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Article

The effect of a firm's zombie status on its innovation in research and development (R&D)-active small and medium-sized enterprises (SMEs): focusing on the moderating effect of zombie congestion

Hyoung Ryul Ma[1], Debra Sabatini Dwyer[2]

[1]Office of Strategic R&D Planning (OSP), Seoul, Korea
[2]Economics, Farmingdale State College, Farmingdale, NY, USA

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Corresponding author
Hyoung Ryul Ma
Tel: +82-2-6009-8767
E-mail: designme74@gmail.com

ORCID
Hyoung Ryul Ma
https://orcid.org/0000-0002-4211-0019
Debra Sabatini Dwyer
https://orcid.org/0000-0002-1266-4272

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Abstract

This study examines the relationship between a firm's zombie status and its innovation, focusing on the moderating effect of zombie congestion. Using data from small and medium-sized enterprises (SMEs) in government-sponsored research and development (R&D) projects, this study drew key findings. First, zombie firms invest more in R&D than non-zombie firms, and the moderation effect of zombie congestion in an industry on a zombie firm's R&D investment is revealed. Second, zombie firms that engage in R&D are more likely to achieve technological success than non-zombie firms, although the likelihood of realizing commercial success is not significantly different. However, there is no evidence of zombie congestion moderating the relationship between zombie status and innovation output. We conclude that, in R&D-active SMEs, their zombie status would not negatively impact their innovation. The industry-level zombie congestion moderates the relationship between a zombie status and R&D investment. Policymakers need to adopt industry-specific strategies to address zombie firms.

Keywords: zombie firm, innovation, zombie congestion, research and development (R&D) investment, government-sponsored R&D project, small and medium enterprises

Introduction

Zombie firms refer to economically unviable companies that barely survive on government subsidies or low-interest loans, losing their competitive edge. They form due to misdirected bank lending, low-interest rates, and government support. Weak banking systems perpetuate them by lending to unsustainable firms to cover bad debts (Acharya et al., 2019; Blattner et al., 2019; Caballero et al., 2008), while low-interest rates allow distressed companies to borrow more (Borio, 2018; McGowan et al., 2017; Nurmi et al., 2020). Government financial support can also lead to poor investment behavior and inefficient capital use (Liu et al., 2019).

The term gained attention from a study by Caballero et al. (2008) on Japan's economic stagnation. Zombie firms have become a global issue due to slow economic growth, the Global Financial Crisis, and the COVID-19 pandemic, which have increased cheap credit and financial support, leading to more unviable firms worldwide (Acharya et al., 2019; Banerjee & Hofmann, 2018; Blattner et al., 2019).

Korea has a significant number of zombie firms, making up 13.7% of all listed firms (Bank of Korea, 2018). This hinders resource allocation and poses risks to the financial system. The problem is linked to Korea's declining long-term growth rate, caused by a lack of creative talent and technology since the 1997 Asian financial crisis (Kim, 2016).

Many studies have examined zombie firms and their impact on the broader economy. They find that these firms negatively affect productivity, job creation, and investment within their industries. Industries dominated by zombie firms tend to have lower levels of investment, job creation, and productivity (Caballero et al., 2008; McGowan et al., 2018). Additionally, zombie firms undermine the effectiveness of government interventions, such as subsidies, financial support, and taxation. For example, Chang et al. (2021) discovered that increased government intervention could result in the creation or maintenance of more zombie firms.

Due to these negative impacts, the Korean National Assembly Budget Office advises against awarding research and development (R&D) projects to zombie firms (NABO, 2016). The Korea Institute for Industrial Economics and Trade argues that zombie firms limit funding opportunities for more promising companies (KIET, 2016). As a result, the Korea Evaluation Institute of Industrial Technology (KEIT) restricts zombie firms from participating in more than three government R&D projects concurrently (General Operational Guideline for Industrial Technology Innovation Program, 2020).

Given the negative impact of zombie firms on resource allocation and the macroeconomy, it seems reasonable to consider policies that restrict these firms from receiving government R&D project awards. However, some firms may become zombies due to temporary financial difficulties from ongoing R&D investments and economic fluctuations. Therefore, it is crucial to investigate whether restricting these firms from receiving innovation funding is justified. This study aims to explore the relationship between a firm's zombie status and its innovation, with a focus on how zombie congestion affects this relationship. The study will use data from small and medium-sized enterprises (SMEs) participating in government R&D projects.

