Rising Markups, Zombie Firms, And Misallocation *

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Abstract

We provide novel evidence on the relation between rising markups and the allocative efficiency of zombie lending. Using a large dataset of Italian firms for the 2007-2016 period, we show that the fraction of zombie firms is significantly larger in sectors with higher and more dispersed markups. Importantly, we also show that in these sectors, zombie firms are more dynamic and more likely to transition to the top of the markups and market share distributions. These findings hold both cross sectionally and within sectors over time, and they are consistent with a model of firm dynamic with heterogeneous markups, financial frictions, and the option to perform productivity-enhancing investments, which is available to a subset of firms in the economy. We solve the model and use it to simulate industries with different markup levels of top firms. We show that, even though zombie loans are potentially available to all firms because lenders cannot discriminate firms types, low productivity firms with high upside potential are more likely to receive them in equilibrium, the more so the larger the markups of top firms, thus increasing both the share of firms transitioning to the top and aggregate productivity. In terms of policy implications, our theoretical and empirical results emphasize it is important to take into account the dynamism and market structures of different sectors, to correctly evaluate the positive and negative reallocation effects of zombie lending.

Keywords: *Zombie Firms, Market Power, Markups, Misallocation, Firm Dynamics*

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1. Introduction

Several studies have documented an increase in firm profitability and markups over recent decades. Within industries, rising markups have been driven primarily by the gains of the top firms, resulting in widening gaps between them and the other firms (e.g., see, among others, De Loecker et al., 2020 and Díez et al., 2021). An important factor to explain this trend is the emergence of new intangible technologies, characterized by network externalities, which allow larger firms to exploit these scale-related competitive advantages, and hence make it more difficult for new firms to enter and compete (e.g., among others, see De Ridder, 2024). Less explored in this literature is the role of finance. Do financial factors and the allocation of credit matter for competition and aggregate outcomes in industries affected by these technological trends?

Another strand of literature analyses the inefficiencies in the allocation of credit caused by "zombie lending". Zombie firms are entities that are materially in distress (e.g. have deteriorating returns) but avoid default through the support of their lenders. By "zombie lending" we refer to lenders continuously providing credit toward zombie firms to avoid the recognition of loan losses, the so-called "evergreening" of loans (e.g. see, among others, Blattner et al., 2023; Álvarez et al., 2023; Faria-e Castro et al., 2024 and Acharya et al., 2022). While this literature shows theoretically and empirically the incentives of banks to extend zombie loans, and documents several types of aggregate implications, less is known about what types of firms are more likely to benefit from these types of loans in equilibrium, and how they affect industry outcomes in the context of rising markups.

In this paper, we answer these questions by developing a firm dynamics framework with heterogenous markups, financial frictions, and productivity-enhancing investments, and by testing its predictions using a large dataset of Italian firms from ORBIS.

In the model, firms pay a fixed cost to enter and begin operating with a low-productivity technology. We call these firms "laggards". Lines of credit are available to them, with a premium over the risk free interest rate that reflects their default risk. Over time, firms can invest to become more productive, and those that succeed become highly productive "leaders", who charge higher markups and are more profitable. Firms are also subject to revenue uncertainty and if their profits are negative, they need to accumulate debt in order to keep producing.

We make three key assumptions: first, not all new firms have the potential to become leaders, only a fraction of them, which is larger than zero, but smaller than one. We call these

"*high-potential*" laggards, and the other firms "*stagnant*" laggards. Second, lenders extend zombie loans with some probability to firms in financial difficulty. These are firms that face high interest payments relative to their revenues, and their expected profits for the current period are negative. In other words, we model zombie loans following the empirical literature, as lending given at favorable interest rates, which has the effect of prolonging the life of highly indebted and loss making companies (Caballero et al., 2008; Faria-e Castro et al., 2024). Third, lenders are not able to discriminate between types of low productivity borrowers. Namely, they do not know whether or not they have the potential to become leaders in the future.

We believe these assumptions are plausible. The first is consistent with the recent literature showing that new firms are intrinsically heterogeneous at birth, with only a small fraction of them having high growth potential (e.g. see Sterk et al., 2021). The second is a reduced-form way to model evergreening incentives for lenders. When faced with distressed borrowers, banks often find it optimal to extend new loans at favourable terms rather than recognize losses. Recent empirical and theoretical evidence shows that this behavior emerges from banks' incentives to avoid loan loss recognition (Begenau et al., 2020; Blattner et al., 2023; Bonfim et al., 2023) or as a strategy to gamble for resurrection (Acharya et al., 2021). More closely related to our setup Faria-e Castro et al. (2024) show that under full information, banks optimally chose to lend at better terms to more leveraged firms. The third assumption simply states that lenders cannot perfectly identify the growth potential of borrowers when they provide zombie loans.

We calibrate and solve the model, and then simulate several industries that differ only in terms of the productivity of leaders, while the productivity of laggards is constant and normalised to one. Since a free entry condition holds for each industry, in equilibrium expected profits for new entrants are the same across industries. However, in equilibrium the higher is the productivity of leaders, the more dispersed is the distribution of markups among incumbents, with top firms having larger markups both in absolute terms and relative to the other firms in the industry.

Our first testable prediction of the model is that, *in an industry, the larger are leaders' markups, the larger is the share of zombie firms.*

This correlation is driven by the incentives of the high-potential laggards. Both them and the stagnant laggards, after a sequence of negative profitability shocks accumulate debt, and the expected excess cost of interest payments reduces their expected next-period profits. When these become negative, these firms become "eligible" for zombie loans. However, the high-potential firms are those that are more likely to stay in operation, because of the option value to become

leaders in the future, while the other firms are less valuable and more likely to exit conditional on receiving a bad profitability shock.

Thus in equilibrium the higher are leaders' markups, the higher the share of zombie firms is among those with the potential to become future leaders. Moreover, these firms also invest more intensely in productivity enhancing activities, because the gains from succeeding are higher, since leaders are more profitable in the high markup industries.

This leads to our second testable prediction: *the larger is the markup of top firms, the more likely zombie firms are to become leaders in the future.*

We test and confirm the empirical predictions of the model using detailed firm-level data from Italy between 2007-2016. We compute firm-level markups following De Loecker et al. (2020), and we use them to obtain measures of markup dispersion and markup of top firms for every industry and year in the sample. Our model implies that higher markup dispersion across industries correlates with higher markups of top firms, and therefore we can test the prediction of the model using either variations in dispersion or variation in top markups. We use the former as our benchmark measure, but we verify that all results hold when using the latter. Furthermore, our predictions are derived by comparing equilibria across industries and therefore their direct empirical counterpart is cross-industry evidence. Nonetheless, we confirm that all the results hold if we include industry-year fixed effects, thus controlling for all industry invariant characteristics and focusing on within industry variation.

First, we document that increases in markup dispersion correlate with larger zombie shares both across and within sectors. In particular, a one standard deviation increase in sector-level markup dispersion (0.56) is associated with 36 percent higher shares of zombie firms (0.9 percentage points higher).

Second, we show that as markup dispersion increases, the likelihood of zombie firms reaching the top quartile of market share and markup distribution over the subsequent four years increases substantially. In other words, the larger the markups for top firms in an industry, the more likely zombies are to ever become top firms in the future, thus confirming the second prediction of the model. Quantitatively, while zombie firms are on average less likely to become leaders than other firms, their chances are significantly better in sectors with higher and more dispersed markups. In particular, increasing the markup dispersion from the bottom 25th to the top 75th percentile distribution increases the likelihood of zombie firms becoming leaders (e.g. being in the top quartile of the market share) by 11.8 percentage points. The effect is even stronger for

markups, where the same increase in dispersion relates to a 10.1% increase in reaching the top quartile and offsets 82% of the initial "zombie disadvantage". We further document this positive relation between sector markup dispersion and zombie dynamism also for employment levels and investment rates. Together, these findings strongly support our model's key mechanism that market structure fundamentally shapes zombie firms' potential for future improvements.

Summing up, this paper provides novel theoretical predictions on the relation between rising markups and zombie lending, which are confirmed by the empirical evidence. With respect to the studies arguing that rising markups are caused by technological changes that favours dominant firms (e.g. De Ridder, 2024), we show that zombie lending can have previously uncovered beneficial reallocation effects. Our model shows that, in industries with large differences in markups between top firms and the rest, an higher amount of zombie loans increase in equilibrium the share of firms with high potential relative to the other firms, increasing also the fraction of highly productive firms, the level of competition, and aggregate productivity.

In terms of the literature on zombie firms, we believe our findings are complementary with, and not in contrast to, other studies that highlight the potential misallocation effects of zombie lending (see Acharya et al., 2024 for a recent survey of the literature). On the one hand, one could extend our model in directions that allow for misallocation effects similar to those highlighted by the literature. For example, if we assumed that no productivity enhancing innovation is possible (that is, top firms are "exogenously" born leaders) then the model would imply zombie loans misallocate resources because they would reduce the fraction of top firms in the industries.

On the other hand, these alternative versions of the model are consistent with our first testable prediction, but not with the second. Since we strongly confirm the latter in the data, we believe the novel role of zombie lending identified in this paper is empirically relevant, and might partly counteract, especially for high markup industries, the negative effects highlighted by the literature. In terms of policy implications, this means it is important to consider the dynamism of a sector, as well its type of technology and market structure, to correctly evaluate the positive and negative reallocation effects of zombie lending.

2. Model

We consider a firm dynamics model with imperfect competition, financial frictions, productivity-enhancing investment, and variable markups. We keep the model as simple as possible by

employing three simplifying assumptions. First, we introduce variable markups by adopting the quadratic utility approach of Melitz and Ottaviano (2008). Second, financial frictions are introduced by restricting lenders to offer only one type of lending contract, which is a line of credit with a borrowing limit and a fixed interest rate premium over the risk free interest rate. Third, rather than microfounding lenders' decisions to extend "zombie loans", we assume that financially distressed firms receive such lending with an exogenous probability. Nonetheless, we argue that the main qualitative predictions of the model do not depend on these assumptions and would also hold in a more complex model with a more realistic market structure, and with more micro-founded types of financial imperfections and lending behavior.

2.1. Consumers

The representative consumer's utility function is given by:

$$U_t = A \int_{i \in N} q_{it} \, di - \frac{\gamma}{2} \int_{i \in N} q_{it}^2 \, di - \frac{\eta}{2} \left(\int_{i \in N} q_{it} \, di \right)^2 + C \tag{1}$$

where q_{it} is the quantity consumed of variety i in period t; N is the set of all varieties; $\gamma > 0$ measures the degree of substitutability between varieties; $\eta > 0$ captures the intensity of competition among firms; C is the consumption of an homogeneous good chosen as numéraire. The consumer's budget constraint is:

$$\int_{i \in N} p_{it} q_{it} \, di + C = I \tag{2}$$

where p_{it} is the price of variety i in period t; I is the consumer's income. Maximizing utility subject to the budget constraint yields the inverse demand function for each variety:

$$p_{it} = 1 - \gamma q_{it} - \eta Q_t \tag{3}$$

where $Q_t = \int_{i \in N} q_{it} \, di$ is the total consumption of all varieties.

