Uncertainty Creates Zombie Firms: Implications for Industry Dynamics and Creative Destruction*

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May 2024

Abstract

We show how the threat of "uncertainty-induced zombification" — creditors' willingness to keep their distressed borrowers alive when faced with uncertainty — shapes various industry dynamics. Under a real options framework, we demonstrate that unlevered firms become reluctant to invest and disinvest in anticipation that uncertainty induces creditors to convert defaulting rival firms into zombies. We validate our theory using dynamic, industry-specific estimates of expected uncertainty-induced zombification together with loan contract-level data. Empirically, higher uncertainty-led rival zombification expectations prompt healthy firms to reduce their costly-to-reverse capital investment and disinvestment, hiring, and establishment-level openings and closures (intensive and extensive margins are affected). We confirm those dynamics using granular, near-universal data on the asset allocation decisions of global shipping firms. Critically, uncertainty-led zombification expectations depress healthy firms' sales, profits, and stock returns. Our results reveal nuanced effects on creative destruction — while healthy firms' asset allocation slows down, their innovation activity accelerates. Our findings highlight a novel channel through which uncertainty shapes firms' capital accumulation, distorting their real and financial policies and performance.

KEYWORDS: Uncertainty, zombie firms, investment, disinvestment, employment, innovation
JEL CLASSIFICATION: G31, G32, D22, D25

*We are grateful to Nikolaos Artavanis, Charles Hadlock, and seminar and conference participants at Florida International University, FMA FEB-RN Seminar Series, Louisiana State University, Roma Tre University, University of Houston, University of Virginia, and the 2024 CMU-Pitt-PSU Finance Conference for many valuable comments and suggestions. All errors remain our own.

1 Introduction

Large-scale shocks such as the Japanese real estate crash, the Global Financial Crisis, and the European sovereign debt crisis have led banks to extend credit to insolvent firms, a phenomenon commonly referred to as "zombie lending" (see, e.g., Caballero et al. (2008), Acharya et al. (2019, 2022, 2024), and Chopra et al. (2021)).[1] Zombie lending emerges because the high level of uncertainty that accompanies economic shocks can make it optimal for banks to speculate on the recovery of defaulting borrowers. Prior work has shown that the presence of zombies may distort firms' incentives to invest (see McGowan et al. (2018) and Acharya et al. (2021)). No existing study has modeled and empirically identified the dynamics connecting uncertainty, rival zombification, and the optimal real and financial decisions of competing firms in an industry.

We theoretically demonstrate and empirically verify that healthy firms' capital allocation decisions are shaped by the *expectation* of zombification in their industries (rather than its *ex-post realization* alone). The realization of such expectations is, however, highly uncertain as it is unclear (1) if and when distressed firms will default; (2) whether banks will convert defaulting firms into zombies; and (3) how long zombies will be able to stay afloat. We show how the "threat of zombification" alone can induce healthy firms to optimally delay their costly-to-reverse decisions, which bears long-term consequences to their industries. We build the theoretical foundations for this mechanism using a real options model of an industry in which levered and unlevered firms compete. The model implies that higher potential for zombification makes the unlevered firms reluctant to (both) expand and contract their capacity, generating multifaceted real options effects across their industries. The economic mechanism we uncover is distinct from the realized-zombification effects found in other work (e.g., Caballero et al. (2008) and Acharya et al. (2021)). This happens because all economic agents in our model — firms and lenders — are forward looking. In order to validate our theoretical predictions, we use data from U.S. public firms as well as near-universal private and public firms from the global shipping

[1] "Zombification" refers to creditor-borrower firm relationships that evolve into a situation where creditors choose to support financially distressed borrower firms with subsidized debt (see Caballero et al. (2008)).

industry to show that the threat of uncertainty-induced zombification prompts healthy firms to reduce their investment and disinvestment, negatively affecting their long-run performance.

We establish the microeconomic underpinnings for our results by laying out a real options model of an industry in which a continuum of levered and unlevered firms use their capacity to produce and sell output at a price driven by demand and aggregate output. Demand in this industry follows a two-state Markov-switching geometric Brownian motion (GBM) with a low growth–high uncertainty state ("recession") and a high growth–low uncertainty state ("expansion"). If levered firms default on their debt in the recession state, their creditors may find it optimal to roll over the debt — converting the defaulting firms into zombie firms rather than liquidating them. This zombification motive arises as high uncertainty in recessions, often combined with government guarantees on creditors' debt, creates an incentive to speculate on the recovery of the defaulting borrowers. It follows that the continued presence of zombie firms keeps output prices low, potentially hindering the creative destruction process — investment in new capital and disinvestment of old capital — necessary for the unlevered firms to recover.

The novel and unique aspect of our theory is that unlevered firms rationally anticipate creditors' zombification incentives and accordingly adjust their costly-to-reverse real decisions. Specifically, a greater threat of uncertainty-induced zombification prompts those firms to delay their investment and disinvestment. There are two mechanisms underlying these results. The first is that zombie firms depress the output price, rendering all capacity units less profitable ("first-moment effect"). The second is that there is uncertainty about when and how many zombie firms may eventually emerge ("second-moment effect"). While both effects lead unlevered firms to delay their investment, the second effect dominates the first under realistic parameter values such that they also delay their *disinvestment*. Intuitively, when there is high uncertainty about the future creation of zombies in the industry, unlevered firms optimally retain their capacity longer to avoid irreversible costs associated with reacquiring capacity when only relatively few rival firms become zombies. Once the zombification uncertainty is resolved, a greater share of zombie firms induces unlevered firms to delay investing but to speed up disinvesting.

We evaluate the predictions of our model using a large dataset on firms' real decisions and long-run performance from a variety of sources. As a first step, we estimate firms' time-varying expectations of uncertainty-induced zombification in their industries. Our main empirical specifications relate these estimates to various outcomes capturing firms' investment, disinvestment, and performance while controlling for other observed and unobserved determinants of those outcomes. To do so, we first follow Acharya et al. (2019, 2022) and Altman et al. (2024) in defining an *existing zombie firm* either as (1) a firm with an interest coverage ratio below one and an Altman's Z-score below zero ("standard zombie"); or (2) a firm satisfying those two conditions but also receiving subsidized credit ("credit-subsidized zombie").[2] Using Dealscan loan contract-level data, we validate our zombie firm definitions, showing that loans to zombie firms attract lower spreads, are less often secured, and more often involve a single lender relative to loans to comparable firms in the industry, in agreement with the findings of Faria-e-Castro et al. (2024). We further show that zombie loans are extended by relatively smaller, poorly capitalized, and riskier banks. New to the literature, we find that the tendency for zombie firms to receive more favorable lending terms increases in periods of higher uncertainty — precisely when our theory predicts that lenders have the strongest incentives to keep them alive.

We next estimate the *expectation of uncertainty-induced distressed-rival zombification* in an industry. We do so based on industry-specific rolling-window forecasting regressions of a zombie-firm indicator variable on lagged proxies for uncertainty, multiple control variables (including a firm's prior zombie status), and a set of fixed effects, calculating the estimate as the end-of-window, logit-transformed fitted value based on the uncertainty proxies. Since a wide range of uncertainty proxies capturing financial, political, and real uncertainty strongly predict zombification, we use as our main uncertainty metric the first principal component from eight common uncertainty measures drawn from prior studies (cf. Jurado et al. (2015), Baker et al. (2016), and Cascaldi-Garcia et al. (2023)). We validate the out-of-sample predictive

[2] Following Caballero et al. (2008), we assume that a firm receives subsidized credit when its interest rate lies below the theoretically most favorable rate for that firm given its circumstances.

performance of our forecasts by plotting their receiver operating characteristic (ROC) curve, finding a relatively high estimate for the area under the ROC curve (AUC).

Our main empirical tests delve into the real capacity investment and employment decisions of healthy (i.e., non-zombie) U.S. public firms. In particular, we show that those firms curb their investment into fixed assets in response to greater expected uncertainty-induced zombification in their industries. They also cut back on their disinvestment, as measured by the sale of property, plant, and equipment. Going further, we use establishment-level data to show that these firms curtail their openings and closures of establishments as well as employment growth in response to that threat. The documented effects are economically significant. A one-standard-deviation increase in the estimated threat of zombification is associated with a 0.9 percentage-point lower establishment opening rate, about 6% of the mean rate (15%). Furthermore, we demonstrate that the effects of expected rival zombification are typically stronger than those of existing zombification, highlighting that zombie firms trigger important real distortions long before they eventually materialize in industries. Since a greater threat of zombification can, in contrast to other forms of uncertainty, only imply negative future news, we also show that healthy firms suffer from decreases in their sales growth, profit growth, asset turnover, and future stock returns as the zombification threat materializes.

We dig deeper into the economic mechanism underlying our results by testing various additional implications from our theory. The negative externalities of expected uncertainty-led rival zombification on healthy same-industry firms require an assumption that those firms have limited market power — their demand is sufficiently elastic that the presence of zombies depresses output prices. Accordingly, we show that our effects are confined to subsamples of industry-years with low markups (higher competition). Further, firms accelerate their breakthrough innovation in response to higher expected uncertainty-induced zombification in their industry, consistent with a product differentiation — reducing demand elasticity — motive. These findings are new and useful in helping us disambiguate our proposed mechanism from the general impact of uncertainty on investment. Following up on our model prediction that the real-options dynamics are more acute for costlier-to-reverse decisions, we show that firms with greater asset inflexibility (following Gu et al. (2018)) respond disproportionately in terms of both their investment and disinvestment. Corroborating our findings on *incumbent* firm responses, we show that *new* business entries are also depressed in the presence of a greater zombification threat. Our results reveal a novel and nuanced insight into the effect of higher zombification expectations under uncertainty on creative destruction — while firms' asset allocation through investment and disinvestment slows down, their innovation activity accelerates.

For granular context, we examine the capital allocation decisions of private and public firms in the global shipping industry. The shipping industry is well-suited for tests of our theoretical predictions as media and industry reports frequently emphasize how the sector is particularly prone to zombification.[3] Moreover, shipping firms can be characterized as competing on output in segmented vessel-size- and route-based markets, which matches well with our model structure (Stopford (2009)). Critically, our detailed data on the fleets, new ship orders, ship demolitions, and secondary ship market transactions allow us to track all margins of shipping firms' investment and disinvestment decisions at the *asset level*, providing a uniquely insightful view into how firms adjust their asset base in response to uncertainty-induced zombification.

Consistent with our theory, we find that healthy firms curb their investment into (and demolition of) shipping vessels in response to the threat of zombification in their various markets. The estimated effects are of greater economic significance in this setting. A one-standard-deviation increase in the threat of zombification is associated with a reduction in ship investment rates by almost three percentage points, around 23% of the baseline rate (13%). Notably, these dynamics are more pronounced among new ship orders and ship demolitions (in contrast to used ship purchases and sales) and in shipping subsectors with a longer time-to-build lag between ordering a new ship and its delivery, once again suggesting that zombification fears disproportionately impact firms' costlier-to-reverse decisions.

[3] For example, see "South Korea Takes Aim at Zombie Companies," *Financial Times*, November 25, 2015, "People are Afraid These 'Zombie Ships' are the First Sign of Global Economic Collapse," *The Telegraph*, January 20, 2016, and "Zombie Companies Return to Shipping," *Lloyd's List*, April 26, 2017.

This paper adds to a large literature on the spillover effects of zombie firms on the economy. Peek and Rosengren (2005) and Caballero et al. (2008) show that zombie firms induce healthy firms to curb their investment into capital and labor in Japan during the "lost decade" (the 1990s), a finding that has been confirmed in other contexts (see, e.g., McGowan et al. (2018), Acharya et al. (2019), Hu and Varas (2021), Bonfim et al. (2023), and Schmidt et al. (2023)). Acharya et al. (2021) report that the negative externalities of zombie firms arise as their presence depresses output prices and raises input costs, lowering the sales growth, markups, and profit growth of healthy rival firms. Relative to these works, our study establishes an unexplored channel by which forward-looking healthy firms not only react to existing zombies but also — and more pronouncedly — to the *threat of uncertainty-induced zombification* in their industries by cutting back on various margins of their capital accumulation and capacity utilization decisions.

We further contribute to the literature on how uncertainty shapes corporate real decisions and aggregate economic outcomes. Bernanke (1983) and McDonald and Siegel (1986) are among the earliest theoretical works to show that it is optimal to delay costly-to-reverse decisions in the presence of high uncertainty. On the empirical front, a host of studies including Leahy and Whited (1996), Bloom (2009), Kellogg (2014), Basu and Bundick (2017), and Kumar et al. (2023), among others, show that high uncertainty depresses corporate investment and that these effects are amplified by the costs of irreversibility (Kim and Kung (2017) and Campello et al. (2024)) and financial frictions (Alfaro et al. (2024)). Our work relates to these studies by highlighting that the threat of rival zombification contributes significantly to the impact of overall uncertainty on economic activity.

The remainder of the paper proceeds as follows. In Section 2, we set up a real options model of an industry in which forward-looking healthy firms optimally adapt their policies to the threat of zombification. Section 3 discusses our data and methodology. In Section 4, we offer our more general piece of evidence based on U.S. public firms. In Section 5, we present granular evidence based on public and private firms from the shipping industry. Section 6 concludes. We offer theoretical derivations and more detailed variable definitions in the appendix.

2 Theoretical Framework

We lay out a real options model in which heightened uncertainty incentivizes creditors to keep defaulting levered firms artificially alive, turning them into zombies to speculate on their recovery. The model demonstrates that healthy firms in the same industry rationally anticipate lenders' zombification incentives, inducing them to delay costly-to-reverse real decisions, and negatively affecting their future performance. We offer theoretical derivations, closed-form solutions, and further technical details in Appendix A.

2.1 Set Up

2.1.1 Economic Assumptions

Consider an industry populated by a number of infinitely small firms with mass n operating over a continuous and infinite horizon indexed by $t \in [0, +\infty)$. The firms are endowed with an identical amount of capacity $\bar{K}$ per firm unit, with each capacity increment producing one output-good increment per firm and time unit when the firm switches on the increment. Switching on the capacity increments is costless and instantaneous, and the cost of producing Q output units in an instant is $C(Q) = \frac{1}{2}\kappa Q^2$, where $\kappa \geq 0$ is a constant parameter.

Firms produce a homogeneous product and choose their production output independently and simultaneously, thereby playing a Cournot-style game. This way, rival firms create competitive pressure, influencing each others' utilization and investment policies. Equivalently, we can model competition in input markets where firms compete for access to resources such as capital and labor. Ultimately, both competition forces create similar congestion effects in real markets and have the same net effect on firms' operating profits and firm values.[4]

We assume that a proportion of firms are highly financially levered and at risk of defaulting and possibly being turned into zombies. We denote the mass of those firms by n_L. The remain-

[4]In Appendix A.7, we formally show that our model generates identical predictions for competition in output market or input markets. Intuitively, both forces generate the same quadratic costs which equally impact firms' operating profits and which then carries through to their values, outcomes, and optimal real decisions.

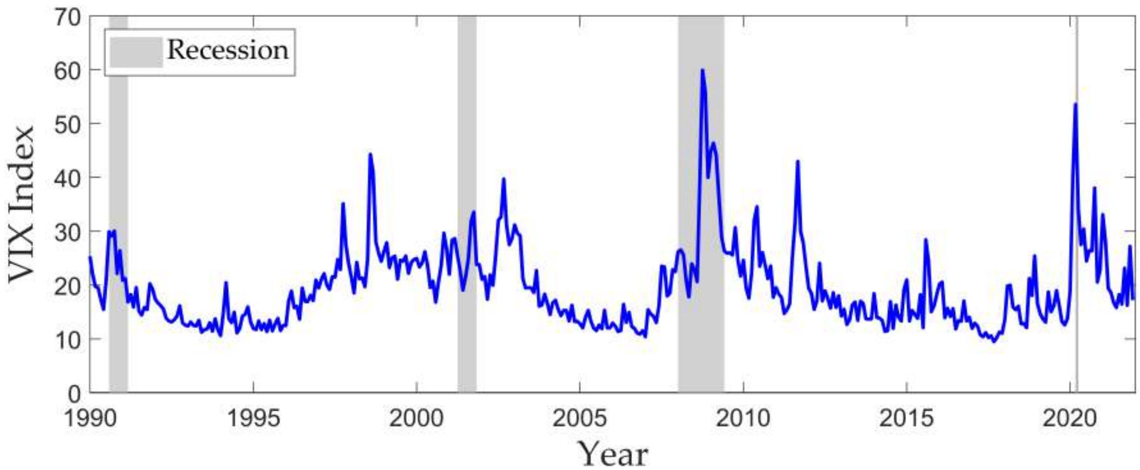

Figure 1. The figure plots the VIX index realization over the sample period from the start of 1990 to the end of 2021. The gray shaded areas are NBER recession periods.

ing firms are financially healthy and we assume for simplicity that these firms are unlevered and rely exclusively on equity financing (Strebulaev and Yang (2013)). That proportion of firms is denoted by $n_u = n - n_L$.[5] Highly levered firms may exist because adverse idiosyncratic shocks forced them to raise debt in the past to continue operating.[6]

Firms sell their output at a stochastic price governed by demand and the aggregate output produced by all firms in the industry. We assume that demand, θ, obeys:

$$d\theta = \alpha_X \theta \, dt + \sigma_X \theta \, dB, \tag{1}$$

where α_X and σ_X are the time-varying demand drift rate and volatility, respectively, and B is a Brownian motion. Conversely, X is an independent continuous-time two-state Markov switching process with state space $\{H, L\}$ specifying the state-specific (constant) demand drift rate and volatility. We follow the VIX-based evidence in Figure 1 and Bloom et al. (2018) in

[5]While the number of levered firms (n_L) varies endogenously through the exit of some defaulting firms, we keep the number of unlevered firms (n_U) fixed without loss of generality. It is straightforward to endogenize n_U. In this setting, the entry decision of new firms mirrors the investment decisions of existing firms. Thus, our model is flexible enough to motivate predictions about business entries (see, e.g., Dixit and Pindyck (1994)).

[6]In our main model, we do not endogenize financial leverage choices and instead focus comprehensively on various real decisions such as capacity utilization, investment, and disinvestment. Notwithstanding, our predictions for real policies carry through to financial policies (as in Alfaro et al. (2024)). Adding endogenous capital structure dynamics would come at the expense of the closed-form solution of our model and blur the resulting intuition.

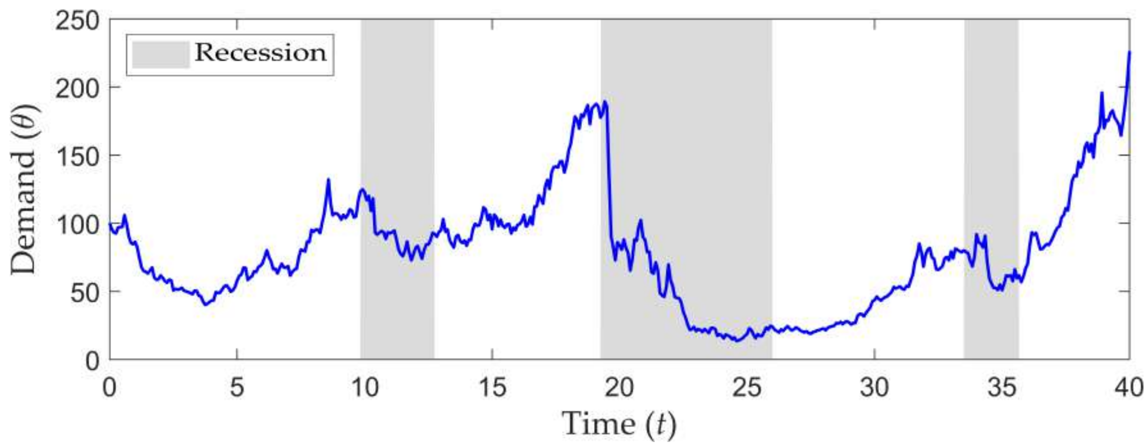

Figure 2. The figure plots a demand process realization. The stochastic process parameters are: $\alpha_H = 0.08$, $\alpha_L = -0.04$, $\sigma_H = 0.20$, $\sigma_L = 0.40$, $p_H = 0.30$, and $p_L = 0.10$. The gray shaded areas are recession states.

assuming that the drift rate and volatility are negatively correlated, implying $\alpha_H > \alpha_L$ and $\sigma_H < \sigma_L$. As such, we can conveniently interpret the H (L) state as an expansion (recession) state. The likelihood of switching into a new state or staying in the current state is given by the standard transition probability matrix:

$$\begin{pmatrix} \underbrace{1 - p_H dt}_{=\text{Prob}[X=L|L]} & \underbrace{p_H dt}_{=\text{Prob}[X=H|L]} \\ \underbrace{p_L dt}_{=\text{Prob}[X=L|H]} & \underbrace{1 - p_L dt}_{=\text{Prob}[X=H|H]} \end{pmatrix}, \tag{2}$$

where p_H and p_L are constant parameters in $[0, 1]$. Intuitively, p_H and p_L are the conditional probabilities of switching from the recession to the expansion state and into the opposite direction over a dt interval, respectively, such that these parameters control the persistence of the states. Using the parameter values in the caption, Figure 2 plots a sample path from stochastic process in (1). Similar to us, Guo et al. (2005), Bloom (2009), Bhamra et al. (2010), Bhamra and Shim (2017), Bloom et al. (2018), and Alfaro et al. (2024) use such a regime-switching process to study various real and financial corporate decisions along business cycle fluctuations.

Given the demand value θ, the stochastic price at which each of the firms sells output dynamically is determined by the downward-sloping demand curve:

$$P = \theta - \gamma\left(\int_{u=0}^{n_U} Q_{U,u}\,du + \int_{v=0}^{n_L} Q_{L,v}\,dv\right), \tag{3}$$

where $Q_{U,u}$ and $Q_{L,v}$ are the one-firm-unit amounts of output produced by the unlevered and the levered firms, respectively, and $\gamma > 0$ is the (constant) slope of the demand function.

2.1.2 Financial Assumptions

We now characterize how levered firms service their debt, the bounded payoffs to the creditors, and the debt renegotiation option whose exercise can turn defaulting firms into zombie firms. We assume that the levered firms are contractually obligated to first service their debt in each instant, requiring them to pay a constant and continuous coupon payment equal to $c > 0$ per firm and time unit to creditors. We assume that levered firms cannot completely insulate themselves from debt obligations by way of saving cash or hedging. As such, the levered firms default when their operating profits drop below the coupon payment.

Upon default, creditors can either roll over the debt or liquidate the defaulting firms.[7] When choosing to rollover, the debt contract transforms into a payment-in-kind instrument. Under this arrangement, defaulting firms pay "whatever they can" until they become able to pay a higher coupon $c^* > c$ to compensate for the missed payments (see, e.g., Gryglewicz and Mayer (2023) and Skrastins (2023)). In essence, creditors offer temporarily subsidized debt to the defaulting firms, but with the chance of receiving higher payments later.

When providing loans, creditors can rely on government guarantees for subsidized debt as in Acharya et al. (2021).[8] As a result, creditors know that renegotiated payments can never drop

[7] One could envision a scenario in which healthy firms would buy the assets of zombies in their industries; potentially using bank credit to do so. While our model does not explicitly discuss capital reallocation across firms in this manner (financed acquisitions), it would be unlikely that healthy firms invest in the unproductive capacity of defaulting firms in times when demand is low and uncertainty high.

[8] Acharya et al. (2021, Foonote 14) list examples of government guarantees in the U.S. including the Depository Institutions Deregulation and Monetary Control Act, Transaction Account Guarantee Program, Debt Guarantee Program, and Bank Term Funding Program, all of which provide debt guarantees to banks.

below $b < c$ since if they do, creditors are bailed out by the government. Intuitively, government guarantees make the renegotiated debt instrument more call-option-like, incentivizing creditors to speculate on the recovery of defaulting firms and to turn those firms into zombie firms in the high–uncertainty (recession) state.

