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

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Abstract

We show that firms become reluctant to invest and disinvest when uncertainty induces creditors to convert their distressed rivals 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 zombification prompts healthy firms to reduce (dis)investment, establishment-level hiring, openings, and closures (intensive and extensive margins are affected). Uncertainty-led rival zombification further depresses healthy firms' productivity and market valuations. Granular data on shipping companies' asset allocation show that investment irreversibility and time-to-build amplify these effects (new ship orders and demolitions are most affected). The results we report are distinct from general effects of uncertainty and amplified in more competitive industries. They reveal a "zombie–uncertainty multiplier" with implications for creative destruction: while fixed capital (dis)investment slows, innovation accelerates. Our findings highlight a novel channel through which uncertainty shapes industry capital accumulation, distorting firms' real policies and performance.

KEYWORDS: Uncertainty, zombie firms, investment, employment, innovation, competition
JEL CLASSIFICATION: G31, G32, D22, D25, E44

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1 Introduction

Large-scale shocks such as the Japanese real estate crash, the Global Financial Crisis, and the European sovereign debt crisis led banks to extend credit to insolvent firms, a phenomenon often referred to as "zombie lending" (Caballero et al. (2008), Acharya et al. (2022, 2024), and Chopra et al. (2021)).[1] Zombie lending may emerge when the heightened level of uncertainty that accompanies economic shocks makes it optimal for creditors to speculate on the recovery of defaulting borrowers (Bruche and Llobet (2014)). Prior work has shown that the presence of zombies distorts firms' incentives to invest (McGowan et al. (2018) and Acharya et al. (2021)). No existing study has modeled and empirically identified the dynamics connecting uncertainty, zombification, and the optimal real and financial decisions of firms competing 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. The realization of such expectations is uncertain as it is unclear: (1) if and when distressed firms will default; (2) whether creditors 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 make healthy 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 prior work (e.g., Caballero et al. (2008) and Acharya et al. (2021)), leading to different outcomes. This happens because all economic agents in our model — borrowers, creditors, and rival firms — are forward-looking. We test and confirm our model predictions using data from U.S. public firms as well as the near-universe of private and public firms from the global shipping industry.

We establish the microeconomic underpinnings for our results using a real options industry model 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. As in Bloom et al. (2018), demand shocks in this industry follow a two-state Markov-switching geometric Brownian motion 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 defaulting firms into zombie firms rather than liquidating them. This zombification motive arises as high uncertainty in recessions — often combined with government guarantees — creates an incentive to speculate on the recovery of the defaulting borrowers. It follows that the continued presence of zombie firms keeps

[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, e.g., Caballero et al. (2008)).

output prices low, hindering the creative destruction process — investment in new capital and disinvestment of old capital — necessary for the unlevered firms to recover.[2]

We use a dynamic, partial equilibrium framework that builds on Bloom (2009) to derive implications for forward-looking firms' and creditors' optimal decisions. A salient aspect of our theory is that unlevered firms rationally anticipate creditors' zombification incentives and preemptively adjust their costly-to-reverse decisions. The model reveals two mechanisms underlying this result. The first is that zombie firms depress output prices, rendering all existing capacity units less profitable ("first-moment effect"). The second is that there is uncertainty about when and how many zombies may 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 of reacquiring capacity when only relatively few rivals become zombies. Once the zombification uncertainty is resolved, a greater share of zombies induces unlevered firms to delay investing but to speed up disinvesting.

We evaluate our model predictions using a large dataset comprising firms' real decisions and long-run performance from multiple 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 that capture firms' investment, disinvestment, value, and performance, while controlling for other observed and unobserved drivers of those outcomes. In doing so, we first follow the literature (e.g., Caballero et al. (2008) and Acharya et al. (2022)) in identifying *existing zombie firms*. Using Dealscan loan contract-level data, we validate our zombie-firm definitions and show 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 their industries (see Faria-e-Castro et al. (2024)). We also show that zombie loans are extended by relatively smaller, poorly capitalized, and riskier banks. In addition, we show that zombie firms receive more favorable lending terms in periods of high uncertainty, precisely when our theory predicts that lenders have the strongest incentives to keep zombies alive.

We next estimate the expectation of *uncertainty-led distressed-rival zombification* in an industry. We do so using industry-specific rolling-window forecasting regressions of zombie-firm indicators on lagged uncertainty proxies, multiple control variables (including interest rates and 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 financial, political, and real uncertainty proxies predict zombification, we select our baseline uncertainty metric as the first principal component of eight common measures

[2]We model zombie-led "congestion" in output prices for simplicity. In an appendix to the paper, we alternatively model congestion in the competition for input factors (e.g., capital or labor).

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 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).[3] The key innovation of our approach is that it captures the combination of states of elevated uncertainty *and* industry-years where banks' incentives to zombify distressed rivals are particularly high.[4]

Our main empirical tests examine the real capacity investment and employment decisions of healthy (i.e., non-zombie) firms. We show that those firms curb their investment in 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 the threat of zombification. The documented effects are economically significant. A one-standard-deviation increase in the estimated threat of zombification is associated with a one percentage point lower establishment opening rate, about 7% of the mean rate (15%). As a greater threat of zombification — in contrast to other forms of uncertainty — implies only negative news, we also find that healthy firms suffer losses in their input productivity and market valuations as the zombification threat materializes, while experiencing increases in their capacity overhang (i.e., the extent to which their installed capacity exceeds optimal levels).

We dig 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 firms require an assumption that 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 firm-years with low rival product differentiation (higher similarity). Furthermore, we find that firms accelerate breakthrough innovation as expected uncertainty-led rival zombification rises, reflected in greater future product differentiation and consistent with a motive to reduce demand elasticity. These findings are new and useful in helping us disambiguate our proposed mechanism from the general impact of uncertainty on investment. Our tests address the concern that the negative spillover effects of zombie firms may be attributed to negative first-moment shocks to the firm performance distribution (Schivardi et al. (2020)) by exploiting instrumental variables that capture quasi-exogenous variation in uncertainty (cf. Alfaro et al. (2024)). Finally, 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

[3]The appendix provides an exhaustive set of robustness tests combining alternative measures of uncertainty as well as zombie firm identifiers.

[4]We verify this fact in appendix tests relating our measure to various bank characteristics, which show a clear link to risky and undercapitalized banks. These tests are useful in establishing the validity of our measure.

into the effect of uncertainty-led zombification 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 testing our theoretical predictions, given the extent to which it is prone to zombification. In addition, shipping firms can be characterized as competing on output in segmented vessel-size-based and route-based markets, which aligns with our model structure (Stopford (2009)). Our data on the stock of vessels (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 unique insight into how firms adjust their asset base in response to uncertainty-induced zombification. We find that estimated effects are of greater economic significance in this setting. Moreover, investment 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. Our results show that zombification threats disproportionately impact firms' costlier-to-reverse decisions.

Our paper adds to the literature on the spillover effects of zombie firms on the economy. Peek and Rosengren (2005) and Caballero et al. (2008) show that zombie firms prompted healthy firms to curb investment into capital and labor in Japan during the "lost decade" (the 1990s), a finding that has been confirmed in other contexts (e.g., McGowan et al. (2018) and Acharya et al. (2019)). Closer to our study, Acharya et al. (2021) report that output prices drop and input costs rise after the emergence of zombies, reducing the profits of industry rivals. Relative to these papers, our study establishes a distinct, independent channel by which forward-looking healthy firms not only react to existing zombies but also — and more pronouncedly — to the *threat of uncertainty-led zombification* in their industries by cutting on various margins of their capital accumulation and capacity utilization decisions.

We also contribute to the literature on how uncertainty shapes corporate decisions and aggregate 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 Bloom (2009), Kellogg (2014), and Kumar et al. (2023), show that high uncertainty depresses corporate investment and that these effects are amplified by the costs of irreversibility (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 to the impact of overall uncertainty on economic activity.

2 Theoretical Framework

We lay out a real options model in which heightened uncertainty incentivizes creditors to keep defaulting 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' incentives, inducing them to delay costly-to-reverse decisions, negatively affecting their future performance. We offer technical derivations and closed-form solutions 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, playing a Cournot-style game (Brander and Lewis (1986)).[5] Rival firms thus 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.[6]

We assume that a proportion of firms are highly financially levered and at risk of defaulting, potentially being turned into zombies. We denote the mass of those firms by n_L. The remaining 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 $n_U = n - n_L$.[7] Highly levered firms may exist because adverse idiosyncratic shocks forced them to raise debt in the past to continue operating.[8]

[5]We use this setup for tractability and to isolate the industry-congestion channel. To wit, the "mass n" of firms can be interpreted as a large-but-finite number of symmetric competitors, with the integral notation serving as a convenient approximation. This structure is standard in real-options models featuring strategic firm interactions and is in line with, for example, Aguerrevere (2003, 2009) and Aretz and Pope (2018).

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

[7]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 decisions of new firms mirror 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)).

[8]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.

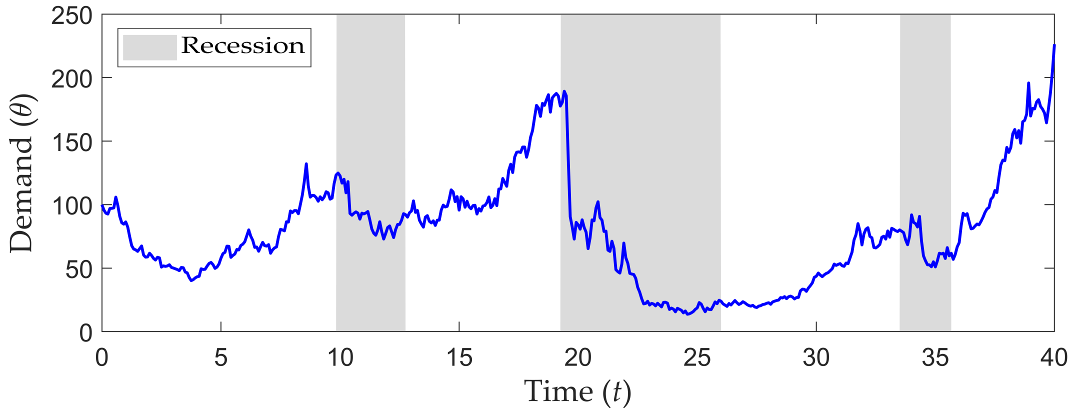

Figure 1. The figure plots a realization for the demand shift θ. The parameters are: $\alpha_H = 0.08$, $\alpha_L = -0.04$, $\sigma_H = 0.20$, $\sigma_L = 0.40$, $p_H = 0.30$, and $p_L = 0.10$. The gray shaded areas are recession states.

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 the shift in 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 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 Appendix Figure B.1 and Bloom et al. (2018) in assuming that the drift rate and volatility are negatively correlated; $\alpha_H > \alpha_L$ 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 a transition probability matrix, characterized by the constant parameters p_H and p_L 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 1 plots a sample path from the stochastic process in equation (1). Similar to us, Guo et al. (2005), Bloom (2009), Bhamra et al. (2010), 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 shift θ, the stochastic price at which each of the firms sells output dynamically is determined by the downward-sloping demand curve:

$$P = \theta - \gamma \left(\int_{u=0}^{n_U} Q_{U,u}\, du + \int_{v=0}^{n_L} Q_{L,v}\, dv \right), \tag{2}$$

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 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 in the industry may default when their operating profits drop below the coupon payment.

Upon default, creditors can either roll over the debt or liquidate the defaulting firms.[9] 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. This renegotiation structure implies a single default episode in the model: once a levered firm hits the default boundary, it either exits immediately or remains in the payment-in-kind state until recovery to c^* (see Appendix A.2), and we abstract from subsequent re-default dynamics for tractability.

When providing loans, creditors may rely on government guarantees for subsidized debt as in Acharya et al. (2021).[10] As a result, creditors know that renegotiated payments can never drop below $b < c$ since if they do, creditors are bailed out. 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. We illustrate the payoff to creditors in Figure 2. If there are no government guarantees for loans ($b = 0$), as in Panel A, creditors receive a cash flow of up to the renegotiated coupon, c^*, every period. Overall, the creditors' position is similar to a continuous flow of debt as in Merton's (1974) structural credit model. The concavity of the payoff makes creditors averse to uncertainty. Turning to an economy with a minimum loan guarantee ($b > 0$), as in Panel B, creditors are now assured of receiving at least a cash flow of b every period. The payoff function now indicates a convex region (low Π) where creditors

[9] 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 is high. We provide evidence of this in Appendix Table B.6, in which we show that (if anything) such firms significantly *reduce* their mergers and acquisitions activity.

[10] Acharya et al. (2021) list such guarantees in the U.S., such as the Depository Institutions Deregulation and Monetary Control Act, the Transaction Account Guarantee Program, the Debt Guarantee Program, and the Bank Term Funding Program, all of which provide debt guarantees to banks. Similar schemes exist in many other countries. Recent episodes, such as the 2023 resolution of Silicon Valley Bank, illustrate that extraordinary backstops can extend to institutions outside the set of globally systemically important banks.

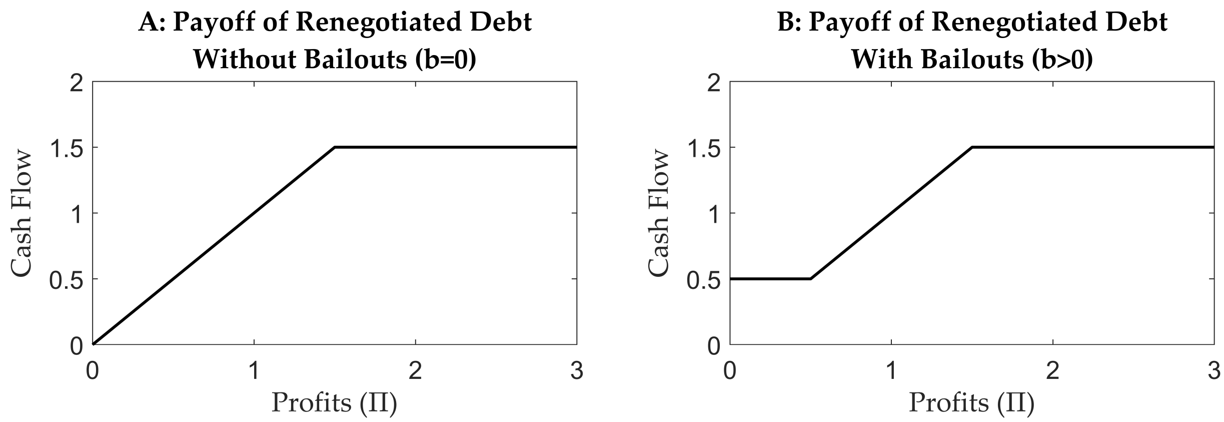

Figure 2. The figure plots the per-period cash flow to creditors upon rolling over their defaulting borrowers' debt as a function of the borrowers' profits, Π. Panel A assumes the absence of loan guarantees ($b = 0$), while Panel B shows the effect of an exemplary minimum loan guarantee ($b > 0$).

behave like equity holders and a concave region (high Π) where creditors dislike uncertainty. In the language of financial options, government bailouts turn the short put option of creditors in Panel A into a bull call spread in Panel B.

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 firms' assets ensures that creditors convert only a fraction of defaulting firms into zombies.[11]

2.2 Optimal Policies and 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:

$$\Pi_{Y,i} = PQ_{Y,i} - \frac{1}{2}\kappa Q^2_{Y,i}, \tag{3}$$

where $Y \in \{U, L\}$, P is given by equation (2), 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

[11]The idiosyncratic liquidation value, L_X, is intended to capture within-industry dispersion in liquidation frictions such as collateral quality and asset specificity across defaulting firms. This dispersion ensures that, conditional on the same aggregate state X, rollover is not an edge-case outcome. Instead, creditors optimally convert some distressed firms into zombies and liquidate others, delivering an interior zombification share, $\psi(X)$.

output amounts dynamically to maximize profits, so we have the first-order condition:

$$\theta-\gamma\left(\int_{u=0}^{n_U} Q_{U,u}\,du+\int_{v=0}^{n_L} Q_{L,v}\,dv\right)-\gamma Q_{Y,i}-\kappa Q_{Y,i}=0, \tag{4}$$

where the sum of the integrals 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 (4) 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 — turn the firm into a zombie — whenever the value of the rolled-over debt exceeds the firm's liquidation value; else they liquidate the firm. Relying on the value for the demand shift 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:*

$$\mathscr{C}(\theta,X)=\mathfrak{C}(\theta,X;c^*)+\frac{b}{r}-\mathfrak{C}(\theta,X;b), \tag{5}$$

where for a general constant $a>0$:

$$\mathfrak{C}(Z,X;a)=c_{1,X}Z^{\beta_1}+c_{2,X}Z^{\beta_2}+c_{0,X}Z^2, \tag{6}$$

$c_{0,X}$ 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 (5) 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. We explore the expected duration of zombification in Appendix A.2.