2.2. Firms

2.2.1. Technology

Firm i in period t has productivity z_{it} and marginal cost $c_{it} = \frac{w}{z_{it}}$. $w > 0$ is the unitary cost of the variable production input. Profits are:

$$\pi_{it} = (p_{it} - c_{it})q_{it} - F_{it} \tag{4}$$

Where F_{it} is a positive cost of production that is drawn every period from a uniform distribution:

$$F_{it} \in [\underline{F}, \overline{F}]$$

We use (3) to compute $q_{it} = \dfrac{1 - p_{it} - \eta Q_t}{\gamma}$ and we substitute it into profits:

$$\pi_{it} = (p_{it} - c_{it})\frac{A - p_{it} - \eta Q_t}{\gamma} - F_{it} \tag{5}$$

The first order condition for the optimal price yields :

$$p_{it} = \frac{A + c_{it} - \eta Q_t}{2} \tag{6}$$

And the markup is:

$$p_{it} - c_{it} = \frac{A - c_{it} - \eta Q_t}{2} \tag{7}$$

Therefore, firms with higher productivity and lower marginal costs c_{it} in equilibrium have higher markups. We substitute p_{it} and q_{it} to obtain:

$$\pi(z_{it}, F_{it}) = \frac{(A - \frac{w}{z_{it}} - \eta Q_t)^2}{4\gamma} - F_{it} \tag{8}$$

We denote the expectation of $\pi(z_{it}, F_{it})$ over the value of F_{it} as $\pi^e(z_{it})$:

$$\pi^e(z_{it}) = \frac{(A - \frac{w}{z_{it}} - \eta Q_t)^2}{4\gamma} - E(F_{it})$$

2.2.2. Firm Types

There are three types of firms. The first type has high productivity z^{High}. We call them "*leaders*". The second type has a productivity equal to z^{Low}, with $z^{Low} < z^{High}$, but are able to perform productivity-enhancing investments, which with some probability will allow them to reach z^{High}. We call these firms "*high-potential laggards*". Finally, the third type has a productivity equal to $z^{Low} < z^{High}$, but is not able to make a productivity-enhancing investment. We call them "*stagnant laggards*". Firms draw their types at the time of entry. In the simulations presented in this draft, we assume that all firms enter initially with productivity equal to z^{Low}, and gradually a fraction of those that are high-potential laggards eventually become leaders. We will, however, also summarise the results of counterfactual simulations in which firms are born either leaders or stagnant laggards, so no productivity improvements are possible during operation.

All firms die with an exogenous probability of $1 - d$, where $0 < d < 1$ is the continuation probability. Moreover, firms will optimally choose to default when the net present value of revenues from continuing to operate their business becomes negative. This never happens in equilibrium for leaders, while it can happen for laggards, as explained below.

2.2.3. Financial Frictions

We introduce in the model two frictions. First, firms face costly external finance. We assume the lenders can only offer one type of debt contract: a line of credit with upper limit $\bar{b}$ and interest rate equal to $r + \tau$, where r is the risk free interest rate and $\tau > 0$ is a premium to compensate for the debt's riskiness. Intuitively, if the firm stops operating, its only collateral is its residual value $\phi < \bar{b}$. Therefore, τ compensates for the probability of facing losses on the debt contract in case $b > \phi$ at the time of the firm's exit. The presence of this cost is irrelevant for leaders, which are very productive and are net savers. However, it is costly for low productivity firms, which even though they are on average profitable, might accumulate debt over time after a sequence of bad shocks, and hence have to pay additional financing costs which reduce their net present value. Once this becomes negative, a firm finds it optimal to exit.

Second, lenders have the option to modify the lending contract to reduce the borrowing rate, and have a preference for doing so for highly indebted borrowers. There is a large literature that documents the incentives for banks to roll over debt for highly indebted and poor performing firms, because it is optimal for them to avoid recognizing capital losses (Caballero et al., 2008; Bruche

and Llobet, 2014; Acharya et al., 2021, 2019; Blattner et al., 2023)[1]. Therefore, rather than micro-founding in detail this behaviour, we introduce it in the model with the following assumption: all firms that at the beginning of the period expect negative average profits, $\pi^e(z_{it}) < 0$, with probability ζ receive a loan contract modification so that their premium falls from τ to $\tau^z < \tau$. The consequence of this modification is that these firms become "Zombies", in the sense that they are low performing firms with high debt that are kept alive by very favourable lending conditions. It is important to consider three aspects of this assumption: first, it makes sense from the standpoint of a lender that wants to reduce the possibility of a borrower's default. Firms with negative expected profits have low value, and are on average more likely to default in future periods than the firms with positive expected profits. Therefore, they are the natural candidates to receive zombie loans. Second, is consistent with the empirical literature on zombie firms, which identifies them as those that pay low interest rates despite having high debt and low profits (Caballero et al., 2008; Acharya et al., 2019, 2022, 2024). Third, it implies lenders are not able to discriminate between types of laggard firms. This way we allow for the possibility that zombie lending is particularly inefficient when it is directed to stagnant laggards, that have a lower probability to repay it than high potential laggards.

2.2.4. Leaders

When a firm becomes leader, it maintains the same productivity level until it dies with probability $1 - d$. Its value at time t, measured as the net present value of profits, is:

$$V_{it}^{Leader}\left(z^{High}\right) = \pi^e\left(z^{High}\right) + \frac{d}{R} V_{it+1}^{Leader}\left(z^{High}\right) = \frac{R\ \pi^e\left(z^{High}\right)}{R-d} \tag{9}$$

Where $R = 1 + r$ is the gross real interest rate. As mentioned above, $\pi^e\left(z^{High}\right)$ is expected profits, where the expectation is over the realization of the per-period fixed cost of operations F_{it}.

2.2.5. Laggards

At the beginning of period t, laggards have debt equal to b_t and productivity equal to z^{Low}. Their value is denoted by $V_{i,t}^{J}\left(z^{Low}, b_{it}\right)$, where $J \in \{HPL, HPZL, SL, SZL\}$. These acronyms respectively indicate "High Potential Laggard","High Potential Zombie Laggard","Stagnant Laggard", and "Stagnant Zombie Laggard".

[1] A detailed and comprehensive list is included in Acharya et al. (2022).

The presence of the spread τ^J means that, for laggards, profits are affected by the extra cost of servicing debt:

$$\pi^J(z_{it}, b_{it}, F_{it}) = \frac{(A - \frac{w}{z_{it}} - \eta Q)^2}{4\gamma} - F_{it} - \tau^J b_{it} \mathbb{1}(b_{it} > 0) \tag{10}$$

Where $\tau^J = \tau$ for non-zombie laggards , and $\tau^J = \tau^Z < \tau$ for zombie laggards. $\mathbb{1}(b_{it} > 0)$ is an indicator function equal to 1 if the argument is satisfied and zero otherwise. Define as $\pi^e(z^{Low})$ the expected value of profits in period t before knowing the realization of the fixed cost F_{it}:

$$\pi^{e,J}(z^{Low}) \equiv E\left[\pi^J\left(z^{Low}, b_{it}, F_{it}\right) | F_{it} \leq F_{it}^{*,J}\right] \tag{11}$$

$F_{it}^{*,J}$ is the threshold value of fixed costs above which the firm does not continue, because its continuation value becomes negative. We describe both values below. Notice that negative expected profits $\pi^{e,J}(z^{Low})$ are consistent with positive continuation values, for two reasons. Because the firm might improve its productivity and become a more profitable leader; Even in the absence of this possibility, because it might have a sequence of good F_{it} draws, use the revenues to reduce its debt and its interest payments, and increase its future expected profits.

When a laggard firm has negative expected profits, $\pi^{e,J}(z^{Low}) < 0$, with probability ζ it becomes a "laggard zombie", which means its spread falls from τ to τ^z. Intuitively, the firm receives a favourable contract modification from the lender, which wants to keep it alive.[2] A firm remains in zombie status until either it exits or it becomes a leader.

We assume that laggard firms do not distribute dividends, and therefore their budget constraint is:[3]

$$b_{it+1} - b_{it} = r b_{it} + \pi^J\left(z^{Low}, b_{it}, F_{it}\right) - I_{it} \tag{12}$$

$b_{it+1} - b_{it}$ denotes the change in the borrowing from the credit line.[4] $I_{it} \geq 0$ is the investment in productivity improvement, which is available for high potential laggards. Finally, note that the amount drawn from the credit line cannot exceed an exogenous borrowing limit $\bar{b}$. If at the

[2]Note that even though τ^z could be negative, we restrict the interest rate on the loan to be positive, so $r + \tau^z \geq 0$.

[3]Since they are risk neutral, this assumption is without loss of generality. It is optimal to retain earnings if they face some probability to be constrained now or in the future, and they are indifferent between retaining or distributing earnings if they become so wealthy that they are financially unconstrained.

[4]The total interest paid is $(r + \tau^J)b_{it}$, where the part in excess to the risk free interest rate $\tau^J b_{it}$ is already included into the profits function $\pi^J\left(z^{Low}, b_{it}, F_{it}\right)$.

beginning of a period the limit is violated because $b_{it} > \bar{b}$, the firm is liquidated.

If $b_{it} < \bar{b}$, the firm observes the fixed cost draw F_{it}, and it exits voluntarily if the value of continuing net of current profits is negative. Denote as $V_{i,t}^{Cont,J}\left(z^{Low}, b_{it}, F_{it}\right)$ as the continuation value of a type J firm, then $F_{it}^{*,J}$ is the value that satisfies $V_{i,t}^{Cont,J}\left(z^{Low}, b_{it}, F_{it}^{*,J}\right) = 0$. In other words, $F_{it}^{*,J}$ is the maximum fixed cost that the firm can pay, because its continuation value would become negative above it. Therefore the probability of not exit voluntarily is $p^{cont,J} = \dfrac{F_{it}^{*,J} - \underline{F}}{\overline{F} - \underline{F}}$

High Potential Laggards

The initial value of an high potential laggard firm is:

$$\begin{aligned} V_{i,t}^{HPL}\left(z^{Low}, b_{it}\right) = \mathbb{1}[\pi^e(z^{Low}) < 0]\zeta V_{i,t}^{HPZL}\left(z^{Low}, b_{it}\right) \\ + \Omega\left[\mathbb{1}(b_{it} < \bar{b}) p^{cont} E\left[V_{i,t}^{Cont,HPL}\left(z^{Low}, b_{it}\right) \,\middle|\, F_{it} \leq F_{it}^{*,HPL}\right]\right] \end{aligned} \tag{13}$$

where $\Omega \equiv 1 - \zeta\mathbb{1}[\pi^e(z^{Low}) < 0]$. The equation above reflects the fact that, when the firm has negative expected profits and the indicator function $\mathbb{1}[\pi^e(z^{Low}) < 0]$ is equal to one, the firm transitions to Zombie status with probability ζ. Otherwise, conditional on debt not hitting the borrowing limit, the last term in square brakets is the expected continuation value, and $p^{cont,HPL}$ is the continuation probability. The value of a high potential zombie laggard is:

$$V_{i,t}^{HPZL}\left(z^{Low}, b_{it}\right) = \mathbb{1}(b_{it} < \bar{b}) p^{cont,HPZL} E\left[V_{i,t}^{Cont,HPZL}\left(z^{Low}, b_{it}\right) | F_{it} \leq F_{it}^{*,HPZL}\right] \tag{14}$$

