee and Hofmann (2022), who use Cox models to study firm exit rather than the end of zombie episodes.

Let t denote years since the beginning of a zombie spell and let $h_i(t \mid X_{i,t-1})$ be the hazard that spell i ends at time t, conditional on a set of firm-level controls $X_{i,t-1}$. A spell is defined as a maximal sequence of consecutive years in which the firm satisfies the Adalet McGowan et al. (2018) criteria; the failure event is either recovery or exit from the panel while still classified as a zombie. The model is

$$h_i(t \mid X_{i,t-1}) \;=\; h_0(t)\, \exp\!\big(\beta\, \Delta Passive_{i,t} + \gamma X'_{i,t-1}\big) \tag{17}$$

where $\Delta Passive_{i,t}$ represents the change in the firm's passive ownership share, and $X'_{i,t-1}$ includes lagged firm financial characteristics.

In this framework, the hazard ratio (HR) measures how the instantaneous probability that a zombie spell ends responds to dynamic shifts in the firm's ownership structure, holding all other covariates fixed. Formally, compare two otherwise identical spells that differ in their change in passive ownership by a margin of δ. Their hazards satisfy:

$$\frac{h_i(t \mid \Delta Passive_{i,t} = \Delta p + \delta, X_{i,t-1})}{h_i(t \mid \Delta Passive_{i,t} = \Delta p, X_{i,t-1})} = \exp(\beta\delta) \equiv \mathrm{HR}(\delta) \tag{18}$$

Thus, for a one percentage point increase in the growth of passive ownership ($\delta = 0.01$), the hazard ratio is:

$$\mathrm{HR} = \exp(0.01\beta) \tag{19}$$

A hazard ratio below one indicates that an influx of passive ownership reduces the instantaneous exit probability and lengthens expected spell duration. Conversely, a hazard ratio above one would mean that higher passive ownership raises the exit probability and shortens the spell.

Table 8 reports the estimates for the Cox proportional-hazards model. The sample contains 415 zombie spells and 384 failures, with 1,056 spell-years at risk. The remaining spells are right-censored, meaning the firm is still a zombie in the last year of observation.

The model allows for industry-specific baseline hazards by stratifying on NAICS industries, which absorbs systematic cross-industry differences in survival and recovery rates without changing the interpretation of β. In this stratified specification, the estimated hazard ratio for the change in passive ownership is 0.015 and is statistically significant at the 5% level. Because the raw hazard ratio represents a theoretical 100 percentage point shift, we can scale it to evaluate a marginal shock. With $\widehat{\beta} = \ln(0.015) \approx -4.20$, a one percentage point positive shock to passive ownership ($\delta = 0.01$) reduces the exit hazard by a factor of $\exp(\widehat{\beta} \cdot 0.01) \approx 0.959$. Economically, this means that a 1% influx of passive capital drops the probability of exiting the zombie state by roughly 4.1% ($1 - 0.959 = 0.041$) in a given year. This result confirms that once industry-level survival dynamics are accounted for, an exogenous influx of passive capital significantly prolongs financial distress by removing the marginal monitors that distressed firms need most.