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:

$$W = V(\theta, X) + F(\theta, X) + D(\theta, X), \tag{7}$$

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 (see, e.g., Hackbarth and Johnson (2015)). We first compute $V(\theta, X)$, 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.[12] Given that, the firm switches on the unit if demand shift θ exceeds $\theta^P = \theta_Z^P(K) = ((n_U + 1)\gamma + \kappa)K + n_L\gamma \min\{\bar{K}_L, K\}$. 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.[13] Given that, the firm now switches on the unit if θ exceeds $\theta^P = \theta^P(K) = ((n_U+1)\gamma+\kappa)K + \psi(X)n_L\gamma \min\{\bar{K}_L, K\}$. Proposition 2 gives the value of the incremental capacity unit able to produce the K^{th} output increment

[12] 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.

[13] 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), see Appendix A.4.

conditional on creditors' optimal liquidation strategy and before the levered firms default on their debt repayments.

Proposition 2. *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:*

$$\Delta V(\theta,X;K) = \Delta\mathcal{V}(\theta,X;\theta_Z^P) + \left(\Delta\mathcal{V}(Z,X;\theta^P) - \Delta\mathcal{V}(Z,X;\theta_Z^P)\right)\left(q_{3,X}\theta^{\beta_3} + q_{4,X}\theta^{\beta_4}\right), \tag{8}$$

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

$$\Delta\mathcal{V}(\theta,X;\theta_Z^P) = \begin{cases} b_{1,X}\theta^{\beta_1} + b_{2,X}\theta^{\beta_2} & \text{if } \theta \le \theta_Z^P, \\ b_{3,X}\theta^{\beta_3} + b_{4,X}\theta^{\beta_4} + b_{0,X}\theta - \frac{\theta_Z^P}{r} & \text{if } \theta \ge \theta_Z^P, \end{cases} \tag{9}$$

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 Appendices A.3 and A.5. □

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 industry. 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 (9) 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 (8) 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) θ_Z^P before the levered firms' exit but (the lower) θ^P afterwards. Thus, the $\Delta\mathcal{V}(Z,X;\theta^P) - \Delta\mathcal{V}(Z,X;\theta_Z^P)$ 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:

$$V(\theta,X) = \int_0^{\bar{K}} \Delta V(\theta,X;K)\,dK. \tag{10}$$

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 3 then gives the values of those options.

Proposition 3. *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:*

$$\Delta F(\theta, X; K) = \begin{cases} a_{1,X}\theta^{\beta_1} + a_{2,X}\theta^{\beta_2} & \text{if } \theta \leq \theta_X^*, \\ \Delta V(\theta, X; K) + \Delta D(\theta, X; K) - I & \text{if } \theta \geq \theta_X^*, \end{cases} \tag{11}$$

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:

$$\Delta D(\theta, X; K) = \begin{cases} \Delta F(\theta, X; K) - \Delta V(\theta, X; K) + d & \text{if } \theta \leq \theta_X', \\ d_{3,X}\theta^{\beta_3} + d_{4,X}\theta^{\beta_4} & \text{if } \theta \geq \theta_X', \end{cases} \tag{12}$$

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 (11) 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 (12) 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:

$$F(\theta, X) = \int_{\bar{K}}^{\infty} \Delta F(\theta, X; K) dK \quad \text{and} \quad D(\theta, X) = \int_{0}^{\bar{K}} \Delta D(\theta, X; K) dK. \tag{13}$$

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 perfor-

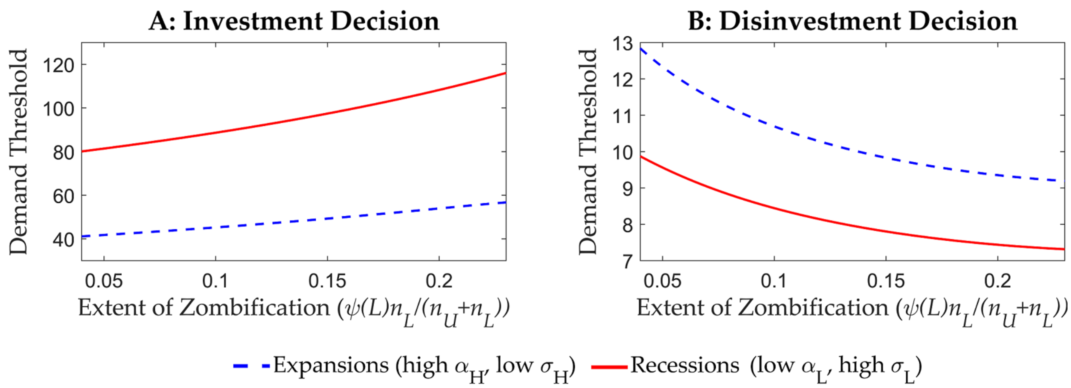

Figure 3. The figure plots the investment (Panel A) and disinvestment (Panel B) triggering demand thresholds for the capacity unit able to produce the $K = 10$ output increment against the proportion of expected rival zombie firms in an industry $\left(\frac{\psi(L)n_L}{n_U+n_L}\right)$. Dashed blue (solid red) lines show those thresholds in the expansion (recession) state. Base-case parameters are described in Section 2.3.

mance of unlevered firms in a (potentially) zombified industry. We also contrast the impact of expected rival zombification with that of existing zombification using simulations of our model.[14]

Throughout this section, we use the demand path and parameter values in Figure 1 ($\alpha_H = 0.08$, $\alpha_L = -0.04$, $\sigma_H = 0.20$, $\sigma_L = 0.40$, $p_H = 0.30$, 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 2.5, respectively. The bailout threshold (b) is 0.5. 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(8) and 6.00 in the recession state, all respectively. While we adopt a baseline parameterization here for illustration, the qualitative comparative statics emphasized below hold across a broad set of economically plausible parameter values.

2.3.1 Rival Zombification and Capacity Choices

Figure 3 shows how the threat of rival zombification conditions the decision of an arbitrary unlevered firm to invest in (Panel A) or disinvest (Panel 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

[14] We intentionally abstract from general equilibrium (GE) effects to retain a tractable model with a closed-form solution; these properties would be lost in a full GE setting and replaced by computationally intensive and opaque numerical analysis. Intuitively, heightened economic uncertainty leaves firms inactive and unresponsive to short-term changes in prices and interest rates, implying that incorporating GE feedback would likely alter the quantitative results little while greatly complicating the analysis (see also Bloom (2009)).

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 shifts have 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 shifts have 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").[15] 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"). The uncertainty about the potential exit of levered firms magnifies the standard uncertainty effect as a larger proportion of the industry might zombify upon default ("*zombie–uncertainty multiplier*"). For a low threat of zombification, the gap between the investment thresholds in the high and low uncertainty state is 80 – 40 = 40 which increases by 50% (to 60) for an industry with a high zombification threat.

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 (Panel A). More interestingly, while the first-moment effect induces unlevered firms to accelerate 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 as fewer future zombie firms than expected materialize.[16]

We offer further supportive evidence for this argument in Figure 4. We do so by plotting the capacity choices of one out of $n_U = 30$ unlevered firms whose demand shifts evolves as in Figure 1 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

[15]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 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.

[16]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.

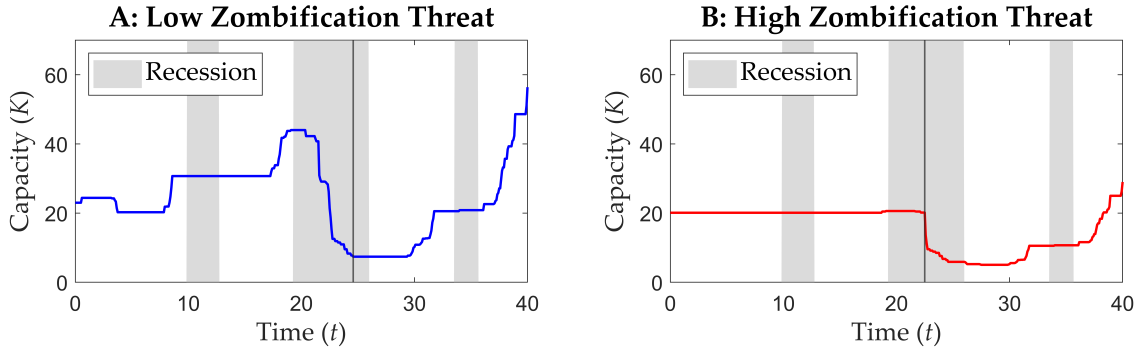

Figure 4. The figure plots the capacity choices of unlevered firms whose demand evolves according to Figure 1 and compete with $n_L = 5$ (Panel A) and $n_L = 60$ (Panel B) levered firms. Vertical lines indicate zombification events. Gray shaded areas are recession. Base-case parameters are described in Section 2.3.

rival zombification. Importantly, expected rival zombification ($t < 25$) leads to more inactivity than 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)).

2.3.2 Rival Zombification and Firm Performance

Figure 5 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 shifts evolve according to Figure 1. 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. Specifically, unlevered firms earn lower sales revenue, are less profitable, utilize less capital, and have lower market values in the presence of a high threat of rival zombification. 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 5 highlights the modulating role of market power as the key channel through which rival zombification exerts its adverse effects 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 depict 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 more pronounced when market power is low (and

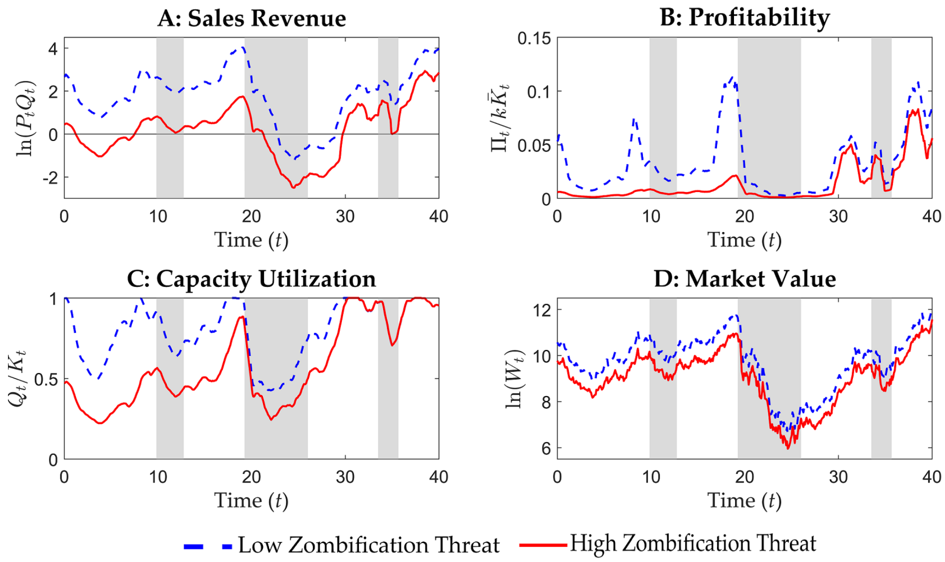

Figure 5. The figure plots the sales (Panel A), profitability (Panel B), capacity utilization (Panel C), and market value (Panel D) of an unlevered firm if demand shifts evolve according to Figure 1. The solid red (dashed blue) lines show performance outcomes for a firm operating in an economy with a 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.

demand is more elastic) compared to when market power is high. The market power economic channel also implies 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 innovation.

3 Measuring Expected Rival Zombification

In this section, we describe our data sources and empirical methodology. Our analysis proceeds in three parts. First, we outline our approach to identifying zombie firms and present loan-level results that support 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, control variables, and fixed effects.

3.1 Data Sources

We retrieve stock data from CRSP, financial statements data from Compustat, capital structure data from Capital IQ, and shipping-firm data from Clarksons and Orbis (details to follow). We obtain aggregate uncertainty indices 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) and T-Bill rates from the Federal Reserve Economic Data (FRED). 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). Following Altman et al. (2024), we exclude firms in the financial (SIC 6000–6799) and public administration (SIC 9100–9999) sectors. We winsorize all firm-level (but not aggregate) variables at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. Our overall sample period runs from 1990 through 2020. The starting point corresponds to the first year in which all eight of our uncertainty measures (detailed below) are jointly available on a consistent basis. It ends in 2020 to avoid capturing the unique and transient pandemic dynamics in corporate survival and credit allocation, shaped at least in part by the extraordinary fiscal and monetary support rendered during this period (see, e.g., Benmelech and Tzur-Ilan (2020) and Albuquerque and Iyer (2024)).

Appendix Table B.1 offers descriptive statistics for our main variables. They include investment and disinvestment rates, existing and expected rival zombification rates, firm outcomes and controls (Panel A), establishment and employment variables (Panel B), and asset allocation and zombification measures specific to the global shipping industry (Panel C). We define variables in the following sections and provide details in Appendix Table B.2. The statistics align with those reported elsewhere (e.g., Kim and Kung (2017) and Campello et al. (2024)).

3.2 Modeling Expected Rival Zombification

3.2.1 Identifying 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 it can be applied to virtually all public firms and that it may capture forms of rival zombification not explicitly arising from the provision of subsidized credit. The interest coverage ratio condition also neatly maps to the notion of default in our model.

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 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 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.

3.2.2 Validating Zombie Firm Classification with Loan-Level Data

We use Dealscan loan-level data to verify that the firms we classify as zombies are 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:

$$\begin{aligned} LoanTerm_{i,j,k,t} \quad = \quad & \beta\, Zombie_{i,j,t} + \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,t} + \\ & \boldsymbol{\delta}'\mathbf{LoanControls}_{i,j,k,t} + \sum_j \alpha_j + \sum_t \alpha_t + \varepsilon_{i,j,k,t}, \end{aligned} \tag{14}$$

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-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.[17] 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.2.

Table 1 presents the results from estimating equation (14), 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

[17] We are unable to include firm fixed effects in this specification owing to insufficient time-variation in a firm's zombie status within the sample of syndicated loan originations.

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 suggests that our credit-subsidized zombie classification scheme identifies firms that are indeed more likely to be receiving credit subsidies.[18]

TABLE 1 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 with 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 increases with greater uncertainty. In doing so, we aim to validate a central tenet of our model, which posits 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$^{\text{th}}$ percentile else zero, *Moderate*, which takes the value of one when VIX lies between the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile else zero, and *High*, which takes the value of one when VIX lies above the 90$^{\text{th}}$ percentile else zero. We then estimate a modified version of equation (14) 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 1. 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.

We compactly depict the coefficient estimates for the interaction terms (and respective confidence intervals) for both our zombie classification schemes in Figure 6. Panel A shows that the coefficients follow a monotonic decreasing pattern as uncertainty increases. Notably, both

[18]To ensure that our zombie firm definitions do not inadvertently identify growth firms, in Appendix Table B.7 we explore the robustness of our baseline results to adding further restrictions on zombie firms' sales growth (required to be negative) and Tobin's Q (required to be below the industry median). Following Banerjee and Hofmann (2022), we additionally impose a restriction that requires a firm to report an ICR below one for two consecutive years, ensuring that we are not classifying firms that experience transient shocks as zombies. Our results are, therefoere, robust to numerous overlapping and correlated zombie firm identification criteria (see also Acharya et al. (2022)).