If it continues, the firm learns its cost X_{it} of performing productivity enhancing activities. All high potential laggards, regardless on whether or not they are zombies, can invest in these activities. The cost $X_{it} > 0$ is drawn every period from a uniform distribution independent across firms:

$$X_{it} \in [\underline{X}, \overline{X}] \tag{15}$$

This investment allows the firm to become a leader with probability ξ. Therefore, the value of a high potential firm $Y \in \{HPL, HPZL\}$, conditional on not investing is:

$$V_{it}^{Y,NI}\left(z^{Low}, b_{it}, F_{it}\right) = \pi\left(z^{Low}, b_{it}, F_{it}\right) + \frac{d}{R} V_{it+1}^{Y}\left(z^{Low}, b_{it+1}\right) \tag{16}$$

While the value conditional on investing is:

$$V_{it}^{Y,I}\left(z^{Low},b_{it},F_{it}\right)=\pi\left(z^{Low},b_{it},F_{it}\right)+\frac{d}{R}\left[\xi V_{it+1}^{Leader}\left(z^{High}\right)+\left(1-\xi\right)V_{it+1}^{Y}\left(z^{Low},b_{it+1}\right)\right] \tag{17}$$

A firm finds it optimal to invest if $V_{it}^{Y,I}\left(z^{Low},b_{it},F_{it}\right)-X_{it}>V_{it}^{Y,NI}\left(z^{Low},b_{it},F_{it}\right)$. Therefore we can define the maximum investment cost as $X_{it}^{*,Y}=V_{it}^{X,I}\left(z^{Low},b_{it},F_{it}\right)-V_{it}^{Y,NI}\left(z^{Low},b_{it},F_{it}\right)$

The investment probability is then $p^{INV,Y}=\dfrac{X_{it}^{*,Y}-\underline{X}}{\overline{X}-\underline{X}}$, and the expected investment cost conditional on performing productivity enhancing activities is $X^{e}=0.5\left(X_{it}^{*,Y}+\underline{X}\right)$. Therefore, the continuation value is:

$$V_{i,t}^{Cont,Y}\left(z^{Low},b_{it}\right)=p^{INV,Y}\left[V_{it}^{Y,I}\left(z^{Low},b_{it},F_{it}\right)-X^{e}\right]+\left(1-p^{INV,Y}\right)V_{it}^{Y,NI}\left(z^{Low},b_{it},F_{it}\right) \tag{18}$$

The investment in productivity improvement I_{it} is therefore equal to X_{it} for firms that decide to invest, and zero otherwise.

Stagnant Laggards

The continuation value for Stagnant Laggards is much simpler, because these firms cannot invest to increase productivity. Therefore, for $S\in\{SL,SZL\}$:

$$V_{i,t}^{Cont,S}\left(z^{Low},b_{it}\right)=\pi\left(z^{Low},b_{it},F_{it}\right)+\frac{d}{R}V_{it+1}^{S}\left(z^{Low},b_{it+1}\right) \tag{19}$$

The investment in productivity improvement I_{it} is always equal to zero for these firms.

2.2.6. Entry

New firms pay an initial cost κ to enter and have zero debt. With probabilities b^{L}, b^{P} and $1-b^{L}-b^{P}$ they discover being leaders, high potential laggards, or stagnant laggards, respectively. Therefore the free entry condition is:

$$b^{L}V_{i,t}^{leader}\left(z^{High}\right)+b^{P}V_{i,t}^{HPL}\left(z^{Low},0\right)+(1-b^{L}-b^{P})V_{i,t}^{SL}\left(z^{Low},0\right)-\kappa=0 \tag{20}$$

2.2.7. Aggregate Equilibrium

Assume N firms are in operation. Total quantity produced is $Q = \sum_{i=1}^{N} q_i$. Substituting $q_{it} = \frac{1-p_{it}-\eta Q}{\gamma}$ and rearranging we obtain:

$$Q = \frac{N - \sum_{i=1}^{N} c_i}{2\gamma + N\eta} \tag{21}$$

After simulating the model for many period, we obtain the steady state distribution of marginal costs. We use it to compute $\sum_{i=1}^{N} c_i$. Then equations 20 and 21 jointly determine the aggregate equilibrium values of Q and N.

3. Calibration and simulation results

We normalise to 1 the productivity of laggards z^{Low}, and to zero the probability of being born leader b^L and the lower bound values $\underline{F}$ and $\underline{X}$. We calibrate the remaining parameters so that the simulated industry matches several key characteristics of the empirical data. Table 1 shows the matched moments. The table also shows the model's parameter most closely related to each moment, even though for most moments the mapping is not one-to-one. Rather, sets of moments are jointly matched by several parameters together.

Table 1 excludes only one parameter, the probability to start as high potential laggard b^P. To be more precise, b^P together with the success rate of productivity enhancing investment ξ jointly match the observed rate of transitions from below median to top markups. We set $b^P = 0.3$, so 30% of firms are born as high potential laggards, and 70% as stagnant laggards. This implies a value of $\xi = 1.25\%$. Reducing or increasing b^P would require changing ξ to match the rate of transitions to top. However, as discussed in Section 4.1, these changes would not affect our qualitative results as long as b^P is not extremely small (very close to zero) or extremely large (very close to one).

4. Model's results

Figures 1 and 2 show the results from simulating several industries that have the same benchmark parameters, except for the leaders' productivity levels (z^{High}). Note that all these different industry equilibria satisfy the same free entry condition. In other words, changing z^{High} effectively changes the dispersion in productivity and markups, while equilibrium aggregate prices and

Table 1:
Calibration

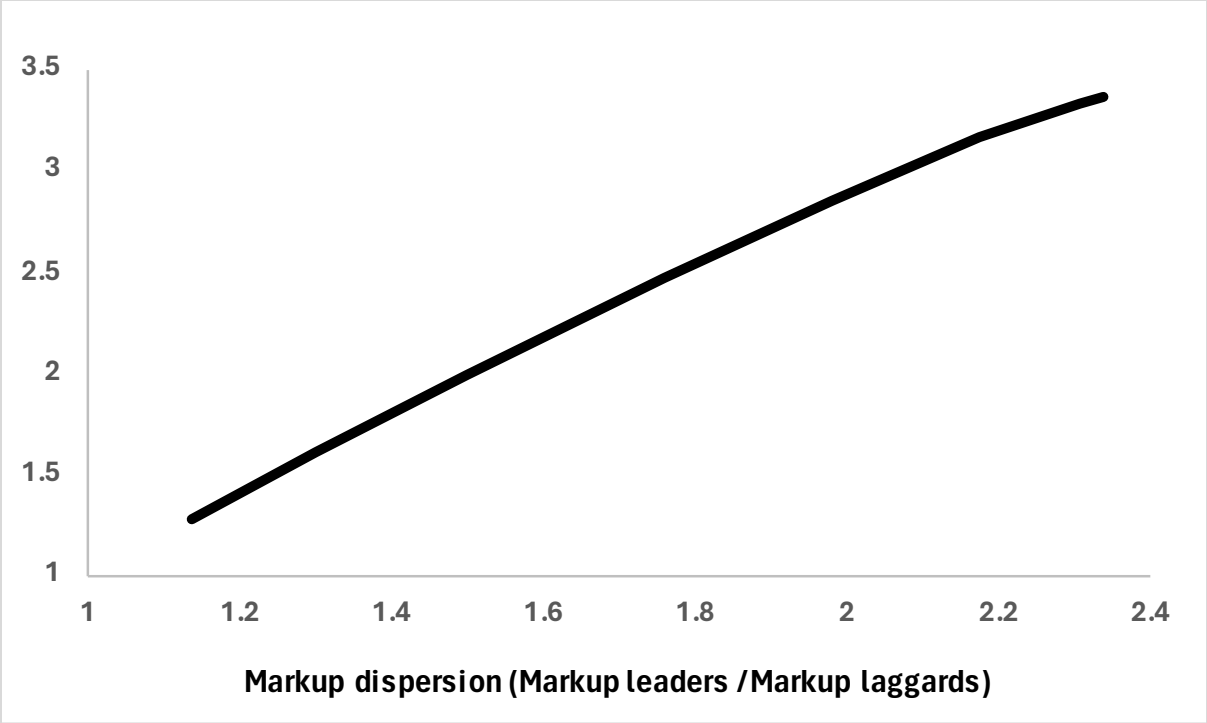
Moment	Data	Model	Related Parameter	Value
Interest rate	2	2	Real interest rate, r	2%
Hazard rate in long run	4%	4%	Exogenous exit probability, $1-d$	4%
Bankruptcy rate	0.13%	0.4%	Borrowing limit, $\overline{b}$	15
Share of zombie firms over total firms	2.5%	3.44%	Probability to receive zombie loans, ζ	0.6%
Average markup (weighted)	1.43	1.24	Substitutability between varieties, γ	5
Ratio top 95th markups over median	2.518	2.29	Productivity of leaders, z^{High}	5
Avg Profit rate (EBIT to assets)	5.7%	6.1%	Entry cost, κ	0.9
Firms avg. age in years	15	19.8	Variable input cost, w	6
Average fixed cost over sales	35%	0.14%	Upper limit of fixed cost, $\overline{F}$	0.3
Median debt over sales	63%	44%	Intensity of competition, η	0.25
Share transition from below median markup to top 95% markup	0.34%	0.33%	Probability to succeed in enhancing productivity, ξ	1.25%
Average productivity enhancing investment (Net intangibles investment over sales)	8%	16%	Upper limit of investment cost, $\overline{X}$	0.45
Premium over AAA borrowing rate, 75th percentile	2.14%	2.14%	Borrowing premium for laggards, τ	2.14%
Premium over AAA borrowing rate, zombie firms	≤ 0	0	Borrowing premium for laggard zombies, τ^Z	0

quantities adjust so that the expected value at entry is the same across all the simulations. On the horizontal axis, we report the markup dispersion of each simulation. Figure 1 shows that higher markup dispersion within industries closely correlates with top firms' markups. Therefore our cross industry predictions can be tested in the data by using either measure.

Figure 2 shows that a higher markup dispersion has two opposite effects on laggard firms. On the one hand, it reduces their profitability, because of the competitive pressure from the most productive leaders, and eventually causes an increase in exits. On the other hand, it increases the incentives to invest to increase productivity. This increases X^*, the maximum investment cost threshold below which such investment is profitable, and increases the share of firms that invest, and therefore also the share of transitions to top productivity. This implies that the share of highly productive firms also increases, putting further pressure on low-productivity firms and further increasing firm exits.