Table 8: Cox proportional hazards of exiting zombie status

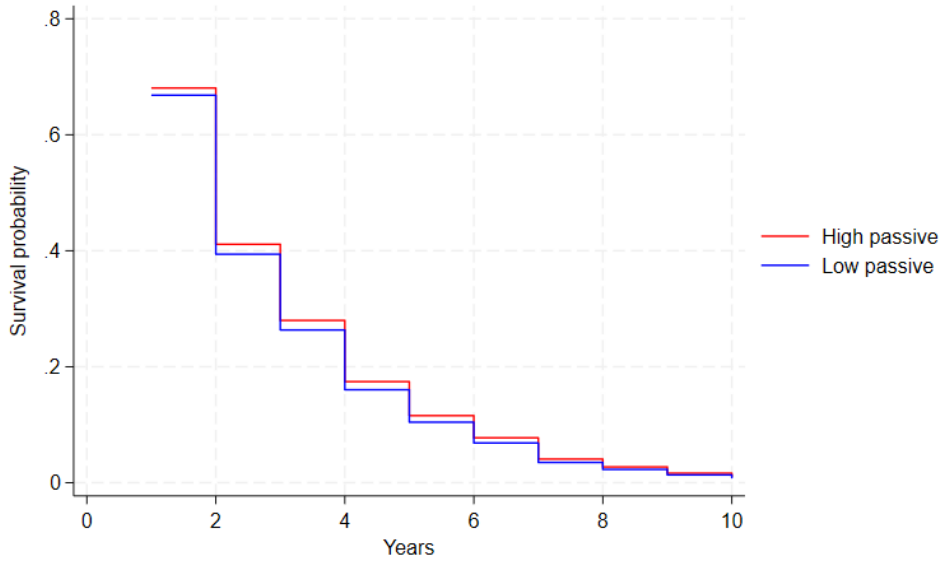
	Hazard Ratio	**Std. Error**
	(1)	(2)
$\Delta \boldsymbol{Passive}_t$	**0.015****	**(0.014)**
$Size_{t-1}$	1.015	(0.032)
$Return\text{-}on\text{-}Assets_{t-1}$	4.296***	(2.257)
$Leverage_{t-1}$	1.224	(0.331)
$Liquidity_{t-1}$	0.929**	(0.030)
$Fixed\ Assets_{t-1}$	0.959	(0.315)
$Book\text{-}to\text{-}Market_{t-1}$	0.766***	(0.051)
$External\ Dependence_{t-1}$	1.010***	(0.004)
Number of subjects	415	
Number of failures	384	
Time at risk	1,056	
Industry strata	Yes	

Notes: This table reports hazard ratios and standard errors from a stratified Cox proportional hazard model estimating the duration of zombie spells. The primary variable $\Delta Passive_{i,t}$ represents the annual change in passive ownership. The model utilizes industry baseline hazards via NAICS strata. All firm level controls are lagged by one period. Standard errors are adjusted for 388 clusters at the firm level. Stars denote significance at the 10%, 5%, and 1% levels, respectively.

Figure 6 plots the predicted survival functions implied by the estimated Cox model. The curves report the probability that a zombie spell remains ongoing as a function of its duration, evaluated at the 25th and 75th percentiles of passive ownership, while holding all other covariates at their sample means.

The figure shows that zombie spells with high passive ownership are more persistent. Survival probabilities are similar at the start of the episode, but from roughly two to five years into the spell the high-passive curve lies systematically above the low-passive curve, and it remains weakly higher over most of the duration distribution as spells eventually terminate. These survival patterns are consistent with the hazard-ratio estimates in Table 8: higher passive ownership lowers the exit hazard and lengthens expected zombie duration. Taken together with the causal evidence in Section 5, these findings suggest that passive investors not only increase the likelihood that firms enter zombie status, but also slow the resolution of distress once it arises.

Figure 6: Probability of remaining a zombie



Notes: The figure plots predicted survival probabilities from the Cox model of Table 8 for zombie spells with low (25th percentile) and high (75th percentile) passive ownership. Curves are evaluated holding all other covariates at their sample means, so differences reflect only variation in passive ownership.

8 Conclusion

This paper examines how the rise of passive institutional ownership has influenced the dynamics of financially distressed public firms in the United States. While naive descriptive estimates of this relationship suffer from severe selection bias, my causal analysis reveals a previously overlooked mechanism: the rise of passive investing introduces a critical distortion into the market selection process, directly facilitating the creation and survival of zombie firms.

Exploiting exogenous variation from granular mutual fund liquidity shocks, I document a cycle of persistent financial distress driven by the quiet life hypothesis. First, a governance channel dictates the onset of financial distress. High passive ownership creates a severe governance vacuum, shielding managers from the monitoring needed to force painful operational restructuring. This entrenchment allows managers to enjoy the quiet life, slowly deteriorating firm productivity and pushing marginally distressed firms below the critical interest coverage threshold.

Second, a conditional credit channel accelerates this decline. Recognizing the agency costs of this governance vacuum, rational creditors penalize unmonitored firms by demanding higher risk premiums (Adler et al., 2025), which directly inflates the cost of debt. Crucially, this penalty is concentrated in stable, low-volatility environments, supporting a substitution effect between internal monitoring and market discipline. In highly volatile environments, intense market turbulence naturally substitutes for corporate governance, rendering the monitoring gap irrelevant to creditors (Qiu and Yu, 2009). Conversely, in stable environments where the quiet life is viable, lenders proactively reprice debt, cementing the firm's distressed status.