Finally, when choosing to liquidate defaulting firms, creditors receive an uncertain residual value, L_X. We take that the log residual value of each firm is distributed as $N(\mu_{L,X}, \sigma^2_{L,X})$, whose mean, $\mu_{L,X}$, is higher in booms than recessions whereas its variance, $\sigma^2_{L,X}$, is higher in recessions than booms (see, e.g., Shleifer and Vishny (1992) and Acharya et al. (2007)). Notably, the additional uncertainty embedded in the liquidation value of firm assets ensures that creditors only convert a fraction of defaulting firms into zombies.

Turning to the defaulting firms themselves, it is intuitive to see why they may readily agree to be zombified. We distinguish two corporate decision-makers: managers and shareholders. If managers act in their own interest regardless of what is good for shareholders (i.e., in the presence of agency problems), they will likely agree to zombification in light of the severe negative consequences of bankruptcy on future career and wage outcomes documented by prior work (see, e.g., Graham et al. (2023)). Second, equity holders (or managers acting on their behalf in a firm without agency frictions) will also agree to zombification as the equity holders' call option on the firm's assets expires worthless otherwise (see, e.g., Merton (1974)). In contrast, zombification implies that the call option may still end up in-the-money at a later time.

2.2 Optimal Policies & Valuation

2.2.1 Optimal Production Policies

We can write the profits of the i^{th} unlevered (levered) firm per firm and time unit, $\Pi_{U,i}$ ($\Pi_{L,i}$), as:

$$\Pi_{Y,i} = PQ_{Y,i} - \frac{1}{2}\kappa Q^2_{Y,i}, \tag{4}$$

where $Y \in \{U, L\}$, P is given by Equation (3), and $Q_{Y,i}$ is the amount of output per firm unit firm i chooses to produce in the current instant, satisfying $0 \le Q_{Y,i} \le \bar{K}_{Y,i}$. Firms choose their output amounts dynamically to maximize profits, so we have the first-order condition:

$$\theta - \gamma \left(\int_{u=0}^{n_U} Q_{U,u} \, du + \int_{v=0}^{n_L} Q_{L,v} \, dv \right) - \gamma Q_{Y,i} - \kappa Q_{Y,i} = 0, \tag{5}$$

where the sum of the integrals on the left-hand side is the aggregate amount of output produced by all firms and measures the price pressure due to industry competition. The term $\gamma Q_{Y,i}$ is the demand pressure from the firm's own production output. Finally, $\kappa Q_{Y,i}$ captures marginal production costs. Since all unlevered (levered) firms are identical, we have $\int_{u=0}^{n_U} Q_{U,u} du = n_U Q_{U,i}$ ($\int_{v=0}^{n_L} Q_{L,i} dv = n_L Q_{L,i}$). Plugging back into first-order condition (5) and solving for $Q_{U,i}$ and $Q_{L,i}$, we obtain $Q_{U,i} = Q_{L,i} = \frac{\theta}{(n_U + n_L + 1)\gamma + \kappa}$, which is optimal when both types of firm have sufficient capacity to produce that amount of output. When the levered (unlevered) firms are capacity constrained, they produce at their maximum capacity and the others produce at $\frac{\theta - \gamma n_L \bar{K}_L}{(n_U + 1)\gamma + \kappa}$ $\left(\frac{\theta - \gamma n_U \bar{K}_U}{(n_L + 1)\gamma + \kappa} \right)$. When both types are capacity-constrained, they both produce at their maximum capacity.

2.2.2 Optimal Creditor Policies

Creditors optimally roll over the debt of a defaulting levered firm (and thus turn the firm into a zombie firm) whenever the value of the rolled-over debt exceeds the firm's liquidation value; else they liquidate the firm. Relying on the demand value θ at which the firm's operating profits exactly match the coupon payment, Z, Proposition 1 gives the closed-form solution for the value of the rolled-over debt upon a default occurring in state X, $\mathscr{C}(Z, X)$:

Proposition 1. *The rolled-over debt contract value upon a default in state X, $\mathscr{C}(Z, X)$, is:*

$$\mathscr{C}(\theta, X) = \mathfrak{C}(\theta, X; c^*) + \frac{b}{r} - \mathfrak{C}(\theta, X; b), \tag{6}$$

where for a general constant $a > 0$:

$$\mathfrak{C}(Z, X; a) = c_{1,X} Z^{\beta_1} + c_{2,X} Z^{\beta_2} + c_{0,X} Z^2, \tag{7}$$

$c_{0,X}$ determines the value to the creditor from receiving the levered firm's entire operating profits forever, $c_{1,X}$ and $c_{2,X}$ determine the value to the levered firm of being required to pay only the constant a in states in which its operating profits exceed that level, and β_1 and β_2 are the positive roots of a fourth-order polynomial obtained from the appropriate valuation equations.

Proof. See Appendix A.1. □

The value of the rolled-over debt in Equation (6) has two components. First, $\mathfrak{C}(\theta, X; c^*)$ is the present value of perpetually receiving the operating profits of a levered firm, capped at the renegotiated coupon c^*. The term $\frac{b}{r} - \mathfrak{C}(\theta, X; b)$ adds the present value of a potential bailout, ensuring that creditors receive a payment of at least b per period.

As creditors observe the (firm-specific) liquidation value, L_X, upon a default, they roll over the debt if and only if $\mathscr{C}(Z, X) \geq L_X$; else they liquidate the defaulting firm.

Proposition 2 offers an analytical answer to the question how long levered firms require credit-subsidizes after defaulting. To do so, let τ^* denote the first time when firms' profits reach the newly agreed coupon c^*. We denote the equivalent threshold for the demand shift θ by Z^*. The expected time until full recovery can then be calculated as follows:

Proposition 2. *The expected time for levered firms' profits to reach c^*, $\mathbb{E}[\tau^*|\theta, X]$, is:*

$$\mathbb{E}[\tau^*|\theta, X] = -\lim_{u \to 0} \frac{\partial}{\partial u} \mathbb{E}[e^{-u\tau^*}|\theta, X], \tag{8}$$

where the Laplace transform of the first passage time, $\mathbb{E}[e^{-u\tau^*}|\theta, X]$, for some $u > 0$, is:

$$\mathbb{E}[e^{-u\tau^*}|\theta, X] = \frac{\beta_{2,u}\left(\frac{\theta}{Z^*}\right)^{\beta_{1,u}} - \beta_{1,u}\left(\frac{\theta}{Z^*}\right)^{\beta_{2,u}}}{\beta_{2,u} - \beta_{1,u}} - \frac{\left(\frac{\theta}{Z^*}\right)^{\beta_{1,u}} - \left(\frac{\theta}{Z^*}\right)^{\beta_{2,u}}}{\beta_{2,u} - \beta_{1,u}} \frac{\beta_{1,u}\beta_{2,u} + \frac{2u}{\sigma_X^2}}{\beta_{1,u} + \beta_{2,u} + 2\frac{\alpha_X}{\sigma_X^2} - 1}, \tag{9}$$

where $\beta_{1,u}$ and $\beta_{2,u}$ are the positive roots of a fourth-order polynomial obtained from the appropriate valuation equations.

Proof. See Appendix A.2. □

The expectation in Equation (8) can be calculated easily from the closed-form formula (9).

2.2.3 Optimal Capacity Policies and Valuation of the Unlevered Firms

We next derive the dynamic capacity choices and the valuation of the unlevered firms, which are the main focus of our paper. We allow the unlevered firms to adjust their capacity $\bar{K}$ upward (investment) and downward (disinvestment), but assume for simplicity that levered firms operate with fixed capacity due to constraining covenants. Doing so allows us to focus on the real distortions for unlevered firms while likely underestimating our effects as investing zombie firms would bind more production capacity and increase price pressure further, thereby worsening the investment incentives for unlevered firms. Conversely, zombie firms would not disinvest because their gamble to resurrect means that their payment-in-kind financing alleviates them from the financial pressure that might otherwise incentivize costly disinvestment. In sum, we can write the value of an arbitrary unlevered firm (scaled to a unit mass), W, as:

$$W = V(\theta, X) + F(\theta, X) + D(\theta, X), \tag{10}$$

where $V(\theta, X)$, $F(\theta, X)$, and $D(\theta, X)$ are the values of the assets-in-place, growth options, and disinvestment options of the firm, respectively. We first compute $V(\theta, X)$, and then $F(\theta, X)$ and $D(\theta, X)$.

We find the value of the assets-in-place, $V(\theta, X)$, through valuing the incremental capacity units of the firm (see, e.g., Pindyck (1988) and Aretz and Pope (2018)). To do so, we first recognize that the capacity unit able to produce the K^{th} increment yields a profit of $\theta - ((n_U + 1)\gamma + \kappa)K - n_L\gamma \min\{\bar{K}_L, K\}$ (zero) per time unit when switched on (off) *before* some of the levered firms exit.[9] Given that, the firm switches on the unit if demand θ exceeds $\theta_Z^P(K) \equiv ((n_U + 1)\gamma + \kappa)K + n_L\gamma \min\{\bar{K}_L, K\}$. Conversely, that same unit earns a profit of $\theta - ((n_U+1)\gamma+\kappa)K - \psi(X)n_L\gamma\min\{\bar{K}_L, K\}$ (zero) per time unit when switched on (off) *after* some of the levered firms exit, where $\psi(X)$ is the share of levered firms staying upon a default in state X.[10] Given that, the firm now switches on the unit if θ exceeds $\theta^P(K) \equiv ((n_U+1)\gamma+\kappa)K + \psi(X)n_L\gamma\min\{\bar{K}_L, K\}$.

Proposition 3 gives the value of the incremental capacity unit able to produce the K^{th} output increment conditional on creditors' optimal liquidation strategy and before the levered firms default on their debt repayments.

Proposition 3. *The value of an unlevered firm's option to produce output increment K under the creditor's optimal liquidation policy before the levered firms' default is:*

$$\Delta V(\theta, X; K) = \Delta\mathscr{V}(\theta, X; \theta_Z^P(K)) + \left(\Delta\mathscr{V}(Z, X; \theta^P(K)) - \Delta\mathscr{V}(Z, X; \theta_Z^P(K))\right)\left(q_{3,X}\theta^{\beta_3} + q_{4,X}\theta^{\beta_4}\right), \tag{11}$$

where $\Delta\mathscr{V}(\theta, X; \theta_Z^P(K))$, the "perfect zombification" firm value, is:

$$\Delta\mathscr{V}(\theta, X; \theta_Z^P(K)) = \begin{cases} b_{1,X}\theta^{\beta_1} + b_{2,X}\theta^{\beta_2} & \text{if } \theta \le \theta_Z^P(K), \\ b_{3,X}\theta^{\beta_3} + b_{4,X}\theta^{\beta_4} + b_{0,X}\theta - \frac{\theta_Z^P}{r} & \text{if } \theta \ge \theta_Z^P(K), \end{cases} \tag{12}$$

where $b_{0,X}$ is value from the option producing and selling output forever; $b_{1,X}$ to $b_{4,X}$ are the values of the real options to switch on and off the option, $q_{3,X}$ and $q_{4,X}$ are the value from obtaining one dollar upon a default; and β_1, β_2, β_3, and β_4 are the roots of a fourth-order polynomial obtained from the appropriate valuation equations.

Proof. See Appendixes A.3 and A.5. □

[9] The minimum operator ensures that if the levered firms' capacity $\bar{K}_L$ is below the capacity increment K, then only their capacity up to $\bar{K}_L$ (and not K) depresses the output price.

[10] Since all levered firms default simultaneously, and there is an infinite number of them, a strong law of large numbers implies that we always see a constant fraction of those firms leave (specifically those for which the liquidation value realization lies above the value of the renegotiated debt).

Intuitively, $\Delta\mathcal{V}(\theta, X; \theta_Z^P(K))$ is the capacity unit's value when creditors never liquidate defaulting firms and all levered firms stay in the economy forever. Since in that case the capacity unit's profitability never jumps up upon a default, its value aligns with that in a standard Pindyck (1988) model with a state-switching demand process. The upshot is that the $b_{0,X}\theta - \frac{\theta_Z^P}{r}$ term in Equation (12) is the value from the unit producing output forever, while the others adjust that value for the real option to switch on and off the unit.

The second summand on the right-hand side of Equation (11) corrects the capacity unit's value for the possibility that creditors liquidate the fraction $1-\psi(X)$ of defaulting levered firms in expansion or recession states. To better understand that term, recall that the capacity unit's production cost is (the higher) $\theta_Z^P(K)$ before the levered firms' exit but (the lower) $\theta^P(K)$ afterwards. Thus, the $\Delta\mathcal{V}(Z, X; \theta^P(K)) - \Delta\mathcal{V}(Z, X; \theta_Z^P(K))$ term reflects the upward jump in the capacity unit's value due to the downward jump in its production costs induced through the levered firms' exit. Conversely, since $q_{3,X}\theta^{\beta_3} + q_{4,X}\theta^{\beta_4}$ is the present value of one dollar received upon the levered firms defaulting, the entire correction term is the present value of the upward jump in the capacity unit's value upon the levered firms defaulting before the defaults occur.

We can now derive the value of the firm's entire assets-in-place, $V(\theta, X)$, from:

$$V(\theta, X) = \int_0^{\bar{K}} \Delta V(\theta, X; K)\, dK. \tag{13}$$

We next value the options to invest into and disinvest the capacity unit on the K^{th} output increment. To do so, we assume an installation cost of I and a disinvestment gain of d, both per capacity unit and with $I > d$. Proposition 4 then gives the values of those options.

Proposition 4. *The value of an unlevered firm's option to acquire the option to produce output increment K at a unit cost of I under the creditor's optimal liquidation strategy is:*

$$\Delta F(\theta, X; K) = \begin{cases} a_{1,X}\theta^{\beta_1} + a_{2,X}\theta^{\beta_2} & \text{if } \theta \leq \theta_X^*, \\ \Delta V(\theta, X; K) + \Delta D(\theta, X; K) - I & \text{if } \theta \geq \theta_X^*, \end{cases} \tag{14}$$

while the value of the unlevered firm's option to disinvest that same incremental option at a unit gain of d under the creditor's optimal liquidation strategy is:

$$\Delta D(\theta,X;K)=\begin{cases}\Delta F(\theta,X;K)-\Delta V(\theta,X;K)+d & \text{if } \theta\leq\theta'_X,\\ d_{3,X}\theta^{\beta_3}+d_{4,X}\theta^{\beta_4} & \text{if } \theta\geq\theta'_X,\end{cases} \tag{15}$$

where $a_{1,X}$ and $a_{2,X}$ ($d_{3,X}$ and $d_{4,X}$) determine the value of the investment (disinvestment) option, and θ^*_X and θ'_X are the investment and disinvestment threshold, respectively.

Proof. See Appendix A.6. □

The lower line in Equation (14) shows that if demand θ rises above the threshold θ^*_X the firm exercises the growth option, paying the cost I to acquire the option to produce (value of $\Delta V(\theta,X;K)$) plus the option to sell off that option again later (value of $\Delta D(\theta,X;K)$). Conversely, the upper line in Equation (15) reveals that if θ falls below θ'_X, the firm exercises the disinvestment option, giving up the option (value of $\Delta V(\theta,X;K)$) but earning the sales gain d and reacquiring the growth option on that option to produce (value of $\Delta F(\theta,X;K)$). Finally, the other lines capture the values obtained from option exercises in the future.

One can now derive the value of all the firm's investment options, $F(\theta,X)$, and the value of all its disinvestment options, $D(\theta,X)$, from:

$$F(\theta,X)=\int_{\bar{K}}^{\infty}\Delta F(\theta,X;K)dK \quad \text{and} \quad D(\theta,X)=\int_{0}^{\bar{K}}\Delta D(\theta,X;K)dK. \tag{16}$$

2.3 Model Implications and Insights

We now spell out the implications of our model. Specifically, we discuss how the threat of uncertainty-induced rival zombification shapes the dynamic capacity choices and real performance of unlevered firms in a (potentially) zombified industry. We also calculate the expected duration of zombification and contrast the impact of expected rival zombification with that of existing zombification using simulations of our model.

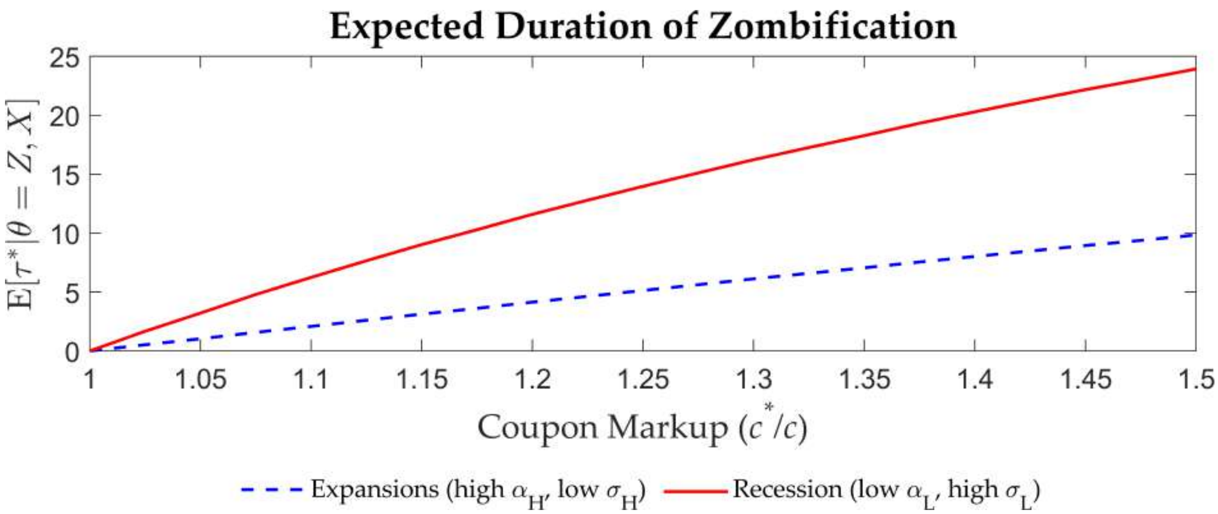

Figure 3. The figure plots the expected time to full recovery from the point of default in an expansion (dashed blue line) and a recession (red solid line) state. We describe the base case parameters in Section 2.3.

Throughout this section, we use the demand path and parameter values in Figure 2 ($\alpha_H =$ 0.08, $\alpha_L = -0.04$, $\sigma_H = 0.20$, $\sigma_L = 0.40$, $p_H = 0.30$, and $p_L = 0.10$), which are similar to the estimates from Bhamra et al. (2010) and Bloom et al. (2018) and imply a long-run probability of being in an expansion (recession) of 0.75 (0.25). We choose a demand slope (γ) of 0.12, a production cost parameter (κ) of 0.10, an investment cost (I) of ten, and a sales gain (d) of seven. We set the expected return of a demand-mimicking portfolio (μ) to 11% and the risk-free rate of return (r) to 2%. We choose an initial (c) and renegotiated (c^*) coupon payment of two and five, respectively. The bailout threshold (b) is 0.1. The expectation, $\mu_{L,H}$, and volatility, $\sigma_{L,X}$, of the natural log of the liquidation value are ln(20) and 3.00 in the expansion and ln(5) and 6.00 in the recession state, all respectively. While we use seemingly arbitrary parameter choices, our illustration of the model's intuition carries over a myriad of different choices.

2.3.1 Duration of Rival Zombification

Figure 3 plots the expected time duration for which levered firms require credit-subsidization as a function of the newly agreed coupon, c^*. To do so, we visualize Equation (8), which calculates how long it takes defaulting firms to recover sufficiently to pay the higher coupon c^* to its

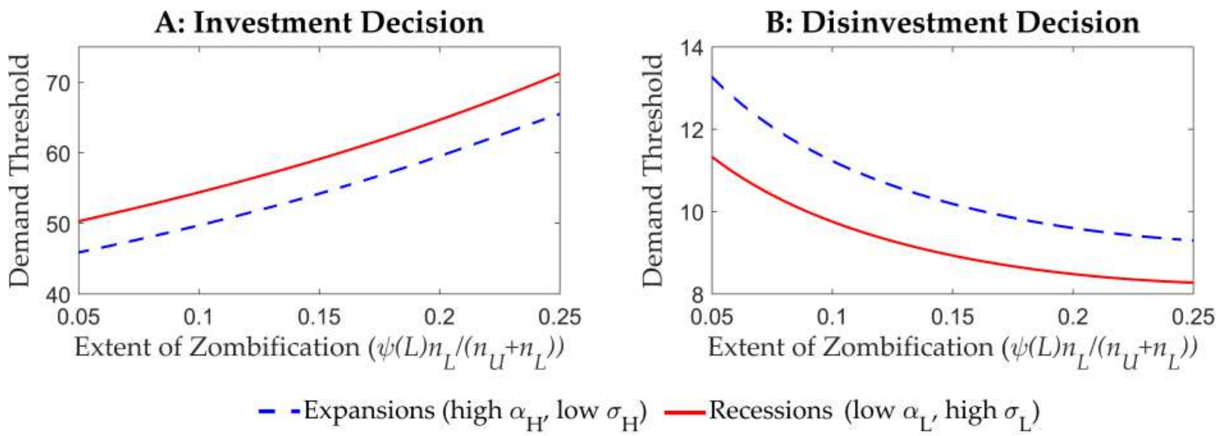

Figure 4. The figure plots the investment (Panel A) and disinvestment (Panel B) triggering demand thresholds for the capacity unit able to produce the $K = 10$ output increment against the proportion of expected rival zombie firms in an industry $\left(\frac{\psi(L)n_L}{n_U+n_L}\right)$. Dashed blue (solid red) lines show those thresholds in the expansion (recession) state. We describe the basecase parameters in Section 2.3.

creditors. For example, agreeing to 20% increased perpetual coupon payments, levered firms require between four and eleven years to reach a level of sufficient profitability to start paying the higher coupon. The results are consistent with the empirical evidence of Banerjee and Hofmann (2022) who estimate a mean duration of firms' zombie status of seven years.

2.3.2 Rival Zombification and Capacity Choices

Figure 4 shows how the threat of rival zombification conditions the decision of an arbitrary unlevered firm to invest into (Panel A) or disinvest (B) the capacity unit able to produce the $K = 10$ output increment separately in the expansion (blue lines) and the recession (red lines) state. To do so, we plot the investment and disinvestment triggering demand thresholds for that unit against the proportion of expected rival zombie firms in the industry $\left(\frac{\psi(L)n_L}{n_U+n_L}\right)$, ranging from 5% up to 25% (see prevalence of zombification in Altman et al. (2024)).

The figure suggests that a greater threat of rival zombification induces the unlevered firms to delay their investment and disinvestment. In particular, while the investment thresholds in Panel A increase with the proportion of levered firms (so that demand has to rise to a higher level before the investment option is exercised), the disinvestment thresholds in Panel B decrease with that proportion (so that demand has to drop to a lower level before the disinvestment option is exercised). The reason is that the threat of rival zombification exerts two effects on the unlevered firms. First, it more strongly depresses the output price, rendering all available capacity units less profitable and inducing the unlevered firms to delay their investment but to speed up their disinvestment ("first-moment effect").[11] Second, however, it also generates greater benefits from waiting to see whether some of the levered firms will default and leave the economy, leading to an upward jump in the value of all available capacity units due to a discrete upward jump in the output price ("second-moment effect").