Figure 3 shows the implications of these forces for the share of zombie firms. Initially, when markup dispersion is very low, the share of firms with zombie loans is zero. This is because all firms are on average profitable and accumulate savings. However as mentioned above, as markup

Figure 1:
Markups of top firms (leaders)



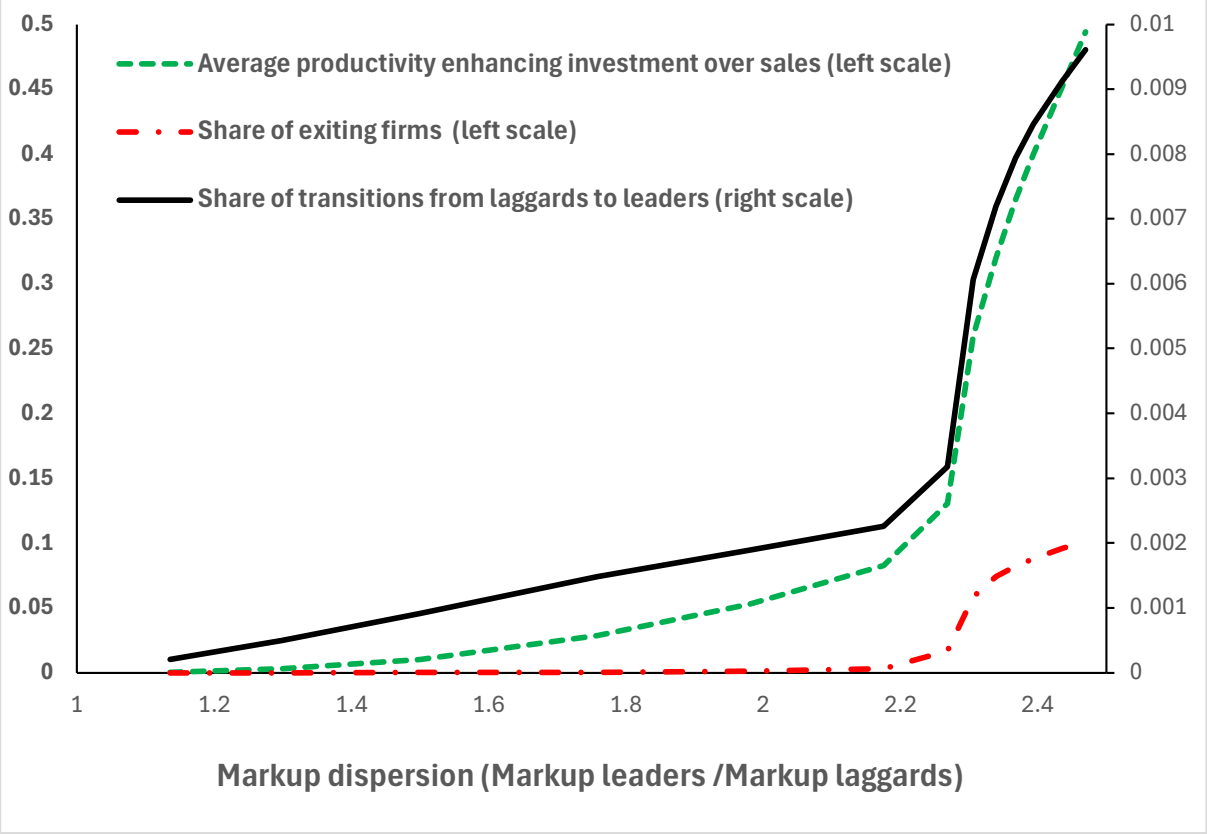
dispersion increases, the competitive pressure lowers profits for laggard firms. The first main result of this paper is to show that, despite both stagnant laggards and high potential laggards have same profitability given the level of debt, and the same chances to receive zombie loans, the latter types are disproportionately more likely to receive these loans in equilibrium. The intuition is as follows. Both types of firms, after a sequence of negative profitability shocks (high draws of the fixed cost F) accumulate debt, and the expected excess cost of interest payments reduces their profits. When expected profits turn negative, these firms become "eligible" for zombie loans.

However, stagnant laggards in this situation have very low value. Their only chance to survive is to receive many positive profit shocks that sufficiently reduce their debt in the future, so that they become profitable again, but this happens with low probability. Therefore, if they do not receive zombie loans, they are very likely to exit shortly afterward. Conversely, high-potential laggards have higher value thanks to the option to become leaders in the future. They remain in operation for longer even if they are loss-making, and therefore are also more likely to change to

zombie status.

These forces are illustrated in Figure 3. As markups dispersion increases, the share of zombie firms increases as well, but such increase is almost exclusively driven by high potential firms. Moreover, zombie firms are also more likely to invest to improve productivity. Both trends are driven by the same factor. Higher dispersion in markups implies higher profits for leaders. Therefore high-potential laggards are both incentivized to invest more in productivity and to stay longer in operation when their current profits are negative because of high debt, thus being more likely to receive zombie loans.

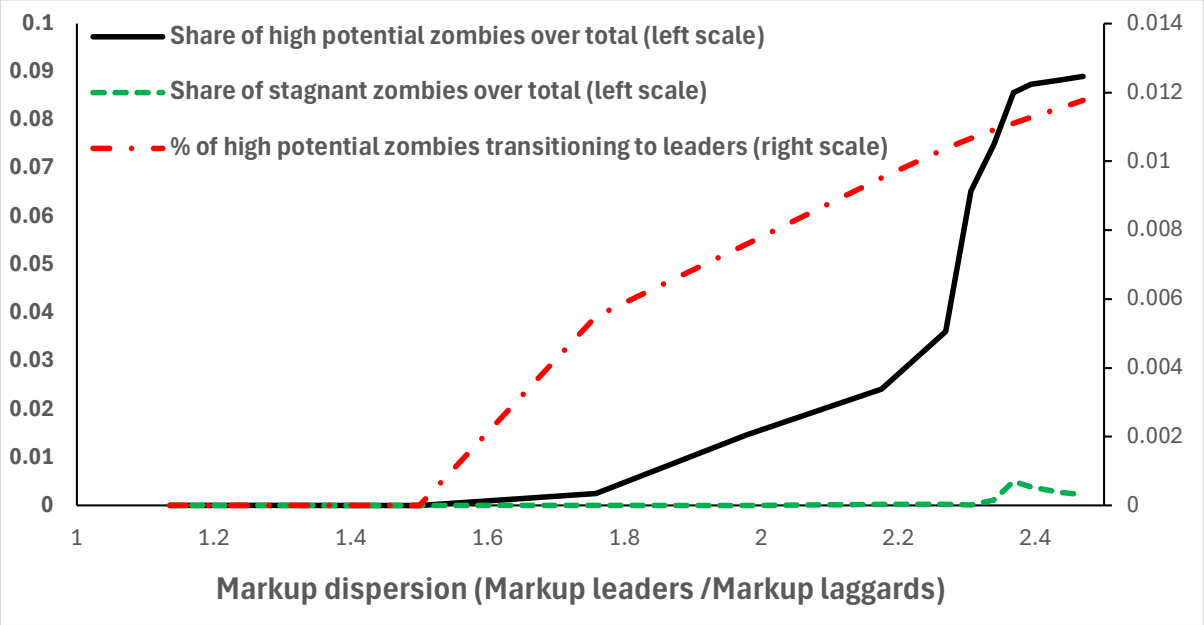
Figure 2:
Markup dispersion and productivity-enhancing investment



It follows that zombie firms are more "dynamic" in sectors with higher top markups, leading to the two following testable predictions of the model:

Prediction 1: *An increase in markup dispersion increases the share of firms receiving zombie loans.*

Figure 3:
Markup dispersion and share of zombie firms



Prediction 2: *An increase in markup dispersion increases the likelihood that firms receiving zombie loans transition in the future to the top of the markup distribution.*

Note that these predictions are derived by comparing equilibria across industries and therefore their direct empirical counterpart is cross-industry evidence. Nonetheless, in our empirical analysis below we confirm that all the results hold if we include industry-year fixed effects, thus controlling for all industry invariant characteristics and focusing on within industry variation.

4.1. Discussion

Before moving to the empirical testing of these predictions, we want to highlight two important considerations.

First, as shown in Figure 4, in this framework zombie loans improve aggregate productivity. The figure considers several counterfactual simulations in which all parameters are kept at the benchmark level except the probability ζ to receive zombie loans. In each of the three panels, the horizontal axis reports the share of firms receiving these loans. The intuition is that as the amount of zombie lending increases, high potential laggards take advantage of it more than stagnant laggards, and therefore their ratio increases (Panel A). Since in equilibrium more laggards have

high potential, there are also more laggards investing in enhancing productivity and transitioning to leader status (Panel B). This increases competition and the pressure for stagnant laggard to exit, further reducing their presence. It follows that in equilibrium there is a higher share of high-productivity leaders, and this increases the weighted average of aggregate productivity (Panel C).

Second, the necessary conditions for this result are: i) lenders cannot discriminate between types of laggard firms that "apply" for zombie loans. They can only observe the expected profits in the current period, not the potential to become leaders in the future. If they could do that, a lender with the objective of avoiding the default of the borrower, would perhaps prioritize stagnant zombies, which are closer to the default region, rather than high-potential zombies. ii) There is a mix of high potential and stagnant laggards in the industry. For the two opposite limit cases of all laggards being of one type only, we would no longer have a productivity-enhancing effect of zombie lending. To see this, suppose only stagnant laggards are present, and leaders are firms that start with top productivity since their birth. In this alternative scenario, we would still observe that higher markup dispersion increases the share of zombie firms, but these would not transition with a higher probability to the top. In this case, more zombie loans would increase the share of laggards relative to leaders, and reduce aggregate productivity. Consider now the opposite case, that only high potential laggards are present. In this case, it is possible to show that more zombie loans increase the number of firms in the industry and aggregate output, but they do not affect the ratio of leaders to laggards, nor aggregate productivity.

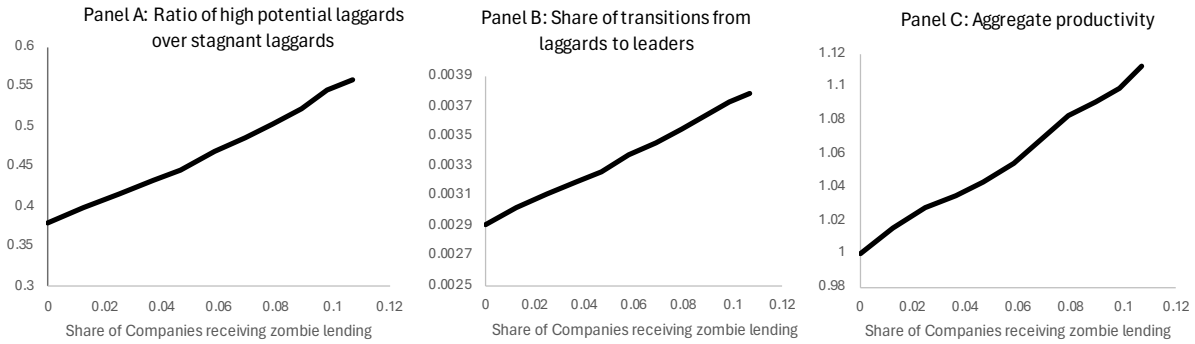
On the one hand, we believe that these necessary conditions are at least partly satisfied in the empirical data. It would be unplausible to assume that only one type of laggard firms exist in an industry or that lenders can perfectly discriminate between these two types.

On the other hand, our testable predictions provide a test of these conditions. If either condition (i) or condition (ii) is not satisfied, we would still observe in the data **Prediction 1**, but we would reject **Prediction 2**.

5. Data & Variable Measurements

To test our prediction, we use Orbis data for Italy provided by Bureau van Dick. Orbis contains harmonized information on a representative sample for publicly listed and private Italian firms. Our data covers the years from 2007 to 2016. To clean the raw data, we closely follow Gopinath

Figure 4:
Share of companies receiving zombie loans and aggregate productivity



et al. (2017); Kalemli-Özcan et al. (2015).

The sample construction involves two main steps: First, we obtain sectoral-level data from Eurostat, including price indices, gross value added, and other industry aggregates. Specifically, we collect data on consumer price indices, and gross value added by industry. These series are processed to construct sector-specific price deflators and value-added measures. We focus particularly on gross value-added series for 10 industry classifications and compile price deflators at the sector level. For manufacturing sectors, we use 2-digit NACE industry deflators when available, while for other sectors we rely on 1-digit industry deflators or aggregate deflators when more granular measures are not available.