Finally, survival analysis resolves the puzzle of how these firms avoid default despite facing punitive credit markets. The equity side provides the missing explanation for long-term persistence. While absolute levels of passive ownership dictate the onset of zombification, the duration of the zombie spell is driven by dynamic changes in the equity structure: a

sudden influx of passive capital displaces informed investors, removes critical marginal discipline precisely when the distressed firm needs it most, and allows entrenched managers to block restructuring and artificially prolong the firm's lifespan.

Viewed collectively, these findings extend the literature on passive ownership and governance by documenting slower market selection when passive investors hold a larger share of equity, describing a broader shift from active, discipline-oriented monitoring to passive, compliance-based governance that has real consequences for firm survival and resource allocation.

Beyond the academic literature, these results speak to a broader debate among practitioners about the market-wide consequences of passive investing.[7] While existing concerns emphasize the dominance of large incumbent firms, the evidence in this paper highlights a complementary mechanism at the other end of the firm-quality distribution: passive ownership also prolongs the survival of financially fragile firms, thereby weakening the process of market selection.

From a policy perspective, the rapid expansion of passive investment has implications beyond asset pricing and corporate governance, affecting macroeconomic efficiency and financial stability. Concentrated ownership in large passive institutions can unintentionally amplify the persistence of inefficient firms, particularly during periods of weak bank balance sheets. Strengthening transparency and stewardship requirements for passive fund managers, and creating incentives for more active monitoring of distressed firms, could help restore market discipline and support the reallocation of resources toward more productive uses.

[7] Inigo Fraser Jenkins, Co-Head of Institutional Solutions at AllianceBernstein, has argued, in his note *"The Dystopian Symbiosis: Passive Investing and Platform Capitalism"*, that cap-weighted passive flows can reinforce incumbency and weaken market discipline. Although his critique concerns dominant firms rather than distressed ones, it reflects a broader concern that passive investing may distort capital allocation.

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Appendix A

A1. Data cleaning

Thomson Reuters Institutional Holdings 13F (S34)

We use the Thomson Reuters Institutional Holdings (13F) Database (S34) to measure aggregate institutional ownership. The raw 13F files are cleaned and harmonized using procedures consistent with Backus et al. (2021).

To facilitate computation, I retain only those firm–quarter observations that appear in Compustat. This restriction aligns the S34 sample with firms for which accounting and financial data are available.

I address duplicate 13F filings within a firm-manager-quarter (`cusip`, `mgrno`, `rdate`) combination by selecting the appropriate filing date (`fdate`) based on stock-split activity.

Using CRSP's cumulative share adjustment factor (`cfacshr`), we identify stock splits at the firm-quarter level. If a split occurred during the quarter, we keep the first filing date to avoid retroactive restatements of pre-split share counts; otherwise, we keep the last filing date to capture any subsequent corrections. This procedure harmonizes holdings across managers and prevents double counting due to multiple 13F submissions.

I fill missing values of `shares_outstanding` in S34 using CRSP data, ensuring that the denominator for ownership computations is complete and adjusted for splits.

Thomson Reuters Mutual Fund Holdings (S12)

The S12 Database is used to measure fund-stock positions at a monthly frequency and to construct firm-year ownership by investor type. The raw data are cleaned and aligned as follows.

S12 reports shares outstanding in alternative fields (`shrout1`, `shrout2`) and units. I standardize to an explicit share count by prioritizing `shrout1`, and where missing, converting `shrout2` from thousands to levels.

Thomson S12 may carry forward stale holdings when later filings are missing. Following Kacperczyk et al., (2008), I retain only the first available filing vintage `fdate` per (`fundno`, `cusip`, `rdate`) triplet to avoid duplication and stale carry-forwards. This yields a single observation per report date at the fund–security level.

Then, I merge S12 to CRSP U.S. Stock Database via `cusip` and keep only matches present in both datasets to restrict holdings to exchange-listed common stocks and to inherit CRSP's share/price adjustments. To align positions to report dates, I adjust S12 share counts by CRSP's split factor `cfacshr`.

These steps produce a panel of adjusted holdings restricted to common stocks, with a single non-stale observation per (`fundno`, `cusip`, `report_date`). To match fund holdings with fund characteristics (i.e. fund classifications, expense ratios), I use the linking table MFLINKS provided by the Wharton Financial Institution, which allows to translate the S12 identifier `fundno` to the common identifier `wficn`.