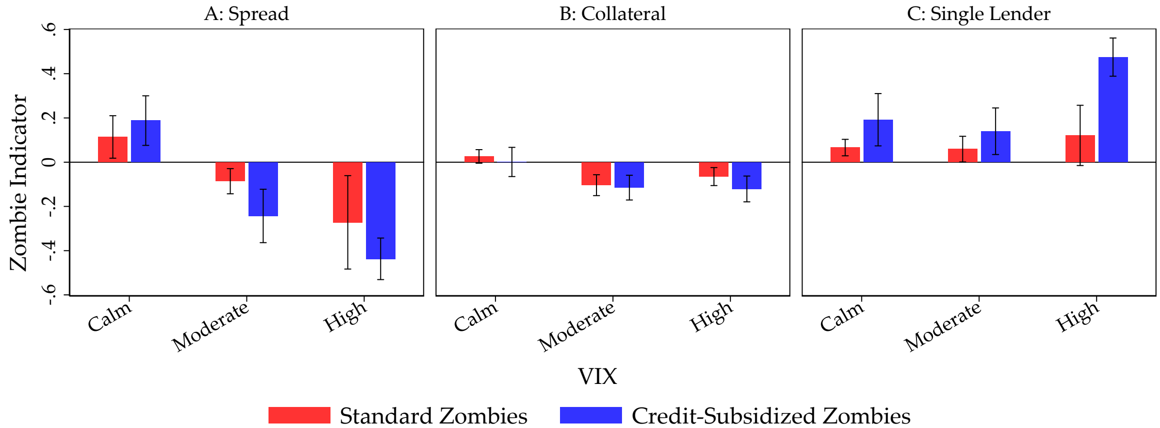

Figure 6. The figure plots the coefficient estimates obtained from a modified version of equation (14) in which various loan terms are regressed on the interaction between an indicator variable for standard (red bars, *Standard Zombie*) and credit-subsidized (blue bars, *Credit-Subsidized Zombie*) zombie 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 equation (14). The error bars indicate 90% confidence intervals. The dependent variables are *Spread* (Panel A), *Collateral* (Panel B), and *Single Lender* (Panel C).

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. Panel C shows 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 6 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.[19]

Finally, we compare the characteristics of banks extending zombie loans with those extending loans to healthy (non-zombie) firms 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.3. Our evidence suggests that banks extending loans to zombie firms are 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 ex-

[19]While we focus these tests on syndicated loans given data availability constraints, we acknowledge that, in absolute terms, zombie lending is unlikely to be widespread in this sample. Nevertheless, our key relative *comparative static* on the relationship between uncertainty and lenders' incentives to engage in zombie lending continues to obtain in this sample, rendering this analysis informative on our conjectured theoretical channel.

perience lower non-performing loans and provision for higher loan losses associated with the credit subsidies they likely provide to their distressed borrowers. These results provide support 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 theory is that healthy firms rationally react to the *expectation* of uncertainty-led 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 panel forecasting regression:

$$\begin{aligned} Zombie_{i,j,t} \quad = \quad & \beta\, Uncertainty_{t-1} + \boldsymbol{\gamma}' \mathbf{MacroControls}_{t-1} \\ & + \zeta\, Zombie_{i,j,t-1} + \boldsymbol{\delta}' \mathbf{FirmControls}_{i,j,t-1} + \sum_i \alpha_i + \varepsilon_{i,j,t} \end{aligned} \tag{15}$$

where $Zombie \in \{$*Standard Zombie*, *Credit-Subsidized Zombie*$\}$, *Uncertainty* is a three-month-lagged (based on each firm's fiscal year-end) uncertainty proxy, **MacroControls** = [*GDP Growth*, *Labor Force*, *Inflation*, *Interest Rate*]′ is a vector of one-year-lagged macro controls, **FirmControls** = [*Small Firm*, *Young 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 or parameter vectors. We include *Interest Rate* as a parsimonious proxy for economy-wide credit market conditions (and the stance of monetary policy) that jointly shift lenders' and firms' financing environment. Notably, our forecasting regressions control for a firm's lagged zombie status. This is important 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 (15) via standard OLS is subject to potential bias 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 this bias, 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 time-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 (2026) 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 industry-specific assets-weighted averages of realized stock volatility (*ARV*) and implied stock volatility (*AIV*). See Appendix Table B.2 for more details about those and other variables and Cascaldi-Garcia et al. (2023) for a survey on uncertainty measures.

Table 2 displays the results from estimating equation (15) separately using each uncertainty proxy over all industries 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 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. Notably, 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, suggesting that uncertainty proxies contain incremental predictive information beyond knowing whether a firm is currently a zombie. For example, the slope coefficient of newspaper-based stock market volatility, *EMV*, is 0.224 (t-statistic: 9.67) 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 over one percentage point. Given that the average share of standard zombie firms is about 8%, this rise is economically meaningful. The table further suggests that financial uncertainty (*VIX*, *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 2 ABOUT HERE.

The results in Table 2 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. As in Alfaro et al. (2024), while some proxies we use are backward-looking by construction, they are commonly interpreted as informative signals about expected uncertainty, which is the object that enters our expectation-formation exercise.

Appendix Table B.5 reports the results from the principal component analysis. Panel A shows the 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* shows variation across financial and non-financial proxies, with *EPU*, *REAL*, and *MACRO* loading positively on that component and the remaining financial uncertainty metrics loading negatively. Panel B suggests that while *PC1* alone explains about 65% of the variation in our eight uncertainty proxies, *PC2* to *PC4* in combination explain about 82% to 95%.

We estimate the time-varying threat of uncertainty-induced zombification in each industry using the principal components derived in the preceding section. 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 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 equation (15)) separately in each of the 50 Hoberg and Phillips (2016) industries (j) over twelve-year rolling windows ($\tau \in \{t-11, t\}$):

$$\begin{aligned} Zombie_{i,j,t} \quad = \quad & \beta_{j,\tau} Uncertainty_{t-1} + \gamma_{j,\tau} MacroControl_{t-1} \\ & + \zeta_{j,\tau} Zombie_{i,j,t-1} + \boldsymbol{\delta}'_{j,\tau} \mathbf{FirmControls}_{i,j,t-1} + \sum_i \alpha_i + \varepsilon_{i,j,t}. \end{aligned} \tag{16}$$

There are two critical differences between the above equation (16) and the previous equation (15). Since equation (16) 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.[20] Correspondingly, we also include the one-year-lagged first principal component of the macroeconomic controls included in equation (15), namely *GDP Growth*, *Labor Force*, *Inflation*, and *Interest Rate*, to capture the macro determinants of zombie firm emergence parsimoniously. As before, we estimate the regressions separately for our two zombie firm definitions, *Zombie* $\in$ {*Standard Zombie*, *Credit-Subsidized Zombie*}. Likewise, we continue to apply the "recursive demeaning" method of Hjalmarsson (2006) in order to mitigate the potential bias induced by the simultaneous presence of firm fixed effects and lagged, persistent regressors.

[20] 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.8 shows that our main results are robust to using both *PC1* and *PC2*.

It is essential to verify that our estimated zombie–uncertainty forecasting sensitivities accurately reflect banks' zombification incentives under heightened uncertainty. We do so by comparing the banks that lend to firms in industry-years with high $\hat{\beta}_{j,\tau}$ (top quartile of the annual distribution) with those lending to firms in low-$\hat{\beta}_{j,\tau}$ industry-years (bottom quartile). The comparisons are reported in Appendix Table B.4. Across the board, the same bank characteristics associated with zombie loans (see Appendix Table B.3) are also associated with banks lending to firms in high-$\hat{\beta}_{j,\tau}$ industries. In other words, higher zombie–uncertainty forecasting sensitivities are observed in industry-years characterized by lending from smaller, less-capitalized, and riskier banks. Those banks continue to have fewer non-performing loans, larger loan loss reserves, and experience more rapid loan growth. As such, the zombie–uncertainty forecasting sensitivity estimates align closely with periods where banks, as predicted by our theory, have stronger incentives to speculate on borrowers' recovery amid heightened uncertainty. These comparisons are reassuring, as they suggest that the estimated sensitivities capture dynamic, cross-industry variation in banks' "zombification" incentives.

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 equation (16) as follows:

$$\textit{Expected Zombification}_{j,t+1} = \text{sigmoid}\left(\hat{\beta}_{j,\tau} \times \textit{Uncertainty}_t\right), \tag{17}$$

where sigmoid$(\cdot)$ is the standard logistic function.[21] In words, equation (17) 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 (an important, theoretically motivated macro state variable on which firms anchor their expectations). They constitute the core variables of interest in our empirical analysis going forward.[22]

[21]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 equation (16) are bounded between 0 and 1. However, this choice comes at the cost of reducing the apparent variation in the resulting variable by compressing its empirical distribution. We address this modeling tradeoff in two ways. First, in Appendix Table B.9, we verify that our results are robust to estimating equation (16) using non-linear discrete choice models such as conditional logistic regression. We opt to use a linear model for equation (16) in our main analysis as this allows us to easily include firm fixed effects in the specification. Second, we verify that our statistical and economic inferences are not affected by the logistic transformation by re-estimating our baseline specifications with a non-standardized version of the *Expected Zombification* variable in Appendix Table B.10.

[22]Since *Expected Zombification* is a generated regressor, we verify that our inferences continue to hold when standard errors are estimated using a cluster bootstrapping procedure (see Section 4.5 and Appendix Table B.11).

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 assess the out-of-sample predictive ability of our forecasting model in Appendix Figure B.2. 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 Performance Outcomes

Our main empirical tests 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:

$$\begin{aligned} RealDecision_{i,j,s,t} &= \beta\, Expected\ Zombification_{j,t-1} + \delta\, Industry\ Uncertainty_{j,t-1} \\ &+ \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,s,t-1} + \boldsymbol{\lambda}'\mathbf{MacroControls}_{s,t-1} + \sum_i \alpha_i + \sum_j \sum_t \alpha_j \times \alpha_t + \varepsilon_{i,j,s,t} \end{aligned} \tag{18}$$

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), *Industry Uncertainty* is the one-year-lagged, annual industry-level average firm size-weighted implied volatility (*AIV*, discussed 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, Interest Rate*]′ is a vector of one-year-lagged macro controls including state s's annual GDP growth, log labor force, and regional inflation rate, and the 3-month T-Bill rate, α_i, α_j, and α_t are firm, industry, and time-trend fixed effects, and β, δ, $\boldsymbol{\gamma}$, and $\boldsymbol{\lambda}$ are parameters or parameter vectors.[23] We rely on Hoberg and Phillips's (2016) 50 product market classi-

[23] Our specifications account for time-varying trends in two ways. First, we include annual industry, state, and regional macro indicators, as well as national interest rates, to control for observable industry and macro trends that may affect our outcome variables. Second, we include dynamic industry-by-trend fixed effects to capture unobserved within-industry trends. The trend component uses three-year windows to avoid subsuming the annual industry and macro controls. These fixed effects are intended to account for factors, such as the effects of *realized* zombification, that may accumulate over time within an industry.

fication to define industries.[24] These and all subsequent specifications are estimated beginning in 2002, owing to the 12-year rolling window burn-in period as described in the construction of *Expected Zombification* in Section 3.2.3. See Appendix Table B.2 for all exact variable definitions.

We use the following real-decision variables as outcomes in equation (18). Our analysis looks into non-zombie firms' real investment, as measured using their capital expenditures over year t scaled by total 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 YTS analysis considers the firms' 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 the two-year-ahead change in their number of workers scaled by start-of-year sales (*Employment Growth*). Finally, our analysis of global public and private shipping firms 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 on the performance of healthy firms:

$$\begin{aligned} RealOutcome_{i,j,s,t} &= \beta\, Expected\ Zombification_{j,t-1} + \delta\, Industry\ Uncertainty_{j,t-1} \\ &+ \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,s,t-1} + \boldsymbol{\lambda}'\mathbf{MacroControls}_{s,t-1} + \sum_i \alpha_i + \sum_j \sum_t \alpha_j \times \alpha_t + \varepsilon_{i,j,s,t} \end{aligned} \tag{19}$$

where $RealOutcome \in$ {*Marginal Product of Capital, Total Factor Productivity, Capacity Overhang, Tobin's Q*}, and other variables, parameters, and parameter vectors are defined as in equation (18). *Marginal Product of Capital* (or *MPK*) is the log of the ratio of firm i's sales to its property, plant, and equipment over year t; *Total Factor Productivity* (or *TFP*) is firm i's log total factor productivity over year t estimated as per Ai et al. (2022); *Capacity Overhang* is firm i's percentage capacity overhang (or extent to which installed capacity deviates from optimal capacity) in year t estimated from a stochastic frontier model following Aretz and Pope (2018); and *Tobin's Q* is the ratio of firm i's market equity value plus book assets value minus book equity value plus deferred taxes to its book value of assets over year t.

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

We empirically study how firms respond to expectations of uncertainty-led rival zombification in their industries. We first do so using firm-level data from Compustat. We then turn to YTS data to explore establishment-level openings and closings, as well as employment decisions.

[24]Our results also hold for the 100-industry version of Hoberg and Phillips (2016) (see Appendix Table B.12).

4.1 Investment

In Table 3, we present the results from estimating equation (18) 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 3 ABOUT HERE.

The results suggest that the expectation of uncertainty-led rival zombification in an industry prompts healthy firms to cut their investment, consistent with our model prediction. In particular, the slope coefficient on *Expected Zombification* is negative and highly statistically significant across both relevant columns (t-statistics of –7.50 and –3.79). Importantly, our specification directly controls for industry-level uncertainty via the inclusion of *Industry Uncertainty* (or the lagged, firm size-weighted average implied volatility in each industry). The presence of this control variable implies that the *Expected Zombification* coefficient is not merely capturing the well-documented direct firm response to economic uncertainty. Rather, the marginal effect of *Expected Zombification* reflects healthy firms reacting to the interactive combination of heightened uncertainty *and* the heightened propensity of the banks lending to firms in that industry to zombify their distressed borrowers.[25] These results reveal the novel, incremental role of our theorized mechanism in which forward-looking healthy firms dynamically respond to expectations of uncertainty-induced zombification in their industry beyond their direct responses to uncertainty itself — in effect, a "zombie–uncertainty multiplier."[26]

The effects of *Expected Zombification* seem reasonable and economically sizeable. Consider, for example, *Expected Zombification* from the zombie definition in column (1). The coefficient of –0.727 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 investment (0.057). This is about a third of the magnitude of a one-standard-deviation drop in *Cash Flow*.

4.2 Disinvestment

We next examine the relationship between expected uncertainty-induced zombification and healthy firms' disinvestment. Columns (2) and (4) of Table 3 display estimates corresponding to

[25] See Appendix Table B.4 (and Section 3.2.3) for analysis of banks' zombification incentives under uncertainty.

[26] In later analyses, we also show that our results are unlikely to be driven by direct firm investment responses to uncertainty by distinguishing across industries with varying differentiation (see Section 4.4). Consistent with our model, reported dynamics are more pronounced in less differentiated industries, which are precisely those in which the negative uncertainty–investment relationship is dampened (or may even turn positive), as per Caballero (1991). We also show that our results are unlikely to be driven by negative first-moment changes in the industry firm-performance distribution, a common critique of studies on the spillover effects of zombie firms advanced by Schivardi et al. (2020). We do so by isolating variation in *Expected Zombification* related to quasi-exogenous shocks to uncertainty using the instrumental variables strategy proposed by Alfaro et al. (2024) (see Section 4.6).

equation (18) featuring our disinvestment proxy, *Disinvestment (Sale of PPE)*, as the dependent variable. Across both columns, greater expected uncertainty-led zombification in an industry is associated with significantly lower disinvestment by healthy firms in that industry. Notably, the negative relationship between disinvestment and expected zombification is consistent with our model prediction that firms will cut back on both costly-to-reverse margins of investment *and* disinvestment, even after controlling for their direct responses to uncertainty on the same capital allocation margins.[27] The economic magnitudes of the disinvestment coefficients are also notable. The estimate in column (2) of –0.342 implies that a one-standard-deviation increase in *Expected Zombification* is associated with a drop in disinvestment of 9% of the mean rate of disinvestment (0.015). This comparatively smaller magnitude is consistent with a particularly new insight of our theory. Notably, our model predicts that, in the case of disinvestment, the first-moment and second-moment forces work in opposite directions, thereby naturally muting the coefficient magnitude relative to investment.

4.3 Establishment and Employment Decisions

In Table 4, we present the results from re-estimating equation (18) on non-zombie 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. 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 4 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. Consistent with our investment results in Table 3, 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 3. Looking into Panel A column (1), a one-standard-deviation increase in *Expected Zombification* induces *Establishment Openings* to drop by about

[27] We plot the dynamics of firms' investment and disinvestment responses in Appendix Figure C.1. It shows that the effects of expected zombification on investment and disinvestment manifest only in the current year, consistent with similar "wait-and-see" dynamics reported by Bloom (2009) in response to uncertainty shocks. Since the reductions in *current* investment and disinvestment are not offset by *future* increases, the transitory effects of expected zombification may have lasting consequences for firms' capital accumulation moving forward.