Second, we process the Orbis firm-level data to address issues of consolidated accounts, since some firms report both consolidated and unconsolidated statements. Following Gopinath et al. (2017), we retain consolidated accounts when both types are available and, in cases of multiple entries due to changes in accounting years, keep the most recent observation. We then proceed with basic cleaning steps by dropping observations with missing or negative values for key variables including sales, total assets, employment, and operating revenue (Kalemli-Özcan et al., 2015; Díez et al., 2021). Financial sector firms (NACE codes 64-66) are excluded from the analysis.

The data is further refined by implementing a series of internal consistency checks. We verify the coherence of financial ratios, including the shares of fixed assets to total assets, current assets to total assets, and various liability measures. Following De Loecker et al. (2020), we drop firm-year observations with missing information regarding their industry of activity. We also

ensure the consistency of debt reporting by comparing different liability measures and removing firms showing unrealistic growth rates in sales or employment (e.g. see Kalemli-Özcan et al., 2015). Finally, we combine the cleaned firm-level variables with the sector-level price deflators. All monetary variables are deflated using the appropriate industry deflators and expressed in 2005 prices. Our final sample provides a comprehensive view of the Italian non-financial business sector.

5.1. Markup Estimation

Following De Loecker et al. (2020), we estimate firm-level markups using the production approach. For any variable input V, the markup is computed as:

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it}Q_{it}}{P_{it}^{V}V_{it}}$$

where θ_{it}^{V} is the output elasticity of variable input V, $P_{it}Q_{it}$ is sales, and $P_{it}^{V}V_{it}$ is total expenditure on the variable input. We estimate output elasticities from a production function:

$$y_{it} = f(v_{it}, k_{it}; \beta) + \omega_{it} + \epsilon_{it}$$

where y_{it} is log output, v_{it} is log variable input, k_{it} is log capital, ω_{it} is productivity, and ϵ_{it} is measurement error. We use the cost of goods sold as our variable input and estimate the production function at the 2-digit industry level using the control function approach of Ackerberg et al. (2015). This allows us to estimate the elasticity of variable inputs in each industry from which we determine the firm-level markups.

5.2. Zombie Identification

We follow Acharya et al. (2024), and combine information on subsidized credit access with measures of firm performance. A firm is classified as a zombie in year t if it simultaneously satisfies a subsidized credit condition and exhibits poor performance. The subsidized credit condition requires that a firm's borrowing cost falls below a benchmark rate: $r_{it} < \tilde{r}_t$, where r_{it} represents firm i's cost of debt in year t, computed as the ratio of interest expenses to total debt averaged over the two years. The benchmark rate $\tilde{r}_t$ represents the minimum interest rate that a top-rated firm would pay in the market, defined as: $\tilde{r}_t = (r_{it}^{p50}|\text{AAA firms})$. The term $\tilde{r}_t$

represents the median credit rate paid by AAA-rated firms in year t.[5]

The poor performance criterion requires that a firm exhibit the following conditions: first, the firm's Interest Coverage Ratio (ICR) falls below the industry median. To avoid the influence of the outliers we consider the ICR over the two years for both the firm level and the industry median. Where the ICR at each point in time is calculated:

$$\text{ICR}_{it} = \frac{\text{EBIT}_{it}}{\text{Interest Expenses}_{it}}$$

EBIT_{it} represents earnings before interest and taxes. This threshold indicates that the firm's operating profits are insufficient to cover its interest expenses. Second, the firm's leverage (debt to asset) is above the sector median. The sector medians are calculated at the two-digit NACE sector level for each year. As argued in Acharya et al. (2024), this identification strategy captures firms that not only receive subsidized credit but also show signs of fundamental economic weakness.

Table 2:
Summary Statistic

	Mean	p5	p25	Median	p75	p95	SD	Min	Max	Observations
EBITDA to Assets $_{i,t}$	0.0934	-0.0240	0.0379	0.0746	0.1314	0.2792	0.0936	-0.1813	0.5029	2,826,415
EBIT to Assets $_{i,t}$	0.0568	-0.0598	0.0145	0.0417	0.0856	0.2257	0.0866	-0.2410	0.4499	2,878,588
ROA to Assets $_{i,t}$	0.0235	-0.0661	0.0003	0.0101	0.0424	0.1491	0.0654	-0.2337	0.3265	2,878,827
Markups $_{i,t}$	1.4262	0.6011	0.8365	1.1169	1.5487	3.5283	1.0513	0.5030	8.2272	2,936,558
Exit Rate $_{i,t}$	0.1443	0.0000	0.0000	0.0000	0.0000	1.0000	0.3514	0.0000	1.0000	2,936,558
Fixed Costs $_{i,t}$	0.3470	0.0741	0.1863	0.3100	0.4738	0.7529	0.2059	0.0236	0.9966	2,807,864
Debt to Sales $_{i,t}$	0.9686	0.2146	0.4041	0.6254	1.0209	2.8548	1.2065	0.1053	12.2093	2,881,849
Age $_{i,t}$	14.9992	1.0000	5.0000	11.0000	22.0000	39.0000	13.2841	0.0000	160.0000	2,936,552
Observations by firm	4.5953	1.0000	2.0000	4.0000	7.0000	10.0000	2.8682	1.0000	10.0000	587,098
Asset-weighted share of zombie $_{t}$	0.0250	0.0151	0.0170	0.0247	0.0299	0.0431	0.0091	0.0151	0.0431	10
Ind-Sales-Weigh.- SD(markups) $_{s,t}$	0.8728	0.1934	0.3766	0.7591	1.2755	1.8741	0.5637	0.0332	2.8315	785

Notes: Data source: Orbis database for Italian firms, 2007-2016. Financial variables are winsorized at the 1st and 99th percentiles. Profitability measures are scaled by total assets. Fixed Costs are SGA expenses over total costs. All monetary values are deflated using industry-specific price deflators (base year 2005).

Table 2 presents the summary statistics of our key variables. The average EBITDA to assets ratio is 9.3 percent, with substantial heterogeneity across firms as evidenced by the interquartile range of 9.4 percentage points (from 3.8 to 13.1 percent). The mean EBIT to assets ratio of 5.7 percent and ROA of 2.4 percent are comparable to those reported in other studies of Italian firms (Schivardi et al., 2020; Gopinath et al., 2017).

Our estimated markups average 1.43, which aligns with recent studies of European firms (Díez

[5]While Orbis does not directly provide firm credit ratings, we estimate each firm's rating category based on its Interest Coverage Ratio (ICR) following the methodology established in Acharya et al. (2019) and Acharya et al. (2021). Specifically, we map firms' ICR values to rating categories using the standard mapping between ICR ranges and credit ratings documented in Damodaran's credit risk database.

et al., 2021). The distribution of markups shows considerable dispersion, with an interquartile range of 0.71 (from 0.84 to 1.55) and a 95th percentile of 3.53. This dispersion, measured by the industry-sales-weighted standard deviation of 0.87, is consistent with findings in De Loecker et al. (2020) for U.S. firms.

Firm leverage, measured by the debt-to-sales ratio, averages 0.97, indicating that the typical firm has debt roughly equal to its annual sales. The substantial right skew in leverage is evident from the 95th percentile of 2.85. Thus we used the median leverage rather than the mean for calibration purposes (see Table 1). The average firm age is 15 years, with significant variation as shown by a standard deviation of 13.3 years.

Particularly noteworthy is the asset-weighted share of zombie firms, which averages 2.5 percent over our sample period, in line with Acharya et al. (2022). The variation in this share over time (from 1.5 to 4.3 percent) suggests meaningful temporal dynamics in the prevalence of zombie firms.

Firms appear in our sample for an average of 4.6 years, with 50 percent of firms observed between 2 and 7 years. This level of panel participation is comparable to other studies using Orbis data (Kalemli-Özcan et al., 2015; Gopinath et al., 2017) and helps mitigate concerns about selection on firm survival. Overall we can track 587,098 distinct firms over the sample period 2007-2016.

6. Empirical Evidence: Model Validation

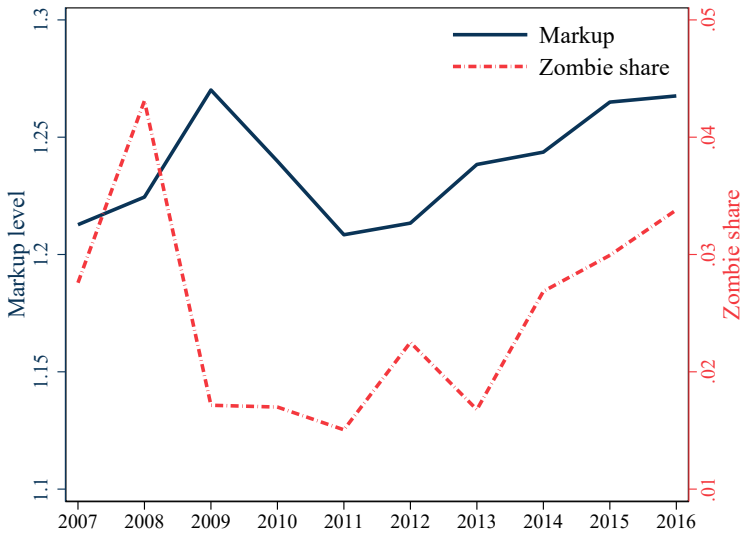
In this section we provide new empirical evidence in line with our model. We first document a series of novel stylized facts about the relationship between zombie firms and markups. Consistent with our model prediction, we find a strong correlation between either markups dispersion, or markups of top firms, and the share of zombie firms. We also show that zombies in highly dispersed markup sectors are more upward mobile, falling in the top categories for market shares, markups, investment, and employment.

6.1. Aggregate Markups and Zombie Shares

First, we document the positive relationship between aggregate markups and the prevalence of zombie firms. Figure 5 plots the evolution of sales-weighted markups (solid blue line, left axis) and the asset-weighted share of zombie firms (dotted red line, right axis) from 2007 to 2016. The

patterns we uncover are consistent with prior evidence on markup trends and zombie prevalence De Loecker et al. (2020); Díez et al. (2021), Acharya et al. (2024). In our sample, the average sales-weighted markup is 1.24, while the share of zombie firms ranges from 1.5% to 3.5% of total firms, with a mean of 2.5%. These two series show strong co-movements: periods of elevated markups systematically coincide with higher zombie shares. This aggregate evidence provides initial support for our model's prediction that markup dispersion and zombie prevalence are interlinked.

Figure 5:
Aggregate Markups and Zombie Share



Note: Orbis database for Italian firms, 2007-2016. The figure shows two series: (1) the aggregate markup (blue solid line, left axis), computed as the sales-weighted average of firm-level markups, and (2) the share of zombie firms (red dashed line, right axis), computed as the asset-weighted fraction of zombie firms in the economy. Both series are reported at an annual frequency.

While these series show strong co-movement, this aggregate relationship may mask substantial heterogeneity across sectors and could be driven by compositional changes in the economy. To strengthen our inference, we exploit variation at the sector-year level, which allows us to account for sector-specific characteristics and aggregate time trends.

6.2. Industry-level Markups Dispersion and Zombie Shares

In this section, we examine the markup-zombie relationship at the sector level. This disaggregated analysis offers two key advantages over the aggregate analysis: first, it enables us to control for sector-specific factors that might simultaneously affect markups and zombie prevalence;

second, it allows us to identify the relationship between markups and zombie share within sectors. Exploiting within-sector variation helps mitigate concerns that our results are driven by structural transformation, economy-wide trends, or persistent cross-sector differences.