This study fills several gaps in the existing academic knowledge. First, there are few studies on the R&D innovation behavior of zombie firms. Second, while previous studies have explored the impact of broad government intervention on zombie firms (Chang et al., 2021; Liu et al., 2019; Qiao & Fei, 2022), this study will focus specifically on R&D funding. Third, by targeting R&D-active SMEs, this study differs from previous research that mainly focused on larger or listed companies (Caballero et al., 2008; Chang et al., 2021; Liu et al., 2019). Lastly, unlike previous research in the Korean context that deals with R&D innovation and recovery from zombie status (Baek et al., 2021; Kam & Jung, 2018; Lee et al., 2023), this study is interested in exploring the impact of zombie status on R&D innovation input and output. The findings will add new academic knowledge on the relationship

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between a firm's zombie status and its R&D innovation behavior. They will also provide practical insights into the effectiveness of policies that restrict zombie firms from receiving government innovation funding.

The remainder of the paper is structured as follows. Section 2 reviews the previous literature on zombie firms. Section 3 describes the research model. Section 4 describes the data and measurement of variables. Estimation results are reported in Section 5. Finally, section 6 will present concluding remarks.

Literature Review and Hypotheses Development

Literature review

The previous research on zombie firms has primarily focused on four areas: (1) the adverse effects of zombie firms on their industries, (2) the negative impact of zombie firms on the performance of non-zombie firms, (3) the negative effect of government intervention on zombie firms, and (4) the recovery of zombie firms.

First, prior research has demonstrated that zombie firms negatively affect their respective industries. Caballero et al. (2008) defined zombie firms as entities that received subsidized credit from banks. They found that industries with a higher concentration of such entities experienced lower levels of capital investment, job creation, and productivity in Japan. McGowan et al. (2018) identified zombies based on the interest-coverage ratio and confirmed that their presence in an industry had a detrimental effect on productivity in OECD countries. This impact manifests in two ways: zombie firms themselves have low productivity levels, and the market congestion caused by such firms can crowd out non-zombie investments and hinder market expansion. Geng et al. (2021) found that zombie firms hinder industrial upgrading in China by 0.85% per 1% increase in zombie firm assets, owing to resource mismatch and innovation suppression. European Commission (2018) also found that zombie firms hinder the growth of other companies, particularly young ones in Europe.

Second, additional studies have shown that zombie firms negatively affect the financialization and innovation of non-zombie firms. Wu & Pan (2023) studied Chinese listed firms and found that zombie firms increase the financialization of non-zombie firms, exacerbating financing constraints. This effect is more pronounced among non-state enterprises, regions with low financial development, and before 2015 supply-side reforms. Qiao et al. (2022) argued that the prevalence of zombie firms reduces the patent output of healthy firms and jeopardizes innovation. Zombie firms distort the credit resources of healthy firms, especially those that are state-owned or in high-tech industries, thereby reducing innovation output. Yu et al. (2023) also confirmed that zombie firms significantly inhibit normal enterprises, especially those with high innovation intensity, through competition distortion and financing constraints.

Third, there have been studies examining the negative impact of government intervention on zombie firms. One study by Qiao & Fei (2022) analyzed data from Chinese industrial firms to investigate the effects of government subsidies on enterprise operating efficiency. The study found that while subsidies generally improve operating efficiency, moral hazard reduces their effectiveness in boosting efficiency and profits in zombie firms. Similarly, Chang et al. (2021) revealed that government intervention could increase the risk of zombie formation, which in turn can cause economic harm. They recommend that market forces should play a greater role in supply-side structural reforms. Another study by Liu et al. (2019) found that Chinese zombie firms that received government subsidies had lower capacity utilization and that subsidies distorted investment behavior, leading to poor performance. The study also showed that the adverse effect of government subsidies on the ability of zombie firms to utilize their capacity is particularly significant in the case of state-owned zombie firms, those with low government intervention, and those with inadequate financial reporting. The findings suggest that subsidies and fiscal policies specific to zombie firms should be used carefully.