7% of its mean. Column (2) reveals that the slope coefficient of *Expected Zombification* on *Establishment Closures* is also negative. Regarding economic significance, a one-standard-deviation rise in *Expected Zombification* in Panel A leads *Establishment Closures* to also drop by about 7% of its mean. The final column shows that the slope coefficient of *Expected Zombification* is also negative and significant on *Employment Growth*. A one-standard-deviation increase in the *Expected Zombification* in Panel A column (3) leads *Employment Growth* to drop by 14% of its mean.[28]

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

We next directly test our theorized channel of zombie firms' continued presence leading to higher output price pressure in their industries. We do so to further distinguish expected distressed-rival zombification from standard firm responses to uncertainty shocks. First, following our model intuition, we assess whether the effect of expected zombification is stronger in competitive industries and absent in *less* competitive industries where rival zombification is of little concern. We do so noting that 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 — in particular, disruptive innovation — consistent with incentives to engage in product differentiation. We do so noting that standard models often predict that higher uncertainty may *reduce* patenting activity (Bhattacharya et al. (2017)). Complementing our 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 (2)). 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 empirical tests. First, healthy firms in industries characterized by greater market power should exhibit little to no response to increased 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 expectations of zombification.

We begin by examining cross-sectional differences in our baseline results as a function of competition, using firm-rival pairwise product differentiation as a proxy. The differentiation

[28]In terms of other investment outcomes, we consistently show that healthy firms' mergers and acquisitions activity is negatively affected in the presence of heightened expected rival zombification (see Appendix Table B.6).

measure is constructed by comparing product description texts in firms' 10-K filings. Specifically, for each firm and year, we take the negative of the average cosine product text similarity between a focal firm and all its rival firms, where rivals are defined as those with the highest product similarity scores (from Hoberg et al. (2024)). The number of rival firms for each focal firm is chosen to approximate the granularity of 3-digit SIC industries. We restrict our attention to subsamples of firm-years with low product differentiation (the bottom quartile of the annual distribution of average product differentiation) and those with high differentiation (the top quartile).

TABLE 5 ABOUT HERE.

Table 5 reports the results of tests in which we replicate the results of Table 3 in subsamples alternately consisting of low product differentiation (odd-numbered columns) and high product differentiation (even-numbered columns) firm-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 marginal to insignificant coefficients in high product differentiation firm-years. In contrast, in firm-years characterized by lower product differentiation, healthy firms strongly respond to the heightened threat of uncertainty-led zombification by cutting back on their investment and disinvestment. This is evident in the statistically significant coefficients on *Expected Zombification* in the odd-numbered columns. Beyond providing support for our proposed 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 3 are merely capturing the general negative uncertainty–(dis)investment relationship, as this effect should be present in both product differentiation 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 5.

We next examine the effects of expected rival zombification on healthy firms' innovation activity by estimating our baseline specification with innovation measures as our outcome variables. We gauge firms' innovation activity by considering two common metrics: the number of patents filed in a given year scaled by lagged assets (*Patent Filings*) and the number of citations accruing to those patents in a given year scaled by lagged assets (*Patent Citations*). 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 6.

TABLE 6 ABOUT HERE.

The coefficient estimates across the relevant 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 in two ways. First, we distinguish firms' patenting output along the lines of their "importance." We do so by relying on a method developed by Kelly et al. (2021) to identify breakthrough patents. Those authors posit that a more important patent shows greater dissimilarity with past patents and greater similarity with future patents. Breakthrough patents are defined as those that lie in the right tail of the distribution of patents by importance. Second, we verify whether firms' attempts to differentiate themselves from their rivals in the product space actually bear fruit. We capture this outcome by taking the negative of the product market fluidity measure developed by Hoberg et al. (2014), which we term Δ*Product Differentiation*. This measure captures the extent to which a focal firm's product text descriptions become more distinct as competitors' product text descriptions change.

With these two measures in hand, we verify whether the innovation increases documented in columns (1), (2), (5), and (6) of Panel A manifest in the form of greater breakthrough patents and increased product differentiation. The results are reported in columns (3), (4), (7), and (8) of Panel A. Those columns indicate that firms exposed to a greater future zombification threat in their industries are more likely to produce highly impactful patents. The positive and statistically significant coefficients on Δ*Product Differentiation* strongly suggest that firms' product offerings become more distinct from the changes in their rivals' product portfolios. Together, these results imply that the documented innovation increases reflect 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.[29]

In Panel B of Table 6, 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.[30] Aggregating the county-level estimates into a state-year panel, we estimate a variation of equation (18) in which all firm-level variables are averaged to the state-year level according to firms' headquarters states. The outcome variable is the annual percentage change in the number of new business entries in a given state in a given year. The results are reported in Panel B

[29]Campello and Kankanhalli (2024) review the evidence on the uncertainty–innovation relationship.

[30]Note that these data capture intended business entries — which is exactly the margin that would be affected based on our theoretical arguments — and not only the creation of firms that survive and grow in the medium term.

of Table 6. Under both zombie definitions, our estimates point to a significant slowdown in new business entries in states where 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 local economies (see also Decker et al. (2016)).

In all, this section offers evidence that healthy firms reduce their investment and disinvestment, establishment openings and closures, and employment growth in response to the expectation of uncertainty-induced zombification in their industries. It also reveals that 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 resulting in product differentiation), 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.

4.5 Firm Performance, Financing, and Robustness

In Appendix D, we examine firm outcomes beyond investment, disinvestment, and innovation. Focusing first on non-zombie firms' performance and productivity, Appendix Table D.1 shows that their *MPK* and *TFP* both decline by about 3 percent of their sample means for a one-standard-deviation increase in *Expected Zombification*, while their *Capacity Overhang* (a measure of excess capacity proposed by Aretz and Pope (2018)) rises, and their *Tobin's Q* falls. These patterns are consistent with the prospect of zombie rivals depressing output prices, thereby slowing capital accumulation and inducing lower capacity utilization. On the financing margin, Appendix Table D.2 shows that healthy firms shore up liquidity: cash increases, while payouts through dividends and repurchases decline. We find modest evidence that debt issuance falls while equity issuance remains little changed. Taken together, these results align with the declining performance, productivity, and capacity utilization predictions of our real options framework and reinforce the link between expected rival zombification and slower real adjustments.

Appendix B reports the results from a series of robustness tests. We address the generated regressor nature of our key *Expected Zombification* variable by implementing a firm-cluster bootstrap of the first and second stages with 1,000 replications following Cameron et al. (2008). The resulting t-statistics in Appendix Table B.11 leave our main inferences unchanged. Additionally, restricting to tangible-asset-heavy industries (manufacturing, mining, and construction) yields effects that are, if anything, stronger, consistent with the setting in which our real-options model maps most closely to firms' capacity and asset-allocation choices (see Appendix Table B.13).

4.6 Quasi-Exogenous Variation in Expected Zombification

In our final analysis of this section, we identify quasi-exogenous variation in firms' zombification expectations by exploiting uncertainty shocks proposed by Alfaro et al. (2024) (henceforth, ABL). We do so in order to address the possibility that our main results may reflect negative first-moment shocks to the performance distribution of firms in an industry. Schivardi et al. (2020) argue that such shocks would simultaneously increase the share of zombies (since standard zombie definitions, including ours, often rely on performance metrics) and reduce healthy firm performance without indicating any actual negative spillover effects from zombie firms.[31] The ABL instrumental variables for uncertainty shocks are well-suited to address this critique as they allow us to isolate the variation in *Expected Zombification* arising from shocks to the second moment of the firm performance distribution that are orthogonal to first-moment changes thereof.

Appendix E details our IV design using the ABL uncertainty instruments. We construct nine shocks by interacting lagged absolute industry exposures to external factors (oil, seven dollar exchange rates, and EPU) with lagged changes in the realized volatility of those factors. The first stage estimates reported in Appendix Table E.2 confirm instrument relevance, and the second-stage coefficients on *Expected Zombification* in Appendix Table E.1 remain negative and statistically significant for both investment and disinvestment, closely matching the OLS magnitudes. By isolating second-moment variation orthogonal to first-moment movements, this approach addresses the concern that our baseline results might be driven by adverse level shocks that simultaneously raise measured zombie shares and depress healthy-firm outcomes.

5 Real Effects of Expected Rival Zombification: 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.

[31]We stress that our results on healthy firms cutting disinvestment largely mitigate this concern: disinvestment would be expected to *increase* — rather than *decrease* — following a negative first-moment shock.

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:

$$\begin{aligned} RealDecision^{S}_{i,j,t} &= \beta\, Expected\ Zombification^{S}_{j,t-1} + \delta\, Trade\ EPU_{t-1} \\ &+ \boldsymbol{\gamma}'\mathbf{FirmControls}_{i,j,t-1} + \lambda Forward\ Return_{j,t-1} + \sum_{i} \alpha_i + \varepsilon_{i,j,s,t} \end{aligned} \tag{20}$$

where $RealDecision^{S}$ is one of a number of real ship-related decisions (described shortly) made by firm i operating in subsector j in year t, $Expected\ Zombification^{S}$ is a forecast of the share of zombies spawning in subsector j over year t at the start of that year, *Trade EPU* is the one-year-lagged average trade policy component of the Baker et al. (2016) EPU index, $\mathbf{FirmControls} = [Size, Cash\ Flow^{S}]'$ is a vector of one-year-lagged firm controls, *Forward Return* is the one-year-lagged, most recent quarterly returns of forward contracts written on the freight rate in subsector j, α_i is a firm fixed effect, and β, δ, $\boldsymbol{\gamma}$, and λ are parameters or parameter vectors.[32] We retrieve the forward freight agreement returns data from the Baltic Exchange via Bloomberg.[33]

Following Campello et al. (2024), we use the following variables as outcomes in equation (20). 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 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 equation (15) 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 the 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 equation (15) separately by subsector but over our full sample period since we

[32] In line with Campello et al. (2024), we use the historical returns of forward contracts on subsector-specific freight rates as our first-moment proxy. 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). The trade component of the Baker et al. (2016) EPU index serves as a shipping industry-wide uncertainty control.

[33] A widely used index of dry-bulk shipping rates is the Baltic Dry Index (BDI). Conceptually, BDI tracks the same underlying freight-rate environment that motivates our more granular, subsector-level forward freight control.

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.

5.2 Ship Purchases, Sales, and Demolitions

Table 7, Panel A presents the results from estimating equation (20) 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 24% of its sample mean and disinvestment to decrease by about 38% 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 7 ABOUT HERE.

We further explore the dynamics of shipping firms' responses to expected uncertainty-led 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' uncertainty–investment responses (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 7 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 entail a significant time lag. These findings shed new light on the role played by the investment process itself in firms' capital accumulation in response to zombification threats.

The results in Table 7 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 preemptively 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. Our empirical work reveals that a greater rival zombification threat induces healthy firms to delay their real investment and disinvestment, establishment openings and closures, and employment growth, negatively affecting their future performance. 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 those that are costlier to reverse, such as new ship orders and existing ship demolitions. Our results highlight the key role of market power in modulating the negative externalities associated with expected rival zombification. Expected rival zombification also impacts financing policies, leading to increased cash holdings, reduced payouts, and reduced debt issuance.

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 and firm performance than previously thought, while impacting creative destruction in a more nuanced way (triggering innovation and product differentiation). While firms and lenders in our framework make optimal, forward-looking decisions, we leave a full welfare analysis of the role of expected zombification for future work.

References

Acharya, Viral V, Sreedhar T Bharath, and Anand Srinivasan, 2007, Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries, *Journal of Financial Economics* 85, 787–821.

Acharya, Viral V, Matteo Crosignani, Tim Eisert, and Christian Eufinger, 2024, Zombie credit and (dis-)inflation: Evidence from Europe, *The Journal of Finance* 79, 1883–1929.

Acharya, Viral V, Matteo Crosignani, Tim Eisert, and Sascha Steffen, 2022, Zombie lending: Theoretical, international, and historical perspectives, *Annual Review of Financial Economics* 14, 21–38.

Acharya, Viral V, Tim Eisert, Christian Eufinger, and Christian Hirsch, 2019, Whatever it takes: The real effects of unconventional monetary policy, *The Review of Financial Studies* 32, 3366–3411.

Acharya, Viral V, Simone Lenzu, and Olivier Wang, 2021, Zombie lending and policy traps, *NBER Working Paper 29606*.

Aguerrevere, Felipe L, 2003, Equilibrium investment strategies and output price behavior: A real-options approach, *The Review of Financial Studies* 16, 1239–1272.

Aguerrevere, Felipe L, 2009, Real options, product market competition, and asset returns, *The Journal of Finance* 64, 957–983.

Ai, Hengjie, Jun E Li, and Jincheng Tong, 2022, Equilibrium value and profitability premiums, *Working Paper, University of Wisconsin-Madison*.

Albuquerque, Bruno, and Roshan Iyer, 2024, The rise of the walking dead: Zombie firms around the world, *Journal of International Economics* 152, 104019.

Alfaro, Ivan, Nicholas Bloom, and Xiaoji Lin, 2024, The finance uncertainty multiplier, *Journal of Political Economy* 132, 577–615.

Altman, Edward I, Rui Dai, and Wei Wang, 2024, Global zombie companies: Measurements, determinants, and outcomes, *Journal of International Business Studies* 55, 723—744.

Aretz, Kevin, and Peter F Pope, 2018, Real options models of the firm, capacity overhang, and the cross section of stock returns, *The Journal of Finance* 73, 1363–1415.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring economic policy uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Baker, Scott R., Nicholas Bloom, Steven J. Davis, and Kyle Kost, 2026, Policy news and stock market volatility, *Journal of Financial Economics* 175, 104187.

Banerjee, Ryan, and Boris Hofmann, 2022, Corporate zombies: Anatomy and life cycle, *Economic Policy* 37, 757–803.

Benmelech, Efraim, and Nitzan Tzur-Ilan, 2020, The determinants of fiscal and monetary policies during the COVID-19 crisis, *NBER Working Paper 27461*.

Bernanke, Ben S, 1983, Irreversibility, uncertainty, and cyclical investment, *The Quarterly Journal of Economics* 98, 85–106.

Bhamra, Harjoat S, Lars-Alexander Kuehn, and Ilya A Strebulaev, 2010, The aggregate dynamics of capital structure and macroeconomic risk, *The Review of Financial Studies* 23, 4187–4241.

Bhattacharya, Utpal, Po-Hsuan Hsu, Xuan Tian, and Yan Xu, 2017, What affects innovation more: Policy or policy uncertainty?, *Journal of Financial and Quantitative Analysis* 52, 1869–1901.

Bloom, Nicholas, 2009, The impact of uncertainty shocks, *Econometrica* 77, 623–685.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry, 2018, Really uncertain business cycles, *Econometrica* 86, 1031–1065.

Bolton, Patrick, Hui Chen, and Neng Wang, 2011, A unified theory of Tobin's q, corporate investment, financing, and risk management, *The Journal of Finance* 66, 1545–1578.

Brander, James A, and Tracy R Lewis, 1986, Oligopoly and financial structure: The limited liability effect, *The American Economic Review* 956–970.

Bruche, Max, and Gerard Llobet, 2014, Preventing zombie lending, *The Review of Financial Studies* 27, 923–956.

Caballero, Ricardo J, 1991, On the sign of the investment-uncertainty relationship, *American Economic Review* 81, 279–288.

Caballero, Ricardo J, Takeo Hoshi, and Anil K Kashyap, 2008, Zombie lending and depressed restructuring in Japan, *American Economic Review* 98, 1943–1977.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller, 2008, Bootstrap-based improvements for inference with clustered errors, *The Review of Economics and Statistics* 90, 414–427.

Campello, Murillo, and Janet Gao, 2017, Customer concentration and loan contract terms, *Journal of Financial Economics* 123, 108–136.

Campello, Murillo, and Gaurav Kankanhalli, 2024, Corporate decision-making under uncertainty: Review and future research directions, *Handbook of Corporate Finance* 548–590.

Campello, Murillo, Gaurav Kankanhalli, and Hyunseob Kim, 2024, Delayed creative destruction: How uncertainty shapes corporate assets, *Journal of Financial Economics* 153, 103786.

Campello, Murillo, Chen Lin, Yue Ma, and Hong Zou, 2011, The real and financial implications of corporate hedging, *The Journal of Finance* 66, 1615–1647.