Since both the first- and second-moment effects induce the unlevered firms to delay their investment, a greater threat of rival zombification must necessarily do the same (see Panel A). More interestingly, while the first-moment effect induces the unlevered firms to speed up their disinvestment, the second-moment effect induces them to delay it. As the second-moment effect dominates, Panel B reveals that a greater threat of rival zombification prompts unlevered firms to delay their disinvestment. Intuitively, the unlevered firms do so to avoid ending up in a situation in which they have to reacquire capacity because only fewer zombie firms than expected materialize in the future.[12]

We offer further supportive evidence for this argument in Figure 5. We do so by plotting the capacity choices of one out of $n_U = 30$ unlevered firms whose demand evolves as in Figure 2 and which competes with $n_L = 5$ (Panel A, "low zombification threat") and with $n_L = 60$ (Panel B, "high zombification threat") levered firms, respectively. The vertical lines around $t = 25$ indicate the zombification events (occurring earlier if there are more levered firms), allowing us to distinguish the effects of expected and existing zombification. The figure shows that the unlevered firm reacts less to demand swings when there is a greater threat of rival zombification. Importantly, expected rival zombification ($t < 25$) leads to more inactivity than

[11]As discussed in Section 2.1.1, rival zombification may also bind resources, effectively increasing input and investment costs for healthy firms. Both the price and cost channels reflect the impact of higher competition in less concentrated industries where firms are price-takers. There is ample empirical evidence for both channels (see, e.g., Acharya et al. (2022) and Darmouni and Sutherland (2024)), so our modeling choice is without loss of generality.

[12]While firms can partially insulate themselves from some types of uncertainty by hedging with derivative instruments (see, e.g., Doshi et al. (2018)), uncertainty-induced expected rival zombification is unlikely to be spanned by traded derivatives, making it impossible for unlevered firms to fully hedge against this type of risk.

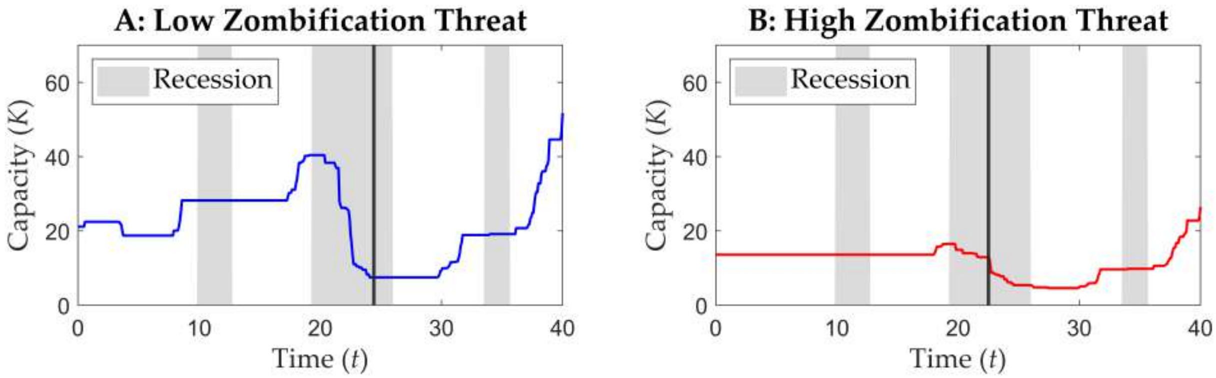

Figure 5. The figure plots the capacity choices of an unlevered firms whose demand evolves according to Figure 2 and which is competing with $n_L = 5$ (Panel A) and $n_L = 60$ (Panel B) levered firms. The vertical lines indicate the zombification events. The gray shaded areas are recession states. We describe the base case parameters in Section 2.3.

existing zombification ($t > 25$), which establishes the mere *threat of rival zombification* as an important and novel driver of dynamic corporate decisions beyond the previously studied existing zombification (Caballero et al. (2008) and Acharya et al. (2019, 2022, 2024)).

2.3.3 Rival Zombification and Firm Performance

Figure 6 more fully characterizes the real effects of expected and existing zombification on unlevered firms' performance by plotting their sales (Panel A), profitability (Panel B), capacity utilization (Panel C), and market value (Panel D) assuming that demand evolves according to Figure 2. The solid red (dashed blue) lines correspond to a firm in an economy with a high zombification threat $n_L = 60$ (low zombification threat with $n_L = 5$).

The figure shows that expected rival zombification depresses firms' real performance and value. To be specific, unlevered firms earn lower sales revenue, are less profitable, utilize less capital, and have lower market values in the presence of a high rival zombification threat. The reason is the first-moment effect of zombie firms suppressing the output price and thus the economic viability of unlevered firms. Intriguingly, with the rival zombification event occurring at around $t = 25$, existing rival zombification continues to subsequently depress real outcomes but results in a weaker effect than expected rival zombification.

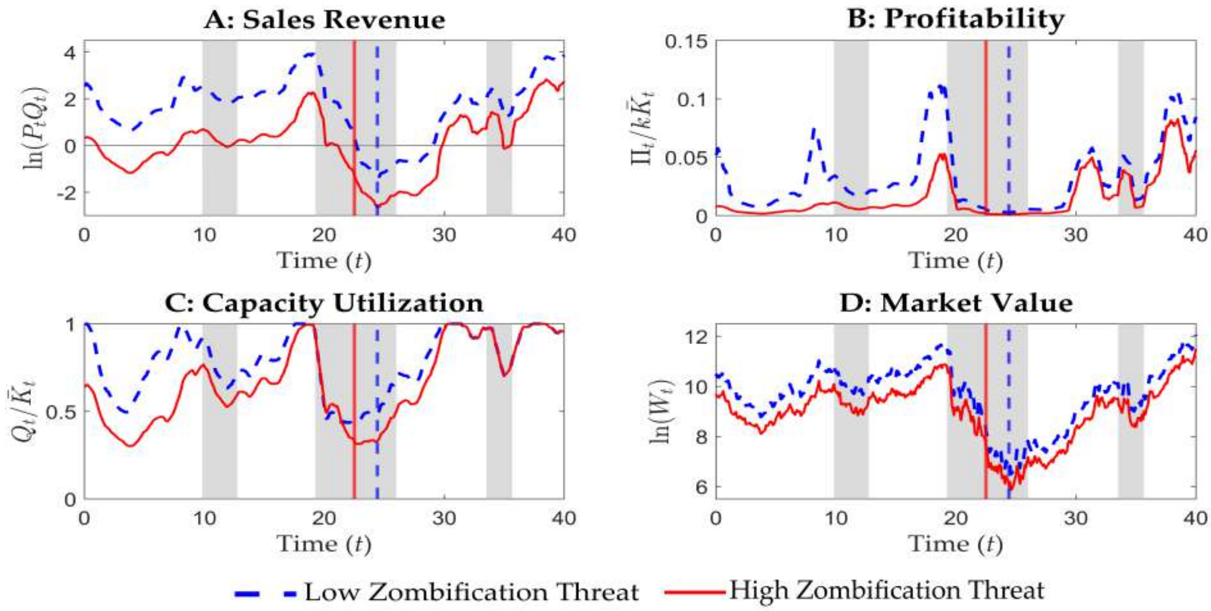

Figure 6. The figure plots the sales (Panel A), profitability (Panel B), capacity utilization (Panel C), and market value (Panel D) of an unlevered firm if demand evolves according to Figure 2. The solid red (dashed blue) lines show performance outcomes for a firm operating in an economy with a high (low) zombification threat where $n_L = 60$ ($n_L = 5$). We simulate at a monthly frequency and plot 12-month moving averages. The vertical lines indicate the zombification events. The gray shaded areas are recession states. We describe the base case parameters in Section 2.3.

Figure 6 furthermore stresses the modulating role of market power as the key channel for rival zombification to exert its depressing consequences on unlevered firms. Expected rival zombification quantifies the threat of the continued burden on unlevered firms if defaulting firms do not leave the economy and instead continue to operate in their industry. The solid red and dashed blue lines visualize the greater zombification threat resulting from a higher number of levered firms n_L (or equivalently a higher demand slope γ) that results in higher prolonged competition and increased price pressure. Our model thus implies that the effects of uncertainty-induced rival zombification on healthy firms should be heightened when market power is low (and demand is more elastic) relative to when market power is high. The market power economic channel also gives rise to the possible implication that healthy firms facing a heightened threat of zombification may take actions to increase their market power (or demand inelasticity) in response to that threat by engaging in product differentiation through increased innovation.

3 Measuring Expected Rival Zombification

In this section, we lay out our data sources and describe the methodology underlying the empirical testing of our model predictions. Our analysis proceeds in three parts. First, we outline our approach to identifying zombie firms, presenting loan-level regression results supporting our zombie classification schemes. Second, we describe and validate the empirical strategy used to estimate healthy firms' expectations of uncertainty-induced rival zombification in their industry. Finally, we introduce our main regression specifications: they project various theoretically motivated real decisions and outcome variables of healthy firms on expected uncertainty-induced rival zombification in their industry, control variables, and fixed effects.

3.1 Data Sources

We retrieve stock data from CRSP, financial statements data from Compustat, and capital structure data from Capital IQ. We download aggregate uncertainty indexes from the CBOE's, Scott Baker, Nicholas Bloom, and Steven Davis', and Sydney Ludvigson's websites. We obtain single-stock three-month implied volatilities from OptionMetrics. We source national and state-level GDP growth from the Bureau of Economic Analysis (BEA). We obtain state-level labor force and regional inflation data from the Bureau of Labor Statistics (BLS). We additionally obtain state-level data on new business entries from the Business Formation Statistics (BFS) produced by the U.S. Census Bureau. We further rely on establishment-level data from Your-Economy Time-Series (YTS) and shipping-firm data from Clarksons and Orbis (details to follow). Following Altman et al. (2024), we exclude firms from the financial (SIC codes 6000—6799) and public administration (SIC codes 9100—9999) sectors. We winsorize all firm-level (but not aggregate) variables at the 1^{st} and 99^{th} percentiles.

Table 1 offers descriptive statistics for the main variables used in our empirical work. The variables include investment and disinvestment rates, measures of existing and expected rival zombification, firm outcome variables, and control variables (Panel A), establishment and employment variables (Panel B), and investment rates and zombification measures specific to the global shipping industry (Panel C). We define the variables in the following sections and provide further details in Appendix Table B.1. The descriptive statistics align with those reported elsewhere (see, e.g., Kim and Kung (2017) and Campello et al. (2024)).

TABLE 1 ABOUT HERE.

3.2 Modeling Expected Rival Zombification

3.2.1 Identifying Current Zombie Firms

The first part of our analysis is to identify current zombie firms in an industry. Prior studies define a zombie firm as a highly distressed firm that is only able to service its debt obligations because it receives subsidized credit from its lenders (see, e.g., Caballero et al. (2008) and Acharya et al. (2022)). Following Altman et al. (2024), we first define a zombie firm as a firm with an interest coverage ratio below one and an Altman Z-score below zero ("standard zombie"). Such a firm needs more credit (via the interest coverage constraint) but is also deeply distressed; presumably only still alive due to support from its lenders. Two key advantages of our first definition are that we can apply it to virtually all public firms and that it may capture forms of rival zombification not explicitly arising through the provision of subsidized credit.

As an alternative, we follow Caballero et al. (2008) and Acharya et al. (2019, 2022) in explicitly requiring a zombie firm to receive subsidized credit ("credit-subsidized zombie"). To do so, we add to the former two constraints the further condition that a zombie firm must pay an effective interest rate on its debt that lies below the theoretically most favorable rate offered to the most creditworthy firms. The identification works as follows. We calculate a firm's effective interest rate as its interest expense scaled by its total debt. Next, we compute the theoretically most favorable rate by splitting the firm's debt into short-term bank debt, long-term bank debt, and bonds using debt structure information from Capital IQ. We then assign the average short-term prime rate over the current year; the average long-term prime rate over the current

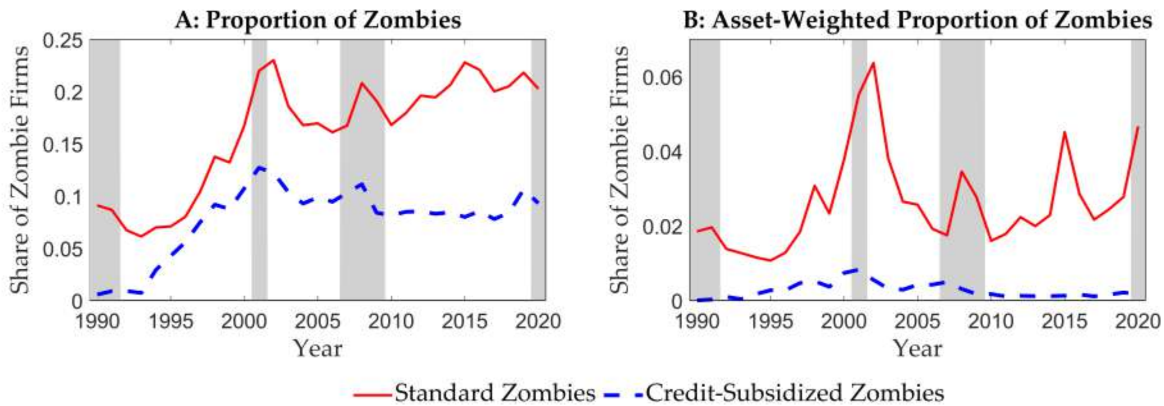

Figure 7. The figure plots the share of standard (solid red line) and credit-subsidized (dashed blue line) zombie firms over our sample period from 1990 to 2020. Panel A plots the equal-weighted share, while Panel B plots the asset-weighted share. The gray shaded areas are NBER recession periods.

year; and the lowest observed coupon rate on convertible bonds over the last five years as the most favorable rates to the three debt types. We finally compute a firm's theoretically most favorable interest rate as a debt-value-weighted average taken over the most favorable rates assigned to the three debt types.

Figure 7 plots the evolution of the share of zombie firms among U.S. public firms separately for each of our zombie-firm definitions over our sample period (equal-weighted in Panel A and asset-weighted in Panel B). In agreement with Altman et al. (2024), Panel A shows that the equal-weighted share of zombie firms markedly rises over our initial sample period from 1990 to 2002, from about 9% to 23% (*Standard Zombie*) or 1% to 12% (*Credit-Subsidized Zombie*). In contrast, that same share of zombie firms stays more constant over the remaining period until 2020. Supporting our model intuition, in both panels the zombie shares tend to rise in recessionary periods. Overall, both measures track each other closely, supporting the findings in Acharya et al. (2022), albeit with lower asset-weighted shares owing to our stricter requirements on Z-scores and ICRs for zombie firms. Appendix Figure B.1 displays the sample average share of zombie firms across selected, capital-intensive industries (including the shipping industry, that we focus on in later tests) containing the highest share of zombie firms in our sample.

3.2.2 Validating Zombie Firm Classification with Loan-Level Data

We next use Dealscan loan-level data to verify that the firms we classify as zombies are indeed highly distressed firms artificially kept alive through subsidized credit. Specifically, we follow Graham et al. (2008), Campello et al. (2011), and Campello and Gao (2017) in estimating the following loan-level panel regression in the sample of newly-initiated term loans and revolvers:

$$\begin{aligned} LoanTerm_{i,j,k,t} &= \beta\, Zombie_{i,j,t} + \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,t} + \\ &\quad \boldsymbol{\delta}'\mathbf{LoanControls}_{i,j,k,t} + \sum_j \alpha_j + \sum_t \alpha_t + \epsilon_{i,j,k,t}, \end{aligned} \tag{17}$$

where $LoanTerm \in \{Spread,\ Collateral,\ Single\ Lender\}$ is a characteristic of a loan by bank syndicate k to firm i in industry j in year t, $Zombie \in \{Standard\ Zombie,\ Credit\text{-}Subsidized\ Zombie\}$, **FirmControls** is a vector of firm controls, **LoanControls** is a vector of loan controls, β, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are parameters or parameter vectors, and α_j and α_t are industry and year fixed effects, respectively. In turn, *Spread* is the natural log of the all-drawn-in spread over LIBOR, *Collateral* is an indicator variable equal to one if the loan is secured and else zero, and *Single Lender* is an indicator variable equal to one if the lender-commitment-share Herfindahl-Hirschman index is one (there is one single lender) and else zero. Conversely, *Standard Zombie* (*Credit-Subsidized Zombie*) is an indicator variable equal to one if a firm is a zombie firm based on our standard (credit-subsidized) zombie definition; else zero. We describe the variables contained in **FirmControls** (*Size*, *Age*, *Profitability*, *Tangibility*, *Market-to-Book*, *Leverage*, and *Rated*) and **LoanControls** (*Loan Size*, *Loan Type*, and *Loan Maturity*) in Appendix Table B.1.

Table 2 presents the results from estimating regression (17), with Panels A and B relying on our standard and credit-subsidized zombie definition, respectively. Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics clustered at both the borrower firm and year levels. Notably, column (1) in both panels suggests that the firms we classify as zombies pay lower interest rates on their new loans relative to otherwise similar firms taking out similar credit facilities. Consistent with the priors used for our zombie classification, while

Panel A reports that our standard zombie firms pay about 11% lower all-drawn-in spreads over LIBOR (t-statistic: –3.18), the corresponding percentage for the credit-subsidized zombies in Panel B is a higher 24% (t-statistic: –4.35). This result suggests that our credit-subsidized zombie classification scheme identifies firms that are indeed more likely to be receiving credit subsidies.

TABLE 2 ABOUT HERE.

Looking into another loan characteristic, column (2) shows that loans to standard and credit-subsidized zombie firms are less often secured, likely due to banks internalizing that they extend credit to distressed firms that have few collateral assets left to pledge. Finally, column (3) demonstrates that zombie loans are more likely to involve just a single lender, with the chance of a single-lender loan rising by about 7% and 15% (t-statistics: 2.28 and 2.47) for standard and credit-subsidized zombie loans, respectively. The upshot is that zombie lending is more akin to relationship than arm's-length lending, with distressed firms receiving *more* (rather than less) lenient loan contract terms (see also Faria-e-Castro et al. (2024)).

We next investigate whether lenders' tendency to offer more favorable loan terms to distressed potential zombie firms (shown in Table 2) increases with greater uncertainty. In doing so, we aim to validate a central tenet of our model that creditors' risk-shifting incentives prompt them to speculate on the recovery of defaulting borrowers when uncertainty increases. To test this idea, we segment our sample period into three regimes of uncertainty based on the level of VIX. Specifically, we define three indicator variables corresponding to each regime, *Calm*, which takes the value of one when VIX is below the 10^{th} percentile else zero, *Moderate*, which takes the value of one when VIX lies between the 10^{th} and 90^{th} percentile else zero, and *High*, which takes the value of one when VIX lies above the 90^{th} percentile else zero. We then estimate a modified version of regression (17) in which we additionally interact the zombie indicator variable, *Zombie*, with the VIX regime indicator variables, *Calm*, *Moderate*, and *High*, while retaining the same controls and fixed effects as in Table 2. The coefficient estimates on each of the three interaction terms indicate how the loan terms we consider vary between zombie and non-zombie borrowers during periods of calm, moderate, and high uncertainty.

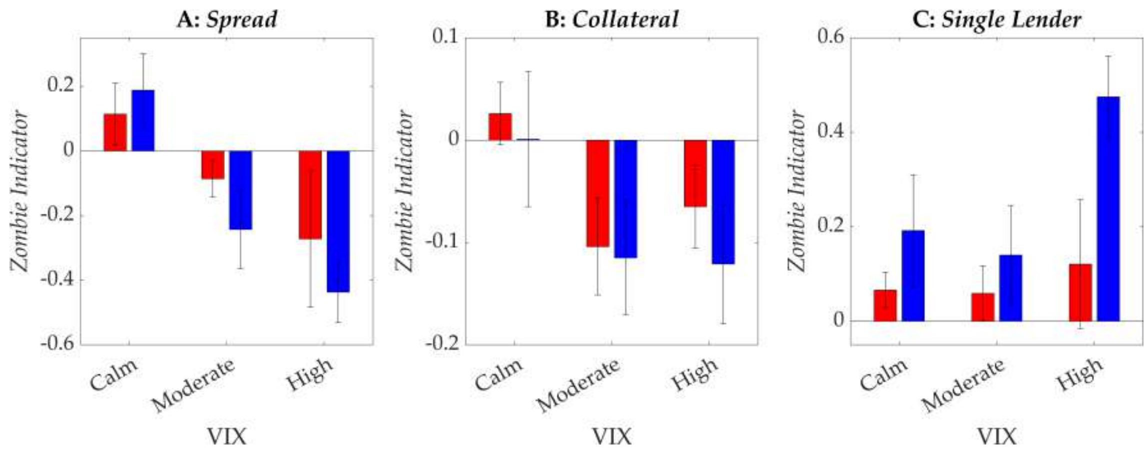

Figure 8. The figure plots the coefficient estimates obtained from a modified version of regression (17) in which various loan terms are regressed on the interaction between an indicator variable for standard (red bars, *Standard Zombie*) and credit-subsidized (blue bars, *Credit-Subsidized Zombie*) zombie firms and indicator variables indicating calm (below 10th percentile, *Calm*), moderate (between 10th and 90th percentile, *Moderate*), and high (above 90th percentile, *High*) VIX periods. All remaining controls and fixed effects are identical to those included in regression (17). The error bars indicate 90% confidence intervals. The dependent variables are *Spread* (Panel A), *Collateral* (Panel B), and *Single Lender* (Panel C).

We compactly depict the coefficient estimates for the interaction terms (and respective confidence intervals) for both our zombie classification schemes in Figure 8. Panel A shows that the coefficients follow a monotonic decreasing pattern as uncertainty increases. Notably, both standard and credit-subsidized zombie firms attract the lowest spreads (relative to non-zombie borrowers) on their new loans during the high VIX period. Zombie firms are also not more likely to post collateral on their new loans during calm VIX periods (Panel B). Conversely, loans to zombie firms are significantly less likely to be secured during moderate and high uncertainty times. Finally, turning to Panel C, we show that loans to zombie firms are most likely to be offered by a single lender in periods of high uncertainty. Altogether, the evidence in Figure 8 is new to the literature and provides solid empirical support for our theoretical conjecture that lenders' incentives to keep distressed borrowers alive are an increasing function of uncertainty.

Finally, we compare the characteristics of banks extending zombie loans with those extending loans to healthy (non-zombie) firms in order to gain insight into banks' "zombification" incentives. We do so by merging our Dealscan loan-level sample with data from Bank Holding Companies' Call Reports. Following Hirtle et al. (2020), we report descriptive statistics for a selection of key variables capturing banks' finances and performance in Appendix Table B.2. Across both panels, banks extending loans to zombie firms tend to be significantly smaller, have lower equity capitalization, and are riskier (have higher volatility of operating performance) than their non-"zombifying" counterparts. This is consistent with our model insight that such banks have greater incentives to speculate on the recovery of their borrowers by keeping them alive as zombies in periods of heightened uncertainty. Accordingly, banks lending to zombies experience lower non-performing loans and provision for higher loan losses associated with the credit subsidies they likely provide to their distressed borrowers. These results generally agree with the findings from prior studies summarized in Acharya et al. (2022) and provide supporting evidence for our theoretical modeling of lenders' decision-making.

3.2.3 Predicting Expected Future Rival Zombification

The second part of our analysis is to model healthy (non-zombie) firms' expectation formation process regarding the potential emergence of zombie rival firms in their industry under heightened uncertainty. The central insight of our theoretical framework is that healthy firms rationally react to the *expectation* of uncertainty-induced zombification in their industries, rather than only its *realization* (as in, e.g., Caballero et al. (2008) and Acharya et al. (2021)). To quantify that expectation, we estimate the following industry-specific panel forecasting regression over either our full sample period or over rolling windows of twelve years:

$$\begin{aligned} Zombie_{i,j,t} \quad = \quad & \beta\, Uncertainty_{t-1} + \boldsymbol{\gamma}'\mathbf{MacroControls}_{t-1} \\ & + \zeta\, Zombie_{i,j,t-1} + \boldsymbol{\delta}'\mathbf{FirmControls}_{i,j,t-1} + \sum_i \alpha_i + \epsilon_{i,j,t} \end{aligned} \tag{18}$$

where $Zombie \in \{Standard\ Zombie, Credit\text{-}Subsidized\ Zombie\}$, *Uncertainty* is a three-month-lagged uncertainty proxy, **MacroControls** $= [GDP\ Growth, Labor\ Force, Inflation]'$ is a vector of one-year lagged macro controls, **FirmControls** $= [Small\ Firm,\ Young\ Firm,\ Manufacturing\ Firm]'$ is a vector of one-year lagged firm controls as in Altman et al. (2024), α_i is a firm fixed effect, and β, ζ, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are parameters.[13] Critically, our forecasting regressions control for a firm's lagged zombie status. This is reasonable as economic agents' expectations formation process will account for the auto-correlation in a firm's zombie status. Moreover, lagged values of variables are typically strong predictors of their current and future values in various time-series financial econometrics applications. We rely on the 50 Hoberg and Phillips (2016) product market classification to define our industries.