Last, there is research focusing on the potential for recovery of zombie firms despite the prevailing negative perspective on them. According to Goto & Wilbur (2019), Japan's zombie firms are financially weak firms sustained by discounted interest rates and evergreen lending, and many exist SME. Although these firms can hinder industry efficiency, many of them can revive, making elimination inappropriate. Nurmi et al. (2020) support this argument, suggesting that zombie firms in Finland are not always truly distressed and can recover. While subsidies increase the likelihood of firms surviving, they do not necessarily aid in the recovery of zombie firms. Baek et al. (2021) also conducted research on zombie firms in Korea. They found that if the zombie firms are young, then government R&D funding and the presence of a research department within the firms can have a positive impact on their revival as normal firms.

Hypotheses development

The existence of zombie firms has been found to have several negative effects on their respective industries, the financialization and innovation of non-zombie firms, and government intervention. In Korea, policymakers have responded to this issue by attempting to limit funding for R&D activities for zombie firms due to their detrimental effects on the macroeconomy. However, it remains unclear whether the negative perceptions of zombie firms can be applied equally to those who engage in R&D activities.

In order to gain a deeper understanding of the relationship between zombie firms and innovation, it is important to consider the possibility of heterogeneity between zombie firms with R&D activities and those without. In Korea, a quite small proportion[1] of firms engage in R&D activity, suggesting that there may be significant differences in behavioral patterns between zombie firms with R&D activities and those without. Moreover, the stylized fact on zombie firms has largely been based on studies targeting relatively large companies, such as listed firms (Caballero et al., 2008; Liu et al., 2019; McGowan et al., 2018; Schaozhen et al., 2019), and as such, the behavior of zombies in SMEs may differ.

Research has shown that SMEs may have a higher potential for recovery from zombie status. For instance, Goto & Wilbur (2019) examined zombie firms in SMEs and found that these firms can revive over time, indicating that uniformly promoting their elimination from the economy may be inappropriate. Similarly, Nurmi et al. (2020) reported that two-thirds of firms with zombie status in Finland became healthy again between 1999 and 2017. They identified cyclical factors, rather than a secular trend, as the main cause of the increase of zombie firms in Finland over 15 years.

[1] According to KOSIS (2022), less than 1% of all firms in Korea implement R&D activity.

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Several studies have investigated the relationship between a firm's financial condition and its decision to invest in R&D. Some have found a weak or little impact of financial constraints on a firm's R&D investment and innovation output. For instance, Alfranseder & Dzhamalova (2014) reported that financially constrained firms invested more in R&D during the 1998 financial crisis than financially non-constrained ones. Similarly, Lahr & Mina (2013) found that financial constraints had little effect on a firm's R&D investment decision. Moreover, Bontempi (2016) and Alfranseder & Dzhamalova (2014) proposed a plausible mechanism underlying a firm's R&D investment behavior. Specifically, a firm's decision to invest in R&D is likely to be influenced more by uncertainty about future market prospects than by its own financial condition. In other words, external demand-side shocks may have a more significant impact on a firm's R&D investment decision than supply-side shocks within the firm. In the context of Korea, the unique characteristics of the country's strong R&D policies may contribute to this uncertainty, significantly impacting firms' own R&D investments. Traditionally, Korea encouraged private R&D investment through government-led initiatives (Kim et al., 2014; Yoon, 2014), primarily using government R&D budgets and policy measures. Many SMEs, lacking sufficient internal R&D budgets, tend to heavily rely on substantial government R&D funding for their technological development. Additionally, firms often view the future technology areas identified by the government as more promising, making them more inclined to invest in these areas.

Other research has shown that firms tend to invest persistently in R&D, a behavior known as R&D smoothing (Brown & Petersen, 2011; Himmelberg & Petersen, 1994). Firms recognize that it takes a relatively long time to translate R&D investment into economic profit. Stopping or reducing R&D investment would entail an additional adjustment cost in restructuring the R&D human resource or facility (Bernstein & Nadiri, 1989; Hall, 2002).

Upon considering all factors mentioned above, including the negative impact of zombie congestion on industry performance, the heterogeneity of zombie firms, the higher potential for recovery among SME, the weak relationship between a firm's financial condition and its decision to invest in R&D and the tendency of firms to invest persistently in R&D, this study proposes that R&D-active firms are unlikely to decrease their R&D investment despite financial difficulties. Instead, they are more likely to continue investing in R&D to escape the zombie status and secure new competitiveness. Consequently, this study will hypothesize the following:

- Hypothesis 1a: A firm's zombie status will not reduce its R&D investment.
- Hypothesis 1b: The effect of a firm's zombie status on its R&D investment will be stronger in industries with a lower share of zombie firms.