CRSP Mutual Fund Summary

I use the CRSP Mutual Fund Summary files to recover stable fund attributes and fees at the fund (or share-class) level and to construct an annual panel of expense ratios.

CRSP's style/objective code (`crsp_obj_cd`) may be intermittently missing within a share class. I forward- and backward-fill `crsp_obj_cd` within `crsp_fundno` over calendar time to obtain a time-complete style series per fund share class.

Merges to holdings require a one-to-one mapping from the CRSP class group (`crsp_cl_grp`) to a CRSP portfolio number (`crsp_portno`) each month. I (i) drop rows with both `crsp_cl_grp` and `crsp_portno` missing, (ii) impute a missing `crsp_cl_grp` using a reference pair within the same {`crsp_fundno`, `crsp_portno`}, and (iii) fill missing `crsp_portno` using a donor from the same `crsp_cl_grp`. I then detect and remove conflicts where a class group maps to multiple `crsp_portno` in the same month, ensuring uniqueness.

Following Evans (2010), I drop observations prior to a fund's first offer date and after

its termination date , eliminating pre-offer incubation periods and post-closure records.

Tickers are standardised within `crsp_fundno`: as in Berk and van Binsbergen (2015) I forward-fill and backward-fill missing `ticker`, enforce a single ticker per fund over time, and drop month-ticker combinations that map to multiple funds in the same month. Remaining missings are replaced with the fund identifier for completeness.

To align annual attributes, I construct a complete `fiscal_yearend` series per fund by (i) month-ending `caldt`, (ii) forward-filling known year-end dates, and (iii) back-filling from future known dates with year adjustments so that the fiscal year-end is weakly after the report date. Expense ratios are completed within each fund by backward- then forward-filling missing values. For each share class and fiscal year, I keep the observation at (or closest before) the fiscal year-end. After having translated the CRSP identifier `crsp_fundno` to the common identifier `wficn` through MFLINKS, I then collapse to the wficn-year level, computing TNA-weighted means of expense ratios across share classes. This file is later linked through `wficn` to S12 holdings to classify funds.

Compustat and CRSP U.S. Stock Database

Compustat North America provides the firm-level accounting data used throughout the analysis. To ensure internal consistency, raw data are processed using standard accounting identities. Missing balance-sheet items (e.g., short- and long-term debt) are reconstructed, and income-statement items are recomputed where necessary to ensure fundamental relations hold (e.g., $\texttt{ebit} = \texttt{sale} - \texttt{cogs} - \texttt{xsga} - \texttt{dp}$).

Stock market data are obtained from the CRSP monthly stock files. I restrict the sample to ordinary common shares (`sharetype` "NS", `securitysubtype` "COM") issued by U.S. corporations (`usincflg` "Y", `issuertype` "CORP" or "ACOR") with regular or new-issue conditional types ("RW" or "NW"). Prices and shares are adjusted for splits and dividends using cumulative adjustment factors (`cfacpr` and `cfacshr`).

Finally, I merge the CRSP market data (`permno`) with Compustat accounting data

(gvkey) using the CRSP/Compustat Merged (CCM) linking table. I retain only primary ("P" or "C") and verified/unresearched ("LC" or "LU") links, matching observations strictly within their valid effective link date ranges (linkdt to linkenddt).

Thomson Reuters LPC's Dealscan Database

Data on syndicated bank loans from Thomson Reuters Dealscan are cleaned and standardized prior to aggregation. First, I identify lead arrangers by normalizing role descriptions (primary_role and additional_roles). A lender is classified as a lead if explicitly flagged by lead_arranger, if they are the sole tranche lender, or if their consolidated role string matches standard lead-institution patterns (e.g., "bookrunner" or "lead-left").

Second, pricing variables are stripped of non-numeric characters. To construct a reliable loan spread, I prioritize the all-in drawn spread (all_in_spread_drawn_bps), falling back on the base rate margin plus any applicable add-on margin when the primary field is missing. Tranche sizes and date fields are similarly standardized to ensure accurate size-weighting and time-to-maturity calculations.