The estimation of the panel forecasting regression (18) via standard OLS is subject to potential biases due to the joint presence of firm fixed effects and lagged, persistent predictors (see, e.g., Hjalmarsson (2006) and Grieser and Hadlock (2019)). In order to mitigate these estimation biases, we follow the recommended "recursive demeaning" methodology of Hjalmarsson (2006). Specifically, for any time t, we demean the dependent variable (by firm) using information from time t onwards and demean the predictor variables (by firm) using information only up until time t. Doing so allows us to recover consistent estimates of our regression coefficients.

We use a comprehensive set of uncertainty proxies, allowing us to remain agnostic about any particular source of uncertainty. Specifically, we look into the CBOE volatility index (*VIX*); Baker et al.'s (2019) newspaper-based stock market volatility tracker (*EMV*); Baker et al.'s (2016) newspaper-based economic-policy uncertainty index (*EPU*); Jurado et al.'s (2015) aggregate financial, real, and macroeconomic uncertainty measures (*FIN*, *REAL*, and *MACRO*); as well as the market-specific assets-weighted averages of realized stock volatility (*ARV*) and implied stock volatility (*AIV*). See Appendix Table B.1 for more details about those and other variables and Cascaldi-Garcia et al. (2023) for a survey on uncertainty measures.

Table 3 displays the results from estimating regression (18) separately using each uncertainty proxy over all markets and the full sample period. Panel A estimates the proportion of future zombie firms based on the "standard definition," while Panel B does so based on the "subsidized-credit definition." In support of the risk-shifting motive for zombification revealed

[13] Specifically, *Small Firm* is an indicator variable equal to one if a firm's sales are below $50 million, *Young Firm* is an indicator variable equal to one if its age is less than ten years, and *Manufacturing Firm* is an indicator variable equal to one if it operates in the manufacturing industry and else zero.

by our theory, the table offers strong evidence that uncertainty breeds future zombification, with this result holding largely independent of our zombie firm definition and the type of uncertainty. Moreover, the positive and highly significant coefficient estimates on the various uncertainty proxies are obtained from a specification that controls for a firm's lagged zombie status. This suggests that the uncertainty proxies contain valuable, incremental predictive information even beyond knowing whether a firm was zombified in the recent past. For example, the slope coefficient of newspaper-based stock market volatility, *EMV*, is 0.182 (t-statistic: 10.91) in Panel A, implying that a one-standard-deviation increase in the *EMV* raises the future share of standard zombie firms in an industry by about 1 percentage point. Given that the average share of standard zombie firms is about 8%, this rise is economically quite meaningful. The table further suggests that financial uncertainty (*EMV* and *FIN*) matters more for the prediction of future zombie emergence than other uncertainty sources, whereas political uncertainty (*EPU*) matters more for the prediction of future standard zombies than for credit-subsidized ones.

TABLE 3 ABOUT HERE.

The results in Table 3 suggest that different types of uncertainty contribute to forecasting the future emergence of zombie firms. Since our goal is to approximate healthy firms' expectations formation process over a range of uncertainty proxies, we summarize the information across the proxies in a parsimonious manner by performing a principal component analysis on the aggregate uncertainty proxies (*VIX*, *EMV*, *EPU*, *FIN*, *REAL*, and *MACRO*) and the firm-weighted averages of the realized and implied stock volatility proxies (*ARV* and *AIV*) across industries, in the spirit of Jurado et al. (2015). Doing so allows us to collapse the information in those proxies into a smaller set of variables and to remain agnostic about any particular source of uncertainty.

Table 4 reports the results from the principal component analysis. Panel A shows the slope coefficients of each uncertainty proxy on the first four principal components (*PC1* to *PC4*). Panel B reports associated diagnostic statistics. As is often the case, the slope coefficients in Panel A show that *PC1* acts as a "level factor." To wit, since the uncertainty proxies all share similar coefficients of around 0.26 to 0.41 on *PC1*, an increase in that component raises all of them. In contrast, *PC2* captures distinct variation across the financial and non-financial proxies, with *EPU*, *REAL*, and *MACRO* loading positively on that component and the remaining financial uncertainty metrics loading negatively. As a result, an increase in *PC2* lowers the financial but raises the non-financial uncertainty proxies. There does not appear to be an obvious interpretation for *PC3* and *PC4*. Finally, Panel B suggests that while the first principal component explains about 65% of the variation in the uncertainty proxies, the first two to four in combination explain about 82% to 95%.

TABLE 4 ABOUT HERE.

We estimate the time-varying threat of uncertainty-induced zombification in each industry using the principal components derived above. Doing so requires us to construct a statistical model to approximate firms' expectation generation process. This construction proceeds in three steps, with the end product being our key variable of interest capturing healthy firms' expectations of the extent to which current uncertainty will spawn future rival zombie firms in their industry, labeled *Expected Zombification*.

Step 1: Estimating zombie–uncertainty forecasting sensitivities

We begin by estimating the following forecasting regression (a counterpart to regression (18)) separately in each of the 50 Hoberg and Phillips (2016) industries (j) over twelve-year rolling windows ($\tau \in \{t-11, t\}$):

$$\begin{aligned} Zombie_{i,j,t} \quad &= \quad \beta_{j,\tau} Uncertainty_{t-1} + \boldsymbol{\gamma}'_{j,\tau}\mathbf{MacroControls}_{t-1} \\ &\quad +\zeta_{j,\tau} Zombie_{i,j,t-1} + \boldsymbol{\delta}'_{j,\tau}\mathbf{FirmControls}_{i,j,t-1} + \sum_i \alpha_i + \epsilon_{i,j,t}. \end{aligned} \tag{19}$$

There are two critical differences between the above regression (19) and the previous regression (18). Since regression (19) is estimated in each industry, j, and using rolling windows, τ, we obtain a *matrix* of industry-by-time-varying estimated zombie–uncertainty forecasting sensitivities (or slope coefficients), $\hat{\beta}_{j,\tau}$, for each industry $j \in [1,50]$ and each twelve-year rolling window $\tau \in \{t-11, t\}$ combination in our sample. Additionally, we use the three-month-lagged first principal component (*PC1*) as our uncertainty proxy in place of the eight aggregate uncertainty measures.[14] As before, we estimate the regressions separately for our two zombie firm definitions, *Zombie* ∈ {*Standard Zombie*, *Credit-Subsidized Zombie*}. Likewise, we continue to apply the "recursive demeaning" method of Hjalmarsson (2006) in order to mitigate the bias induced by the simultaneous presence of firm fixed effects and lagged, persistent regressors.

Step 2: Using zombie–uncertainty forecasting sensitivities to predict future zombification

Next, we form a prediction for *Expected Zombification* by computing the fitted value from the above regression (19) as follows:

$$\textit{Expected Zombification}_{j,t+1} = \sigma\left(\hat{\beta}_{j,\tau} \times \textit{Uncertainty}_t\right), \tag{20}$$

where $\sigma(\cdot)$ is the standard logistic function.[15] In words, equation (20) combines the slope coefficient of the uncertainty principal component (*PC1*) from each industry-specific rolling-window regression with the end-of-window uncertainty *PC1* value. As a result, there are two flavors of *Expected Zombification* corresponding to our choice of either the (1) standard or (2) credit-subsidized definition for the *Zombie* indicator variable. In sum, the *Expected Zombification* variables predict the trend in zombification over time while capturing cross-industry differences in the propensity of a particular firm to become a zombie under heightened uncertainty. They constitute the core variables of interest in our empirical analysis going forward.

[14]We restrict our attention to *PC1* (and, in robustness tests, *PC2*) since they are more interpretable and capture far larger shares of the variation in the eight uncertainty proxies than *PC3* and *PC4*. Our baseline analysis is done using *PC1*, while Appendix Table B.3 shows that our main results are robust to using both *PC1* and *PC2*.

[15]We apply the standard logistic transformation (a positive monotonic transformation) to the fitted values to ease interpretation, ensuring that those values generated from the linear model in regression (19) are bounded between 0 and 1. In Appendix Table B.4, we verify that our results are robust to estimating regression (19) using non-linear discrete choice models such as conditional logistic regression. We opt to use a linear model for regression (19) in our main analysis as this allows us to include firm fixed effects in the specification.

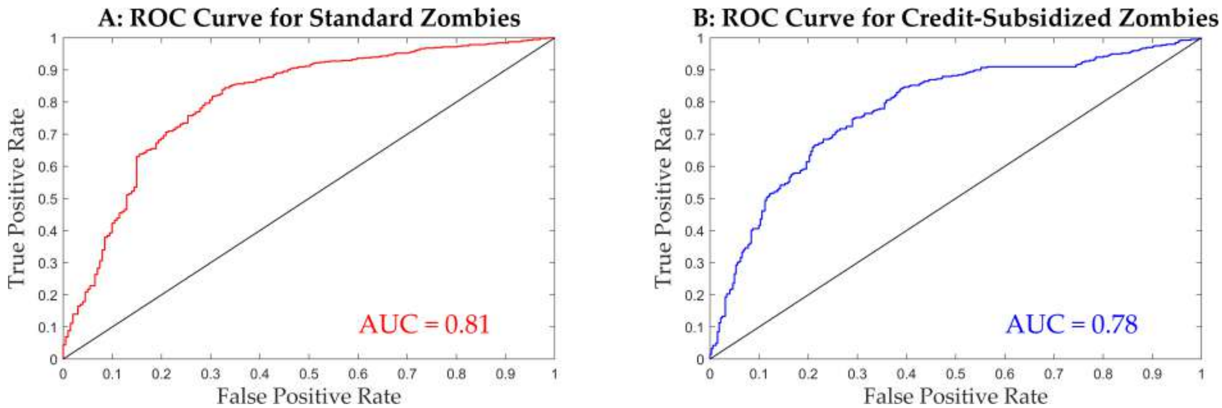

Figure 9. The figure plots prediction diagnostics for our forecasting regression model (19), which we estimate separately in each of the 50 Hoberg and Phillips (2016) industries over twelve-year rolling windows. We plot the receiver operating characteristic (ROC) curve along with the area under the ROC curve (AUC) for *Standard Zombies* (Panel A) and *Credit-Subsidized Zombies* (Panel B).

Step 3: Validating future zombification predictions

As a final step, we validate the predictive performance of our zombification forecasting model. Doing so is critical to verify whether our forecasting model is a reasonable representation of the expectations generation process of rational, forward-looking firms on the extent of future rival zombification they anticipate in their industries. We formally assess the out-of-sample predictive ability of our forecasting model in Figure 9. Panels A and B depict the receiver operating characteristic (ROC) curve along with the associated area under the ROC curve (AUC) statistics for our two zombie classification schemes. Those panels indicate that our forecasting models strongly predict the realization of zombification with relatively high true positive rates and relatively low false positive rates (as evident in the high AUCs). These results are reassuring as they show that our forecasting models are reasonable — zombie firms are indeed more likely to materialize in an industry following higher predicted zombification in that industry.

3.3 Explaining Healthy Firm Decisions and Outcomes

In our main empirical tests, we evaluate our model's prediction that healthy firms exposed to a greater threat of rival zombification in their industries cut back on costly-to-reverse real decisions. To that end, we run the following panel regression in the sample of non-zombie firms:

$$\begin{aligned} RealDecision_{i,j,s,t} &= \beta\, Expected\ Zombification_{j,t-1} + \boldsymbol{\gamma}' \mathbf{FirmControls}_{i,j,s,t-1} \\ &\quad + \boldsymbol{\lambda}' \mathbf{MacroControls}_{s,t-1} + \sum_i \alpha_i + \sum_j \sum_t \alpha_j \times \alpha_t + \epsilon_{i,j,s,t} \end{aligned} \tag{21}$$

where *RealDecision* is one of a number of real decisions (described shortly) made by non-zombie firm i operating in industry j and headquartered in state s over year t, *Expected Zombification* is a real-time forecast of the share of standard or credit-subsidized zombies spawning in industry j over year t at the start of that year (whose construction is described in Section 3.2.3), **FirmControls** = [*Size, Cash Flow, Tobin's Q*]′ is a vector of one-year lagged firm controls, **MacroControls** = [*State GDP Growth, State Labor Force, Regional Inflation*]′ is a vector of one-year lagged macro controls including state s's annual GDP growth, log labor force, and regional inflation rate, α_i, α_j, and α_t are firm, industry, and time fixed effects, and β, $\boldsymbol{\gamma}$, and $\boldsymbol{\lambda}$ are parameters or parameter vectors.[16] We rely on Hoberg and Phillips's (2016) 50 product market classification to define industries. See Appendix Table B.1 for all variable definitions.

We use the following real-decision variables in regression (21). Our U.S. public firm analysis looks into non-zombie firms' real investment, as measured using their capital expenditures over year t scaled by assets at the start of that year (*Investment(Capex)*). We measure firms' disinvestment using the sale of property, plant, and equipment (PPE) over year t, scaled by start-of-year PPE (*Disinvestment (Sale of PPE)*). Our U.S. public firm YTS analysis considers their establishment and employment investment and disinvestment, measured as the number of newly-opened (*Establishment Openings*) or newly-closed (*Establishment Closures*) establishments over year t, both scaled by the number of establishments at the start of the year, and an indicator variable if employment growth is positive, and else zero (*Employment Growth*). Finally, our global

[16] Our specifications account for time-varying trends in two ways. First, we control for observable macro trends that may affect our outcome variables through the inclusion of the annual state and regional macro indicators. Second, we account for unobserved trends within industries through the inclusion of dynamic industry-by-time fixed effects. The time component is defined in three-year windows to avoid subsuming the annual macro controls.

public and private shipping firm analysis examines the purchases, sales, and demolitions of shipping vessels. We discuss the methodology and variables used in that analysis later.

We also estimate the following panel regression in the sample of non-zombie firms to gauge the effect of expected future rival zombification in an industry on the performance of healthy firms in that industry:

$$\begin{aligned} RealOutcome_{i,j,s,t} &= \beta\, Expected\ Zombification_{j,t-1} + \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,s,t-1} \\ &\quad + \boldsymbol{\lambda}'\mathbf{MacroControls}_{s,t-1} + \sum_i \alpha_i + \sum_j \sum_t \alpha_j \times \alpha_t + \epsilon_{i,j,s,t} \end{aligned} \tag{22}$$

where $RealOutcome \in \{Sales\ Growth, Profit\ Growth, Asset\ Turnover,\ Future\ Stock\ Return\}$, and other variables, parameters, and parameter vectors are defined as in regression (21). *Sales Growth* is the net sales growth of firm i over year t; *Profit Growth* is the growth in operating profits (sales minus cost of goods sold) of firm i over year t; *Asset Turnover* is firm i's sales to total assets in year t; and *Future Stock Return* is firm i's forward-looking 48-month compounded, size-, book-to-market-, and momentum-adjusted (as per Daniel et al. (1997) or DGTW) stock return.

4 The Real Effects of Expected Rival Zombification: U.S. Firms

In this section, we investigate how U.S. public firms respond to expectations of uncertainty-induced rival zombification in their industries. Specifically, we focus on outcomes capturing non-zombie firms' investment and disinvestment decisions and their future performance. We first do so using data from Compustat. We next turn to YTS establishment-level data to explore both the establishment opening and closing as well as the employment decisions of those firms.

4.1 Investment

In Table 5, we present the results from estimating regression (21) using *Investment (Capex)* as the dependent variable (columns (1) and (3)). The first of those columns uses the *Standard*

Zombie definition to calculate *Expected Zombification* and to construct the sample; the second of those columns analogously uses the *Credit-Subsidized Zombie* definition.

TABLE 5 ABOUT HERE.

The results suggest that the expectation of uncertainty-induced rival zombification in an industry prompts the healthy firms in that industry to significantly cut their investment, consistent with our theoretical prediction.[17] In particular, the slope coefficient on *Expected Zombification* is negative and highly statistically significant across both relevant columns (*t*-statistics of –8.37 and –7.31). The effects of *Expected Zombification* are also reasonable and economically sizeable in magnitude. Consider, for example, *Expected Zombification* computed from the standard zombie firm definition in column (1). The coefficient of –0.893 implies that a one-standard-deviation increase in *Expected Zombification* leads investment to fall by 0.003, which is over 5% of the sample mean of the investment variable (0.057). This is just slightly less than half the magnitude of a one-standard-deviation decrease in *Cash Flow* and around a third of the magnitude of a corresponding decrease in *Tobin's Q*.

4.2 Disinvestment

We next examine the relationship between expected uncertainty-induced zombification and healthy firms' disinvestment decisions. In columns (2) and (4) of Table 5, we display coefficient estimates corresponding to regression (21) with our disinvestment proxy, *Disinvestment (Sale of PPE)*, as the dependent variable. As before, we consider two definitions of zombification in the estimation of *Expected Zombification*, *Standard Zombies* in column (2) and *Credit-Subsidized Zombies* in column (4). Across both columns, greater expected uncertainty-induced zombification in an industry is associated with significantly lower disinvestment by healthy firms in that industry. This result is notable in light of the difficulties in precisely measuring disinvestment

[17] In later analyses, we show that our results are unlikely to be driven by direct firm investment responses to uncertainty by distinguishing across industries with varying concentrations. Consistent with our model, our dynamics are more pronounced in less concentrated industries, which are precisely the industries in which the negative uncertainty–investment relationship is dampened (or may even turn positive), as per Caballero (1991).

among public firms. Moreover, the negative relationship between disinvestment and expected rival zombification that we find is fully consistent with our model prediction that firms will cut back on both costly-to-reverse margins of investment *and* disinvestment. The economic magnitudes of the disinvestment coefficients are also notable. The estimate in column (2) of –0.450 implies that a one-standard-deviation increase in *Expected Zombification* is associated with a drop in disinvestment of around 9% of the mean rate of disinvestment (0.014).

4.3 Contrasting Expected and Existing Zombification

We next contrast the novel effects of *expected* zombification documented above with the previously-studied negative externalities of *existing* zombification (e.g., Caballero et al. (2008) and Acharya et al. (2021)). Given the highly correlated nature of *Expected Zombification* and *Existing Zombification*, we include them separately in the otherwise same respective specifications. Table 6 presents the results with investment and disinvestment as the outcome variables.

TABLE 6 ABOUT HERE.

In Table 6, columns (1), (3), (5), and (7) repeat the results from Table 5 for comparison purposes, while columns (2), (4), (6), and (8) consider the role of *Existing Zombification* instead. First, we discuss the investment regressions in columns (1), (2), (5), and (6). Importantly, while these results show that (consistent with prior work) healthy firms curb their investment decisions in response to existing zombies, the effect is only statistically significant under our standard zombie definition (see column (2)). Moreover, in column (6), the effect of existing zombification is less statistically and economically significant than the corresponding effect of expected rival zombification (in column (5)), suggesting that healthy firms react more to the *threat* rather than the *materialization* of zombie firms.

We repeat this comparative exercise in columns (3), (4), (7), and (8) of Table 6, considering disinvestment as the outcome variable. It is worth noting that there is *little evidence* that healthy firms respond in terms of their disinvestment to *Existing Zombification* (columns (4) and (8)).

On the other hand, and as shown before, *Expected Zombification* is strongly negatively associated with disinvestment. Taken together, the results in Table 6 jointly suggest that heightened expectations of uncertainty-induced zombification in an industry are associated with "inaction" by healthy firms in that industry, as such firms slow down their asset allocation by cutting both investment and disinvestment. They provide novel empirical evidence on the dominant role of *expected* as opposed to *realized* zombification in shaping forward-looking firms' real decisions.

4.4 Dynamics of Investment and Disinvestment

Motivated by prior work showing that the effects of uncertainty shocks on firms' investment and disinvestment are temporary (Bloom (2009)), in our subsequent analysis, we examine the dynamics of the investment and disinvestment responses documented in Table 5. We do so by estimating modified versions of regression (21) in which we regress *leads* of healthy firms' investment and disinvestment rates on *Expected Zombification*, along with the same set of control variables and fixed effects as before. We consider leads of up to five years ahead for both outcome variables. The dynamic coefficient estimates on our key variable of interest, current-period *Expected Zombification*, are depicted in Figure 10. Panel A considers the investment decisions of healthy firms while Panel B considers their disinvestment decisions.

The two panels of Figure 10 show that the effects of expected uncertainty-induced rival zombification on investment and disinvestment are transitory, manifesting only in healthy firms' current (year zero) decisions. The coefficient estimates on current-period *Expected Zombification* are small in magnitude and of varying sign and statistical significance, depending on the exact outcome and time horizon (beyond year zero) being considered. The relatively short-lived investment and disinvestment reactions are consistent with similar "wait-and-see" dynamics reported by Bloom (2009) in response to uncertainty shocks. They suggest that firms react by delaying, rather than permanently canceling, their investment and disinvestment plans when faced with greater threats of uncertainty-induced zombies emerging in their industries. At the same time, the sharp cuts in *current* investment and disinvestment are not fully

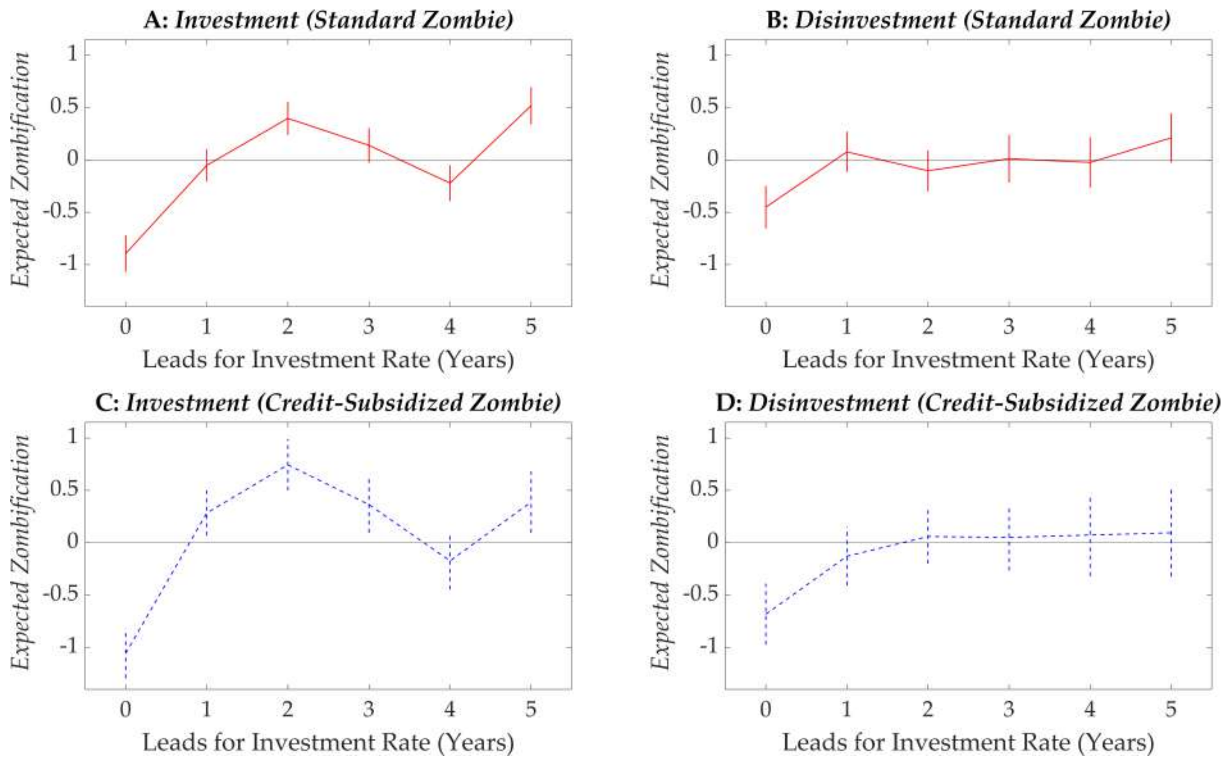

Figure 10. The figure plots the dynamic coefficient estimates obtained from a modified version of regression (21) in which leads of the investment and disinvestment rates (from zero to five years ahead) are regressed on current-period *Expected Zombification* constructed using standard (red lines, *Standard Zombie*) and credit-subsidized (blue lines, *Credit-Subsidized Zombie*) zombie firms. All controls and fixed effects are identical to those included in regression (21). The error bars indicate 90% confidence intervals.

offset by *future* increases, suggesting that these transitory effects of expected zombification may bear longer-term implications for firms' capital accumulation going forward.