With regards to the relationship between a firm's zombie status and its project output, Kam & Jung (2018) discovered that there was no significant difference in the probability of technological success between zombie and non-zombie firms. Their findings were based on a sample of Korean SMEs (7,757) that undertook government-sponsored R&D projects supported by the Ministry of SMEs and Start-ups in Korea. In light of this, this study proposes the following hypotheses:

- Hypothesis 2a: A firm's zombie status will not be negatively associated with its innovation output.
- Hypothesis 2b: The effect of a firm's zombie status on its innovation output will be stronger in industries with a lower share of zombie firms.

Research Model and Methodology

This study adopts the R&D investment framework[2] Detailed from Cincera et al. (2016) to capture the dynamic nature of a firm's R&D investment over time. The framework describes the relationship between a firm's sales and its R&D investment as follows:

$$\frac{\mathbf{R}_{\mathbf{i,t}}}{\mathbf{C}_{\mathbf{i,t-1}}} = \alpha_{\mathrm{i}} + \alpha_{\mathbf{t}} + \lambda_1 \frac{\mathbf{R}_{\mathbf{i,t-1}}}{\mathbf{C}_{\mathbf{i,t-2}}} + \lambda_2 \Delta \mathbf{y}_{\mathbf{i,t}} + \lambda_3 \Delta \mathbf{y}_{\mathbf{i,t-1}} + \lambda_4 \left(\mathbf{c}_{\mathbf{i,t-2}} - \mathbf{y}_{\mathbf{i,t-2}} \right) + \lambda_5 \mathbf{y}_{\mathbf{i,t-2}} + \varepsilon_{\mathbf{i,t}} \tag{1}$$

Where:

R is a firm's annual R&D investment.
C is R&D stock.
c and y are the natural logarithms of R&D stock and sales.

This model captures both short-run dynamics and long-run equilibrium effects, with coefficients λ_1, λ_2, λ_3 indicating short-run effects and λ_4, λ_5 indicating long-run equilibrium. The coefficient (λ_4) is the error-correction term that adjusts disequilibrium, and the coefficient (λ_5) imposes the constant return to scale assumption (Hall et al., 2001).

The study extends this framework to examine the relationship between a firm's R&D investment and its zombie status, assuming zombie firms invest differently than non-zombie firms. Specifically, our model integrates the difference in R&D investment (ϕ_1) and the moderating effect of industry zombie share (ϕ_2). Equation (1) is transformed[3] into the equation (2), as our final research model.

$$\begin{aligned}\frac{\mathbf{R}_{\mathbf{i,t}}}{\mathbf{C}_{\mathbf{i,t-1}}} = {} & \alpha_{\mathbf{i}} + \alpha_{\mathbf{t}} + \lambda_1 \frac{\mathbf{R}_{\mathbf{i,t-1}}}{\mathbf{C}_{\mathbf{i,t-2}}} + \lambda_2 \Delta \mathbf{y}_{\mathbf{i,t}} + \lambda_3 \Delta \mathbf{y}_{\mathbf{i,t-1}} \\ & + \lambda_4 \left(\mathbf{c}_{\mathbf{i,t-2}} - \mathbf{y}_{\mathbf{i,t-2}} \right) + \lambda_5 \mathbf{y}_{\mathbf{i,t-2}} \\ & + \phi_1 \frac{\mathbf{Zombiestatus}_{\mathbf{i,t}}}{\mathbf{C}_{\mathbf{i,t-1}}} \\ & + \phi_2 \frac{\text{Zombie status}_{\mathrm{i,t}} \times \begin{array}{c}\text{Industry with lower}\\ \text{zombie share}_{i}\end{array}}{\mathbf{C}_{\mathbf{i,t-1}}} \\ & + \varepsilon_{i,t}\end{aligned} \tag{2}$$

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[2] Detailed derivation is described in Appendix 1.