Finally, tranches are merged with Compustat identifiers (gvkey) using a restricted Dealscan-Compustat link that requires unambiguous, one-to-one borrower matches. The data are then aggregated to the deal level, assigning each deal the modal gvkey of its tranches, an overall start date (earliest active tranche), and a maturity date (latest maturing tranche). To align with the standard gvkey-fyear accounting panel, these cross-sectional deals are longitudinally expanded, generating a unique firm-year observation for every fiscal year a deal remains active.

A2. Sample construction

Firms without valid industry classification codes (NAICS) or with codes below 100 are excluded, and the sample period is restricted to fiscal years 1990-2024. Financial institutions (SIC 6000–6999) are dropped following Acharya et al. (2022), given their distinct capital-structure and regulatory environments. Only industries with at least 10 unique firms are retained to allow for within-industry variation in ownership and distress dynamics.

All key financial variables are checked for missing, zero, or implausible negative values, and observations failing these criteria are removed. Following Acharya et al. (2022), firms with leverage greater than one are removed. Nominal values are deflated to 2017 U.S. dollars using the FRED deflator. To mitigate the influence of outliers, all continuous variables employed in the analysis are winsorized at the 2nd and 98th percentiles.

To ensure meaningful streak measures and avoid spurious re-entries, I impose two filters at the firm-level: (i) a minimum panel length and (ii) the absence of gaps in fiscal years. First, I drop firms with less than three years of observations, so the retained panel has at least four consecutive years per firm. Second, I detect gaps by comparing each fiscal year t to its neighbors; firms that disappear and later reappear (i.e., with any gap larger than one year) are removed entirely from the sample. This yields a strictly consecutive panel for all retained firms, which is necessary to construct multi-year distress streaks and exits consistently.

A3. Variable construction

Table A1: Variable Construction - Compustat

Variable	Construction
Size	Natural logarithm of total assets: $\ln(\texttt{at})$.
Leverage	Total debt divided by total assets: $(\texttt{dt}/\texttt{at})$.
Interest Coverage	Ebit divided by interest expense: $(\texttt{ebit}/\texttt{xint})$.
Return-on-Assets	Oibdp divided by avg. total assets: $\texttt{oibdp}/[(\texttt{at}_t + \texttt{at}_{t-1})/2]$.
Book-to-Market	Book equity divided by market equity: $\texttt{be}/[\texttt{prcc_f} \times \texttt{csho}]$.
Liquidity	Current assets divided by current liabilities: $\texttt{act}/\texttt{lct}$.
Fixed Assets	Property, plant, and equipment scaled by total assets: $\texttt{ppent}/\texttt{at}$.
External Dependence	How much a firm's investment depends on external finance: $(\texttt{capx} - \texttt{oibdp})/\texttt{capx}$.
Net Equity Issuance	$\ln(\texttt{csho}_t/\texttt{csho}_{t-1})$.
Tobin's Q	Market value of assets divided by book value of assets: $(\texttt{csho} \times \texttt{prcc_c} - \texttt{ceq} + \texttt{at})/\texttt{at}$.
TFP	Computed following Ackerberg et al. (2015).
EBIT Ratio	$\texttt{ebit}/[(\texttt{at}_t + \texttt{at}_{t-1})/2]$.
Volatility	Annualized standard deviation of monthly stock returns (minimum 6 months required).
Z-Score	$3.3 \times (\texttt{ebit}/\texttt{at}) + 0.99 \times (\texttt{sale}/\texttt{at}) + 0.6 \times (\texttt{me}/\texttt{lt}) + 1.2 \times ((\texttt{act} - \texttt{lct})/\texttt{at}) + 1.4 \times (\texttt{re}/\texttt{at})$

Table A2: Variable Construction – Thomson Reuters 13F (S34)

Variable	Construction
Inst. Ownership	Fraction of shares outstanding held by all institutional investors.

Table A3: Variable Construction - Thomson Reuters Mutual Funds (S12)

Variable	Construction
Passive Ownership	Fraction of shares outstanding held by passive funds.

Table A4: Variable Construction - CRSP Mutual Fund

Variable	Construction
Net Inflows	Net investor flows into the fund in year t, defined as sales minus redemptions scaled by lagged total net assets.
Fund Age	Logarithm of the fund's age in years, computed as the time elapsed since the earliest share class's first-offer date.
Fund Size	Logarithm of total net assets at year-end (TNA), aggregated across share classes.
Past Return	Fund's raw annual return in year $t-1$, calculated as the percentage change in net asset value (NAV).