The aim of this section is to provide a direct test of Predictions 1 and 2. As shown in Figure 1, we can in principle both use the variation in markup dispersion and in the level of top firms markups. However, in practice, a measure of dispersion is more reliable because is likely less affected by outliers, and it does not require to take a stand on what is the right percentile of the distribution to define top firms. Therefore, our main explanatory variable is the log of sectoral sales-weighted markup dispersion. Nevertheless, we provide robustness checks using the top quartile of industry-level markups ($\mu_{s,t}^{75th}$).

Figure 6 presents binscatter plots of log zombie shares against two measures of market structure: log industry sales-weighted markup dispersion ($log(sd(\mu)_{s,t})$) in panels (a) and (b), and log industry sales-weighted markup level for industry leaders ($log(\mu_{s,t}^{75th})$) in panels (c) and (d). The left panels - (a) and (c) - include year-fixed effects to absorb common time-varying factors, thus exploiting cross-sectional differences across industries. The right panels - (b) and (d) - add sector fixed effects, thereby focusing on within-sector variation over time.

Both specifications reveal a strong positive relationship between markup dispersion and zombie shares: sectors with higher markup dispersion exhibit higher zombie shares. The stability of the estimated relationship across specifications - with slopes of 0.639 in the cross-section and 0.511 within sectors - suggests this pattern is not driven by unobserved sector-specific characteristics.

We formally test this relationship by estimating the following specification at the sector level:

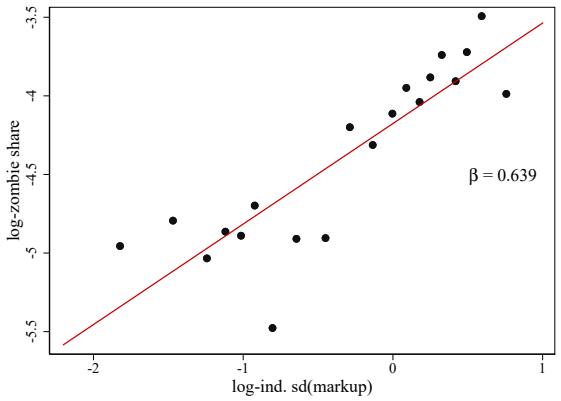
$$log(zombie\ share_{s,t}) = \alpha_t + \alpha_s + \beta_1 log(sd(\mu)_{s,t}) + \Gamma X_{s,t} + \epsilon_{s,t}, \tag{22}$$

where α_t and α_s are time and sector fixed effects, β_1 captures the elasticity of zombie shares with respect to sectoral sales-weighted markup dispersion ($sd(\mu)_{s,t}$), and $X_{s,t}$ is a vector of sector-time controls including real value-added and sector-specific price indices. Standard errors are clustered at the sector level.

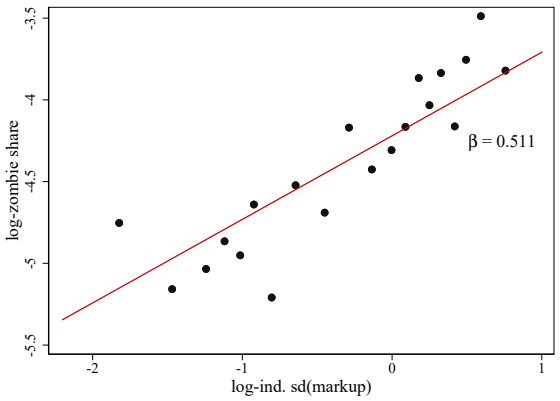
Table 3 presents our main results. Columns (1) and (3) correspond to the binscatter plots in Figure 6, while Columns (2) and (4) add sector-level controls. The patterns strongly support our model's prediction: sectors with higher markup levels—which in our framework corresponds to

Figure 6:
Sector level Markups dispersion and Zombie Shares

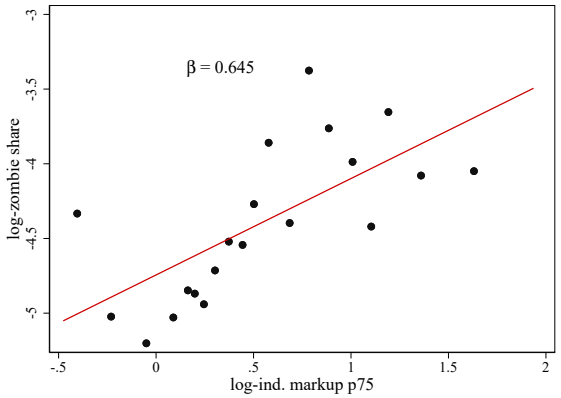
(a) *zombie share and markup dispersion*



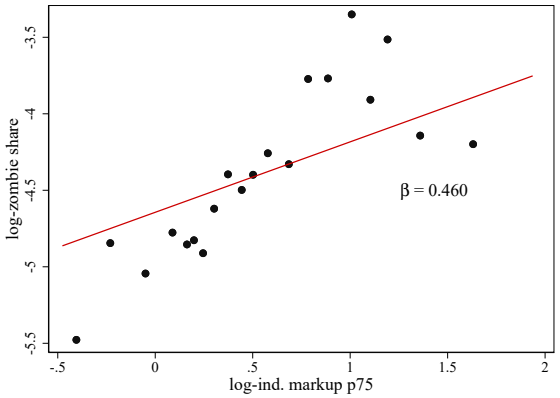
(b) *zombie share and markup dispersion within sector*



(c) *zombie share and markup level*



(d) *zombie share and markup level within sector*



Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: sector-year. The figure presents binscatter plots relating log zombie shares to two measures of market structure: log markup dispersion ($log(sd(\mu_{s,t}))$) in panels (a)-(b) and log markup level of industry leaders ($log(\mu_{s,t}^{75th.})$) in panels (c)-(d). Left panels estimate: $log(zombie\ share_{s,t}) = \alpha_t + \beta_1 log(sd(\mu)_{s,t}) + \epsilon_{s,t}$, where α_t represents year fixed effects. Right panels add sector fixed effects: $log(zombie\ share_{s,t}) = \alpha_t + \alpha_s + \beta_1 log(sd(\mu)_{s,t}) + \epsilon_{s,t}$. Each dot represents the average value within each bin and estimated β coefficients are reported at the top of each panel. For panels (c)-(d), $log(sd(\mu)_{s,t})$ is replaced with $log(\mu_{s,t}^{75th.})$ as the main explanatory variable.

higher incentives to stay in the market—have higher shares of zombie firms. In the cross-sectional analysis, a 1% higher level in the of industry markup dispersion correlates with a 0.60-0.63% higher share of zombie firms. While less precisely estimated, this relationship persists when exploiting within-sector variation, where a 1% difference in markups relates to a 0.50-0.51% higher difference in zombie shares. The stability of coefficients to the inclusion of controls suggests these correlations are not driven by observable sector characteristics. These results confirm **Prediction 1**, where higher markup dispersion is associated with higher shares of firms receiving zombie loans.

To put these magnitudes in perspective, between 2007 and 2016, the median sector-level markup dispersion ($sd(\mu)_{s,t}$) increased by 2.3% ($\log(0.753_{2016})$ - $\log(0.735_{2007})$), related to a 1.4% (2.3×0.605) higher zombie share based on our estimates. Alternatively, a standard deviation increase in markup dispersion (0.56) relates to a 36% increase in zombie share. The within-sector estimates provide similar magnitudes and signs (1.1%) aligning closely with our model's predictions.

Table 3:
Sector level Zombie Share and Markup Dispersion

Main Dependent: log(zombie share$_{s,t}$)				
	Cross-Section		*Within*	
	(1)	(2)	(3)	(4)
$log(sd(\mu)_{s,t})$	0.639***	0.605***	0.511*	0.504*
	(0.125)	(0.131)	(0.294)	(0.296)
Controls		✓		✓
Year F.E.	✓	✓	✓	✓
Industry F.E.	✓	✓	✓	✓
Clustered Std.Errors	Sector	Sector	Sector	Sector
R^2	0.19	0.20	0.56	0.57
Obs	732	732	732	732

Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: sector-year. The dependent variable is the log of zombie shares. The main explanatory variable is the log of sector-level markup dispersion ($log(sd(\mu_{s,t}))$), where markups are weighted by firm sales in an industry. All specifications include year-fixed effects. Columns (1) and (2) report cross-sectional estimates, while columns (3) and (4) add sector-fixed effects. Controls include sector-level real value-added and price indices. Standard errors are clustered at the sector level and reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Overall, Table 3 and Figure 6 suggest a strong relation between sector-level markups and zombie share. Table 4 provides further evidence using our alternative measure, the sales-weighted markup level of industry leaders ($\mu_{s,t}^{75th}$).

The estimates yield similar patterns to our previous results. Between 2007 and 2016, the median markup increase across sectors for industry leaders ($\mu_{s,t}^{75th.}$) increased by 5% ($\log(1.63_{2016})$ - $\log(1.55_{2007})$), implying a 3% higher zombie share based on our estimates. While the within-sector estimates are not significant at conventional levels, their sign and magnitude align with our model's predictions. As mentioned before, these findings align closely with our model's mechanism: when market structure changes lead to higher markup dispersion within a sector, the value of maintaining market presence increases while the one of exiting decreases, leading to a higher prevalence of zombie firms.

To conclude, this evidence confirms the results presented in Figure 1 and Figure 2. In the next section, we test **Prediction 2** of our model in the data.

Table 4:
Sector level Zombie Share and Markup Level

Main Dependent log(zombie share$_{s,t}$)				
	Cross-Section		*Within*	
	(1)	(2)	(3)	(4)
$log(\mu_{s,t}^{75th.})$	0.645***	0.602***	0.460	0.476
	(0.197)	(0.188)	(0.438)	(0.440)
Controls		✓		✓
Year F.E.	✓	✓	✓	✓
Industry F.E.	✓	✓	✓	✓
Clustered Std.Errors	Sector	Sector	Sector	Sector
R^2	0.13	0.16	0.56	0.56
Obs	732	732	732	732

Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: sector-year. The dependent variable is the log of zombie shares. The main explanatory variable is the log of sector-level markup dispersion ($log(\mu_{s,t}^{75th.})$), where markups are weighted by firm sales in an industry. All specifications include year-fixed effects. Columns (1) and (2) report cross-sectional estimates, while columns (3) and (4) add sector-fixed effects. Controls include sector-level real value-added and price indices. Standard errors are clustered at the sector level and reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

6.3. Zombie firms & dynamism: Likelihood of falling in Top-Quartile

Table 5:
Transition Probabilities YoY

Quantiles of log market share$_{f,t}$					
To Portfolio Share Quartile	Q_1	Q_2	Q_3	Q_4	Sum
From Portfolio Share Quartile					
Q_1	0.86	0.13	0.01	0.00	1.00
Q_2	0.09	0.76	0.14	0.00	1.00
Q_3	0.01	0.09	0.79	0.11	1.00
Q_4	0.00	0.00	0.06	0.93	1.00

Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: firm-year.

Having established that sectors with higher markup dispersion exhibit larger shares of zombie firms, we now investigate the behavior of these firms. If zombie firms indeed survive to preserve their option value of future market rents, as our model suggests, we should observe them actively investing to exploit future dominant market positions rather than merely subsisting. Our main contribution is to document that zombie firms in high-markup sectors are more likely to invest and gain market share, with a higher probability of reaching the top quartile of these distributions, thus aligning with our model's predictions.