4.5 Establishment and Employment Decisions

In Table 7, we present the results from re-estimating regression (21) on non-zombie public U.S. firms using establishment-level data from YTS with *Establishment Openings* (column (1)), *Establishment Closures* (column (2)), and *Employment Growth* (column (3)) as the dependent variable. Our real options model would predict similar dynamics for hiring and firing as for investing and disinvesting (see also Bloom (2009)). A key advantage of the YTS data is that they enable us to calculate a firm's employment growth from the number of workers at each establishment operated by the firm. Panel A uses our standard zombie definition and Panel

B uses the credit-subsidized zombie definition. Since the YTS data contain the geographical locations of establishments, we use an employee-weighted average of the state-level macro control variables to more finely account for concurrent changes in local economic conditions.

TABLE 7 ABOUT HERE.

The table confirms that the threat of uncertainty-induced zombification in an industry prompts the healthy firms in that industry to cut back on their establishment openings and closures as well as employment growth. Specifically, in agreement with our investment results in Table 5, column (1) shows that the slope coefficient of *Expected Zombification* on *Establishment Openings* is negative and significant. If anything, the economic magnitude of the opening effect is more pronounced than the broad investment effects in Table 5. Looking into Panel A column (1), a one-standard-deviation increase in *Expected Zombification* induces *Establishment Openings* to drop by about 6% of its sample mean. Notably, column (2) reveals that the slope coefficient of *Expected Zombification* on *Establishment Closures* is also negative, though statistically less significant in Panel B. The final column shows that the slope coefficient of *Expected Zombification* is also negative and significant (in Panel B) on *Employment Growth.* Looking into economic significance, a one-standard-deviation increase in the *Expected Zombification* variable in Panel B column (3) induces *Employment Growth* to drop by about 21% of its mean.

4.6 Performance Outcomes

We next evaluate the future performance of firms exposed to the threat of uncertainty-induced rival zombification. This analysis is informative as it highlights a unique aspect of the specific type of uncertainty we study. To wit, while broader forms of uncertainty (such as those studied in Bloom (2009), Kim and Kung (2017), and Campello et al. (2024)) can imply good and bad future news, uncertainty about the creation of zombie firms in an industry necessarily implies bad future news for the healthy firms in that industry. The key question is: how bad?

Table 8 gives the results from estimating regression (22) on the non-zombie U.S. public firms using *Sales Growth* (column (1)), *Profit Growth* (column (2)), *Asset Turnover* (column (3)), and *Future Stock Return* (column (4)) as the dependent variable. Panel A uses our standard zombie definition and Panel B uses the credit-subsidized zombie definition.

TABLE 8 ABOUT HERE.

The table confirms that the threat of uncertainty-induced zombification in an industry negatively affects the future real outcomes of healthy firms in that industry, lowering their sales growth, profit growth, asset turnover, and stock returns. The results using *Expected Zombification* computed from the standard zombie firm definition in Panel A reveal coefficients on *Expected Zombification* of –8.210, –7.174, –4.062, and –3.691 (t-statistics: –10.34, –5.34, –5.90, and –1.98) in the *Sales Growth*, *Profit Growth*, *Asset Turnover*, and *Future Stock Return* regressions, respectively. As before, the effects are often economically important, with a one-standard-deviation increase in the same *Expected Zombification* variable as above inducing *Profit Growth* to drop by around 17% of its sample mean and *Sales Growth* to drop by up to 25% of its sample mean. While the negative effects on sales growth and profit growth likely arise because zombie firms depress output prices and raise input costs, thereby slowing down capital accumulation (Acharya et al. (2021)), the sales growth effect is plausibly stronger since healthy firms optimally reduce their capacity utilization and produce less in response to zombie rivals (as evident in their declining asset turnover; see column (3)). Next, since a firm's stock market value indicates when it is optimal for a firm to exercise its growth options, the effects on the forward-looking stock returns suggest that the expected creation of zombie firms drives the growth options of healthy firms deeper out-of-the-money with those firms being burdened by unproductive excess capital.[18] As such, these dynamics provide further support for our theorized investment and disinvestment mechanisms.

[18]A richer investigation of the asset pricing implications of expected rival zombification is beyond the scope of our study and is left as an avenue for future work. For example, Morellec and Zhdanov (2019) show how competition dynamics can drive stock returns, in particular the volatility of stock returns.

4.7 Other Outcomes and Robustness

We briefly summarize the results of a set of additional tests, some of which are reported in Appendix B. First, in Table 9 we examine the relationship between expected uncertainty-induced rival zombification in an industry and several outcome variables corresponding to financial decisions made by healthy (non-zombie) firms in that industry. While our model in Section 2 abstracts from these decisions for the sake of tractability, firms' cash and liquidity management, payout, and financing choices are naturally and intuitively linked to the real choices studied in our model (see also Bolton et al. (2011)).

TABLE 9 ABOUT HERE.

The results in Table 9 support our empirical findings on depressed investment, disinvestment, and performance metrics presented in the prior set of tables. The first column shows that greater expectations of uncertainty-induced zombification are associated with healthy firms in the same industry accumulating more cash. This action is consistent with non-zombie firms' precautionary motives and "inaction" (in terms of investment and disinvestment) when faced with a greater threat of zombie rival firms in their industries. The second column presents mixed evidence that healthy firms display relatively muted changes in inventories, consistent with investment into such assets being less costly to reverse. Turning to payouts, column (3) points to a notable decrease in cash returned to shareholders through dividends and repurchases, once again implying healthy firms facing heightened uncertainty-induced zombification expectations in their industry have a greater motive to shore up liquidity on their balance sheets. Lastly, turning to debt and equity financing, the results in columns (4) and (5) provide modest evidence of reduced issuances of debt, though equity financing seems less reliably affected. That healthy firms cut back on payouts and debt issuances when uncertainty-induced zombification expectations are high is also consistent with related results on how financing frictions amplify uncertainty shocks (see Alfaro et al. (2024)).

In the appendix, we examine the robustness of our core investment and disinvestment results within the subsample of firms in the manufacturing, mining, and construction industries (SIC codes 1000—3999). Our reasons for doing so are twofold. First, our theoretical real-options-based model likely maps most closely to the capacity and asset allocation decisions of tangible asset-focused firms in these industries (see, e.g., Dixit and Pindyck (1994) and Bloom et al. (2007)). Second, our investment and disinvestment proxies are likely more precisely measured for such firms with relatively lower intangible intensity (see, e.g., Crouzet and Eberly (2019)). Appendix Table B.5 replicates the results of Table 5, restricted to the aforementioned subsample. Across all columns, the results continue to obtain with, if anything, stronger economic magnitudes and statistical significance. These robustness checks validate that our results are unlikely to be driven by noise. They also provide important support for our model as our results obtain most strongly in the subset of industries for which our model would bear a greater resemblance to real firm decision-making.

4.8 The Modulating Role of Market Power, Innovation, and New Firm Entry

In our subsequent analysis involving U.S. public firms, we more directly test our theorized channel of zombie firms' continued presence leading to higher output price pressure in their industries. We do so in order to distinguish expected distressed-rival zombification from the standard firm responses to uncertainty shocks. First, following our model intuition, we assess whether the effect of expected zombification on investment is stronger in competitive industries and absent from *less* concentrated industries where rival zombification is of little concern. Conversely, a standard "wait-and-see" uncertainty effect would be, if anything, stronger in *more* concentrated industries (Caballero (1991)). Second, we check if firms actively seek to escape their zombie rivals' price pressure through *increased* innovation (particularly, novel and disruptive innovation), consistent with incentives to engage in product market differentiation. In contrast, heightened uncertainty may *reduce* patenting activity (Bhattacharya et al. (2017)). Complementing these tests on *incumbent* healthy firms' responses, we assess whether the competitive pressure associated with a greater uncertainty-induced rival zombification threat depresses *new* firm entry on the extensive margin.

Within our theoretical setup, we note that healthy firms react to expected rival zombification because all firms in the industry, healthy and zombie alike, face a common, downward-sloping demand curve (see equation (3)). The extent to which healthy firms' output price is affected by expected rival zombification thus depends on their market power or price-setting ability. This insight into the modulating role of competition on our theoretical predictions lends itself to several natural empirical tests. First, healthy firms in industries characterized by greater market power should display little to no responses in their real decisions to greater uncertainty-induced expectations of zombification while those in industries characterized by lower market power should display more pronounced responses. Second, healthy firms should respond to greater expected uncertainty-induced rival zombification by taking actions to decrease their demand elasticity, for instance, by engaging in product differentiation through innovation. Relatedly, new firms would be less likely to enter when facing such heightened zombification expectations.

We begin by examining the cross-sectional differences in our baseline results as a function of market power. We follow prior literature by using detailed, annual industry-level data on markups in 4-digit SIC industries from the NBER-CES Manufacturing Industry Database as proxies for market power. As in Bustamante and Donangelo (2017), for each industry and year, the average markup is defined as the value of sales plus the change in inventories minus payroll and cost of materials, all divided by the value of sales plus the change in inventories. We restrict our attention to subsamples of firms in industry-years with high markups (top quartile of the annual distribution of industry markups) and those with low markups (bottom quartile) in Table 10.

TABLE 10 ABOUT HERE.

Table 10 reports the results of tests in which we replicate the results of columns (1) and (3) of Table 5 in subsamples alternately consisting of firms in high markup (odd-numbered columns) and low markup (even-numbered columns) industry-years. Across both zombie definitions, the contrast in coefficients on *Expected Zombification* is striking. Consistent with our theoretical mechanism being muted among firms likely to have higher market power (and thus price-setting ability), *Expected Zombification* attracts insignificant coefficients in high markup industry-years, shown in the odd-numbered columns. On the other hand, in industry-years characterized by low markups (lower market power), healthy firms strongly respond to the heightened threat of uncertainty-induced zombification by cutting back on their investment. This is evident in the highly statistically significant coefficients on *Expected Zombification* in the even-numbered columns. Beyond providing support for our proposed theoretical mechanism, these results are also beneficial in helping us to rule out potential alternative explanations. Specifically, the lack of significant results in the high market power subsample renders it highly unlikely that the negative coefficients on *Expected Zombification* in our baseline tests in Table 5 are merely capturing the general negative uncertainty-investment relationship, as this effect should be present in both markup subsamples. In contrast, our proposed zombie expectations-related mechanism is uniquely characterized by the modulating role of market power, a notion that finds strong support in the results of Table 10.

We next examine the effects of expected rival zombification on healthy firms' innovation activity by estimating our baseline specification in regression (21) with innovation measures as our outcome variables. We gauge firms' innovation activity by considering two common metrics, the number of patents issued in a given year scaled by lagged assets (*Patent Count*) and the number of citations accruing to those patents in a given year scaled by lagged assets (*Citation Count*). Both outcomes are measured two years ahead of *Expected Zombification*, capturing the likely time lag between initiating an R&D project and filing a patent. The results are reported in Panel A of Table 11.

TABLE 11 ABOUT HERE.

The coefficient estimates across all columns of Panel A indicate that healthy firms respond to greater zombification threats by significantly accelerating their innovation. In doing so, they act consistent with their theoretically conjectured incentive to mitigate the impact of anticipated rival zombification by differentiating their outputs from rivals, thereby decreasing demand elasticity and dampening the negative price pressure imposed by zombie rivals.

We dig deeper into this economic mechanism by distinguishing firms' patenting output along the lines of their "importance." We do so by relying on the measures developed by Kelly et al. (2021) on patent importance and breakthrough patents. Those authors posit that a more important patent is one that bears greater dissimilarity with past patents while displaying greater similarity with future patents. Breakthrough patents are defined as those that lie in the right tail of the distribution of patents by importance. Accordingly, we verify whether the innovation increases documented in Panel A manifest in the form of more important and breakthrough patents. The results are reported in Panel B. Columns (1) and (3) show that among patenting firms, expected zombification is associated with greater future patent importance, while columns (2) and (4) indicate that firms exposed to a greater future zombification threat in their industries are more likely to produce highly impactful (or "breakthrough") patents. Together, these results imply that the innovation increases documented in Panel A transpire through firms engaging in more novel and disruptive innovation, consistent with product differentiation motives. Apart from substantiating our model predictions, these findings add to the literature by identifying a novel channel through which uncertainty promotes innovation.[19]

In Panel C of Table 11, we shift our focus away from *incumbent* healthy firms' responses to expected uncertainty-induced distressed-rival zombification and explore whether and how *new* firm entries respond. Following our theoretical arguments, it stands to reason that a greater threat of rival zombie firms remaining in the industry and suppressing output prices renders it less profitable for new firms to undertake risky and costly-to-reverse entry decisions. We test this conjecture by assembling data on the number of new business entries using information from the Business Formation Statistics (BFS) provided by the U.S. Census Bureau. Aggregating the county-level estimates into a state-year panel, we estimate a variation of regression (21) in which all firm-level variables are averaged to the state-year level according

[19] Campello and Kankanhalli (2024) review the mixed evidence in the literature on the relationship between uncertainty and innovation.

to firms' headquarters states. The outcome variable is the natural logarithm of the number of new business entries in a given state in a given year. The results are reported in Panel C of Table 11. Under both zombie definitions, the results point to a significant slowdown in new business entries in states in which healthy firms expect greater zombification in their industries. These results suggest that the negative implications of heightened zombification expectations under uncertainty extend beyond incumbent firms and depress new business entries, potentially impacting dynamism in the local economy (see also Decker et al. (2016)).

4.9 The Modulating Role of Asset Inflexibility

In our final set of U.S. public firm tests, we investigate the role of a second key modulating factor, asset inflexibility, in shaping healthy firms' responses to expected uncertainty-induced rival zombification. Our theory predicts that healthy firms' investment and disinvestment responses to the threat of zombie rivals emerging in their industry under higher uncertainty will be more acute the costlier it is for them to reverse those decisions. Prior work by Gu et al. (2018) identifies asset inflexibility as an informative measure of the costs firms face in scaling up or down their asset base in response to shocks. Following Gu et al. (2018), we define asset inflexibility as the difference between the maximum and the minimum of a firm's operating costs-to-total sales ratio scaled by the standard deviation of the change in the log of the total sales-to-total assets ratio. The idea behind this measure is that if a firm incurs low adjustment costs when disinvesting its assets, it is more likely to do so when facing a negative shock, leading both its sales and its operating costs to drop. Likewise, if a firm can invest with low adjustment costs, it will more likely do so when facing a positive shock. Consequently, such a firm will show little variability in this ratio over time, as reflected in a small max–min difference. Firms facing greater reversibility costs, on the other hand, will intuitively have a larger max–min difference.

As stated above, our theory predicts that the latter set of firms will display considerably stronger investment and disinvestment responses to greater expected uncertainty-induced rival zombification. We verify this conjecture by repeating our baseline tests in subsets of firms with high asset inflexibility (top quartile of the overall distribution, odd-numbered columns) and those with low asset inflexibility (bottom quartile, even-numbered columns) in Table 12.

TABLE 12 ABOUT HERE.

Comparing across each pair of columns, it is apparent that the *Expected Zombification* coefficient estimates are more negative and of greater statistical significance in the odd-numbered columns (high asset inflexibility subsample) as compared to their even-numbered counterparts (low asset inflexibility subsample). In fact, firms with low asset inflexibility — those that can scale their asset base up or down with lower adjustment costs — display no significant disinvestment response to uncertainty, just as our real-options channel would predict.

In sum, this section offers evidence that healthy U.S. public firms reduce their investment, establishment openings and closures, and employment growth in response to the expectation of uncertainty-induced zombification in their industries, providing strong support for our model predictions. In addition, it also reveals that those same firms observe decreases in their sales growth, profit growth, asset turnover, and forward-looking stock returns as the threat materializes and zombie firms eventually start emerging in their industries. They further adopt more cautious financing policies, scaling up their cash holdings while cutting back on payouts and debt financing. Moreover, firms' responses are modulated by the degree of market power in their industries, with lower market power translating to heightened effects. Firms additionally engage in greater innovation (particularly novel, breakthrough innovation) consistent with their incentives to shore up their market power. Conversely, new firms are less likely to enter when incumbent healthy firms face greater rival zombification threats. Finally, firms with greater asset inflexibility face larger investment and disinvestment reversibility costs and, as a consequence, respond more pronouncedly along those two margins.

5 The Real Effects of Expected Rival Zombification: Global Shipping Firms

Our next set of tests aims at validating our theoretical predictions using granular data on shipping firms' capital allocation decisions. The data we use come from Clarksons, a leading maritime research firm (see Campello et al. (2024)). We obtain detailed information on the new vessel orders, secondary market transactions, and demolition activity of shipping firms. Notably, these data include both private and public firms, mitigating a potential concern that our Compustat analysis may undersample zombie firms that straddle the boundary between being listed and not. We use a company-name-matching algorithm to merge the shipping data with financial data from the entire Orbis universe, manually verifying every single match. Our analysis gauges how the expectation of uncertainty-induced rival zombification in narrowly-defined shipping markets shapes healthy firms' ship-level purchase, sale, and demolition decisions. As our global shipping firm sample is significantly different from the U.S. firm sample in Section 4, we first outline how we adapt the methodology introduced in Section 3, offer more details about our unique shipping variables, and discuss our data sources.

5.1 Shipping Firm Methodology & Data

We run the following panel regression on non-zombie shipping firms to determine how these firms react to the threat of uncertainty-induced rival zombification in their markets:

$$\begin{aligned} \textit{RealDecision}^S_{i,j,t} \quad = \quad & \beta\, \textit{Expected Zombification}^S_{j,t-1} + \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,t-1} \\ & + \lambda \textit{Forward Return}_{j,t-1} + \sum_i \alpha_i + \epsilon_{i,j,s,t} \end{aligned} \tag{23}$$

where $\textit{RealDecision}^S$ is one of a number of real ship-related decisions (described shortly) made by firm i operating in subsector j in year t, $\textit{Expected Zombification}^S$ is a forecast of the share of zombies spawning in subsector j over year t at the start of that year, $\mathbf{FirmControls} = [\textit{Size}, \textit{Cash Flow}^S]'$

is a vector of one-year lagged firm controls, *Forward Return* is the prior quarterly returns of forward contracts written on the freight rate in subsector j, α_i is a firm-fixed effect, and β, $\boldsymbol{\gamma}$, and λ are parameters or parameter vectors.[20] We retrieve the forward freight agreement returns data from the Baltic Exchange via Bloomberg.

Following Campello et al. (2024), we use the following variables as outcomes in regression (23). Our investment proxies are the number of all (*All Ship Investment*), new (*New Ship Investment*), and used (*Used Ship Investment*) ship purchases of firm i over year t scaled by the number of ships in its fleet at the start of the year. Our disinvestment proxies are the number of ship disinvestment (*All Ship Disinvestment*), sales (*Ship Sales*), and demolitions (*Ship Demolitions*) of firm i over year t scaled by the number of ships in its fleet at the start of the year. We also condition our tests on the time-to-build (TTB) within a shipping subsector. TTB is defined as the average number of months between ordering a new ship and the ship being built across all new ships ordered in year t in subsector j.

We rely on a modified version of regression (18) to calculate expected rival zombification in a shipping subsector. We are unable to adequately identify distressed shipping firms using Altman's Z-score because we lack data needed to compute that score for many shipping firms (primarily those that are privately owned). Accordingly, we define a shipping firm as a zombie firm if its interest coverage ratio is below one (*Shipping Zombie*). Following Campello et al. (2024), we next use the value-weighted average of three-month-ahead implied volatility taken over all optionable firms in a subsector to capture the unique subsector-specific uncertainty. We then estimate regression (18) separately by subsector but over our full sample period since we do not have enough observations to estimate rolling-window regressions. We finally combine the slope coefficient of the subsector-specific uncertainty proxy with the proxy's value at the end of year $t-1$, to measure uncertainty-induced zombification in a subsector over year t.

[20] In line with Campello et al. (2024), we use the historical returns of forward contracts on subsector-specific freight rates as our first-order moment proxy, and we define eight shipping subsectors (i.e., markets) based on two ship sectors (dry bulkers and tankers) and four size categories within each sector (Handysize, Handymax, Panamax, and Capesize for bulkers and Medium Range, Long Range 1, Long Range 2, and Very Large Crude Carrier for tankers).

5.2 Ship Purchases, Sales, and Demolitions

Table 13, Panel A presents the results from estimating regression (23) on healthy shipping firms, with columns (1) to (6) using *All Ship Investment*, *New Ship Investment*, *Used Ship Investment*, *All Ship Disinvestment*, *Ship Sales*, and *Ship Demolitions* as dependent variables, respectively. Plain numbers are parameter estimates, whereas those in square brackets are t-statistics clustered at the firm level. The tabulated results fully corroborate our U.S. public firm results. To wit, while column (1) shows that a greater threat of uncertainty-induced zombification in a subsector leads the healthy firms in that subsector to cut back on their investment into new ships, the same threat also prompts them to delay their disinvestment of existing ships (column (4)). In terms of economic significance, a one-standard-deviation increase in *Expected Zombification*^{S} induces investment to decrease by about 23% of its sample mean, and disinvestment to decrease by about 36% of its sample mean. The remaining columns suggest that the investment effect comes mostly through new orders of ships, whereas the disinvestment effect comes through both their sale and demolition, as discussed in Campello et al. (2024). These latter results point to the role of irreversibility costs in modulating healthy firms' responses to the expectation of uncertainty-induced zombification.

TABLE 13 ABOUT HERE.

We further explore the dynamics of shipping firms' investment responses to expected uncertainty-led distressed-rival zombification by conditioning the tests in columns (1) through (3) of Panel A on the average time-to-build (TTB) in shipping subsectors. We do so as prior work documents that TTB amplifies firms' investment responses to uncertainty (see, e.g., Kalouptsidi (2014) and Oh and Yoon (2020)). We partition our sample into "Long TTB" and "Short TTB" subsector-years, i.e., subsector-years in the top and bottom quartiles of the annual TTB distribution. There is significant variation across subsectors in TTB — the "Long TTB" sample has an average TTB of around 37 months while "Short TTB" has a corresponding TTB of 23 months. The TTB gap of over a year between these two subsamples corresponds to the annual horizon of our analysis. Panel B of Table 13 displays the results. Odd-numbered columns contain estimates for the “Long TTB” subsample while even-numbered columns display the corresponding “Short TTB” sample estimates. Consistently, we find that the cuts in investment (in general) and new ship orders (in particular) are most pronounced in the “Long TTB” subsample. This suggests that healthy firms are particularly hesitant to undertake costly-to-reverse investment decisions in the presence of heightened uncertainty-induced rival zombification when those decisions are associated with a significant time lag. These findings shed new light on the role played by the investment process itself on firms’ capital accumulation in response to zombification threats.

The results in Table 13 provide further support for our theoretical predictions. The fact that shipping firms disproportionately cut back on their investment in new ships, which embody the latest technologies, suggests that expectations of creditors’ zombification incentives under uncertainty have pernicious effects on the renewal of otherwise healthy firms’ asset base even before those expectations materialize in actual zombie lending decisions.