Table A5: Variable Construction – Dealscan

Variable	Construction
Spread	Average loan spread across all facilities initiated by the firm in a given fiscal year (in log).

Table A6: Variable Construction - ISS

Variable	Construction
E-Index	Computed as in Bebchuk et al. (2009).

Appendix B

Table B1: Impact of passive inflow shocks on net equity issuance

	Net Equity Issuance	
	Coefficient	**Std. Error**
$Z^{+}_{i,t}$ (Positive Shock)	0.015***	(0.002)
$Size_{t-1}$	-0.063***	(0.005)
$Return\text{-}on\text{-}Assets_{t-1}$	0.012	(0.020)
$Leverage_{t-1}$	0.110***	(0.017)
$Liquidity_{t-1}$	-0.003	(0.002)
$Fixed\ Assets_{t-1}$	-0.008	(0.019)
$Book\text{-}to\text{-}Market_{t-1}$	-0.009	(0.009)
$External\ Dependence_{t-1}$	0.000	(0.000)
Constant	0.476***	(0.034)
Observations	20,102	
R^2	0.33	
Firm fixed effects	Yes	
Industry-by-year fixed effects	Yes	

Notes: This table reports the empirical validation of the capital structure mechanism driving the first stage relationship. The dependent variable is the log change in common shares outstanding, winsorized at the 2nd and 98th percentiles. The positive shock represents idiosyncratic liquidity inflows into the Big Three asset managers. The model includes firm level controls lagged by one period. Firm fixed effects and industry-by-year fixed effects are included to absorb unobserved heterogeneity and aggregate macroeconomic shocks. Standard errors are two way clustered by firm and year and are reported in parentheses. Stars denote statistical significance at 10%, 5%, and 1% levels.

Appendix C

Table C1: Predictability of instruments by prior firm health

	(1) $Z^{+}_{i,t}$	**(2)** $Z^{-}_{i,t}$
$\boldsymbol{Z\text{-}score}_{i,t-1}$	0.014	0.033***
	(0.012)	(0.007)
Firm fixed effects	Yes	Yes
Industry-by-year fixed effects	Yes	Yes
Observations	19,917	19,917
R^2	0.81	0.51
Within R^2	0.02%	0.09%

Notes: This table reports the predictability test for the assignment of the granular instrumental variables. The dependent variables are the standardized positive liquidity shock (Column 1) and negative liquidity shock (Column 2). The independent variable is the firm's standardized lagged Altman Z-score. Both specifications are estimated using OLS and include firm and industry-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. While severe financial distress statistically predicts negative outflow shocks due to mechanical index down-weighting, the economic magnitude is negligible. A one standard deviation deterioration in the lagged Z-score corresponds to merely a 0.033 standard deviation shift in the mutual fund outflow, and prior financial distress explains only 0.09% of the within-firm variation. This confirms that the granular shocks are overwhelmingly driven by strictly exogenous platform flows rather than firm-specific capital flight.

Table C2: 2SLS estimates of zombie status controlling for prior financial distress

	(1) First Stage $\Delta Passive_{i,t}$	(2) Second Stage $Zombie_{i,t}$
$Z^{+}_{i,t}$ (Positive Shock)	-0.0015**	
	(0.0006)	
$Z^{-}_{i,t}$ (Negative Shock)	0.0016***	
	(0.0003)	
$\Delta \widehat{Passive}_{i,t}$		4.366**
		(1.914)
$Z\text{-}score_{i,t-1}$	Yes	Yes
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-by-year fixed effects	Yes	Yes
Observations	14,695	14,695
Kleibergen-Paap F-statistic	14.46	
Anderson-Rubin Test p-value	0.024	
Sargan-Hansen J-statistic p-value	0.329	

Notes: This table reports the two stage least squares estimates of the effect of passive ownership on the probability of a firm being classified as a zombie, explicitly controlling for pre-existing financial distress. Column 1 reports the first stage regression of the change in passive ownership on the positive and negative granular instrumental variables. Column 2 reports the second stage regression predicting zombie status. The specification includes the continuous lagged Altman Z-score to absorb mechanical capital flight dynamics. To avoid multicollinearity, only orthogonal baseline controls (firm size, asset tangibility, and external financial dependence) are retained. Firm fixed effects and industry-by-year fixed effects are included to absorb unobserved heterogeneity and aggregate macroeconomic shocks. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.