[3] Putting the right-hand side of the equation (1) as 'A', $\frac{R_{i,t}}{C_{i,t-1}} = A$. Under our assumption, $R_{i,t} = A \times C_{i,t-1} + \phi_1 \times \text{Zombie} + \phi_2 \times \text{Zombie} \times \text{Industry with lower zombie share}$. So, it turns out to be $\frac{R_{i,t}}{C_{i,t-1}} = A + \phi_1 \frac{\text{Zombie}_{i,t}}{C_{i,t-1}} + \phi_2 \frac{\text{Zombie}_{i,t} \times \text{Industry\_lower zombie share}_{i}}{C_{i,t-1}}$

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Where "zombie status" is a binary variable.

Using this model, the study tests:

- Hypothesis 1a: A firm's zombie status will not reduce its R&D investment.
- Hypothesis 1b: The effect of a firm's zombie status on its R&D investment will be stronger in industries with a lower share of zombie firms.

Significant positive or insignificant ϕ_1 will support Hypothesis 1a. Significant positive ϕ_2 will support Hypothesis 1b.

Moreover, although various methods for identifying zombie firms, such as the interest-coverage ratio criterion, profitability criterion, evergreen lending criterion, etc., have been utilized in previous literature, as shown in Table 1, this study adopts the annual interest-coverage ratio criterion for zombie identification. This approach follows the common practice in Korea (Baek et al., 2021; Bank of Korea, 2014; Kam & Jung, 2018; Lee et al., 2023). The interest-coverage ratio criterion is widely recognized for its effectiveness in capturing a firm's financial distress by measuring its ability to meet its interest obligations. This measure is particularly relevant in the context of Korean SMEs for several reasons. First, utilizing the interest-coverage ratio ensures consistency with previous studies conducted in the Korean context, which is crucial for comparability and cumulative knowledge building. Second, the interest-coverage ratio directly reflects a firm's operational viability and its ability to generate sufficient earnings to cover interest payments, making it a critical indicator of financial health and sustainability. The Bank of Korea, for instance, relies on this measure to inform restructuring strategies for financially distressed companies. Lastly, by using a widely accepted measure within the Korean context, the findings of this study will offer more reliable and actionable policy recommendations for Korea's R&D funding policies, thereby ensuring the credibility and practical applicability of our conclusions.

In equation (2), there is a possibility of endogeneity between current R&D investment and lagged R&D investment, as well as between R&D investment and zombie status (Antonakis et al., 2010; Pickup & Evans, 2013). To address this issue, this study will use the two-step System Generalized Method of Moments (system-GMM). The GMM model, which is commonly used for panel data, provides consistent results in the presence of various sources of endogeneity, including unobserved heterogeneity, simultaneity, and dynamic endogeneity (Kim & Park, 2024; Ullah et al., 2018; Wintoki et al., 2012). After estimation, two diagnostic tests — the auto-regressive (AR) test and the Hansen (1982) *J* test — will be performed to check for autocorrelation and to verify the validity of the over-identifying restrictions (Roodman, 2009).

The second model examines the relationship between a firm's zombie status and innovation output from government-sponsored R&D projects, considering technological and commercial success. The model includes project attributes (funding, duration, number of partners) and technological attributes (dummy variables for each technological field, technology readiness level [TRL]) (Malmberg & Maskell, 1997; Martínez-Noya & Narula, 2018; Narula, 2001; Schwartz et al., 2012).