To formally test these relationships, we examine whether zombie firms in sectors with high

Table 6:
Transition Probabilities YoY

Quantiles of investment rate$_{f,t}$					
To Portfolio Share Quartile	Q_1	Q_2	Q_3	Q_4	Sum
From Portfolio Share Quartile					
Q_1	0.45	0.26	0.16	0.12	1.00
Q_2	0.25	0.36	0.24	0.15	1.00
Q_3	0.17	0.25	0.34	0.24	1.00
Q_4	0.14	0.16	0.28	0.42	1.00

Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: firm-year.

markup dispersion are more likely to achieve strong performance across various dimensions over time. Specifically, we analyze whether these firms ever reach the top quartile of the distribution in the subsequent four years for firm-level markups, market share, employment growth, and investment rate. We estimate the following OLS specifications:

$$\mathbb{1}\,\textit{Top-Quartile}\; Y_{i,t+1\to t+4} = \alpha_t + \alpha_s + \alpha_{s,t} + \beta_1 \mathbb{1}\textit{Zombie} + \beta_2 sd(\mu)_{s,t}) + \beta_3 \mathbb{1}\textit{Zombie} \times sd(\mu)_{s,t} + \Gamma X_{i,t} + \varepsilon_{i,t} \quad (23)$$

where $\mathbb{1}\,\textit{Top-Quartile}Y_{i,t\to t+4}$ is an indicator variable equal to one if firm i ever reaches the top quartile of the outcome variable Y's distribution during the period from $t+1$ to $t+4$. Our specification includes time-fixed effects (α_t), sector-fixed effects (α_s), and sector-by-time fixed effects ($\alpha_{s,t}$) to account for unobserved heterogeneity across periods and industries. The vector $X_{i,t}$ comprises firm-level control variables that are orthogonal to zombie status to prevent multicollinearity. Specifically, we control for firm size and age. To account for within-firm correlation and the relative importance of firms in aggregate output, we cluster standard errors at the firm level and weight observations by sales. The coefficient of interest is the interaction between the firm-level zombie indicator ($\mathbb{1}\textit{Zombie}$) and the sales-weighted sector-level markup dispersion ($sd(\mu)_{s,t}$). This interaction term captures how the relationship between zombie status and the probability of reaching the top performance quartile varies with industry markup dispersion.

While our model simulates different industry equilibria - making year-fixed effects the closest empirical counterpart - our preferred specification includes industry-by-year fixed effects. Although this more stringent specification maps less precisely to the model's setup, it offers the

advantage of controlling for unobserved industry-specific factors that might confound our results. This specification exploits both cross-sectional variation across firms within a given year and temporal variation within sectors. In essence, we compare firms with different zombie statuses at varying levels of sector-level markup dispersion, while absorbing any industry-year specific factors.

Before moving to the regression results, we first provide transition probabilities for the firms' log market share and investment rate in Table 5 and Table 6. A concern for the identification of the effect of interest is that the probability of moving across quantiles of market share or investment fluctuates significantly, potentially capturing random fluctuations rather than the effect of interest. These tables show that the probability of firms remaining in the same bins (diagonal elements) is high, suggesting that firms' performance is stable over time, allowing us to make reliable inferences about zombie firms' behavior. Additionally, this persistence supports our model's prediction that zombie firms in high-markup sectors are likely to invest and gain market share, maintaining their positions once improved.

Having shown that firms' performance is stable over time, we formally present the results for Equation 23 in Table 7, documenting that zombie firms in high-markup sectors are more likely to invest and gain market share.

The results reveal substantial heterogeneity in zombie firms' performance across market environments. In our preferred specifications with industry-by-year fixed effects (Columns 3 and 6), zombie firms are 18.9 percent less likely to reach the top quartile of market share and 12.3 percent less likely to achieve top markup performance. Given mean probabilities of 24% and 25% respectively of the outcome variables, these effects represent substantial reductions of approximately 78% (-0.189/0.24) and 49% (-0.123/0.25) relative to the baseline probability. These results are in line with previous findings on the poor performances of zombies (Caballero et al., 2008; Acharya et al., 2019, 2024).

Our key contribution lies in documenting how market structure fundamentally shapes zombie firms' potential for performance improvements. While prior literature has focused on the average negative effects of zombie firms, we show that this performance gap narrows significantly in sectors with higher markup dispersion. Put differently, we empirically confirm **Prediction 2** in the data: an increase in markup dispersion increases the likelihood that zombie firms transition in the future to the top of the market share and markup distribution. The interaction terms of 0.132 and 0.112 for market share and markups respectively, are statistically and economically

Table 7:
Likelihood of Zombies Reaching Top Quartile of Market Share and Markups

Likelihood: $\mathbb{1}$ *Top quartiles*$:t+1 \to t+4_{f,t}$						
	$\mathbb{1}$ *Top quartile log mkt.share*$_{f,t+1\to t+4}$			$\mathbb{1}$ *Top quartile log* $\mu_{f,t+1\to t+4}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Zombie_{f,t}$	-0.148**	-0.187**	-0.189**	-0.124***	-0.122***	-0.123***
	(0.073)	(0.084)	(0.087)	(0.043)	(0.032)	(0.033)
$\mathbb{1}Zombie_{f,t} \times sd(\mu)_{s,t}$	0.120**	0.130**	0.132**	0.095*	0.113***	0.112***
	(0.053)	(0.062)	(0.064)	(0.050)	(0.039)	(0.040)
Controls	✓	✓	✓	✓	✓	✓
Year F.E.	✓			✓		
Industry F.E.		✓			✓	
Year by industry F.E.			✓			✓
Clustered Std.Errors	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.30	0.32	0.32	0.05	0.09	0.09
Obs	2,097,034	2,097,034	2,097,034	2,078,395	2,078,395	2,078,395
Mean Dep.	0.24			0.25		

Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: firm-year. The dependent variable is an indicator equal to one if the firm reaches the top quartile of either log market share (Columns 1-3) or log of markups (Columns 4-6) distribution in the subsequent four years: $t+1$ to $t+4$. The table presents estimates of the relationship between zombie status and the probability of reaching top performance, interacting with industry leaders' markup ($sd(\mu_{s,t})$) as of Equation 23. All specifications include controls for firm size (log of assets) and age. Standard errors are clustered at the firm level and reported in parentheses. Observations are weighted by firm sales. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

significant, and confirm that the zombie disadvantage systematically diminishes as industry markup dispersion increases, suggesting that market power creates opportunities for zombie firms to transition into industry leaders.

To quantify the strength of this relationship, consider the difference between industries at the 25th percentile of markup dispersion (0.37) versus the 75th percentile (0.9). This interquartile difference in market structure reduces the zombie disadvantage substantially. For market share, zombie firms in high-dispersion industries are only 7 percent less likely to reach the top quartile (-0.189 + 0.132 × 0.9), compared to the 18.9 percent disadvantage in low-dispersion industries.[6] The rise in markup dispersion relates to an increase in the likelihood of zombies being in the top quartile of market share by approximately 11.8 percent (0.132 × 1.08), offsetting 63% of the baseline zombie disadvantage (-0.118/-0.189). The effect is even stronger for markups: the zombie disadvantage nearly disappears in high-dispersion industries, with the penalty shrinking from 12.3 to just 2 percent (-0.123 + 0.112 × 0.9). This substantial reduction is driven by a 10.1 percent higher likelihood of reaching the top quartile of markup distribution (0.112 × 0.9),

[6]These calculations represent the total effect of being a zombie firm on the likelihood of reaching the top quartile when markup dispersion increases by 0.9 units (the interquartile difference). In other words, they show the net zombie disadvantage conditional on an interquartile markup dispersion increase.

which offsets 82% of the baseline disadvantage (-0.112/-0.123).

In Table 8, we extend our analysis to examine whether market structure similarly affects zombies' real outcomes, focusing on investment rates and employment growth. In our preferred specifications with industry-by-year fixed effects (Columns (3) and (6)), zombie firms are 2.2 percent less likely to reach the top quartile of investment rates and 1.87 percent less likely to achieve high employment growth. Consistent with the traditional view that zombie firms underinvest and create fewer jobs (Caballero et al., 2008; Blattner et al., 2023; Acharya et al., 2024), we find that the zombie indicator is negatively related to firms being in the top quartile of investment rates and log of employees.

However, as with market share and markups, this investment and employment gap significantly narrows in sectors with higher markups dispersion. The interaction term of 0.108 for investment rates and 0.119 for employment suggests that zombies' real performance disadvantage diminishes as industry concentration increases. Moving from industries at the 25th percentile of markup dispersion (0.37) to the 75th percentile (1.27) would increase zombies' likelihood of being in the top investment quartile by approximately 9.7 percent (0.108×0.9), offsetting about 44% of the baseline investment disadvantage (-0.097/-0.220). Similarly, for employment, this change in market structure offsets 57% of the baseline employment growth disadvantage ($0.119 \times 0.9/0.187$). Consistent with our model predictions, these findings suggest that market power affects zombies' markets, real investment, and employment decisions. In particular as markup dispersion increases, the likelihood for zombie firms to transition to the top employment quartile grows in line with our **Prediction 2**.

In further robustness checks outlined in Table A1 and Table A2, we provide estimates using sector-level industry leader markup (e.g. μ^{75th}). The results are qualitatively analogous to the main results, however, the point estimates are smaller. An interquartile increase in industry leader markup levels (2.57 - 1.19 = 1.38) would increase zombies' likelihood of being in the top markup distribution, and market share quartile by approximately 8.6% (1.38×0.063), offsetting about 45% and 64% of the baseline investment disadvantage for zombies. We find similar magnitudes for employment and investments. Finally, we also confirm that profits, measured as Return on Assets (ROA) are more likely to fall in the top quartile of the distribution of firms in the subsequent four years in Table A3 and Table A4.

Table 8:
Likelihood of Zombies Reaching Top Quartile of Investment and Employees

Likelihood: $\mathbb{1}$ *Top quartiles:* $t+1 \to t+4_{f,t}$						
	$\mathbb{1}^{p75}$ *investment rate*$_{f,t+1\to t+4}$			$\mathbb{1}^{p75}$ *log employees*$_{f,t+1\to t+4}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ *Zombie*$_{f,t}$	-0.256***	-0.230***	-0.220***	-0.151***	-0.183***	-0.187***
	(0.061)	(0.044)	(0.046)	(0.055)	(0.067)	(0.070)
$\mathbb{1}$ *Zombie*$_{f,t} \times sd(\mu)_{s,t}$	0.139**	0.117***	0.108**	0.110***	0.117**	0.119**
	(0.058)	(0.045)	(0.045)	(0.040)	(0.050)	(0.052)
Controls	✓	✓	✓	✓	✓	✓
Year F.E.	✓			✓		
Industry F.E.		✓			✓	
Year by industry F.E.			✓			✓
Clustered Std.Errors	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.01	0.03	0.04	0.30	0.34	0.34
Obs	2,074,328	2,074,328	2,074,328	2,097,034	2,097,034	2,097,034
Mean Dep.	0.24			0.23		

Notes: Data source: Amadeus database for Italian firms, 2007-2016. Unit of analysis: firm-year. The dependent variable is an indicator equal to one if the firm reaches the top quartile of either investment rate (Columns 1-3) or log of employees (Columns 4-6) distribution in the subsequent four years: $t+1$ to $t+4$. The table presents estimates of the relationship between zombie status and the probability of reaching top performance, interacting with industry leaders' markup ($sd(\mu)_{s,t}$) as of Equation 23. All specifications include controls for firm size (log of assets) and age. Standard errors are clustered at the firm level and reported in parentheses. Observations are weighted by firm sales. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

6.4. Discussion

Overall, our empirical analysis provides support for both predictions of the model on the relation between rising markups and zombie lending. Interpreted through the lenses of the model, our findings imply that, in high markup sectors, zombie loans can improve dynamic efficiency and aggregate productivity.