Cascaldi-Garcia, Danilo, Cisil Sarisoy, Juan M Londono, John H Rogers, Bo Sun, Deepa D Datta, Thiago Ferreira, Olesya Grishchenko, Mohammad R Jahan-Parvar, Francesca Loria, Sai Ma, Marius Rodriguez, and Ilknur Zer, 2023, What is certain about uncertainty?, *Journal of Economic Literature* 61, 624–654.

Chen, Wei, Paul Hribar, and Sam Melessa, 2023, Standard error biases when using generated regressors in accounting research, *Journal of Accounting Research* 61, 531–569.

Chopra, Yakshup, Krishnamurthy Subramanian, and Prasanna L Tantri, 2021, Bank cleanups, capitalization, and lending: Evidence from India, *The Review of Financial Studies* 34, 4132–4176.

Darmouni, Olivier, and Andrew Sutherland, 2024, Investment when new capital is hard to find, *Journal of Financial Economics* 154, 103806.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, 2016, Declining business dynamism: What we know and the way forward, *American Economic Review* 106, 203–207.

Dixit, Avinash, and Robert S Pindyck, 1994, *Investment Under Uncertainty* (Princeton University Press).

Doshi, Hitesh, Praveen Kumar, and Vijay Yerramilli, 2018, Uncertainty, capital investment, and risk management, *Management Science* 64, 5769–5786.

Faria-e-Castro, Miguel, Pascal Paul, and Juan M Sánchez, 2024, Evergreening, *Journal of Financial Economics* 153, 103778.

Graham, John R, Si Li, and Jiaping Qiu, 2008, Corporate misreporting and bank loan contracting, *Journal of Financial Economics* 89, 44–61.

Grieser, William D, and Charles J Hadlock, 2019, Panel-data estimation in finance: Testable assumptions and parameter (in) consistency, *Journal of Financial and Quantitative Analysis* 54, 1–29.

Gryglewicz, Sebastian, and Simon Mayer, 2023, Dynamic contracting with intermediation: Operational, governance, and financial engineering, *The Journal of Finance* 78, 2779–2836.

Gulen, Huseyin, and Mihai Ion, 2016, Policy uncertainty and corporate investment, *The Review of Financial Studies* 29, 523–564.

Guo, Xin, Jianjun Miao, and Erwan Morellec, 2005, Irreversible investment with regime shifts, *Journal of Economic Theory* 122, 37–59.

Hackbarth, Dirk, and Timothy Johnson, 2015, Real options and risk dynamics, *The Review of Economic Studies* 82, 1449–1482.

Hirtle, Beverly, Anna Kovner, and Matthew Plosser, 2020, The impact of supervision on bank performance, *The Journal of Finance* 75, 2765–2808.

Hjalmarsson, Erik, 2006, Predictive regressions with panel data, *FRB International Finance Discussion Paper.*

Hoberg, Gerard, Craig Knoblock, Gordon Phillips, Ja Pujara, Zhiqiang Qiu, and Louiqa Raschid, 2024, Using representation learning and web text to identify competitors, *Working Paper, USC*.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423–1465.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product market threats, payouts, and financial flexibility, *The Journal of Finance* 69, 293–324.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng, 2015, Measuring uncertainty, *American Economic Review* 105, 1177–1216.

Kalouptsidi, Myrto, 2014, Time to build and fluctuations in bulk shipping, *American Economic Review* 104, 564–608.

Kellogg, Ryan, 2014, The effect of uncertainty on investment: Evidence from Texas oil drilling, *American Economic Review* 104, 1698–1734.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2021, Measuring technological innovation over the long run, *American Economic Review: Insights* 3, 303–320.

Kim, Hyunseob, and Howard Kung, 2017, The asset redeployability channel: How uncertainty affects corporate investment, *The Review of Financial Studies* 30, 245–280.

Kumar, Saten, Yuriy Gorodnichenko, and Olivier Coibion, 2023, The effect of macroeconomic uncertainty on firm decisions, *Econometrica* 91, 1297–1332.

McDonald, Robert, and Daniel Siegel, 1986, The value of waiting to invest, *The Quarterly Journal of Economics* 101, 707–727.

McGowan, Müge Adalet, Dan Andrews, and Valentine Millot, 2018, The walking dead? Zombie firms and productivity performance in OECD countries, *Economic Policy* 33, 685–736.

Merton, Robert C, 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.

Morellec, Erwan, and Alexei Zhdanov, 2019, Product market competition and option prices, *The Review of Financial Studies* 32, 4343–4386.

Oh, Hyunseung, and Chamna Yoon, 2020, Time to build and the real-options channel of residential investment, *Journal of Financial Economics* 135, 255–269.

Peek, Joe, and Eric S Rosengren, 2005, Unnatural selection: Perverse incentives and the misallocation of credit in Japan, *American Economic Review* 95, 1144–1166.

Pindyck, Robert S, 1988, Irreversible investment, capacity choice, and the value of the firm, *American Economic Review* 78, 969–985.

Schivardi, Fabiano, Enrico Sette, and Guido Tabellini, 2020, Identifying the real effects of zombie lending, *The Review of Corporate Finance Studies* 9, 569–592.

Shleifer, Andrei, and Robert W Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *Journal of Finance* 47, 1343–1366.

Skrastins, Janis, 2023, Barter credit: Warehouses as a contracting technology, *The Journal of Finance* 78, 2009–2047.

Stopford, Martin, 2009, *Maritime Economics 3rd Edition* (Routledge).

Strebulaev, Ilya A, and Baozhong Yang, 2013, The mystery of zero-leverage firms, *Journal of Financial Economics* 109, 1–23.

Table 1. 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 year fixed effects. The loan-contract terms are the 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 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 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 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 + Year 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 + Year FEs	Yes	Yes	Yes
R^2	0.49	0.28	0.53
Observations	35,047	37,215	7,796

Table 2. 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. (2026); 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 a firm's lagged zombie status, an indicator variable equal to one if the lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's lagged age is below ten years and else zero (*Young Firm*), and lagged country-level macro controls including *GDP Growth*, *Labor Force*, *Inflation*, and *Interest Rate*. 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 Proxies:							
	VIX	*EMV*	*EPU*	*FIN*	*REAL*	*MACRO*	*ARV*	*AIV*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: *Standard Zombie*								
Uncertainty	0.099***	0.224***	0.020***	0.138***	0.244***	0.111***	0.022***	0.058***
	[6.44]	[9.67]	[6.81]	[6.65]	[5.83]	[5.13]	[3.06]	[3.68]
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	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02
Observations	85,630	85,630	85,630	85,630	85,630	85,630	85,612	68,412
Panel B: *Credit-Subsidized Zombie*								
Uncertainty	0.029**	0.082***	0.007***	0.040**	0.054*	0.020	0.008	0.016
	[2.47]	[4.79]	[2.88]	[2.54]	[1.78]	[1.33]	[1.35]	[1.41]
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	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Observations	60,954	60,954	60,954	60,954	60,954	60,954	60,939	55,182

Table 3. 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 trend 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 three-month-lagged 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 the lagged firm value is below $50 million and else zero (*Small Firm*), an indicator variable equal to one if the firm's lagged age is below ten years and else zero (*Young Firm*), and the lagged first principal component extracted from our country-level macro controls (*GDP Growth*, *Labor Force*, *Inflation*, and *Interest Rate*). We define our industries using the 50 Hoberg and Phillips (2016) industry classification. 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 lagged assets (*Size*), its lagged sum of EBIT, depreciation, and R&D expenses scaled by two-year-lagged assets (*Cash Flow*), its lagged Tobin's Q (*Tobin's Q*), the lagged industry-specific firm-size weighted average implied volatility (*Industry Uncertainty*), and macro variables consisting of the lagged *State GDP Growth*, *State Labor Force*, *Regional Inflation*, and *Interest Rate* (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	–0.727***	–0.342***	–0.510***	–0.438***
	[–7.50]	[–3.26]	[–3.79]	[–2.64]
Industry Uncertainty	–0.013***	–0.013**	–0.032***	–0.017***
	[–2.95]	[–2.10]	[–6.20]	[–2.72]
Size	–0.013***	–0.003***	–0.013***	–0.003**
	[–12.31]	[–3.11]	[–11.69]	[–2.51]
Cash Flow	0.061***	–0.014***	0.059***	–0.019***
	[12.18]	[–3.57]	[9.96]	[–4.45]
Tobin's Q	0.008***	–0.001*	0.010***	–0.000
	[13.51]	[–1.75]	[13.89]	[–0.88]
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	32,289	23,704	28,189	20,295

Table 4. 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 trend fixed effects. All remaining variables are as defined in Table 3. 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	–2.570***	–1.379***	–6.558***
	[–2.64]	[–4.16]	[–2.50]
Firm Controls	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes
R^2	0.01	0.01	0.02
Observations	16,602	16,602	15,310
Panel B: *Credit-Subsidized Zombie*			
Expected Zombification	–2.963*	–0.723	–7.822*
	[–1.67]	[–1.18]	[–1.80]
Firm Controls	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes
R^2	0.01	0.01	0.01
Observations	14,298	14,298	13,241

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

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 trend 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). Odd-numbered columns contain estimates from the subsample of firms with low product differentiation, in the bottom quartile of the annual distribution of the ETNIC-3 text-based product differentiation measure averaged across all rivals. Even-numbered columns contain estimates from the subsample of firms in the top quartile of the annual distribution of average product differentiation. Product differentiation is a pairwise text-based measure of textual differentiation of firms' product descriptions (negative of cosine similarity), averaged across all rival firms in a year defined with sufficient granularity to match 3-digit SIC industries (see Hoberg et al. (2024) for more details). All remaining variables are as defined in Table 3. 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*	
	Product Differentiation		Product Differentiation		Product Differentiation		Product Differentiation	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Zombification	–1.806***	–0.040	–0.569**	–0.339*	–2.395***	0.154	–0.942**	–0.520
	[–6.98]	[–0.24]	[–2.12]	[–1.70]	[–4.57]	[0.74]	[–2.01]	[–1.53]
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 × Trend FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.07	0.01	0.01	0.11	0.08	0.01	0.01
Observations	7,741	7,876	5,224	5,925	6,816	6,684	4,505	4,952

Table 6. 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 outcome variables and state-level new business entries variables on expected zombification (*Expected Zombification*), controls, as well as firm, industry, state, and trend fixed effects. Innovation outcome variables are measured two years ahead. Our outcome variables in Panel A are *Patent Filings*, or the count of patents filed by a firm in a given year divided by lagged total assets (columns (1) and (5)), *Patent Citations*, or the count of citations of a firm's filed patents in a given year divided by total assets (columns (2) and (6)), *Patent Breakthrough*, or the ratio of patents filed in a given year that are in the top 10% of *Patent Importance* to total patents filed by that firm in that year (columns (3) and (7)), where *Patent Importance* is 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, and Δ*Product Differentiation*, which is the negative of product market fluidity as per Hoberg et al. (2014), based on the cosine similarity of a firm's product description in its 10-K filings relative to annual changes in the product descriptions of its rivals (columns (4) and (8)). Our outcome variable in Panel B is the annual percentage change in the number of new businesses formed in a given state in a given year. The specifications in Panel B are estimated at the state-year level, averaging all firm-year variables based on the firms' headquarters states. All remaining variables are as defined in Table 3. 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 Proxies:				Innovation Proxies:			
	Patent Filings	*Patent Citations*	*Patent Breakthrough*	Δ*Product Differentiation*	*Patent Filings*	*Patent Citations*	*Patent Breakthrough*	Δ*Product Differentiation*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Zombification	0.078***	1.388***	1.202**	35.584***	0.104**	1.379*	1.574**	25.132***
	[2.95]	[3.95]	[2.13]	[10.42]	[2.08]	[1.87]	[2.20]	[4.27]
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 × Trend FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.03
Observations	27,555	27,555	8,252	27,319	24,467	24,467	7,277	24,131

Panel B: Business Entries

	Zombification Proxy Based On:	
	Standard Zombie	*Credit-Subsidized Zombie*
	(1)	(2)
Expected Zombification	–5.345***	–9.693***
	[–3.62]	[–3.56]
Average Firm Controls	Yes	Yes
Macro Controls	Yes	Yes
State FEs	Yes	Yes
Time FEs	Yes	Yes
R^2	0.13	0.11
Observations	741	736

Table 7. 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}), firm and subsector 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). Conversely, we use a firm's total ship disinvestment, 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). 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 (top quartile), while the even-numbered columns in Panel B are estimated within the subsample of firm-years with a "short" time-to-build (bottom quartile). 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. The construction of *Expected Zombification*^{S} is detailed in Section 5.1. 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	–0.965**	–0.905**	–0.035	–0.507**	–0.226	–0.244*
	[–2.18]	[–2.11]	[–0.59]	[–2.30]	[–1.56]	[–1.81]
Firm and Subsector 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	–2.275***	1.581	–2.176***	1.609	–0.037	–0.028
	[–3.32]	[1.10]	[–3.36]	[1.12]	[–0.34]	[–0.58]
Firm and Subsector 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	0.04	0.02
Observations	339	241	339	241	339	241

Online 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 4. *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:*

$$\mathfrak{C}(\theta, X; a) = \begin{cases} c_{1,X}\theta^{\beta_1} + c_{2,X}\theta^{\beta_2} + c_{0,X}\theta^2 & \text{if } \theta \le \theta_q, \\ c_{3,X}\theta^{\beta_3} + c_{4,X}\theta^{\beta_4} + \frac{a}{r} & \text{if } \theta \ge \theta_q. \end{cases} \tag{A.5}$$

Proof. When profits are low (θ near Z), unlevered and 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:

$$\Pi = (\theta - (n_U + n_L)\gamma Q^*) Q^* - \frac{1}{2}\kappa (Q^*)^2 = A\theta^2, \tag{A.6}$$

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:

$$\max\{a - \Pi, 0\} = \begin{cases} a - A\theta^2 & \text{if } \theta \in (0, \theta_q], \\ 0 & \text{if } \theta \in [\theta_q, \infty). \end{cases} \tag{A.7}$$

In each of the two economic states, the creditor's continuation value $\mathscr{C} = \mathscr{C}(\theta, X)$ needs to satisfy the usual risk-neutral valuation condition:

$$\mathbb{E}^{\mathbb{Q}}[d\mathscr{C}] + (a - \max\{a - \Pi, 0\})\, dt = r\mathscr{C}\, dt. \tag{A.8}$$

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 shifts grow at rate α_X while attracting a risk premium μ, which is the return of a portfolio that perfectly replicates the randomness of demand shifts. Let $\delta_X = \mu - \alpha_X$ denote the expected-return shortfall. Equation (A.8) turns into a system of coupled ordinary differential equations (ODEs):

$$\begin{aligned}(r-\delta_H)\theta\mathscr{C}^H_\theta + \frac{1}{2}\sigma^2_H\theta^2\mathscr{C}^H_{\theta\theta} - r\mathscr{C}^H + p_L\left(\mathscr{C}^L - \mathscr{C}^H\right) + a - \max\{a-\Pi, 0\} = 0,\\ (r-\delta_L)\theta\mathscr{C}^L_\theta + \frac{1}{2}\sigma^2_L\theta^2\mathscr{C}^L_{\theta\theta} - r\mathscr{C}^L + p_H\left(\mathscr{C}^H - \mathscr{C}^L\right) + a - \max\{a-\Pi, 0\} = 0,\end{aligned} \tag{A.9}$$

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 $\lim_{\theta\to\infty}\mathscr{C}(\theta, X) = \frac{a}{r}$.