Table 1. Empirical literature summary

Authors	Data		Zombie identification	Dependent variables	Main independent variables	Methodology
	Region	Firm type				
Caballero et al. (2008)	Japan	Listed firm (1981–2002)	Interest payments criterion	Investment rate, Δlog (employment), and productivity	Non-zombie (1/0), industry zombie percentage, sales growth	Fixed effects
McGowan et al. (2018)	9 OECD countries	All types of firms (2003–2013)	Interest coverage ratio criterion, Age>=10yrs	Investment rate, Δlog (employment), level of multifactor productivity	Non-zombie (1/0), industry zombie share	Fixed effects
Geng et al. (2021)	China	All state-owned enterprises (SOEs) and non-SOEs (1998–2007)	Profitability criterion+Evergreen lending criterion +Interest payments criterion	The level of industrial upgrading is measured by the change in the share of high-tech industries in a province's total industrial output	The proportion of zombie firm assets in an industry	Fixed effects (Bartik method)
European Commission (2018)	19 European Union countries	Non-financial firms in the manufacturing and services sectors (2008–2013)	Interest coverage ratio criterion	Investment rate, ΔLog(Employment), labor productivity, multifactor productivity	Non-zombie (1/0), industry zombie share	Fixed effects
Qiao & Fei (2022)	China	All types of firms (1998–2013)	Negative profits for at least three consecutive years	Enterprise operating efficiency	Government subsidy amount, zombie (1/0)	Two-stage endogeneity test (2SLS)
Chang et al. (2021)	China	Listed firms (2008–2016)	Negative net profits (except for non-recurring gains and losses) for three consecutive years	Zombie firm (1/0)	Degree of government intervention (0–10)	Probit estimation
Liu et al. (2019)	China	Listed firm (2007–2016)	Profitability criterion+Evergreen lending criterion +Interest payments criterion	Capacity utilization increment	Subsidy to Zombie(1/0), amount of subsidy to zombie	Fixed effects, random effect, mixed effect
Goto & Wilbur (2019)	Japan	SMEs (2009–2014)	Profitability criterion+Evergreen lending criterion +Interest payments criterion	Zombie (1/0)	ROA (Return on assets), Zombie dummy (t–1), Log(capital)	Fixed effect panel logit model
Nurmi et al. (2020)	Finland	All types of firms (1999–2017)	Interest coverage ratio criterion	Probability of exiting the zombie status	Productivity, employment, capital intensity, age	Discrete-time proportional hazard duration model
Baek et al. (2021)	Korea	All types of firms (2012–2019)	Interest coverage ratio criterion	Recovery of zombie to non-zombie firm (1/0)	Start-up (1/0), R&D/sales, research department (1/0), government R&D support (1/0)	Panel probit model
Kam & Jung (2018)	Korea	SMEs (2013–2014)	Interest coverage ratio criterion	Project success (1/0), sales growth (1/0)	Zombie (1/0), zombie (1/0)×project success (1/0)	Logit model
Lee et al. (2023)	Korea	All types of firms (2017–2019)	Interest coverage ratio criterion	Recovery of zombie to non-zombie firm (1/0)	Product innovation (1/0), service innovation (1/0), business process innovation (1/0)	Propensity score matching

R&D, research and development; SME, small and medium-sized enterprises.

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$$\begin{aligned} log\left(\text{odds ratio}\right) = Log\left(\frac{\Pr\left(\text{Technological success}_{\mathbf{i}} = \mathbf{Y}\right)}{\Pr\left(\text{Technological success}_{\mathbf{i}} = \mathbf{N}\right)}\right) \\ = \alpha_{\mathbf{i}} + \beta_1 \times \text{Zombie status}_{\mathbf{i}} + \beta_2 \times \text{Zombiembie status}_{\mathbf{i}} \\ \times \text{Industry with lower zombie share}_{\mathbf{i}} \\ + \beta_3 \times \text{Project fund}_{\mathbf{i}} + \beta_4 \times \text{Project duration}_{\mathbf{i}} \\ + \beta_5 \times \text{Collaboration structure}_{\mathbf{i}} \\ + \beta_7 \times \text{Technological field} + \varepsilon_{\mathbf{i,t}} \end{aligned} \tag{3}$$

$$\begin{aligned} log\left(\text{odds ratio}\right) = Log\left(\frac{\Pr\left(\text{Technological success}_{\mathbf{i}} = \mathbf{Y}\right)}{\Pr\left(\text{Technological success}_{\mathbf{i}} = \mathbf{N}\right)}\right) \\ = \alpha_{\mathbf{i}} + \beta_1 \times \text{Zombie status}_{\mathbf{i}} + \beta_2 \times \text{Zombie status}_{\mathbf{i}} \\ \times \text{Industry with lower zombie share}_{\mathbf{i}} \\ + \beta_3 \times \text{Project fund}_{\mathbf{i}} + \beta_4 \times \text{Project duration}_{\mathbf{i}} \\ + \beta_5 \times \text{Collaboration structure}_{\mathbf{i}} \\ + \beta_6 \times \text{Technological readiness level}_{\mathbf{i}} \\ + \beta_7 \times \text{Technological field} + \varepsilon_{\mathbf{i,t}} \end{aligned} \tag{4}$$

Where i represents each government-sponsored R&D project.