6 Concluding Remarks

We posit that financially sound (“healthy”) firms pre-emptively react to the expectation of uncertainty-induced rival zombification rather than only its realization in their industries. Using a real options model of an industry in which levered and unlevered firms compete based on output, we show that the unlevered firms optimally delay their asset allocation decisions in response to the threat that uncertainty induces creditors to turn defaulting levered rival firms into zombie firms. In our empirical work, we use industry-specific rolling-window regressions of a zombie indicator on uncertainty, controls, and fixed effects, calculating the threat of zombification as the end-of-window fitted value based on various uncertainty proxies. We next report that a greater rival zombification threat induces healthy U.S. public firms to delay their real investment, establishment openings and closures, and employment growth, negatively affecting their future performance. Our results highlight the key role of market power and asset inflexibility in modulating the negative externalities of expected rival zombification. Expected rival zombification also impacts financing policies, leading to increased cash holdings, reduced payouts, and reduced debt issuance. We further report that such a threat also induces healthy private and public firms from the global shipping industry to delay their investment and disinvestment of shipping vessels, particularly costlier to reverse new ship orders and existing ship demolitions.

Our results provide evidence for a novel channel through which uncertainty exerts a detrimental effect on firms' asset allocation decisions. They suggest that environments of high uncertainty may be more damaging to capital accumulation, firm performance, and creative destruction than previously thought.

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Table 1. Descriptive Statistics

In this table, we report descriptive statistics for our analysis variables. While Panel A focuses on our Compustat variables, Panels B and C consider our Your-Economy Time-Series (YTS) and Clarkson-Orbis shipping variables, respectively. The descriptive statistics include the total number of observations (N), the mean, the standard deviation (SD), the first quartile (Q1), the median, and the third quartile (Q3). See Appendix Table B.1 for the exact definitions of our analysis variables.

	N	Mean	SD	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Compustat, Outcome, and Control Variables						
Investment	32,322	0.057	0.065	0.019	0.036	0.068
Disinvestment	23,866	0.015	0.045	0.000	0.000	0.007
Expected Zombificationst	32,322	0.500	0.003	0.499	0.500	0.501
Expected Zombification^{su}	28,236	0.500	0.002	0.499	0.500	0.501
Existing Zombificationst	32,322	0.083	0.097	0.015	0.048	0.116
Existing Zombification^{su}	28,236	0.044	0.063	0.000	0.017	0.053
Sales Growth	32,235	0.097	0.299	-0.021	0.060	0.159
Profit Growth	32,235	0.126	0.469	-0.035	0.064	0.184
Asset Turnover	32,235	1.154	0.858	0.584	0.962	1.490
Future Stock Return	21,887	1.010	0.700	0.566	0.877	1.258
Patent Count	27,585	0.005	0.016	0.000	0.000	0.001
Citation Count	27,585	0.037	0.169	0.000	0.000	0.000
Patent Importance	6,128	0.147	0.154	0.035	0.162	0.265
Patent Breakthrough	8,494	0.350	0.857	0.000	0.000	0.000
Size	32,322	6.682	1.964	5.318	6.684	8.031
Cash Flow	32,322	0.154	0.125	0.092	0.144	0.212
Tobin's Q	32,322	1.844	1.200	1.140	1.471	2.087
State GDP Growth	32,322	0.019	0.021	0.008	0.020	0.033
State Labor Force	32,322	15.416	0.836	14.871	15.404	16.053
Regional Inflation	32,322	0.022	0.011	0.016	0.022	0.030
Panel B: Your-Economy Time-Series (YTS) Variables						
Establishment Openings	16,608	0.152	0.349	0.000	0.032	0.154
Establishment Closures	16,608	0.084	0.118	0.000	0.040	0.125
Employment Growth	16,397	0.058	0.343	-0.039	0.000	0.060
Panel C: Clarkson-Orbis Shipping Variables						
All Ship Investments	1,054	0.135	0.351	0.000	0.000	0.000
New Ship Investments	1,054	0.128	0.346	0.000	0.000	0.000
Used Ship Investments	1,054	0.007	0.034	0.000	0.000	0.000
All Ship Disinvestments	1,054	0.044	0.144	0.000	0.000	0.000
Ship Sell-Offs	1,054	0.028	0.101	0.000	0.000	0.000
Ship Demolitions	1,054	0.013	0.071	0.000	0.000	0.000
Expected Zombification^{S}	1,054	0.548	0.033	0.523	0.537	0.568
Size	1,054	6.501	4.245	4.303	6.973	9.736
Cash Flow^{S}	1,054	0.137	0.149	0.062	0.109	0.190
Forward Return	1,054	0.102	0.380	-0.087	0.098	0.334

Table 2. Effect of Zombification on Syndicated Lending Terms

In this table, we report the results from panel regressions of loan-contract terms on a zombie indicator, controls, and industry and time fixed effects. The loan-contract terms are the natural log of a loan's all-drawn-in spread over LIBOR (column (1)); an indicator variable equal to one if it is secured and else zero (column (2)); and an indicator variable equal to one if there is a single lender and else zero (column (3)). While Panel A defines a zombie as a firm with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), Panel B additionally requires that a zombie receives subsidized credit (*Credit-Subsidized Zombie*). The control variables are the natural log of the borrower's assets (*Size*); the number of years since it first appeared in Compustat (*Age*); its operating income scaled by assets (*Profitability*), its net property, plant, and equipment scaled by assets (*Tangibility*), its market-to-book ratio (*Market-to-Book*), its leverage ratio (*Leverage*), an indicator variable equal to one if the borrower is rated and else zero (*Rated*), the natural log of the outstanding loan amount (*Loan Size*), an indicator variable equal to one if the loan is a term loan and else zero (*Loan Type*), and the natural log of the loan's months-to-maturity (*Loan Maturity*). We include only new term loans and revolvers in our regressions. Industry fixed effects are based on the 50 Hoberg and Phillips (2016) industry definitions. Plain numbers are coefficient estimates, whereas those in square brackets are *t*-statistics computed from standard errors clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Spread	*Collateral*	*Single Lender*
	(1)	(2)	(3)
Panel A: *Standard Zombie*			
Standard Zombie	–0.106***	–0.092***	0.065**
	[–3.18]	[–3.67]	[2.28]
Firm & Loan Controls	Yes	Yes	Yes
Industry + Time FEs	Yes	Yes	Yes
R^2	0.47	0.26	0.56
Observations	39,884	42,438	10,197
Panel B: *Credit-Subsidized Zombie*			
Credit-Subsidized Zombie	–0.244***	–0.109***	0.151**
	[–4.35]	[–3.76]	[2.47]
Firm & Loan Controls	Yes	Yes	Yes
Industry + Time FEs	Yes	Yes	Yes
R^2	0.49	0.28	0.53
Observations	35,047	37,215	7,796

Table 3. Effect of Uncertainty on Zombification: Time-Series Regressions

In this table, we report the results from panel regressions of a zombie indicator on each of several three-month-lagged uncertainty measures, controls, and firm fixed effects. While Panel A defines a zombie as a firm with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), Panel B additionally requires that a zombie receives subsidized credit (*Credit-Subsidized Zombie*). The uncertainty measures include the CBOE volatility index (*VIX*); the newspaper-based equity market volatility tracker (*EMV*) of Baker et al. (2019); the economic policy uncertainty index (*EPU*) of Baker et al. (2016); the aggregate financial (*FIN*), real (*REAL*), and macroeconomic (*MACRO*) uncertainty indexes of Jurado et al. (2015); the firm size-weighted average of realized stock-return volatility over the last twelve months per industry (*ARV*); and the firm size-weighted average of implied stock return volatility over the last month per industry (*AIV*). We use the 50 Hoberg and Phillips (2016) industry definitions in our calculations of both *ARV* and *AIV*. The control variables include an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Uncertainty Proxy							
	VIX	*EMV*	*EPU*	*FIN*	*REAL*	*MACRO*	*ARV*	*AIV*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: *Standard Zombie*								
Uncertainty	0.112***	0.182***	0.011***	0.206***	0.309***	0.149***	1.204***	0.131***
	[8.32]	[10.91]	[3.58]	[12.01]	[5.80]	[7.03]	[10.94]	[12.10]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.45
Observations	85,630	85,630	85,630	85,630	85,630	85,630	85,625	68,418
Panel B: *Credit-Subsidized Zombie*								
Uncertainty	0.033***	0.073***	-0.001	0.079***	0.081*	0.049***	0.821***	0.085***
	[2.76]	[5.03]	[-0.24]	[5.21]	[1.75]	[2.81]	[7.79]	[8.42]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34
Observations	60,954	60,954	60,954	60,954	60,954	60,954	60,951	55,212

Table 4. Principal Component Analysis of Uncertainty Measures

In this table, we report the results from a principal component analysis (PCA) run on our eight uncertainty measures. While Panel A gives the slope coefficients of the eight uncertainty measures on the first four principal components (*PC1* to *PC4*), Panel B reports diagnostic statistics derived from that analysis. The uncertainty measures include the CBOE volatility index (*VIX*); the newspaper-based equity market volatility tracker (*EMV*) of Baker et al. (2019); the economic policy uncertainty index (*EPU*) of Baker et al. (2016); the aggregate financial (*FIN*), real (*REAL*), and macroeconomic (*MACRO*) uncertainty indexes of Jurado et al. (2015); the firm size-weighted average of realized stock-return volatility over the last twelve months per industry (*ARV*); and the firm size-weighted average of implied stock return volatility over the last month per industry (*AIV*). We use the 50 Hoberg and Phillips (2016) industry definitions in our calculations of both *ARV* and *AIV*. The diagnostics include the eigenvalue and the explained variation of the first four principal components.

	Principal Component			
	$PC1$	$PC2$	$PC3$	$PC4$
	(1)	(2)	(3)	(4)
Panel A: Principal Component Loadings				
VIX	0.39	–0.23	–0.19	0.09
EMV	0.40	–0.24	0.14	0.13
EPU	0.26	0.59	0.14	0.63
FIN	0.41	–0.14	–0.11	0.24
REAL	0.31	0.56	0.08	–0.27
MACRO	0.36	0.27	–0.18	–0.64
ARV	0.36	–0.26	–0.47	0.05
AIV	0.30	–0.28	0.81	–0.17
Panel B: Principal Component Diagnostics				
Eigenvalue	5.23	1.38	0.61	0.41
Explained Variation	65%	17%	8%	5%

Table 5. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment

In this table, we report the results from panel regressions of public non-zombie firms' investment and disinvestment on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. While we use CAPEX scaled by lagged assets as the investment proxy in columns (1) and (3), we use the sale of property, plant, and equipment (PPE) scaled by lagged PPE as the disinvestment proxy in columns (2) and (4). To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in columns (1) and (2) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (3) and (4) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.893***	–0.450***	–1.056***	–0.682***
	[–8.37]	[–3.64]	[–7.31]	[–3.85]
Size	–0.013***	–0.003***	–0.013**	–0.003**
	[–12.04]	[–2.97]	[–11.51]	[–2.46]
Cash Flow	0.061***	–0.014***	0.060***	–0.019***
	[12.23]	[–3.61]	[10.06]	[–4.35]
Tobin's Q	0.008***	–0.000	0.010***	–0.000
	[14.17]	[–1.28]	[14.30]	[–0.75]
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	32,322	23,725	28,236	20,325

Table 6. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Expected and Existing Zombification

In this table, we report the results from panel regressions of public non-zombie firms' investment and disinvestment on expected zombification (*Expected Zombification*), existing zombification (*Existing Zombification*), controls, as well as firm, industry, and time fixed effects. While we use CAPEX scaled by lagged assets as the investment proxy in columns (1), (2), (5), and (6), we use the sale of property, plant, and equipment (PPE) scaled by lagged PPE as the disinvestment proxy in columns (3), (4), (7), and (8). To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in columns (1) to (4) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (5) to (8) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombification Proxy Based On:							
	Standard Zombie				*Credit-Subsidized Zombie*			
	Investment		*Disinvestment*		*Investment*		*Disinvestment*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Zombification	–0.893***		–0.450***		–1.056***		–0.682***	
	[–8.37]		[–3.64]		[–7.31]		[–3.85]	
Existing Zombification		–0.051***		0.001		–0.012		0.011
		[–5.83]		[0.06]		[–1.30]		[0.89]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.08	0.01	0.01	0.08	0.08	0.01	0.01
Observations	32,322	32,322	23,725	23,725	28,236	28,236	20,325	20,325

Table 7. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Establishment-Level Evidence

In this table, we report the results from panel regressions of public non-zombie firms' establishment openings (column (1)), establishment closures (column (2)), and employment growth (column (3)) on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in Panel A choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in Panel B additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are *t*-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Investment and *Disinvestment* Variables:		
	Establishment Openings	*Establishment Closures*	*Employment Growth*
	(1)	(2)	(3)
Panel A: *Standard Zombie*			
Expected Zombification	–2.869***	–0.997***	–1.023
	[–3.04]	[–3.10]	[–0.88]
Firm Controls	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes
R^2	0.01	0.01	0.01
Observations	16,608	16,608	16,828
Panel B: *Credit-Subsidized Zombie*			
Expected Zombification	–5.080***	–0.402	–5.953***
	[–3.29]	[–0.65]	[–3.08]
Firm Controls	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes
R^2	0.01	0.01	0.01
Observations	14,318	14,318	14,553

Table 8. Real Effects of Zombie Firms on Non-Zombie Firms' Performance

In this table, we report the results from panel regressions of public non-zombie firms' real outcome variables on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. Our outcome variables are *Sales Growth* over the past year (column (1)), *Profit Growth* over the past year (column (2)), *Asset Turnover* over the past year (column (3)), and *Future Stock Return*, the forward-looking 48-month compounded, size-, book-to-market-, and momentum-adjusted (DGTW) firm stock return (column (4)). To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in Panel A choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in Panel B additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are *t*-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Firm Performance Variable:			
	Sales Growth	*Profit Growth*	*Asset Turnover*	*Future Stock Return*
	(1)	(2)	(3)	(4)
Panel A: *Standard Zombie*				
Expected Zombification	–8.210***	–7.174***	–4.062***	–3.691**
	[–10.34]	[–5.34]	[–5.90]	[–1.98]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.06	0.10	0.07	0.09
Observations	32,235	32,259	32,342	21,647
Panel B: *Credit-Subsidized Zombie*				
Expected Zombification	–8.312***	–5.276**	–2.160**	–9.246***
	[–6.16]	[–2.34]	[–2.29]	[–3.04]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.06	0.11	0.06	0.10
Observations	28,161	28,191	28,254	18,182

Table 9. Financial Effects of Zombie Firms on Non-Zombie Firms' Liquidity, Payouts, and Financing

In this table, we report the results from panel regressions of public non-zombie firms' financing outcome variables on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. Our outcome variables are cash savings over the past year, or the annual log change in cash and cash equivalents (column (1)), inventory, or inventories divided by lagged assets (column (2)), total payouts in the form of dividends and repurchases all divided by lagged assets (column (3)), debt financing, or the annual change in total debt over lagged assets (column (4)), and equity financing, or the annual change in preferred stock plus the annual change in common equity plus the annual change in minority interest, minus the annual change in retained earnings, all divided by lagged assets (column (5)). To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in Panel A choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in Panel B additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Financing Variable:				
	Cash Savings	*Inventory*	*Total Payouts*	*Debt Financing*	*Equity Financing*
	(1)	(2)	(3)	(4)	(5)
Panel A: *Standard Zombie*					
Expected Zombification	8.739***	–0.349***	–0.869***	–1.550***	–0.730
	[3.46]	[–4.42]	[–7.51]	[–4.40]	[–1.63]
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.03	0.04	0.03	0.08
Observations	32,151	32,040	30,504	32,303	32,342
Panel B: *Credit-Subsidized Zombie*					
Expected Zombification	9.703***	–0.170	–0.797***	–2.825***	0.754
	[2.64]	[–1.44]	[–4.24]	[–4.44]	[1.04]
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.03	0.03	0.04	0.09
Observations	28,091	27,948	26,487	28,242	28,254

Table 10. Real Effects of Zombie Firms on Non-Zombie Firms' Investment: Industry Markups

In this table, we report the results from panel regressions of public non-zombie firms' investment on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. We use CAPEX scaled by lagged assets as our investment proxy. Odd-numbered columns contain estimates from the subsample of firms belonging to industries (4-digit SIC codes) with high markups, in the top quartile of the annual distribution of average markups across all firms in each 4-digit SIC industry. Even-numbered columns contain estimates from the subsample of firms belonging to industries in the bottom quartile of the annual distribution of average markups. Markups are calculated at the industry-year level using data from the NBER-CES Manufacturing Industry Database, and following the definition of Bustamante and Donangelo (2017). Specifically, for each industry and year, the average markup is defined as the value of sales plus the change in inventories minus payroll and cost of materials, all divided by the value of sales plus the change in inventories. To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in columns (1) and (2) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (3) and (4) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Markup		Markup	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Expected Zombification	–0.493	–1.117***	–0.010	–1.541***
	[–0.83]	[–3.88]	[–0.01]	[–3.45]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.08	0.08	0.10
Observations	1,717	3,084	1,684	2,595

Table 11. Real Effects of Zombie Firms on Non-Zombie Firms' Innovation and Business Entries

In this table, we report the results from panel regressions of public non-zombie firms' innovation variables and new business entries variables on expected zombification (*Expected Zombification*), controls, and fixed effects. Our outcome variables in Panel A are *Patent Count*, or the count of patents issued to a firm in a given year divided by lagged total assets (columns (1) and (3)) and *Citation Count*, or the count of citations accruing to a firm's issued patents in a given year divided by total assets (columns (2) and (4)). Our outcome variables in Panel B are *Patent Importance*, or the average log importance of a patent, averaged across all patents filed by a given firm in a given year, where the importance is the ratio of a patent's similarity with future patents to its dissimilarity with previous patents as per Kelly et al. (2021), with patent similarity measured over a 5-year horizon (columns (1) and (3)) and *Patent Breakthrough*, or the log count of patents filed in a given year that are in the top 10% of *Patent Importance* as defined before (columns (2) and (4)). Our outcome variable in Panel C is the log count of new business formation in a given state in a given year. The specifications in Panel C are estimated at the state-year level, averaging all firm-year variables based on the firms' headquarters states. To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in columns (1) and (2) in Panels A and B (column (1) in Panel C) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (3) and (4) in Panels A and B (column (2) in Panel C) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

Panel A: Innovation

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Innovation Proxy		Innovation Proxy	
	Patent Count	*Citation Count*	*Patent Count*	*Citation Count*
	(1)	(2)	(3)	(4)
Expected Zombification	0.123***	2.109***	0.094**	1.143*
	[4.94]	[6.54]	[2.13]	[1.71]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
R^2	0.04	0.05	0.03	0.04
Observations	27,585	27,585	24,513	24,513

Panel B: Breakthrough Innovation

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Innovation Proxy		Innovation Proxy	
	Patent Importance	*Patent Breakthrough*	*Patent Importance*	*Patent Breakthrough*
	(1)	(2)	(3)	(4)
Expected Zombification	2.906***	23.306***	2.391***	28.510***
	[5.22]	[6.07]	[3.40]	[4.93]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
R^2	0.09	0.08	0.09	0.07
Observations	5,899	8,273	5,179	7,314

Panel C: Business Entries

	Zombification Proxy Based On:	
	Standard Zombie	*Credit-Subsidized Zombie*
	(1)	(2)
Expected Zombification	–5.478***	–17.654***
	[–2.57]	[–3.57]
Average Firm Controls	Yes	Yes
Macro Controls	Yes	Yes
State FEs	Yes	Yes
Time FEs	Yes	Yes
R^2	0.03	0.06
Observations	741	736

Table 12. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Asset Inflexibility

In this table, we report the results from panel regressions of public non-zombie firms' investment on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. We use CAPEX scaled by lagged assets as our investment proxy (columns (1) and (2)) and the sale of property, plant, and equipment (PPE) scaled by lagged PPE as the disinvestment proxy (columns (3) and (4)). Odd-numbered columns contain estimates from the subsample of firms with high asset inflexibility, in the top quartile of the overall distribution of asset inflexibility defined as in Gu et al. (2018). Even-numbered columns contain estimates from the subsample of firms belonging to the bottom quartile of the overall distribution of asset inflexibility. Following Gu et al. (2018), we define asset inflexibility as the difference between the maximum and the minimum of a firm's operating costs-to-total sales ratio scaled by the standard deviation of the change in the log of the total sales-to-total assets ratio, calculated over a firm's entire history of Compustat data starting from 1950. To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in Panel A choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in Panel B additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Investment		*Disinvestment*	
	Asset Inflexibility		Asset Inflexibility	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Panel A: *Standard Zombie*				
Expected Zombification	–1.003***	–0.832***	–0.721**	–0.404
	[–3.38]	[–4.02]	[–2.44]	[–1.59]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.07	0.09	0.01	0.01
Observations	6,486	7,235	4,783	5,458
Panel B: *Credit-Subsidized Zombie*				
Expected Zombification	–1.208***	–0.811***	–1.067***	–0.625
	[–3.64]	[–2.78]	[–2.91]	[–1.60]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.07	0.09	0.01	0.01
Observations	5,770	6,171	4,210	4,536

Table 13. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Shipping Firms Sample

In this table, we report the results from panel regressions of public & private non-zombie shipping firms' investment and disinvestment on expected zombification (*Expected Zombification*^{S}), controls, and firm fixed effects. In Panel A, we use a firm's total, new, and used ship purchases over a year scaled by its total vessels at the start of that year to measure investment in columns (1) to (3), respectively. Conversely, we use a firm's total ship retirements, sales, and demolitions over a year scaled by its total vessels at the start of that year to measure disinvestment in columns (4) to (6), respectively. In Panel B, we focus on a firm's total ship purchases (columns (1) and (2)), new ship purchases (columns (3) and (4)), and used ship purchases (columns (5) and (6)), over a year scaled by its total vessels at the start of that year to measure investment. The odd-numbered columns in Panel B are estimated within the subsample of firm-years with a "long" time-to-build (TTB) while the even-numbered columns in Panel B are estimated within the subsample of firm-years with a "short" time-to-build (TTB). The time-to-build (or TTB) of a firm-year is the average number of months between ordering a new ship and the ship being built across all new ships ordered in that year in the subsector with the maximum number of ships owned by that firm in that year. "Long TTB" firm-years are those in the top quartile of the annual TTB distribution while "Short TTB" firm-years are those in the bottom quartile of the annual TTB distribution. To compute *Expected Zombification*^{S}, we separately run full-sample regressions of a zombie indicator on the three-month-lagged value-weighted average implied volatility taken over all firms in a subsector and controls per subsector. We choose as zombies those firms with an interest coverage below one. The control variables include a firm's lagged zombie indicator, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and the lagged quarterly returns of forward contracts written on subsector-specific freight rates (*Forward Return*). We next combine the slope estimate of the average implied volatility variable with its end-of-window value. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT and depreciation scaled by two-year lagged assets (*Cash Flow*^{S}), and the lagged quarterly returns of forward contracts written on subsector-specific freight rates (*Forward Return*). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

Panel A: Full Sample Regressions

	Investment Proxy			*Disinvestment* Proxy		
	All Ships	*New Ships*	*Used Ships*	*All Ships*	*Sold Ships*	*Demolished Ships*
	(1)	(2)	(3)	(4)	(5)	(6)
Expected Zombification^S	–0.947**	–0.891**	–0.032	–0.482**	–0.209	–0.239*
	[–2.16]	[–2.10]	[–0.53]	[–2.19]	[–1.44]	[–1.79]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.03	0.03	0.02	0.03	0.02	0.03
Observations	1,054	1,054	1,054	1,054	1,054	1,054

Panel B: Subsample Regressions

	Investment Proxy					
	All Ships		*New Ships*		*Used Ships*	
	Long TTB	Short TTB	Long TTB	Short TTB	Long TTB	Short TTB
	(1)	(2)	(3)	(4)	(5)	(6)
Expected Zombification^S	–2.462***	1.641	–2.299***	1.669	–0.106	–0.029
	[–3.96]	[1.14]	[–3.97]	[1.16]	[–0.90]	[–0.61]
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.03	0.08	0.03	0.02	0.02
Observations	339	241	339	241	339	241

Internet Appendices

Appendix A Mathematical Proofs

A.1 Creditor's Continuation Value

In this appendix, we derive the creditor's continuation value if they agree to keep the levered firms alive. The present value of all future cash flows to the creditors is:

$$\mathscr{C}(\theta,X) = \mathbb{E}^{\mathbb{Q}}\left[\int_0^\infty \min\{\max\{\Pi_t,b\},c^*\}e^{-rt}\,dt\right] \tag{A.1}$$

$$= \mathbb{E}^{\mathbb{Q}}\left[\int_0^\infty (c^* - \max\{c^* - \Pi_t, 0\})\,e^{-rt}\,dt - \int_0^\infty (b - \max\{b - \Pi_t, 0\})\,e^{-rt}\,dt\right] + \frac{b}{r} \tag{A.2}$$

$$= \mathfrak{C}(\theta,X;c^*) - \mathfrak{C}(\theta,X;b) + \frac{b}{r}, \tag{A.3}$$

where we introduce, for some $a > 0$, the auxiliary function:

$$\mathscr{C}(\theta,X;a) = \mathbb{E}^{\mathbb{Q}}\left[\int_0^\infty \min\{\Pi_t,a\}e^{-rt}\,dt\right] = \mathbb{E}^{\mathbb{Q}}\left[\int_0^\infty (a - \max\{a - \Pi_t, 0\})\,e^{-rt}\,dt\right]. \tag{A.4}$$

Proposition 5. *Let $a > 0$ be a constant. Define $A = \frac{\gamma + \frac{1}{2}\kappa}{((n_U + n_L + 1)\gamma + \kappa)^2}$ and $\theta_q = \sqrt{\frac{a}{A}}$. Then:*

$$\mathfrak{C}(\theta,X;a) = \mathbb{E}^{\mathbb{Q}}\left[\int_0^\infty (a - \max\{a - \Pi_t, 0\})\,e^{-rt}\,dt\right] \tag{A.5}$$

$$= \begin{cases} c_{1,X}\theta^{\beta_1} + c_{2,X}\theta^{\beta_2} + c_{0,X}\theta^2 & \text{if } \theta \le \theta_q, \\ c_{3,X}\theta^{\beta_3} + c_{4,X}\theta^{\beta_4} + \frac{a}{r} & \text{if } \theta \ge \theta_q. \end{cases} \tag{A.6}$$

Proof. When profits are low (and θ near Z), the unlevered firms and the levered firms both produce optimally $Q^* := \frac{\theta}{(n_U + n_L + 1)\gamma + \kappa}$ per unit of time. The levered firms' net profit per unit of time is:

$$\Pi = (\theta - (n_U + n_L)\gamma Q^*)Q^* - \frac{1}{2}\kappa(Q^*)^2 = A\theta^2, \tag{A.7}$$

where $A = \frac{\gamma + \frac{1}{2}\kappa}{((n_U + n_L + 1)\gamma + \kappa)^2} > 0$.