The general solution to the homogeneous ODE system in equation (A.9) is:

$$\mathscr{C}(\theta, X) = c_{1,X}\theta^{\beta_1} + c_{2,X}\theta^{\beta_2} + c_{3,X}\theta^{\beta_3} + c_{4,X}\theta^{\beta_4}, \tag{A.10}$$

where β_1 and β_2 (β_3 and β_4) are the positive (negative) solutions of the fourth-order polynomial:

$$Q_H(\beta)Q_L(\beta) = p_H p_L, \tag{A.11}$$

defined by the characteristic polynomials:

$$Q_H(\beta) = (r-\delta_H)\beta + \frac{1}{2}\sigma^2_H\beta(\beta-1) - r - p_L, \tag{A.12}$$

$$Q_L(\beta) = (r-\delta_L)\beta + \frac{1}{2}\sigma^2_L\beta(\beta-1) - r - p_H. \tag{A.13}$$

Plugging equation (A.10) in equation (A.9) shows that the coefficients satisfy the conditions:

$$c_{1,L} = -\frac{c_{1,H}}{p_L}Q_H(\beta_1), \tag{A.14}$$

$$c_{2,L} = -\frac{c_{2,H}}{p_L}Q_H(\beta_2), \tag{A.15}$$

$$c_{3,L} = -\frac{c_{3,H}}{p_L}Q_H(\beta_3), \tag{A.16}$$

$$c_{4,L} = -\frac{c_{4,H}}{p_L}Q_H(\beta_4). \tag{A.17}$$

The instantaneous profits from equation (A.7) add a particular solution to equation (A.10), while the boundary conditions remove solution components. Thus, the continuation value is:

$$\mathscr{C}(\theta, X) = \begin{cases} c_{1,X}\theta^{\beta_1} + c_{2,X}\theta^{\beta_2} + c_{0,X}\theta^2 & \text{if } \theta \le \theta_q, \\ c_{3,X}\theta^{\beta_3} + c_{4,X}\theta^{\beta_4} + \frac{a}{r} & \text{if } \theta \ge \theta_q, \end{cases} \tag{A.18}$$

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 value-matching and smooth-pasting at $\theta = \theta_q$:

$$c_{1,H}(\theta_q)^{\beta_1} + c_{2,H}(\theta_q)^{\beta_2} + c_{0,H}(\theta_q)^2 = c_{3,H}(\theta_q)^{\beta_3} + c_{4,H}(\theta_q)^{\beta_4} + \frac{a}{r}, \tag{A.19}$$

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

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

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

We state the solution to the ODE system (A.9) subject to equations (A.19) to (A.22) 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:

$$\begin{aligned} c_{4,H} = &-c_{0,H}\frac{\left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3-H_1\beta_1}{H_2\beta_2-H_1\beta_1}\right)\frac{\frac{2-\beta_1}{\beta_2-\beta_1}+\frac{p_L\rho_H+\rho_L H_1}{(H_2-H_1)\rho_L}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1}-\frac{H_3-H_1}{H_2-H_1}} - \frac{2-\beta_1}{\beta_2-\beta_1} - \frac{2p_L\rho_H+H_1\beta_1\rho_L}{(H_2\beta_2-H_1\beta_1)\rho_L}}{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4\beta_4-H_1\beta_1}{H_2\beta_2-H_1\beta_1} - \left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3-H_1\beta_1}{H_2\beta_2-H_1\beta_1}\right)\frac{\frac{\beta_4-\beta_1}{\beta_2-\beta_1}-\frac{H_4-H_1}{H_2-H_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1}-\frac{H_3-H_1}{H_2-H_1}}}(\theta_q)^{2-\beta_4} \\ &+ \frac{\left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3-H_1\beta_1}{H_2\beta_2-H_1\beta_1}\right)\frac{\frac{H_1+p_L}{H_2-H_1}-\frac{\beta_1}{\beta_2-\beta_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1}-\frac{H_3-H_1}{H_2-H_1}} - \frac{H_1\beta_1}{H_2\beta_2-H_1\beta_1} + \frac{\beta_1}{\beta_2-\beta_1}}{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4\beta_4-H_1\beta_1}{H_2\beta_2-H_1\beta_1} - \left(\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3\beta_3-H_1\beta_1}{H_2\beta_2-H_1\beta_1}\right)\frac{\frac{\beta_4-\beta_1}{\beta_2-\beta_1}-\frac{H_4-H_1}{H_2-H_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1}-\frac{H_3-H_1}{H_2-H_1}}}\frac{a}{r}(\theta_q)^{-\beta_4}. \end{aligned} \tag{A.23}$$

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

$$c_{3,H} = -c_{4,H}\frac{\frac{\beta_4-\beta_1}{\beta_2-\beta_1} - \frac{H_4-H_1}{H_2-H_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}}(\theta_q)^{\beta_4-\beta_3} + c_{0,H}\frac{\frac{2-\beta_1}{\beta_2-\beta_1} + \frac{p_L\rho_H+\rho_L H_1}{(H_2-H_1)\rho_L}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}}(\theta_q)^{2-\beta_3} - \frac{\frac{H_1+p_L}{H_2-H_1} - \frac{\beta_1}{\beta_2-\beta_1}}{\frac{\beta_3-\beta_1}{\beta_2-\beta_1} - \frac{H_3-H_1}{H_2-H_1}}\frac{a}{r}(\theta_q)^{-\beta_3}. \tag{A.24}$$

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

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

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

$$c_{1,H} = -c_{2,H}(\theta_q)^{\beta_2-\beta_1} + c_{3,H}(\theta_q)^{\beta_3-\beta_1} + c_{4,H}(\theta_q)^{\beta_4-\beta_1} - c_{0,H}(\theta_q)^{2-\beta_1} + \frac{a}{r}(\theta_q)^{-\beta_1}. \tag{A.26}$$

$\square$

A.2 Duration of Zombification

In this section, we calculate the expected length of time defaulting firms rely on credit subsidies. To do so, let τ^* denote the first time when firms' profits reach the newly agreed coupon c^*. We

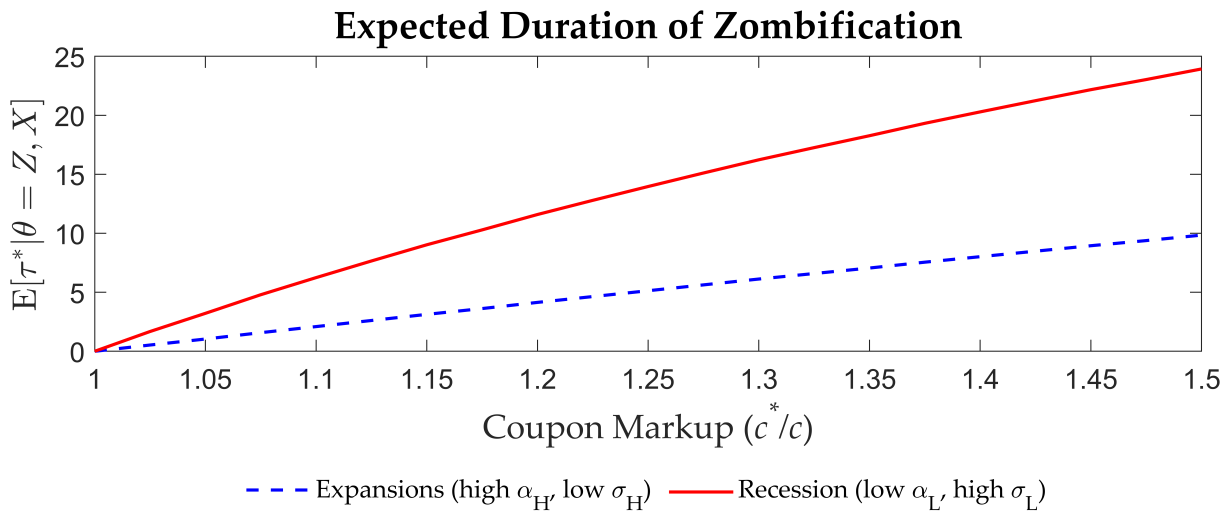

Figure A.1. The figure plots the expected time to full recovery from the point of default in an expansion (dashed blue line) and a recession (red solid line) state. Base-case parameters are described in Section 2.3.

denote the equivalent threshold for the demand shift θ by Z^*. The expected time until full recovery can then be calculated as follows:

Proposition 5. *The expected time for levered firms' profits to reach* c^*, $\mathbb{E}[\tau^*|\theta, X]$, *is:*

$$\mathbb{E}[\tau^*|\theta, X] = -\lim_{u \to 0} \frac{\partial}{\partial u} \mathbb{E}[e^{-u\tau^*}|\theta, X], \tag{A.27}$$

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

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

where $\beta_{1,u}$ *and* $\beta_{2,u}$ *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.

Figure A.1 plots the expected time duration for which levered firms require credit subsidies as a function of the newly agreed coupon, c^*. To do so, we graphically illustrate equation (A.27), which calculates how long it takes defaulting firms to recover sufficiently to pay the higher coupon c^* to their 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.

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

We next turn to the pricing of an 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 ODE system

$$\begin{aligned}(r-\delta_H)\theta\Delta\mathscr{V}^H_\theta + \frac{1}{2}\sigma^2_H\theta^2\Delta\mathscr{V}^H_{\theta\theta} - r\Delta\mathscr{V}^H + p_L\left(\Delta\mathscr{V}^L - \Delta\mathscr{V}^H\right) + \max\{\theta-\theta^P, 0\} = 0,\\ (r-\delta_L)\theta\Delta\mathscr{V}^L_\theta + \frac{1}{2}\sigma^2_L\theta^2\Delta\mathscr{V}^L_{\theta\theta} - r\Delta\mathscr{V}^L + p_H\left(\Delta\mathscr{V}^H - \Delta\mathscr{V}^L\right) + \max\{\theta-\theta^P, 0\} = 0.\end{aligned} \tag{A.30}$$

Using the general solution from equation (A.10), 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

$$\Delta\mathscr{V}(\theta, X; K) = \begin{cases} b_{1,X}\theta^{\beta_1} + b_{2,X}\theta^{\beta_2} & \text{if } \theta \le \theta^P,\\ b_{3,X}\theta^{\beta_3} + b_{4,X}\theta^{\beta_4} + b_{0,X}\theta - \frac{\theta^P}{r} & \text{if } \theta \ge \theta^P,\end{cases} \tag{A.31}$$

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.14) to (A.17), the coefficients need to satisfy the following conditions:

$$b_{1,L} = -\frac{b_{1,H}}{p_L}Q_H(\beta_1), \tag{A.32}$$

$$b_{2,L} = -\frac{b_{2,H}}{p_L}Q_H(\beta_2), \tag{A.33}$$

$$b_{3,L} = -\frac{b_{3,H}}{p_L}Q_H(\beta_3), \tag{A.34}$$

$$b_{4,L} = -\frac{b_{4,H}}{p_L}Q_H(\beta_4). \tag{A.35}$$

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

$$b_{1,H}(\theta^P)^{\beta_1} + b_{2,H}(\theta^P)^{\beta_2} = b_{3,H}(\theta^P)^{\beta_3} + b_{4,H}(\theta^P)^{\beta_4} + b_{0,H}\theta^P - \frac{\theta^P}{r}, \tag{A.36}$$

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

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

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

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

$$
\begin{aligned}
b_{4,H} = {} & \frac{(H_2\beta_2 - H_1\beta_1) b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1} - (H_1\beta_1 b_{0,H} + p_L b_{0,L}) + \frac{H_1 b_{0,H} + p_L b_{0,L} - (H_2 - H_1) b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)}{H_1\beta_1 - H_4\beta_4 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1} - \frac{H_1 - H_4 - (H_2 - H_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)} (\theta^P)^{1-\beta_4} \\
& - \frac{(H_2\beta_2 - H_1\beta_1)\frac{\beta_1}{\beta_2 - \beta_1} - H_1\beta_1 + \frac{H_1 + p_L - (H_2 - H_1)\frac{\beta_1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)}{H_1\beta_1 - H_4\beta_4 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1} - \frac{H_1 - H_4 - (H_2 - H_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \left(H_1\beta_1 - H_3\beta_3 - (H_2\beta_2 - H_1\beta_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} \right)} \frac{(\theta^P)^{1-\beta_4}}{r}.
\end{aligned}
\tag{A.40}
$$

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

$$
\begin{aligned}
b_{3,H} = {} & -b_{4,H} \frac{H_1 - H_4 - (H_2 - H_1)\frac{\beta_1 - \beta_4}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} (\theta^P)^{\beta_4 - \beta_3} - \frac{H_1 b_{0,H} + p_L b_{0,L} - (H_2 - H_1) b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} (\theta^P)^{1-\beta_3} \\
& + \frac{H_1 + p_L - (H_2 - H_1)\frac{\beta_1}{\beta_2 - \beta_1}}{H_1 - H_3 - (H_2 - H_1)\frac{\beta_1 - \beta_3}{\beta_2 - \beta_1}} \frac{(\theta^P)^{1-\beta_3}}{r}.
\end{aligned}
\tag{A.41}
$$

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

$$
b_{2,H} = -b_{3,H} \frac{\beta_1 - \beta_3}{\beta_2 - \beta_1} (\theta^P)^{\beta_3 - \beta_2} - b_{4,H} \frac{\beta_1 - \beta_4}{\beta_2 - \beta_1} (\theta^P)^{\beta_4 - \beta_2} - b_{0,H} \frac{\beta_1 - 1}{\beta_2 - \beta_1} (\theta^P)^{1-\beta_2} + \frac{\beta_1}{\beta_2 - \beta_1} \frac{(\theta^P)^{1-\beta_2}}{r}. \tag{A.42}
$$

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

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

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. The share of levered firms staying as a zombie upon default in state X is:

$$
\psi(X) = \mathbb{Q}[\mathscr{C}(Z,X) \geq L_X | X] = \Phi\left(\frac{\ln(\mathscr{C}(Z,X)) - \mu_{L,X}}{\sigma_{L,X}} \right) \tag{A.44}
$$

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

A.5 Discount Factor for Levered Firms' Exit

In this section, we value the benefit to the value of the unlevered firms' production option stemming from the increase in market power once some levered firms leave the industry.

Applying the law of total expectation yields:

$$\Delta V(\theta,X;K)=\Delta\mathcal{V}(\theta,X;\theta_Z^P)+\big(\Delta\mathcal{V}(Z,X;\theta^P)-\Delta\mathcal{V}(Z,X;\theta_Z^P)\big)\mathbb{E}^{\mathbb{Q}}\big[e^{-r\tau}|X\big], \tag{A.45}$$

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

In the absence of arbitrage, $Q(\theta,X;Z)=\mathbb{E}^{\mathbb{Q}}[e^{-r\tau}|X]$ needs to satisfy the ODE system:

$$\begin{aligned}(r-\delta_H)\theta Q_\theta^H+\frac{1}{2}\sigma_H^2\theta^2Q_{\theta\theta}^H-rQ^H+p_L\big(Q^L-Q^H\big)=0,\\ (r-\delta_L)\theta Q_\theta^L+\frac{1}{2}\sigma_L^2\theta^2Q_{\theta\theta}^L-rQ^L+p_H\big(Q^H-Q^L\big)=0.\end{aligned} \tag{A.46}$$

Because of the upper limit $\lim\limits_{\theta\to\infty}Q(\theta,X;Z)=0$, the general solution for $\theta>Z$ is:

$$Q(\theta,X;Z)=q_{3,X}\theta^{\beta_3}+q_{4,X}\theta^{\beta_4}, \tag{A.47}$$

where the coefficients need to satisfy:

$$q_{3,L}=-\frac{q_{3,H}}{p_L}Q_H(\beta_3), \tag{A.48}$$

$$q_{4,L}=-\frac{q_{4,H}}{p_L}Q_H(\beta_4). \tag{A.49}$$

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

$$q_{3,H}Z^{\beta_3}+q_{4,H}Z^{\beta_4}=1, \tag{A.50}$$

$$q_{3,L}Z^{\beta_3}+q_{4,L}Z^{\beta_4}=1. \tag{A.51}$$

The solution to the equation system is given by:

$$q_{3,H}=\frac{p_L+Q_H(\beta_4)}{Q_H(\beta_4)-Q_H(\beta_3)}Z^{-\beta_3}, \tag{A.52}$$

$$q_{4,H}=\frac{p_L+Q_H(\beta_3)}{Q_H(\beta_3)-Q_H(\beta_4)}Z^{-\beta_4}. \tag{A.53}$$

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 ODE system:

$$(r-\delta_H)\theta\Delta F_\theta^H + \frac{1}{2}\sigma_H^2\theta^2\Delta F_{\theta\theta}^H - r\Delta F^H + p_L\left(\Delta F^L - \Delta F^H\right) = 0, \tag{A.54}$$

$$(r-\delta_L)\theta\Delta F_\theta^L + \frac{1}{2}\sigma_L^2\theta^2\Delta F_{\theta\theta}^L - r\Delta F^L + p_H\left(\Delta F^H - \Delta F^L\right) = 0. \tag{A.55}$$