Rather than contrasting previous studies, our findings highlight a novel and complementary mechanism through which zombie lending affects industry dynamics and aggregate efficiency. While the existing literature has primarily focused on the potential misallocation effects of zombie lending (Blattner et al., 2023; Acharya et al., 2022, 2024), our results suggest that in sectors characterized by high markup dispersion, zombie loans may also play a role in promoting dynamic efficiency. As discussed in section 4.1, this complementarity stems from two key insights. First, the mechanisms analyzed in our model could coexist with other factors that generate the misallocation effects highlighted in the literature, particularly in environments where firms are born with persistent productivity differences. Second, our empirical results, by strongly confirming **Prediction 2**, support the conclusion that this novel role of zombie lending is

empirically relevant and might partly counteract the negative effects highlighted by the literature, especially in high markup industries.

Our contribution lies in identifying a previously unexplored channel through which zombie lending affects industry outcomes while acknowledging that this mechanism operates alongside, rather than instead, the misallocation effects established in the existing literature. In terms of policy implications, this means it is important to consider the dynamism of a sector, as well as its type of technology and market structure, to correctly evaluate the positive and negative reallocation effects of zombie lending.

7. Conclusion

This paper examines the relationship between rising markups and zombie firms through the lens of a firm dynamic model with heterogeneous markups, financial frictions, and productivity-enhancing investments. Our theoretical and empirical analysis reveals a novel firm-level mechanism through which markup dispersion shapes the industry composition of zombie firms and, in turn, their potential for future growth. We show that the interaction between market structure and zombie lending has important implications for industry dynamics and aggregate efficiency, as it affects both the selection of which firms receive zombie credit and their subsequent productivity trajectories.

In the model, firms pay a fixed cost to enter and begin operating with low productivity as "laggards". These firms have access to borrowing facilities - e.g. a credit line - and only a fraction of laggards have the potential to invest and become highly productive "leaders". When firms accumulate debt to keep producing after facing negative profits shocks, they may receive a "zombie loan" - subsidized credit that keeps them operating despite their poor performance. As markup dispersion increases, the higher potential profits of industry leaders create stronger incentives for high-potential laggards to remain in operation, even when experiencing net losses, making them more likely to receive a "zombie loan". These firms, upon receiving credit, are more likely to invest in productivity-enhancement technology due to larger rewards for succeeding in it. Our key model predictions thus tell that industries with higher markup dispersion exhibit both a higher share of zombie firms and an increased likelihood for these firms to become industry leaders. The latter prediction stems from the interaction between the option value of becoming a leader and the availability of zombie credit, which allows high-potential firms to continue

pursuing productivity improvements despite temporary financial distress.

We test and confirm these predictions using detailed firm-level data from Italy between 2007-2016. First, we document that an increase in sector-level markup dispersion relates to higher shares of zombie firms. Second, and more importantly, we show that zombie firms in sectors with higher markup dispersion are substantially more likely to reach the top quartile of the market share and markup distribution, thus being more likely to be industry leaders. Similar patterns emerge for employment level and investment rates.

Our findings suggest that in high markup sectors, zombie firms might enhance dynamic efficiency by preserving the option value of becoming future market leaders. Rather than contrasting previous studies highlighting the misallocation effects of zombie lending, our results identify a complementary mechanism through which zombie credit affects industry outcomes. This distinction is of particular relevance for sectors with high markup dispersion and significant growth opportunities (e.g. information technology).

In terms of policy implications, our analysis suggests that evaluating the impact of zombie lending requires careful consideration of industry characteristics, particularly the degree of markup dispersion and potential for productivity improvements. While zombie lending creates misallocation in some contexts, our findings indicate that in industries with high markup dispersion, it can help preserve valuable growth options and promote dynamic efficiency. Therefore, policies aimed at addressing zombie lending should be calibrated to account for these industry-specific factors rather than applying a one-size-fits-all approach.

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A. Appendix

B. Zombie Firms & Innovation: Likelihood of falling in Top-Quartile

Table A1:
Likelihood of Zombies Reaching Top Quartile of Market Share and Markups

Likelihood: $\mathbb{1}$ *Top quartiles:* $t+1 \to t+4_{f,t}$						
	$\mathbb{1}$ *Top quartile log mkt.share*$_{f,t+1\to t+4}$			$\mathbb{1}$ *Top quartile log* $\mu_{f,t+1\to t+4}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ *Zombie*$_{f,t}$	-0.148*	-0.188**	-0.191**	-0.128**	-0.132***	-0.136***
	(0.081)	(0.092)	(0.095)	(0.050)	(0.038)	(0.040)
$\mathbb{1}$ *Zombie*$_{f,t} \times \mu_{s,t}^{75th.}$	0.057*	0.062*	0.063*	0.057*	0.062**	0.063**
	(0.031)	(0.036)	(0.037)	(0.032)	(0.026)	(0.027)
Controls	✓	✓	✓	✓	✓	✓
Year F.E.	✓			✓		
Industry F.E.		✓			✓	
Year by industry F.E.			✓			✓
Clustered Std.Errors	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.30	0.32	0.32	0.07	0.09	0.09
Obs	2,097,034	2,097,034	2,097,034	2,078,395	2,078,395	2,078,395
Mean Dep.	0.24			0.25		

Notes: Data source: Amadeus database for Italian firms, 2007-2016. Unit of analysis: firm-year. The dependent variable is an indicator equal to one if the firm reaches the top quartile of either log market share (Columns 1-3) or log markup (Columns 4-6) distribution in the subsequent four years: $t+1$ to $t+4$. The table presents estimates of the relationship between zombie status and the probability of reaching top performance, interacting with industry leaders' markup ($\mu_{s,t}^{75th.}$) as of Equation 23. All specifications include controls for firm size (log of assets) and age. Standard errors are clustered at the firm level and reported in parentheses. Observations are weighted by firm sales. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Table A2:
Likelihood of Zombies Reaching Top Quartile of Investment and Employees

Likelihood: $\mathbb{1}$*Top quartiles:* $t+1 \to t+4_{f,t}$						
	$\mathbb{1}^{p75}$*investment rate*$_{f,t+1\to t+4}$			$\mathbb{1}^{p75}$*log employees*$_{f,t+1\to t+4}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Zombie_{f,t}$	-0.283***	-0.260***	-0.249***	-0.151**	-0.186**	-0.191**
	(0.064)	(0.047)	(0.049)	(0.060)	(0.073)	(0.077)
$\mathbb{1}Zombie_{f,t} \times \mu_{s,t}^{75th.}$	0.089**	0.080***	0.075***	0.053**	0.057**	0.059*
	(0.036)	(0.028)	(0.028)	(0.023)	(0.029)	(0.030)
Controls	✓	✓	✓	✓	✓	✓
Year F.E.	✓			✓		
Industry F.E.		✓			✓	
Year by industry F.E.			✓			✓
Clustered Std.Errors	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.01	0.03	0.04	0.30	0.34	0.34
Obs	2,074,328	2,074,328	2,074,328	2,097,034	2,097,034	2,097,034
Mean Dep.	0.24			0.23		

Notes: Data source: Orbis database for Italian firms, 2007-2016. Unit of analysis: firm-year. The dependent variable is an indicator equal to one if the firm reaches the top quartile of either investment rate (Columns 1-3) or log of employees (Columns 4-6) distribution in the subsequent four years: $t+1$ to $t+4$. The table presents estimates of the relationship between zombie status and the probability of reaching top performance, interacting with industry leaders' markup ($\mu_{s,t}^{75th.}$) as of Equation 23. All specifications include controls for firm size (log of assets) and age. Standard errors are clustered at the firm level and reported in parentheses. Observations are weighted by firm sales. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Table A3:
Likelihood of Zombies Reaching Top Quartile of ROA

Likelihood: $\mathbb{1}$*Top quartile of ROA :* $t+1 \to t+4_{f,t}$			
	$\mathbb{1}$*Top quartile of ROA :* $t+1 \to t+4_{f,t}$		
	(1)	(2)	(3)
$\mathbb{1}Zombie_{f,t}$	-0.257***	-0.196***	-0.195***
	(0.043)	(0.030)	(0.030)
$\mathbb{1}Zombie_{f,t} \times sd(\mu_{s,t})$	0.064**	0.028	0.027
	(0.029)	(0.021)	(0.021)
Controls	✓	✓	✓
Year F.E.	✓		
Industry F.E.		✓	
Year by industry F.E.			✓
Clustered Std.Errors	Firm	Firm	Firm
R^2	0.01	0.03	0.04
Obs	2,083,803	2,083,803	2,083,803
Mean Dep.	0.23		

Notes: Data source: Amadeus database for Italian firms, 2007-2016. Unit of analysis: firm-year. The dependent variable is an indicator equal to one if the firm reaches the top quartile of either log market share (Columns 1-3) or log markup (Columns 4-6) distribution in the subsequent four years: $t+1$ to $t+4$. The table presents estimates of the relationship between zombie status and the probability of reaching top performance, interacting with industry leaders' markup ($sd(mu_{s,t})$) as of Equation 23. All specifications include controls for firm size (log of assets) and age. Standard errors are clustered at the firm level and reported in parentheses. Observations are weighted by firm sales. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Table A4:
Likelihood of Zombies Reaching Top Quartile of ROA - Markup Level

Likelihood: $\mathbb{1}$ *Top quartile of ROA* : $t+1 \rightarrow t+4_{f,t}$			
	$\mathbb{1}$ *Top quartile of ROA* : $t+1 \rightarrow t+4_{f,t}$		
	(1)	(2)	(3)
$\mathbb{1}Zombie_{f,t}$	-0.266***	-0.205***	-0.203***
	(0.048)	(0.033)	(0.032)
$\mathbb{1}Zombie_{f,t} \times \mu_{s,t}^{75th.}$	0.037**	0.020*	0.019
	(0.017)	(0.012)	(0.012)
Controls	✓	✓	✓
Year F.E.	✓		
Industry F.E.		✓	
Year by industry F.E.			✓
Clustered Std.Errors	Firm	Firm	Firm
R^2	0.01	0.03	0.04
Obs	2,083,803	2,083,803	2,083,803
Mean Dep.	0.23		

Notes: Data source: Amadeus database for Italian firms, 2007-2016. Unit of analysis: firm-year. The dependent variable is an indicator equal to one if the firm reaches the top quartile of either log market share (Columns 1-3) or log markup (Columns 4-6) distribution in the subsequent four years: $t+1$ to $t+4$. The table presents estimates of the relationship between zombie status and the probability of reaching top performance, interacting with industry leaders' markup ($\mu_{s,t}^{75th.}$) as of Equation 23. All specifications include controls for firm size (log of assets) and age. Standard errors are clustered at the firm level and reported in parentheses. Observations are weighted by firm sales. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.