To calculate the continuation value, we need to compare the operating profits, Π, with the constant a. Comparing the profit to a yields $A\theta^2 - a = 0 \Leftrightarrow \theta = \sqrt{\frac{a}{A}} =: \theta_q$. Thus:

$$\max\{a - \Pi, 0\} = \begin{cases} a - A\theta^2 & \text{if } \theta \in (0, \theta_q], \\ 0 & \text{if } \theta \in [\theta_q, \infty). \end{cases} \tag{A.8}$$

In each of the two volatility states, the creditor's continuation value at time τ_Z from Equation (A.2), $\mathscr{C} = \mathscr{C}(\theta, X)$, needs to satisfy the usual risk-neutral valuation condition:

$$\mathbb{E}^{\mathbb{Q}}[d\mathscr{C}] + (a - \max\{a - \Pi, 0\})\,dt = r\mathscr{C}\,dt. \tag{A.9}$$

This condition imposes that in a risk-neutral world expected capital gains and instantaneous cash flows add up to the return on a risk-free investment. In the real world, demand grows at rate α_X while attracting a risk premium μ, which is the return of a portfolio that perfectly replicates the randomness of demand. Let $\delta_X = \mu - \alpha_X$ denote the expected-return shortfall such that the real-world demand drift $\mu - \delta_X$ changes to $r - \delta_X$ in a risk-neutral world. With this in mind, Itô's Lemma translates the no-arbitrage pricing condition in Equation (A.9) into a system of coupled ordinary differential equations (ODEs):

$$\begin{aligned} (r-\delta_H)\theta\mathscr{C}^H_\theta + \frac{1}{2}\sigma_H^2\theta^2\mathscr{C}^H_{\theta\theta} - r\mathscr{C}^H + p_L\left(\mathscr{C}^L - \mathscr{C}^H\right) + a - \max\{a-\Pi,0\} = 0,\\ (r-\delta_L)\theta\mathscr{C}^L_\theta + \frac{1}{2}\sigma_L^2\theta^2\mathscr{C}^L_{\theta\theta} - r\mathscr{C}^L + p_H\left(\mathscr{C}^H - \mathscr{C}^L\right) + a - \max\{a-\Pi,0\} = 0, \end{aligned} \tag{A.10}$$

where subscripts denote partial derivatives and superscripts economic regimes. The first three terms are alike the usual diffusion terms (see, e.g., Dixit and Pindyck (1994)). The following summands correct for the possibility of jumping to the different regime. The final two summands add the current cash flows as an inhomogeneity. The ODE system has to be solved subject to the boundary conditions $\lim_{\theta\to 0}\mathscr{C}(\theta, X) = 0$ and $\lim_{\theta\to\infty}\mathscr{C}(\theta, X) = \frac{a}{r}$.

Guessing the homogeneous solution to be of the familiar type $\mathscr{C}^H = a^H\theta^\beta$ and $\mathscr{C}^L = a^L\theta^\beta$ leads us to define the characteristic polynomials:

$$Q_H(\beta) = (r-\delta_H)\beta + \frac{1}{2}\sigma_H^2\beta(\beta-1) - r - p_L, \tag{A.11}$$

$$Q_L(\beta) = (r-\delta_L)\beta + \frac{1}{2}\sigma_L^2\beta(\beta-1) - r - p_H. \tag{A.12}$$

To solve both ODEs simultaneously, we study the degree four polynomial equation:

$$Q_H(\beta)Q_L(\beta) = p_H p_L, \tag{A.13}$$

whose positive solutions we denote by β_1 and β_2 and its negative solutions by β_3 and β_4. The general solution to the homogeneous ODE system in Equation (A.10) is hence given by:

$$\mathscr{C}(\theta, X) = c_{1,X}\theta^{\beta_1} + c_{2,X}\theta^{\beta_2} + c_{3,X}\theta^{\beta_3} + c_{4,X}\theta^{\beta_4}. \tag{A.14}$$

Plugging this solution into that homogeneous ODE system reveals that the coefficients have to satisfy the following conditions:

$$c_{1,L} = -\frac{c_{1,H}}{p_L} Q_H(\beta_1), \tag{A.15}$$

$$c_{2,L} = -\frac{c_{2,H}}{p_L} Q_H(\beta_2), \tag{A.16}$$

$$c_{3,L} = -\frac{c_{3,H}}{p_L} Q_H(\beta_3), \tag{A.17}$$

$$c_{4,L} = -\frac{c_{4,H}}{p_L} Q_H(\beta_4). \tag{A.18}$$

The instantaneous profits from Equation (A.8) add particular solutions to this homogeneous solution, while imposing the boundary conditions remove some solution components. Thus, the creditor's continuation value is:

$$\mathscr{C}(\theta, X) = \begin{cases} c_{1,X}\theta^{\beta_1} + c_{2,X}\theta^{\beta_2} + c_{0,X}\theta^2 & \text{if } \theta \le \theta_q, \\ c_{3,X}\theta^{\beta_3} + c_{4,X}\theta^{\beta_4} + \frac{a}{r} & \text{if } \theta \ge \theta_q, \end{cases} \tag{A.19}$$

where $c_{0,X} = \frac{A}{\rho_X}$ with $\rho_H = \frac{Q_H(2)Q_L(2) - p_H p_L}{p_L - Q_L(2)}$ and $\rho_L = \frac{Q_H(2)Q_L(2) - p_H p_L}{p_H - Q_H(2)}$.

The coefficients $c_{i,X}$ are identified by the following by value-matching and smooth-pasting conditions at $\theta = \theta_q$:

$$c_{1,H}(\theta_q)^{\beta_1} + c_{2,H}(\theta_q)^{\beta_2} + c_{0,H}(\theta_q)^2 = c_{3,H}(\theta_q)^{\beta_3} + c_{4,H}(\theta_q)^{\beta_4} + \frac{a}{r}, \tag{A.20}$$

$$c_{1,H}\beta_1(\theta_q)^{\beta_1} + c_{2,H}\beta_2(\theta_q)^{\beta_2} + 2c_{0,H}(\theta_q)^2 = c_{3,H}\beta_3(\theta_q)^{\beta_3} + c_{4,H}\beta_4(\theta_q)^{\beta_4}, \tag{A.21}$$

$$c_{1,L}(\theta_q)^{\beta_1} + c_{2,L}(\theta_q)^{\beta_2} + c_{0,L}(\theta_q)^2 = c_{3,L}(\theta_q)^{\beta_3} + c_{4,L}(\theta_q)^{\beta_4} + \frac{a}{r}, \tag{A.22}$$

$$c_{1,L}\beta_1(\theta_q)^{\beta_1} + c_{2,L}\beta_2(\theta_q)^{\beta_2} + 2c_{0,L}(\theta_q)^2 = c_{3,L}\beta_3(\theta_q)^{\beta_3} + c_{4,L}\beta_4(\theta_q)^{\beta_4}. \tag{A.23}$$

We state the solution to the ODE system (A.10) subject to Equations (A.20) to (A.18) recursively, calculating $c_{4,H}$ in closed-form and deriving all other coefficients from that solution. For ease of notation, we write $Q_H(\beta_i) = H_i$ for $i \in \{1,2,3,4\}$. The first solution is given by:

$$\begin{aligned} c_{4,H} = {} & -c_{0,H} \frac{\left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3 - H_1\beta_1}{H_2\beta_2 - H_1\beta_1}\right) \frac{\frac{2-\beta_1}{\beta_2-\beta_1} + \frac{p_L\rho_H + \rho_L H_1}{(H_2-H_1)\rho_L}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}} - \frac{2-\beta_1}{\beta_2-\beta_1} - \frac{2p_L\rho_H + H_1\beta_1\rho_L}{(H_2\beta_2 - H_1\beta_1)\rho_L}}{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4\beta_4 - H_1\beta_1}{H_2\beta_2 - H_1\beta_1} - \left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3 - H_1\beta_1}{H_2\beta_2 - H_1\beta_1}\right) \frac{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4-H_1}{H_2-H_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}}} (\theta_q)^{2-\beta_4} \\ & + \frac{\left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3 - H_1\beta_1}{H_2\beta_2 - H_1\beta_1}\right) \frac{\frac{H_1+p_L}{H_2-H_1} - \frac{\beta_1}{\beta_2-\beta_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}} - \frac{H_1\beta_1}{H_2\beta_2 - H_1\beta_1} + \frac{\beta_1}{\beta_2-\beta_1}}{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4\beta_4 - H_1\beta_1}{H_2\beta_2 - H_1\beta_1} - \left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3 - H_1\beta_1}{H_2\beta_2 - H_1\beta_1}\right) \frac{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4-H_1}{H_2-H_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}}} \frac{a}{r} (\theta_q)^{-\beta_4}. \end{aligned} \tag{A.24}$$

Given $c_{4,H}$, we can easily calculate $c_{3,H}$ as follows:

$$c_{3,H} = -c_{4,H} \frac{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4-H_1}{H_2-H_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}} (\theta_q)^{\beta_4-\beta_3} + c_{0,H} \frac{\frac{2-\beta_1}{\beta_2-\beta_1} + \frac{p_L\rho_H+\rho_L H_1}{(H_2-H_1)\rho_L}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}} (\theta_q)^{2-\beta_3} - \frac{\frac{H_1+p_L}{H_2-H_1} - \frac{\beta_1}{\beta_2-\beta_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}} \frac{a}{r} (\theta_q)^{-\beta_3}. \tag{A.25}$$

Given $c_{4,H}$ and $c_{3,H}$, we can easily calculate $c_{2,H}$ as follows:

$$c_{2,H} = c_{3,H} \frac{\beta_3-\beta_1}{\beta_2-\beta_1} (\theta_q)^{\beta_3-\beta_2} + c_{4,H} \frac{\beta_4-\beta_1}{\beta_2-\beta_1} (\theta_q)^{\beta_4-\beta_2} - \frac{2-\beta_1}{\beta_2-\beta_1} c_{0,H} (\theta_q)^{2-\beta_2} - \frac{\beta_1}{\beta_2-\beta_1} \frac{a}{r} (\theta_q)^{-\beta_2}. \tag{A.26}$$

Given $c_{4,H}$, $c_{3,H}$ and $c_{2,H}$, we can easily calculate $c_{1,H}$ as follows:

$$c_{1,H} = -c_{2,H}(\theta_q)^{\beta_2-\beta_1} + c_{3,H}(\theta_q)^{\beta_3-\beta_1} + c_{4,H}(\theta_q)^{\beta_4-\beta_1} - c_{0,H}(\theta_q)^{2-\beta_1} + \frac{a}{r}(\theta_q)^{-\beta_1}. \tag{A.27}$$

Finally, given the above, $c_{1,L}$, $c_{2,L}$, $c_{3,L}$, and $c_{4,L}$ are available through Equations (A.15) to (A.18).

□

A.2 Duration of Zombification

In this section, we calculate the expected time defaulting firms rely on credit-subsidization. Let Z^* denote the demand level where levered firms' profits reach the newly agreed coupon c^*. Let τ^* be the first time that the demand shift θ reaches Z^*. Given $u > 0$, the Laplace transform of the stopping time τ^* is well-known to be:

$$\mathbb{E}[e^{-u\tau^*}|\theta, X] = \frac{\beta_{2,u}\left(\frac{\theta}{Z^*}\right)^{\beta_{1,u}} - \beta_{1,u}\left(\frac{\theta}{Z^*}\right)^{\beta_{2,u}}}{\beta_{2,u}-\beta_{1,u}} - \frac{\left(\frac{\theta}{Z^*}\right)^{\beta_{1,u}} - \left(\frac{\theta}{Z^*}\right)^{\beta_{2,u}}}{\beta_{2,u}-\beta_{1,u}} \frac{\beta_{1,u}\beta_{2,u} + \frac{2u}{\sigma_X^2}}{\beta_{1,u}+\beta_{2,u}+2\frac{\alpha_X}{\sigma_X^2}-1}, \tag{A.28}$$

where $\beta_{1,u}$ and $\beta_{2,u}$ (with $\beta_{1,u} > \beta_{2,u}$) are the positive roots to the fourth-order polynomial:

$$\left(\frac{1}{2}\sigma_H^2\beta(\beta-1) + \alpha_H\beta - p_L - u\right)\left(\frac{1}{2}\sigma_L^2\beta(\beta-1) + \alpha_L\beta - p_H - u\right) = p_H p_L. \tag{A.29}$$

Calculating the partial derivative of $\mathbb{E}[e^{-u\tau^*}|\theta, X]$ with respect to u is straight-forward, albeit tedious. The partial derivative can be closely approximated using finite differences.

A.3 Incremental Production Option If Levered Firms Never Leave the Industry

We next turn to the pricing of the unlevered firm's K^{th} incremental production option which reflects the value of producing and selling the K^{th} marginal output unit. Given a production threshold θ^P, the option value, $\Delta\mathscr{V} = \Delta\mathscr{V}(\theta, X; \theta^P)$, satisfies the no-arbitrage pricing condition

$$\mathbb{E}^{\mathbb{Q}}[d\Delta\mathscr{V}] + \max\{\theta - \theta^P, 0\} dt = r\Delta\mathscr{V} dt. \tag{A.30}$$

Itô's Lemma translates this condition into a system of ODEs,

$$\begin{aligned}(r-\delta_H)\theta\Delta\mathscr{V}^H_\theta + \frac{1}{2}\sigma_H^2\theta^2\Delta\mathscr{V}^H_{\theta\theta} - r\Delta\mathscr{V}^H + p_L\left(\Delta\mathscr{V}^L - \Delta\mathscr{V}^H\right) + \max\{\theta-\theta^P, 0\} = 0,\\ (r-\delta_L)\theta\Delta\mathscr{V}^L_\theta + \frac{1}{2}\sigma_L^2\theta^2\Delta\mathscr{V}^L_{\theta\theta} - r\Delta\mathscr{V}^L + p_H\left(\Delta\mathscr{V}^H - \Delta\mathscr{V}^L\right) + \max\{\theta-\theta^P, 0\} = 0.\end{aligned} \tag{A.31}$$

Using the general solution from Equation (A.14), adding the inhomogeneities, and taking the usual boundary conditions, $\lim_{\theta\to 0}\Delta\mathscr{V}(\theta, X; K) = 0$ and $\lim_{\theta\to\infty}\Delta\mathscr{V}(\theta, X; K) = b_{0,X}\theta - \frac{\theta^P}{r}$, into account, the value of the K^{th} incremental production asset is

$$\Delta\mathscr{V}(\theta, X; K) = \begin{cases} b_{1,X}\theta^{\beta_1} + b_{2,X}\theta^{\beta_2} & \text{if } \theta \le \theta^P,\\ b_{3,X}\theta^{\beta_3} + b_{4,X}\theta^{\beta_4} + b_{0,X}\theta - \frac{\theta^P}{r} & \text{if } \theta \ge \theta^P,\end{cases} \tag{A.32}$$

where $b_{0,H} = \frac{\delta_L + p_H + p_L}{\delta_L\delta_H + \delta_L p_L + \delta_H p_H}$ and $b_{0,L} = \frac{\delta_H + p_H + p_L}{\delta_L\delta_H + \delta_L p_L + \delta_H p_H}$.

Akin to Equations (A.15) to (A.18), the coefficients need to satisfy the following conditions:

$$b_{1,L} = -\frac{b_{1,H}}{p_L}Q_H(\beta_1), \tag{A.33}$$

$$b_{2,L} = -\frac{b_{2,H}}{p_L}Q_H(\beta_2), \tag{A.34}$$

$$b_{3,L} = -\frac{b_{3,H}}{p_L}Q_H(\beta_3), \tag{A.35}$$

$$b_{4,L} = -\frac{b_{4,H}}{p_L}Q_H(\beta_4). \tag{A.36}$$

Finally, the coefficients are uniquely identified by additionally imposing the following value-matching and smooth-pasting conditions at $\theta = \theta^P$:

$$b_{1,H}(\theta^P)^{\beta_1} + b_{2,H}(\theta^P)^{\beta_2} = b_{3,H}(\theta^P)^{\beta_3} + b_{4,H}(\theta^P)^{\beta_4} + b_{0,H}\theta^P - \frac{\theta^P}{r}, \tag{A.37}$$

$$b_{1,H}\beta_1(\theta^P)^{\beta_1} + b_{2,H}\beta_2(\theta^P)^{\beta_2} = b_{3,H}\beta_3(\theta^P)^{\beta_3} + b_{4,H}\beta_4(\theta^P)^{\beta_4} + b_{0,H}\theta^P, \tag{A.38}$$

$$b_{1,L}(\theta^P)^{\beta_1} + b_{2,L}(\theta^P)^{\beta_2} = b_{3,L}(\theta^P)^{\beta_3} + b_{4,L}(\theta^P)^{\beta_4} + b_{0,L}\theta^P - \frac{\theta^P}{r}, \tag{A.39}$$

$$b_{1,L}\beta_1(\theta^P)^{\beta_1} + b_{2,L}\beta_2(\theta^P)^{\beta_2} = b_{3,L}\beta_3(\theta^P)^{\beta_3} + b_{4,L}\beta_4(\theta^P)^{\beta_4} + b_{0,L}\theta^P. \tag{A.40}$$

We next state the coefficients that solve the above conditions. We do so recursively, calculating $b_{4,H}$ in closed-form and deriving all other coefficients from that solution. For ease of notation, we write $Q_H(\beta_i) = H_i$ for $i \in \{1, 2, 3, 4\}$. The first solution is given by

$$
\begin{aligned}
b_{4,H} = {} & \frac{(H_2\beta_2 - H_1\beta_1) b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1} - (H_1\beta_1 b_{0,H} + p_L b_{0,L}) + \frac{H_1 b_{0,H} + p_L b_{0,L} - (H_2 - H_1) b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)}{H_1\beta_1 - H_4\beta_4 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1} - \frac{H_1 - H_4 - (H_2 - H_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)} (\theta^P)^{1-\beta_4} \\
& - \frac{(H_2\beta_2 - H_1\beta_1)\frac{\beta_1}{\beta_2 - \beta_1} - H_1\beta_1 + \frac{H_1 + p_L - (H_2 - H_1)\frac{\beta_1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)}{H_1\beta_1 - H_4\beta_4 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1} - \frac{H_1 - H_4 - (H_2 - H_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)} \frac{(\theta^P)^{1-\beta_4}}{r}.
\end{aligned}
\tag{A.41}
$$

Given $b_{4,H}$, we can easily calculate $b_{3,H}$ as follows

$$
\begin{aligned}
b_{3,H} = {} & -b_{4,H} \frac{H_1 - H_4 - (H_2 - H_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} (\theta^P)^{\beta_4 - \beta_3} - \frac{H_1 b_{0,H} + p_L b_{0,L} - (H_2 - H_1) b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} (\theta^P)^{1-\beta_3} \\
& + \frac{H_1 + p_L - (H_2 - H_1)\frac{\beta_1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \frac{(\theta^P)^{1-\beta_3}}{r}.
\end{aligned}
\tag{A.42}
$$

Given $b_{4,H}$ and $b_{3,H}$, we can easily calculate $b_{2,H}$ as follows

$$
b_{2,H} = -b_{3,H} \frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} (\theta^P)^{\beta_3 - \beta_2} - b_{4,H} \frac{\beta_1 - \beta_4}{\beta_2 - \beta_1} (\theta^P)^{\beta_4 - \beta_2} - b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1} (\theta^P)^{1-\beta_2} + \frac{\beta_1}{\beta_2 - \beta_1} \frac{(\theta^P)^{1-\beta_2}}{r}.
\tag{A.43}
$$

Given $b_{4,H}$, $b_{3,H}$, and $b_{2,H}$, we can easily calculate $b_{1,H}$ as follows

$$
b_{1,H} = -b_{2,H} (\theta^P)^{\beta_2 - \beta_1} + b_{3,H} (\theta^P)^{\beta_3 - \beta_1} + b_{4,H} (\theta^P)^{\beta_4 - \beta_1} + b_{0,H} (\theta^P)^{1-\beta_1} - \frac{(\theta^P)^{1-\beta_1}}{r}.
\tag{A.44}
$$

Finally, given the above, $b_{1,L}$, $b_{2,L}$, $b_{3,L}$, and $b_{4,L}$ are available through Equations (A.33) to (A.36).

A.4 Leaving The Economy

A levered firm stays as a zombie in the economy if its continuation value during default exceeds its residual value, $\mathscr{C}(Z,X) \geq L_X$. Suppose that each of the n_L levered firms draws its own idiosyncratic recovery value according to $\ln(L_X) \sim N(\mu_{L,X}, \sigma^2_{L,X})$. Then, only a fraction of the defaulting levered firms continues as zombies. Given the state X, the continuation value $\mathscr{C}(Z,X)$ is a constant. In state X, we thus only expect $\mathbb{Q}[\mathscr{C}(Z,X) \leq L_X | X] n_L$ firms to leave the economy. We can calculate that probability as follows:

$$
\mathbb{Q}[\mathscr{C}(Z,X) \leq L_X | X] = \Phi\left(-\frac{\ln(\mathscr{C}(Z,X)) - \mu_{L,X}}{\sigma_{L,X}} \right),
\tag{A.45}
$$

where Φ is the cumulative distribution function of a standard normal distribution.