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

$$\Delta F(\theta, X; K) = a_{1,X}\theta^{\beta_1} + a_{2,X}\theta^{\beta_2}, \tag{A.56}$$

where the coefficients need to satisfy the additional conditions

$$a_{1,L} = -\frac{a_{1,H}}{p_L}Q_H(\beta_1), \tag{A.57}$$

$$a_{2,L} = -\frac{a_{2,H}}{p_L}Q_H(\beta_2). \tag{A.58}$$

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

$$\Delta D(\theta, X; K) = d_{3,X}\theta^{\beta_3} + d_{4,X}\theta^{\beta_4}. \tag{A.59}$$

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

$$d_{3,L} = -\frac{d_{3,H}}{p_L}Q_H(\beta_3), \tag{A.60}$$

$$d_{4,L} = -\frac{d_{4,H}}{p_L}Q_H(\beta_4). \tag{A.61}$$

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

$$\Delta F(\theta_X^*, X; K) + I = \Delta V(\theta_X^*, X; K) + \Delta D(\theta_X^*, X; K), \tag{A.62}$$

$$\Delta D(\theta_X', X; K) + \Delta V(\theta_X', X; K) = d + \Delta F(\theta_X', X; K). \tag{A.63}$$

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

$$\Delta F_\theta(\theta_X^*, X; K) = \Delta V_\theta(\theta_X^*, X; K) + \Delta D_\theta(\theta_X^*, X; K), \tag{A.64}$$

$$\Delta D_\theta(\theta_X', X; K) + \Delta V_\theta(\theta_X', X; K) = \Delta F_\theta(\theta_X', X; K). \tag{A.65}$$

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:

$$P_{Y,i} = \theta - \gamma Q_{Y,i}, \tag{A.66}$$

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:

$$\Pi_{Y,i} = \theta Q_{Y,i} - \left(\gamma + \frac{1}{2}(1 + n_u + n_L)\right) Q_{Y,i}^2. \tag{A.67}$$

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

$$Q^*_{Y,i} = \frac{\theta}{2\gamma + \kappa(1 + n_u + n_L)}. \tag{A.68}$$

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

$$Q^*_{Y,i} = \frac{\theta}{(n_u + n_L + 1)\gamma + \kappa}. \tag{A.69}$$

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

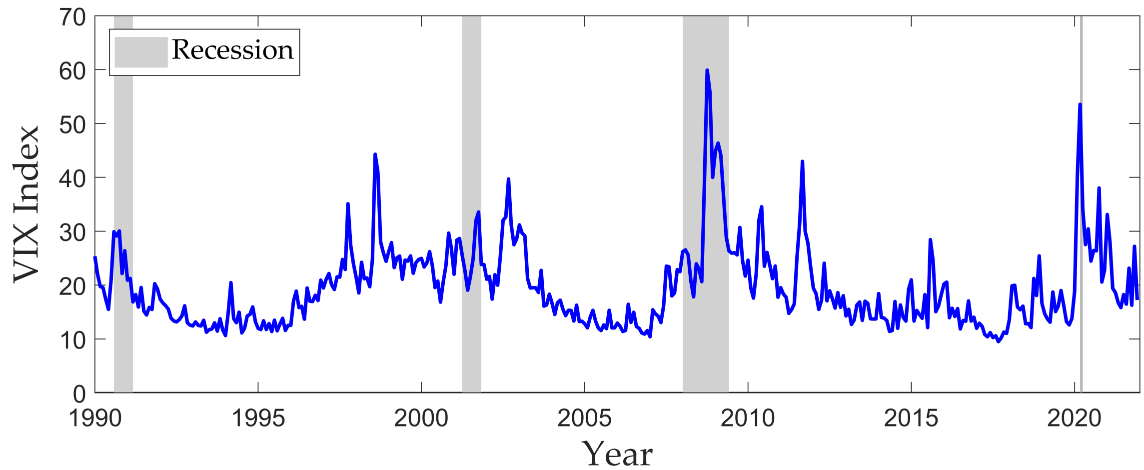

Figure B.1. The figure plots the VIX index realization, with gray shaded areas derived from NBER recession periods.

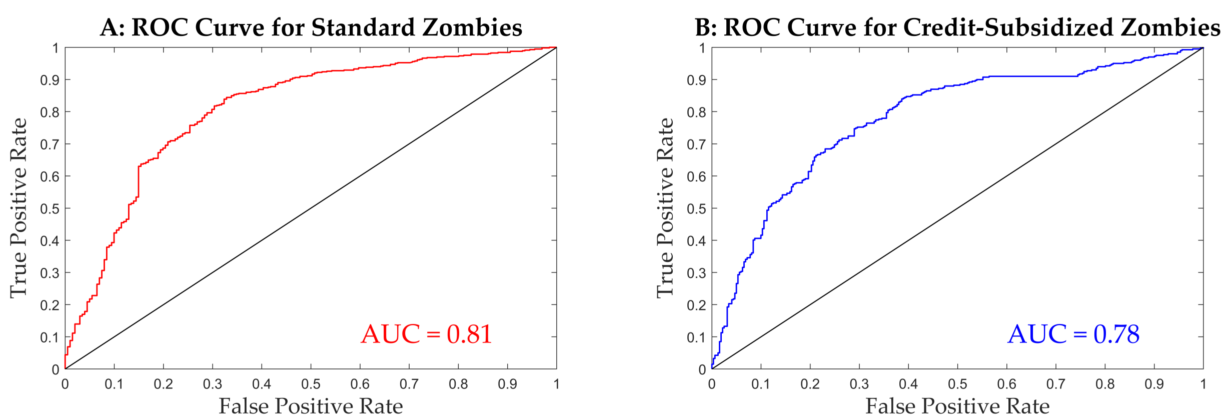

Figure B.2. The figure plots prediction diagnostics for our forecasting regression model (16), which we estimate separately in each of the 50 Hoberg and Phillips (2016) industries over twelve-year rolling windows. We plot the receiver operating characteristic (ROC) curve along with the area under the ROC curve (AUC) for *Standard Zombies* (Panel A) and *Credit-Subsidized Zombies* (Panel B).

Table B.1. Descriptive Statistics

In this table, we report descriptive statistics for our Compustat, other outcome, and control variables (Panel A), Your-Economy Time-Series (YTS) variables (Panel B), and Clarkson-Orbis shipping variables (Panel C). 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.2 for variable definitions.

	N	Mean	SD	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Compustat, Outcome, and Control Variables						
Investment	32,289	0.057	0.065	0.019	0.036	0.068
Disinvestment	23,845	0.015	0.045	0.000	0.000	0.007
Expected Zombificationst	32,289	0.501	0.004	0.499	0.500	0.502
Expected Zombification^{su}	28,189	0.500	0.002	0.499	0.500	0.501
Existing Zombificationst	32,289	0.083	0.097	0.015	0.048	0.116
Existing Zombification^{su}	28,189	0.044	0.063	0.000	0.017	0.053
Marginal Product of Capital (MPK)	32,177	0.771	1.159	0.155	0.844	1.426
Total Factor Productivity (TFP)	17,500	0.365	0.583	0.004	0.334	0.663
Capacity Overhang	26,173	0.441	0.108	0.367	0.423	0.497
Tobin's Q	32,177	1.829	1.192	1.138	1.463	2.071
Cash Savings	32,307	0.141	0.166	0.026	0.081	0.193
Total Payouts	30,543	0.033	0.055	0.000	0.010	0.039
Debt Financing	32,270	0.026	0.145	-0.027	0.000	0.039
Equity Financing	32,307	0.049	0.220	-0.002	0.006	0.025
Patent Filings	27,555	0.005	0.016	0.000	0.000	0.001
Patent Citations	27,555	0.037	0.168	0.000	0.000	0.000
Patent Breakthrough	8,478	0.045	0.148	0.000	0.000	0.000
Δ*Product Differentiation*	32,052	–5.863	3.053	–3.602	–5.235	–7.454
Size	32,289	6.684	1.964	5.321	6.685	8.032
Cash Flow	32,289	0.154	0.125	0.092	0.144	0.212
Industry Uncertainty	32,289	0.322	0.096	0.255	0.297	0.369
State GDP Growth	32,289	0.019	0.021	0.008	0.020	0.033
State Labor Force	32,289	15.417	0.836	14.872	15.404	16.053
Regional Inflation	32,289	0.022	0.011	0.016	0.022	0.030
Interest Rate	32,289	0.001	0.001	0.000	0.001	0.002
Panel B: Your-Economy Time-Series (YTS) Variables						
Establishment Openings	16,602	0.152	0.349	0.000	0.033	0.154
Establishment Closures	16,602	0.084	0.118	0.000	0.040	0.125
Employment Growth	15,046	0.193	0.839	-0.149	0.009	0.308
Panel C: Clarkson-Orbis Shipping Variables						
All Ship Investment	1,054	0.135	0.351	0.000	0.000	0.000
New Ship Investment	1,054	0.128	0.346	0.000	0.000	0.000
Used Ship Investment	1,054	0.007	0.034	0.000	0.000	0.000
All Ship Disinvestment	1,054	0.044	0.144	0.000	0.000	0.000
Ship Sales	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 B.2. Variable Definitions

In this table, we provide exact 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, Panel D corresponds to our Your-Economy Time-Series (YTS) public firm variables, and Panel E describes our Clarkson-Orbis shipping firm variables.

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 (as determined by its interest expense falling below the theoretically most favorable interest rate available at that point in time) and else zero.
Spread	Log 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) for a loan and else zero.
Size	Log 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	Log of the outstanding loan amount.
Loan Type	Indicator variable equal to one for term loans and zero for revolvers.
Loan Maturity	Log 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. (2026)).
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	Log of the national labor force.
Interest Rate	Three-month T-Bill rate.

Panel C: Compustat Panel Regression Variables	
Investment	Ratio of a firm's capital expenditures to lagged assets.
Disinvestment	Ratio of a firm's sales of property, plant, and equipment to 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*.
Marginal Product of Capital	Log of the ratio of a firm's sales to its property, plant, and equipment.
Total Factor Productivity	A firm's log total factor productivity estimated as per Ai et al. (2022).
Capacity Overhang	The percentage capacity overhang of a firm estimated from a stochastic frontier model following Aretz and Pope (2018).
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.
Cash Savings	Ratio of a firm's cash and cash equivalents to total assets.
Total Payouts	Ratio of a firm's total dividends and repurchases to lagged assets.
Debt Financing	Ratio of a firm's change in total debt to lagged assets.
Equity Financing	Ratio of the sum of changes in preferred stock, cash, and minority interests, net of the change in retained earnings of a firm, to lagged assets.
Patent Filings	Number of patents filed by a firm in a year divided by lagged assets.
Patent Citations	Number of citations of a firm's filed patents in a year divided by lagged assets.
Patent Breakthrough	Ratio of the count of patents filed by a firm in a given year that are in the top 10% of *Patent Importance* divided by total patents filed by a firm. *Patent Importance* is the average log importance of a patent, averaged across all patents filed by a 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.
Δ*Product Differentiation*	Negative of product market fluidity as per Hoberg et al. (2014), based on the cosine similarity of a firm's product description in its 10-K filings relative to changes in the product descriptions of its rivals.
Size	Log of a firm's total assets.
Cash Flow	Ratio of a firm's EBIT plus depreciation minus R&D expenses to lagged assets.
Business Entries	Annual percentage change in the number of new business formations in a state.
Industry Uncertainty	Annualized industry-specific firm-size weighted average implied volatility (*AIV* defined above) over the last twelve months.
State GDP Growth	Annual state-level GDP growth.
State Labor Force	Log 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	Ratio of a firm's two-year-ahead change in employment to its start-of-year total sales.

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 returns of the forward contract on the 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	Log of a firm's total assets.
Cash Flow^S	Ratio of the sum of a firm's EBIT and depreciation to lagged assets.
Trade EPU	Trade policy component of the Baker et al. (2016) EPU index.

Table B.3. 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 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, 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 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 Volatility	331	0.004	137,158	0.004	0.001***	8.30

Table B.4. Descriptive Statistics for Banks in High and Low Zombie–Uncertainty $\hat{\beta}_{j,\tau}$ Industries

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 firms in industry-years in the top quartile of the annual distribution of zombie–uncertainty forecasting sensitivities, $\hat{\beta}_{j,\tau}$, (columns (1) and (2)) and those with a positive commitment share of a loan to firms in industry-years in the bottom quartile of the annual distribution of zombie–uncertainty forecasting sensitivities, $\hat{\beta}_{j,\tau}$, (columns (3) and (4)). 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). The estimation of zombie–uncertainty forecasting sensitivities, $\hat{\beta}_{j,\tau}$, is detailed in Section 3.2.3. 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 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, 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.

	High $\hat{\beta}_{j,\tau}$		*Low* $\hat{\beta}_{j,\tau}$			
	N	Mean	N	Mean	Difference	*t*-statistic
	(1)	(2)	(3)	(4)	(2)–(4)	(5)
Panel A: *Standard Zombie Loans*						
Log Assets	191	0.188	191	0.628	–0.441***	–4.61
Deposits-to-Liabilities	191	0.098	191	0.606	–0.507***	–6.06
Equity-to-Loans	191	0.241	191	0.635	–0.395***	–5.20
Loan Type HHI	136	0.455	136	0.350	0.105	1.28
Non-Performing Loans (NPL)	191	0.135	191	0.745	–0.610***	–6.57
Loan Loss Reserve	191	0.534	191	0.345	0.189**	2.12
Asset Growth	191	0.676	191	0.140	0.536***	5.89
Loan Growth	191	0.739	191	0.124	0.615***	6.85
ROA Volatility	191	0.591	191	0.189	0.402***	5.58
Panel B: *Credit-Subsidized Zombie Loans*						
Log Assets	171	0.010	171	0.438	–0.428***	–5.45
Deposits-to-Liabilities	171	0.185	171	0.288	–0.103	–1.33
Equity-to-Loans	171	0.158	171	0.359	–0.200***	–2.91
Loan Type HHI	121	0.271	121	0.235	0.036	0.40
Non-Performing Loans (NPL)	171	0.092	171	0.488	–0.396***	–4.42
Loan Loss Reserve	171	0.340	171	0.266	0.074	0.86
Asset Growth	171	0.449	171	0.148	0.301***	3.50
Loan Growth	171	0.443	171	0.100	0.343***	4.11
ROA Volatility	171	0.371	171	0.180	0.191**	2.33

Table B.5. 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 (defined in Appendix Table B.2). 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.

	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 B.6. Real Effects of Zombie Firms on Non-Zombie Firms' Investment: Mergers and Acquisitions

In this table, we report the results from panel regressions of public non-zombie firms' mergers and acquisitions (M&A) activities on expected zombification (*Expected Zombification*), controls, as well as firm, industry, and trend fixed effects. Our outcome variables are *M&A Expenses* or mergers and acquisitions expenditures divided by lagged assets (columns (1) and (3)) and *SDC Deal Value* or the total sum of M&A deal values reported in SDC divided by lagged assets (columns (2) and (4)). All remaining variables are as defined in Table 3. Unless noted otherwise, in all subsequent tables, 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*	
	M&A Expenses	*SDC Deal Value*	*M&A Expenses*	*SDC Deal Value*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.815***	–0.446**	–1.566***	–0.625
	[–4.07]	[–2.02]	[–4.24]	[–1.49]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.03	0.02	0.03	0.03
Observations	32,289	32,309	28,189	28,207

Table B.7. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Alternative Zombie Definition

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 trend fixed effects. We include two additional constraints on either zombie firm definition by requiring firms to have negative sales growth and Tobin's Q below the industry median. All remaining variables are as defined in Table 3.

	Zombification Proxy Based On:			
	Standard Zombie (2Y ICR Condition) Plus Constraints on Tobin's Q & Sales Growth		*Credit-Subsidized Zombie (2Y ICR Condition) Plus Constraints on Tobin's Q & Sales Growth*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.704***	–0.676***	–0.796***	–1.028***
	[–4.07]	[–2.84]	[–4.04]	[–4.08]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	31,716	23,296	26,932	19,364

Table B.8. 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 trend fixed effects. 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. All remaining variables are as defined in Table 3.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.173***	–0.116**	–0.033	–0.241***
	[–3.68]	[–2.20]	[–0.50]	[–2.68]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	32,289	23,704	28,189	20,295

Table B.9. 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 trend fixed effects. 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. All remaining variables are as defined in Table 3.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.016***	–0.011***	–0.012***	–0.004
	[–6.73]	[–3.43]	[–4.64]	[–1.39]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	28,220	20,756	20,300	14,521

Table B.10. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Non-Standardized Zombie Variable

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 trend fixed effects. To compute *Expected Zombification*, we separately run twelve-year rolling-window regressions of a zombie indicator on the three-month-lagged first principal component extracted from our uncertainty proxies, controls, and firm fixed effects per industry. We combine the slope estimate of the principal component with its end-of-window value to calculate *Expected Zombification*, without applying the standard logistic transformation on the final constructed variable. All remaining variables are as defined in Table 3.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.182***	–0.085***	–0.128***	–0.110***
(Non–Standardized)	[–7.50]	[–3.26]	[–3.79]	[–2.64]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	32,289	23,704	28,189	20,295

Table B.11. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Bootstrapped Standard Errors

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 trend fixed effects. All remaining variables are as defined in Table 3. Plain numbers are coefficient estimates, whereas those in square brackets are *t*-statistics computed using bootstrapped standard errors calculated by resampling firm clusters 1,000 times under the cluster bootstrapping method described in Cameron et al. (2008) in the first-stage regressions estimating *Expected Zombification*. Specifically, we re-estimate those regressions 1,000 times, construct and store the resulting *Expected Zombification* value, then re-estimate the main specification 1,000 times using the generated *Expected Zombification* variable. The standard errors for each coefficient are obtained by using the standard deviation of the respective distributions of these 1,000 coefficient estimates (as discussed in Chen et al. (2023)).

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.727***	–0.342***	–0.510**	–0.438***
	[–5.99]	[–3.11]	[–2.17]	[–2.63]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	32,289	23,704	28,189	20,295

Table B.12. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Alternative Industry Definition

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 trend fixed effects. We define our industries using the 100 Hoberg and Phillips (2016) industry classification. All remaining variables are as defined in Table 3.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–0.636***	–0.272***	–1.306***	–0.242*
	[–6.58]	[–3.06]	[–8.12]	[–1.80]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.09	0.01	0.09	0.01
Observations	31,073	22,785	25,892	18,639

Table B.13. 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 trend fixed effects. We restrict the sample to firms in the manufacturing, mining, and construction industries (SIC 1000–3999). All remaining variables are as defined in Table 3.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification	–1.153***	–0.379**	–0.978***	–0.726***
	[–7.22]	[–2.32]	[–5.00]	[–3.13]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.08	0.01	0.08	0.01
Observations	18,138	13,456	15,616	11,423

Appendix C The Dynamics of Investment and Disinvestment

In this appendix, we examine the dynamics of the (dis)investment responses documented in Table 3. We do so by estimating modified versions of equation (18) 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 four years ahead for both outcome variables. The dynamic coefficient estimates on our key variable of interest, start-of-year *Expected Zombification*, are depicted in Figure C.1. Panel A considers the investment decisions of healthy firms, while Panel B considers their disinvestment decisions.

The two panels of Figure C.1 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 start-of-year *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, as the sharp cuts in *current* investment and disinvestment are not offset by *future* increases, the transitory effects of expected zombification may bear longer-term implications for firms' capital accumulation going forward.

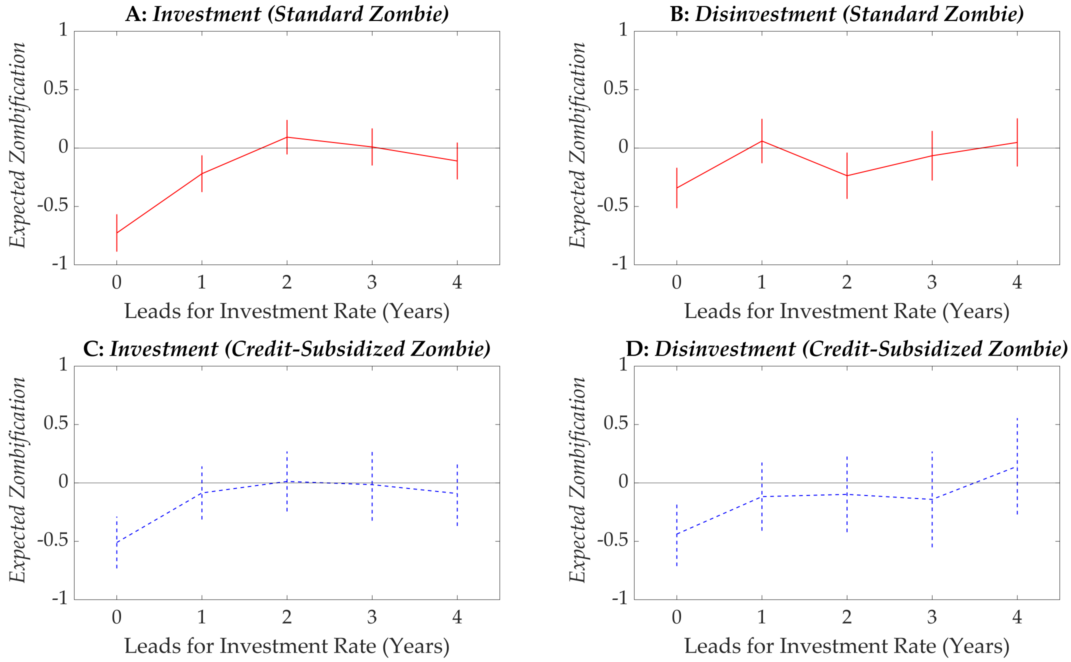

Figure C.1. The figure plots the dynamic coefficient estimates obtained from a modified version of equation (18) in which leads of the investment and disinvestment rates (from zero to four years ahead) are regressed on start-of-year *Expected Zombification* constructed using standard (red lines, *Standard Zombie*) and credit-subsidized (blue lines, *Credit-Subsidized Zombie*) zombie firms. All controls and fixed effects are identical to those included in equation (18). The error bars indicate 90% confidence intervals.

Appendix D Performance and Financing Outcomes

In the tests that follow, we evaluate the future performance of firms exposed to the threat of uncertainty-induced rival zombification. This analysis 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), Gulen and Ion (2016), Kim and Kung (2017), and Campello et al. (2024)) can imply good and bad 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?

Appendix Table D.1 gives the results from estimating equation (19) on non-zombie firms using *Marginal Product of Capital* (column (1)), *Total Factor Productivity* (column (2)), *Capacity Overhang* (column (3)), and *Tobin's Q* (column (4)) as the dependent variable. Panel A uses our standard zombie definition and Panel B uses the credit-subsidized zombie definition.

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 productivity and market valuations while raising their capacity overhang. As before, the effects are often economically important, with a one-standard-deviation increase in the same *Expected Zombification* variable as above inducing both *MPK* and *TFP* to drop by about 3% of their respective sample means. While the negative effects on productivity likely arise because zombie firms depress output prices and raise input costs, thereby slowing down capital accumulation (cf. Acharya et al. (2021)), the *TFP* effect suggests that healthy firms optimally reduce their capacity utilization and produce less in response to zombie rivals (as evident in their increasing *Capacity Overhang*; see column (3)). Finally, since both a firm's capacity overhang and its stock market valuation indicate when it is optimal for a firm to exercise its growth options, the effects on *Capacity Overhang* (though statistically insignificant in Panel B) and *Tobin's Q* 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.[34] These dynamics give further support for our theorized investment and disinvestment mechanisms.

Next, we briefly summarize the results of a set of additional tests performed. In Appendix Table D.2, we examine the relationship between expected uncertainty-induced rival zombification in an industry and several outcome variables corresponding to financial decisions made by healthy firms in that industry. While Section 2 abstracts from these decisions for the sake of tractability, firms' decisions regarding cash savings, payout policy, and financing choices are intuitively linked to the real choices studied in our model (see also Bolton et al. (2011)).

The results 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 accumulating more cash. This action is consistent with non-zombie firms' precautionary motives and investment and disinvestment "inaction" when faced with a greater threat of zombie rival firms in their industries. Turning to payouts, column (2) 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 have a greater motive to shore up liquidity on their balance sheets. Lastly, turning to debt and equity financing, the results in columns (3) and (4) provide modest evidence of reduced issuances of debt, though equity financing seems less significantly 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)).

[34] 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, particularly the volatility of stock returns.

Table D.1. 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 trend fixed effects. Our outcome variables are the *Marginal Product of Capital* or *MPK* (column (1)), *Total Factor Productivity* or *TFP* (column (2)), *Capacity Overhang* (column (3)), and *Tobin's Q* (column (4)). See Appendix Table B.2 for the exact definitions. All remaining variables are as defined in Table 3. Note that *Tobin's Q* is omitted from the set of firm control variables in column (4).

	Firm Performance Variables:			
	MPK	*TFP*	*Capacity Overhang*	*Tobin's Q*
	(1)	(2)	(3)	(4)
Panel A: *Standard Zombie*				
Expected Zombification	–4.831***	–2.540***	0.357*	–7.801***
	[–6.11]	[–3.53]	[1.83]	[–5.32]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.06	0.01	0.09	0.07
Observations	32,177	17,398	26,099	32,309
Panel B: *Credit-Subsidized Zombie*				
Expected Zombification	–3.979***	–2.370***	0.267	–6.833**
	[–2.76]	[–2.53]	[0.83]	[–2.31]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.04	0.01	0.09	0.06
Observations	28,093	14,241	22,415	28,207

Table D.2. 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 trend fixed effects. Our outcome variables are cash savings over the past year, or the ratio of cash and cash equivalents to total assets (column (1)), total payouts in the form of dividends and repurchases all divided by lagged assets (column (2)), debt financing, or the annual change in total debt over lagged assets (column (3)), 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 (4)). All remaining variables are as defined in Table 3.

	Financing Variables:			
	Cash Savings	*Total Payouts*	*Debt Financing*	*Equity Financing*
	(1)	(2)	(3)	(4)
Panel A: *Standard Zombie*				
Expected Zombification	0.341**	–0.475***	–1.518***	–0.632
	[1.98]	[–5.17]	[–4.93]	[–1.53]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.04	0.08
Observations	32,307	30,472	32,270	32,309
Panel B: *Credit-Subsidized Zombie*				
Expected Zombification	0.763**	–0.328*	–2.246***	–0.708
	[2.38]	[–1.83]	[–3.77]	[–0.87]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.05	0.09
Observations	28,205	26,441	28,195	28,207

Appendix E Details of IV Analysis

In this appendix, we describe our IV methodology in detail and explicate the associated results. Alfaro et al. (2024) exploit industry-level heterogeneity in exposures to external shocks, such as changes in energy prices, exchange rates, and policy uncertainty, to construct their IVs. ABL model the exposure of firm i in industry j to these factors as follows:

$$r_{i,t}^{\text{risk\_adj}} = \alpha_j + \sum_f \beta_j^f r_t^f + \varepsilon_{i,t} \tag{E.1}$$

where $r_{i,t}^{\text{risk\_adj}}$ represents the daily risk-adjusted return of the firm, r_t^f denotes the percentage change in factor f (e.g., changes in oil prices or exchange rates), β_j^f captures the industry-specific sensitivity to changes in each of these aggregate factors, and α_j is industry j's intercept. ABL consider nine factors — oil prices, seven exchange rates with respect to the U.S. Dollar, and the Baker et al. (2016) EPU index. The instrumental variables are then constructed by multiplying the three-year lagged absolute value of the time-varying sensitivities, $|\beta_{j,t-3}^f|$, by the one-year lagged realized volatility of the aggregate factors, $\Delta\sigma_{t-1}^f$. The instrument for lagged uncertainty shock $z_{i,t-1}^f$ is thus given by:

$$z_{i,t-1}^f = |\beta_{j,t-3}^f| \cdot \Delta\sigma_{t-1}^f \tag{E.2}$$

This formulation ensures that the instruments capture exogenous variation in uncertainty that is orthogonal to first-moment shocks (such as changes in commodity prices). For example, in the case of oil prices, firms with positive exposure (e.g., oil exploration firms) and firms with negative exposure (e.g., airlines) will have different *directional* sensitivities, while firms in both industries are *positively* exposed to oil price volatility. In our context, we estimate a modified version of regression (18) using IV-2SLS in which *Expected Zombification* is instrumented by the nine ABL uncertainty IVs. The second-stage results are reported in Appendix Table E.1.[35]

The investment and disinvestment *Expected Zombification* coefficients in Appendix Table E.1 are negative and statistically significant, conforming with our baseline OLS estimates reported in Table 3.[36] The IV analysis results suggest that even when we isolate the component of variation in healthy firms' expectations of zombification in their industry that is related to quasi-exogenous variation in uncertainty, we continue to find that they cut back on their investment and disinvestment as predicted by our theory. It is, therefore, unlikely that the observed reductions in healthy firms' capital allocation can be attributed solely to declining first moments.

[35] See Appendix Table E.2 for the first-stage results.

[36] Reassuringly, the high first-stage F-ratios indicate that the ABL IVs are strong instruments for *Expected Zombification*. The slight differences in observation counts between the specifications estimated in Table E.1 and those in Table 3 owe to the ABL IVs being missing for some observations in our base sample. We verify that re-estimating our baseline specifications in the common sample produces virtually identical estimates and inferences as those reported in Table 3, implying that the sample differences are immaterial.

Table E.1. Real Effects of Zombie Firms on Non-Zombie Firms' Investment and Disinvestment: Instrumented *Expected Zombification*

In this table, we report the results from second-stage regressions of public non-zombie firms' investment and disinvestment on instrumented expected zombification (*Expected Zombification*), controls, as well as firm, industry, and trend fixed effects, estimated using IV-2SLS. In the first-stage regression, *Expected Zombification* is instrumented by the nine second-moment instruments provided by Alfaro et al. (2024). See Section 4.6 for more details. All remaining variables are as defined in Table 3. First-stage results are reported in Appendix Table E.2.

	Zombification Proxy Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
	Investment	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Expected Zombification (Instrumented)	–0.894***	–0.458**	–3.054***	–1.233**
	[–4.82]	[–1.96]	[–5.53]	[–2.06]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
R^2	0.09	0.01	0.07	0.01
First-Stage *F*-Ratio	342.49	232.13	102.10	77.00
Observations	30,315	22,201	26,331	18,910

Table E.2. Instrumented *Expected Zombification*: First-Stage Results

This table reports output from the first-stage regression corresponding to the second-stage instrumental variables regression reported in Table E.1. The dependent variable is *Expected Zombification*. In the first-stage regression, *Expected Zombification* is instrumented by the nine second-moment instruments provided by Alfaro et al. (2024). See Section 4.6 for more details.

First-Stage Outcome Variable:	*Expected Zombification* Based On:			
	Standard Zombie		*Credit-Subsidized Zombie*	
Second-Stage Outcome Variable:	*Investment*	*Disinvestment*	*Investment*	*Disinvestment*
	(1)	(2)	(3)	(4)
Oil IV (z^{Oil})	0.005***	0.004**	0.004***	0.005***
	[3.81]	[2.27]	[6.28]	[5.12]
CAD IV (z^{CAD})	0.002**	0.002	–0.001**	–0.002***
	[2.45]	[1.55]	[–2.10]	[–2.70]
EUR IV (z^{EUR})	–0.015***	–0.014***	–0.003***	–0.002***
	[–15.96]	[–12.78]	[–5.12]	[–3.78]
JPY IV (z^{JPY})	0.007***	0.007***	0.003***	0.003***
	[7.17]	[5.77]	[5.10]	[4.11]
AUD IV (z^{AUD})	–0.032***	–0.029***	–0.015***	–0.014***
	[–25.09]	[–20.36]	[–16.80]	[–13.24]
SEK IV (z^{SEK})	0.005***	0.004***	–0.001	–0.001
	[4.29]	[3.17]	[–1.13]	[–0.96]
CHF IV (z^{CHF})	–0.015***	–0.016***	–0.006***	–0.007***
	[–18.06]	[–16.69]	[–10.90]	[–10.21]
GBP IV (z^{GBP})	0.008***	0.008***	0.009***	0.010***
	[7.97]	[6.06]	[13.83]	[11.92]
EPU IV (z^{EPU})	1.396***	1.536***	0.843***	1.071***
	[6.84]	[6.11]	[6.66]	[6.47]
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Industry × Trend FEs	Yes	Yes	Yes	Yes
First-Stage *F*-Ratio	342.49	232.13	102.10	77.00
Observations	30,315	22,201	26,331	18,910