For convenience, we set $\psi(X) = \mathbb{Q}[\mathscr{C}(Z,X) \geq L_X | X] = \Phi\left(\frac{\ln(\mathscr{C}(Z,X)) - \mu_{L,X}}{\sigma_{L,X}} \right)$ to be the share of levered firms staying as a zombie upon default in state X.

A.5 Discount Factor for Levered Firms' Exit

In this section, we value the correction term which adds to the value of the unlevered firms' production option and captures the increase in market power once some levered firms leave the industry.

Applying the law of total expectation yields

$$\Delta V(\theta, X; K) = \Delta \mathscr{V}(\theta, X; \theta_Z^P) + \big(\Delta \mathscr{V}(Z, X; \theta^P) - \Delta \mathscr{V}(Z, X; \theta_Z^P)\big)\mathbb{E}^{\mathbb{Q}}\big[e^{-r\tau}|X\big], \tag{A.46}$$

where τ denotes the hitting time $\tau = \min\{t > 0 : \Pi_t = c\} = \min\{t > 0 : \theta_t = Z\}$.

In the absence of arbitrage, the "expected discount factor" $Q(\theta, X; Z) = \mathbb{E}^{\mathbb{Q}}[e^{-r\tau}|X]$ needs to satisfy the risk-neutral pricing rule

$$\mathbb{E}^{\mathbb{Q}}[dQ] = rQdt. \tag{A.47}$$

Itô's Lemma translates this valuation condition into a system of coupled ODEs,

$$\begin{aligned}(r-\delta_H)\theta Q_\theta^H + \frac{1}{2}\sigma_H^2\theta^2 Q_{\theta\theta}^H - rQ^H + p_L\big(Q^L - Q^H\big) = 0,\\ (r-\delta_L)\theta Q_\theta^L + \frac{1}{2}\sigma_L^2\theta^2 Q_{\theta\theta}^L - rQ^L + p_H\big(Q^H - Q^L\big) = 0.\end{aligned} \tag{A.48}$$

Suppose the default has not occurred yet ($\theta > Z$). Taking the upper limit $\lim_{\theta\to\infty} Q(\theta, X; Z) = 0$ into account, the general solution is

$$Q(\theta, X; Z) = q_{3,X}\theta^{\beta_3} + q_{4,X}\theta^{\beta_4}, \tag{A.49}$$

where the coefficients need to satisfy

$$q_{3,L} = -\frac{q_{3,H}}{p_L}Q_H(\beta_3), \tag{A.50}$$

$$q_{4,L} = -\frac{q_{4,H}}{p_L}Q_H(\beta_4). \tag{A.51}$$

At the default point, $\theta = Z$, the coefficients satisfy the value-matching conditions

$$q_{3,H}Z^{\beta_3} + q_{4,H}Z^{\beta_4} = 1, \tag{A.52}$$

$$q_{3,L}Z^{\beta_3} + q_{4,L}Z^{\beta_4} = 1. \tag{A.53}$$

The solution to the equation system is given by:

$$q_{3,H} = \frac{p_L + Q_H(\beta_4)}{Q_H(\beta_4) - Q_H(\beta_3)}Z^{-\beta_3}, \tag{A.54}$$

$$q_{4,H} = \frac{p_L + Q_H(\beta_3)}{Q_H(\beta_3) - Q_H(\beta_4)}Z^{-\beta_4}. \tag{A.55}$$

A.6 Capacity Adjustment Options

In this section, we determine the value of the unlevered firms' scale-adjustment options. Disinvestment and investment options can be interpreted as coupled compounded options written on an underlying incremental option to produce.

The value of the growth option, $\Delta F = \Delta F(\theta, X; K)$, satisfies the usual no-arbitrage pricing rule which translates into the following system of ODEs

$$(r-\delta_H)\theta \Delta F_\theta^H + \frac{1}{2}\sigma_H^2 \theta^2 \Delta F_{\theta\theta}^H - r\Delta F^H + p_L\left(\Delta F^L - \Delta F^H\right) = 0, \tag{A.56}$$

$$(r-\delta_L)\theta \Delta F_\theta^L + \frac{1}{2}\sigma_L^2 \theta^2 \Delta F_{\theta\theta}^L - r\Delta F^L + p_H\left(\Delta F^H - \Delta F^L\right) = 0. \tag{A.57}$$

Incorporating the boundary condition $\lim_{\theta\to 0} \Delta F(\theta, X; K) = 0$, the value of the growth option is

$$\Delta F(\theta, X; K) = a_{1,X}\theta^{\beta_1} + a_{2,X}\theta^{\beta_2}, \tag{A.58}$$

where the coefficients need to satisfy the additional conditions

$$a_{1,L} = -\frac{a_{1,H}}{p_L} Q_H(\beta_1), \tag{A.59}$$

$$a_{2,L} = -\frac{a_{2,H}}{p_L} Q_H(\beta_2). \tag{A.60}$$

In analogy to the above, the value of the contraction option, $\Delta D(\theta, X; K)$, is

$$\Delta D(\theta, X; K) = d_{3,X}\theta^{\beta_3} + d_{4,X}\theta^{\beta_4}. \tag{A.61}$$

This solution incorporates the limit $\lim_{\theta\to\infty} \Delta D(\theta, X; K) = 0$ and requires the coefficients to satisfy

$$d_{3,L} = -\frac{d_{3,H}}{p_L} Q_H(\beta_3), \tag{A.62}$$

$$d_{4,L} = -\frac{d_{4,H}}{p_L} Q_H(\beta_4). \tag{A.63}$$

To uniquely identify the solution, we further impose the following value-matching and smooth-pasting conditions at the exercise boundaries, θ_X^* and θ_X'. The four value-matching conditions are:

$$\Delta F(\theta_X^*, X; K) + I = \Delta V(\theta_X^*, X; K) + \Delta D(\theta_X^*, X; K), \tag{A.64}$$

$$\Delta D(\theta_X', X; K) + \Delta V(\theta_X', X; K) = d + \Delta F(\theta_X', X; K). \tag{A.65}$$

These conditions equate the cost (gain) and gain (cost) of investing (disinvesting) into the K^{th} marginal unit of capacity. The corresponding smooth-pasting conditions ensure optimality and are:

$$\Delta F_\theta(\theta_X^*, X; K) = \Delta V_\theta(\theta_X^*, X; K) + \Delta D_\theta(\theta_X^*, X; K), \tag{A.66}$$

$$\Delta D_\theta(\theta_X', X; K) + \Delta V_\theta(\theta_X', X; K) = \Delta F_\theta(\theta_X', X; K). \tag{A.67}$$

Taken together, this equation system has to be solved numerically.

A.7 Input Market Congestion

In this appendix, we show that modeling competitive forces in input markets is equivalent to congestion effects in output markets. Suppose each firm produces a unique output good but relies on a homogeneous production input factor. The output price for the i^{th} firm is given by the downward-sloping demand curve:

$$P_{Y,i} = \theta - \gamma Q_{Y,i}, \tag{A.68}$$

where $Y \in \{U, L\}$. The output price is unaffected by the number of rival firms in the industry and their production policies. To model input market competition, we scale the firms' production cost function by the number of firms in the industry such that producing $Q_{Y,i}$ output units costs $\frac{1}{2}\kappa(1+n_u+n_L)Q_{Y,i}^2$. Utilizing capital and producing output is thus costlier when there are many rival firms demanding the same production input. A firm's profit per unit of time is:

$$\Pi_{Y,i} = \theta Q_{Y,i} - \left(\gamma + \frac{1}{2}(1+n_u+n_L)\right) Q_{Y,i}^2. \tag{A.69}$$

The firm's optimal production policy without capacity constraints is:

$$Q_{Y,i}^* = \frac{\theta}{2\gamma + \kappa(1+n_u+n_L)}. \tag{A.70}$$

In Section 2.2.1 of our main paper, we derived the optimal production policy under output market competition to be:

$$Q_{Y,i}^* = \frac{\theta}{(n_u+n_L+1)\gamma + \kappa}. \tag{A.71}$$

Thus, the model version with input market competition is equivalent up to reparametrization to the model version with output market competition presented in our main paper. In particular, optimal utilization policies and the resulting values of assets-in-places and capacity adjustment options are identical and generate the same predictions about firms' choices and outcomes. Intuitively, the reason is that production costs and the demand slope both create quadratic costs and their effects on firms' profits are thus not separately identifiable. This model feature was already noted by Pindyck (1988).

Appendix B Additional Figures and Tables

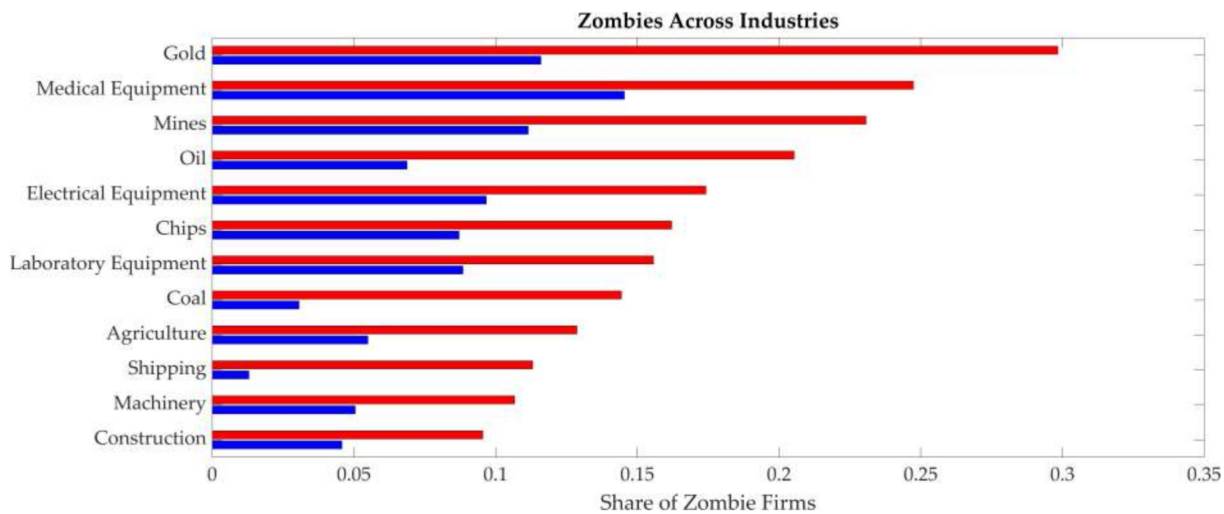

Figure B.1. This figure displays the sample industry average shares of standard (red bars) and credit-subsidized (blue bars) zombie firms across a selected set of the highest zombie firm share industries.

Table B.1. Variable Definitions

In this table, we offer variable definitions. While Panel A focuses on our Dealscan variables, Panel B and C consider our variables used to measure expected zombification and those used in our main public firm panel regressions, respectively. Conversely, Panels D and E look into our Your-Economy Time-Series (YTS) public firms variables and our Clarkson-Orbis shipping-firm variables, respectively.

Variable	**Definition**
Panel A: Dealscan Regression Variables	
Standard Zombie	Indicator variable equal to one if a firm's Z-score is below zero and its interest coverage is below one and else zero.
Credit-Subsidized Zombie	Indicator variable equal to one if *Standard Zombie* = 1 and the firm receives subsidized credit and else zero.
Spread	Natural logarithm of the all-drawn-in loan spread over LIBOR.
Collateral	Indicator variable equal to one if a loan is secured and else zero.
Single Lender	Indicator variable equal to one if the lender-commitment-share Herfindahl-Hirschman index is one (there is a single lender) and else zero.
Size	Natural logarithm of a firm's total assets.
Age	Number of years since the firm first appeared in Compustat.
Profitability	Ratio of a firm's operating income to total assets.
Tangibility	Ratio of a firm's net property, plant, and equipment to total assets.
Market-to-Book	Ratio of a firm's market equity value plus total assets minus book equity value to total assets.
Leverage	Ratio of the sum of a firm's short-term and long-term debt to total assets.
Rated	Indicator variable equal to one if a firm is rated and else zero.
Loan Size	Natural logarithm of the outstanding loan amount.
Loan Type	Indicator variable equal to one for term loans and zero for revolvers.
Loan Maturity	Natural logarithm of the number of months until the loan's maturity date.
Panel B: Variables Used to Predict Zombification	
VIX	CBOE volatility index (VIX).
EMV	Newspaper-based stock market volatility tracker (see Baker et al. (2019)).
EPU	Economic policy uncertainty index (see Baker et al. (2016)).
FIN	Common financial uncertainty (see Jurado et al. (2015)).
REAL	Common real uncertainty (see Jurado et al. (2015)).
MACRO	Common macroeconomic uncertainty (see Jurado et al. (2015)).
ARV	Industry-specific average realized stock return volatility (firm size-weighted).
AIV	Industry-specific average implied stock return volatility (firm size-weighted).
Small Firm	Indicator variable equal to one if a firm's sales are below 50 million dollars and else zero.
Young Firm	Indicator variable equal to one if a firm is listed for less than ten years and else zero.
GDP Growth	Annual national GDP growth over the past year.
Inflation	National inflation rate.
Labor Force	Natural logarithm of the national labor force.

Panel C: Compustat Panel Regression Variables	
Investment	Ratio of a firm's capital expenditures to one-year lagged assets.
Disinvestment	Ratio of a firm's sales of property, plant, and equipment to one-year lagged property, plant, and equipment.
Expected Zombificationst (PC1)	Zombification predicted through industry time-series regressions using the first principal component.
Expected Zombificationst (PC2)	Zombification predicted through industry time-series regressions using the first two principal components.
Expected Zombification^{su} (PC1)	Credit-subsidized zombification predicted through industry time-series regressions using the first principal component.
Expected Zombification^{su} (PC2)	Credit-subsidized zombification predicted through industry time-series regressions using the first two principal components.
Existing Zombification	Share of zombie firms in an industry at the end of year *t*.
Sales Growth	Ratio of a firm's sales to one-year lagged sales minus one.
Profit Growth	Annual change in operating profits (sales minus COGS) scaled by absolute lagged operating profits.
Asset Turnover	Ratio of a firm's sales to assets.
Future Stock Return	Forward-looking 48-month compounded, size-, book-to-market-, and momentum-adjusted (DGTW) firm stock return.
Patent Count	Count of patents issued to a firm in a year divided by one-year lagged assets.
Citation Count	Count of citations accruing to a firm's issued patents in a year divided by one-year lagged assets.
Patent Importance	Average log importance of a patent, averaged across all patents filed by a given firm in a given year. The importance is the ratio of a patent's similarity with future patents to its dissimilarity with previous patents as per Kelly et al. (2021), with patent similarity measured over a 5-year horizon. This measure is available for firms filing at least one patent in a given year.
Patent Breakthrough	Log count of patents filed in a given year that are in the top 10% of *Patent Importance* as defined above.
Cash Savings	Log of the ratio of a firm's cash to one-year lagged cash.
Inventory	Ratio of a firm's inventory to assets.
Total Payouts	Ratio of total dividends and repurchases to one-year lagged assets.
Debt Financing	Ratio of a firm's change in total debt to one-year lagged assets.
Equity Financing	Ratio of the sum of changes in preferred stock, cash, and minority interests net the change in retained earnings to one-year lagged assets.
Tobin's Q	Ratio of a firm's market equity value plus book assets value minus book equity value plus deferred taxes to book value of assets.
Size	Natural logarithm of a firm's total assets.
Cash Flow	Ratio of a firm's EBIT plus depreciation minus R&D expenses to one-year lagged assets.
Business Entries	Natural logarithm of the count of annual new business formation in a given state.
State GDP Growth	Annual state-level GDP growth.
State Labor Force	Natural logarithm of the state's labor force.
Regional Inflation	Annual regional inflation.

Panel D: YTS Panel Regression Variables	
Establishment Openings	Ratio of a firm's establishment openings to its start-of-year establishments (only establishments with at least 20 workers).
Establishment Closures	Ratio of a firm's establishment closures to its start-of-year establishments (only establishments with at least 20 workers).
Employment Growth	Indicator variable if employment growth is positive, and else zero.

Panel E: Clarkson-Orbis Shipping Panel Regression Variables	
Shipping Zombie	Indicator variable equal to one if a firm's interest coverage is below one and else zero.
AIV	Shipping-subsector-specific implied stock-return volatility (value-weighted).
Small	Indicator variable equal to one if a firm's sales are below 50 million dollars and else zero.
Age	Number of years since the firm is included in Orbis.
Forward Return	Quarterly return of the forward contract on a shipping-subsector-specific freight rate.
All Ship Investment	Number of all ship purchases scaled by start-of-year number of ships.
New Ship Investment	Number of new ship purchases scaled by start-of-year number of ships.
Used Ship Investment	Number of used ship purchases scaled by start-of-year number of ships.
All Ship Disinvestment	Number of all ship retirements scaled by start-of-year number of ships.
Ship Sales	Number of all ship sales scaled by start-of-year number of ships.
Ship Demolitions	Number of all ship demolitions scaled by start-of-year number of ships.
Expected Zombification^S	Zombification predicted through shipping-subsector-specific time-series regressions using the implied volatility variable.
Size	Natural logarithm of a firm's total assets.
Cash Flow^S	Ratio of the sum of a firm's EBIT and depreciation to one-year lagged assets.

Table B.2. Descriptive Statistics for Banks Lending to Zombie and Non-Zombie Firms

In this table, we report descriptive statistics for a selection of banking variables for bank-years associated with a positive commitment share of a loan (term loan or revolver in Dealscan) to a zombie firm (*Zombie Loans*, columns (1) and (2)) in that year and those with a positive commitment share of a loan to a non-zombie firm (*Non-Zombie Loans*, columns (3) and (4)) in that year. Panel A reports statistics where zombie firms are classified based on our *Standard Zombie* definition (firms with an Altman Z-score below zero and an interest coverage below one), while Panel B reports statistics where zombie firms are classified based on our *Credit-Subsidized Zombie* definition (additionally requiring that zombies receive subsidized credit). Data on the banking variables are derived from Bank Holding Companies' Call Reports. Exact variable definitions and data items follow Hirtle et al. (2020). *Log Assets* is the natural log of total assets, *Deposits-to-Liabilities* is the percentage ratio of deposits to total liabilities, *Equity-to-Loans* is the percentage ratio of total equity capital to total loans, *Loan Type HHI* is the HHI of credit card loans, residential real estate loans, commercial real estate loans, and commercial and industrial loans, *Non-Performing Loans (NPL)* is the percentage ratio of non-performing loans to total loans, *Loan Loss Reserve* is the percentage ratio of loan loss reserves to total loans, *Asset Growth* is the percentage year-over-year total asset growth, *Loan Growth* is the percentage year-over-year total loan growth, *ROA* is the annualized percentage ratio of net income to total assets, and *ROA Volatility* is the standard deviation of *ROA* over the next 8 quarters. The descriptive statistics include the total number of observations (N), the mean, the difference between means in columns (2) and (4), and the *t*-statistic of the difference. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombie Loans		*Non-Zombie Loans*			
	N	Mean	N	Mean	Difference	*t*-statistic
	(1)	(2)	(3)	(4)	(2)–(4)	(5)
Panel A: *Standard Zombie Loans*						
Log Assets	4,949	16.531	145,595	16.562	–0.031***	–17.77
Deposits-to-Liabilities	4,948	0.727	145,036	0.734	–0.007***	–7.65
Equity-to-Loans	4,949	0.168	145,595	0.174	–0.006***	–6.99
Loan Type HHI	1,250	0.308	61,147	0.295	0.013***	5.58
Non-Performing Loans (NPL)	4,011	0.018	107,149	0.019	–0.001***	–2.89
Loan Loss Reserve	4,949	0.019	145,595	0.018	0.001***	13.29
Asset Growth	4,920	0.080	145,066	0.082	–0.002	–1.49
Loan Growth	4,920	0.066	145,066	0.079	–0.013***	–7.29
ROA	4,949	0.010	145,595	0.010	0.000	–1.14
ROA Volatility	4,892	0.004	144,369	0.004	0.000***	10.79
Panel B: *Credit-Subsidized Zombie Loans*						
Log Assets	333	16.228	138,366	16.564	–0.336***	–60.91
Deposits-to-Liabilities	333	0.783	137,854	0.732	0.051***	14.58
Equity-to-Loans	333	0.165	138,366	0.177	–0.011***	–3.61
Loan Type HHI	64	0.329	60,184	0.296	0.033***	3.19
Non-Performing Loans (NPL)	267	0.015	104,653	0.019	–0.004***	–4.26
Loan Loss Reserve	333	0.019	138,366	0.017	0.001***	4.10
Asset Growth	333	0.125	137,834	0.081	0.044***	7.52
Loan Growth	333	0.124	137,834	0.078	0.046***	7.09
ROA	333	0.011	138,366	0.011	0.000	0.31
ROA Volatility	331	0.004	137,158	0.004	0.001***	8.30

Table B.3. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Alternative Uncertainty Measure

In this table, we report the results from panel regressions of public non-zombie firms' investment and disinvestment on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. While we use CAPEX scaled by lagged assets as the investment proxy in columns (1) and (3), we use the sale of property, plant, and equipment (PPE) scaled by lagged PPE as the disinvestment proxy in columns (2) and (4). To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first two principal components extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in columns (1) and (2) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (3) and (4) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimates of the principal components with their end-of-window values to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.406***	–0.029	–0.523***	–0.366***
	[–4.78]	[–0.29]	[–4.57]	[–2.61]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	32,322	23,725	28,236	20,325

Table B.4. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Conditional Logistic Regression Estimates

In this table, we report the results from panel regressions of public non-zombie firms' investment and disinvestment on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. While we use CAPEX scaled by lagged assets as the investment proxy in columns (1) and (3), we use the sale of property, plant, and equipment (PPE) scaled by lagged PPE as the disinvestment proxy in columns (2) and (4). To compute *Expected Zombification*, we separately run twelve-year rolling-window conditional logistic regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies and controls per industry. While the zombification variables in columns (1) and (2) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (3) and (4) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.023***	–0.011***	–0.017***	–0.007**
	[–10.08]	[–4.12]	[–6.48]	[–2.43]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.07	0.01
Observations	23,523	17,218	16,671	11,920

Table B.5. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Manufacturing Firms Sample

In this table, we report the results from panel regressions of public non-zombie firms' investment and disinvestment on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and time fixed effects. We restrict the sample to firms in the manufacturing, mining, and construction industries (SIC 1000—3999). While we use CAPEX scaled by lagged assets as the investment proxy in columns (1) and (3), we use the sale of property, plant, and equipment (PPE) scaled by lagged PPE as the disinvestment proxy in columns (2) and (4). To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. While the zombification variables in columns (1) and (2) choose as zombies those firms with an Altman Z-score below zero and an interest coverage below one (*Standard Zombie*), those in columns (3) and (4) additionally require that zombies receive subsidized credit (*Credit-Subsidized Zombie*). The controls include a firm's lagged zombie status, an indicator variable equal to one if one-year lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's one-year lagged age is below ten years and else zero (*Young Firm*), and one-year lagged GDP growth (*GDP Growth*). We use the 50 Hoberg and Phillips (2016) industry classification to define our industries. We next combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*. Our controls are a firm's one-year lagged assets (*Size*), its one-year lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year lagged assets (*Cash Flow*), its one-year lagged Tobin's Q (*Tobin's Q*), and macro variables consisting of *State GDP Growth*, *State Labor Force*, and *Regional Inflation* (coefficients omitted for brevity). Plain numbers are coefficient estimates, whereas those in square brackets are t-statistics computed from standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–1.286***	–0.488**	–1.576***	–1.011***
	[–7.58]	[–2.41]	[–6.94]	[–3.56]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Time FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.00	0.08	0.01
Observations	18,158	13,473	15,651	11,452