Using these models, the study tests:

- Hypothesis 2a: A firm's zombie status will not be negatively associated with its innovation output.
- Hypothesis 2b: The effect of a firm's zombie status on its innovation output will be stronger in industries with a lower share of zombie firms.

Significant positive or insignificant β_1 will support Hypothesis 2a. Significant positive β_2 will support Hypothesis 2b.

Data and Variables

Data and variables for hypothesis 1a and 1b

Our firm-level data include 1,461 SMEs that received more than one government grant before the end of 2015 from the KEIT, the largest funding agency for industrial R&D. The firms participated as a principal research organization for their government-sponsored R&D projects. Each firm's financial information was also acquired through Korean Enterprise Data, a credit reporting company. The data covers financial information from 2005 through 2015 for each firm, which spans 11 years. Considering that a small portion of SMEs perform R&D activity and government funding agencies choose R&D beneficiary firms on a competitive basis (Ma et al., 2022), our data represents well R&D-active SMEs and is suitable for our research objective to find innovation behavior in R&D-active zombie firms.

In Fig. 1, we observe a considerable gap between firms with and without a zombie status. Over the entire period, firms with a zombie status have shown lower R&D investment. Remarkably, firms with a zombie status seem to have suffered more from the global financial crisis. In 2009, their R&D investments showed a considerable decline, particularly in firms with a zombie status. All

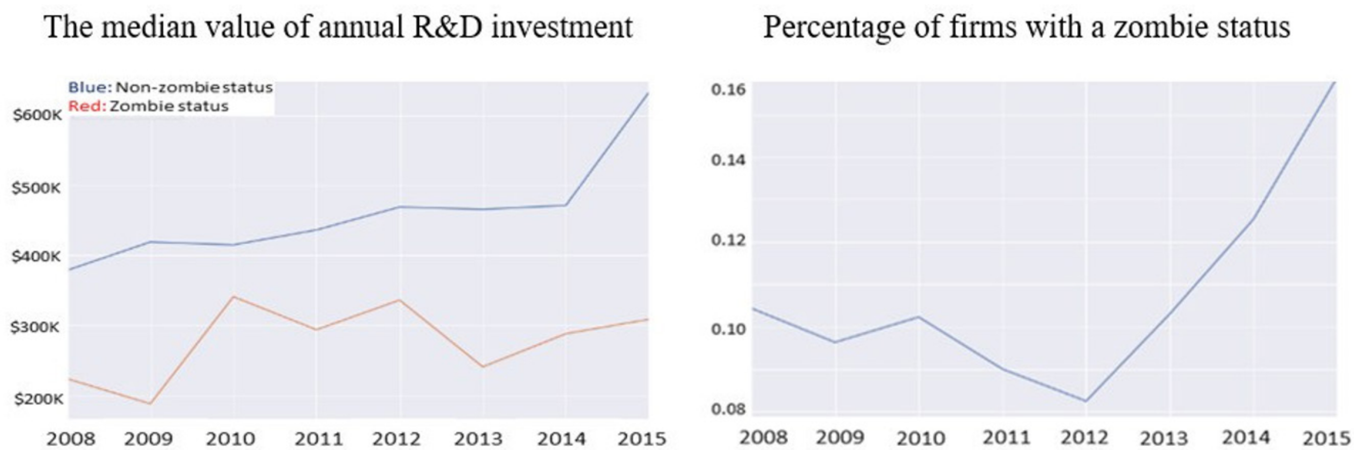

Fig. 1. Time trend of major variables. R&D, research and development.

these, however, need cautious interpretation because these are simple results that do not control for each firm's dynamics and heterogeneity. Instead, this study will provide a more reliable estimation through the dynamic panel data analysis considering the within-firm effect (i.e., the effect of a firm's zombie status on its R&D investment occurring within the firm over the years).

The mean of a firm's zombie status is 0.11 in Table 2, implying that 11% of all firm-year observations fall into the category of zombie status. This is consistent with the findings of the Bank of Korea (2014), which reported that zombie firms accounted for about 10% to 15% of all firms. In this study, the firm's zombie status is a dummy variable defined as one if its annual interest-coverage ratio remains below one consecutively over the past three years (i.e., persistent interest-coverage ratio <1) and otherwise 0. Fig. 1 shows that the annual percentage of a firm's zombie status has risen rapidly since 2012. In 2015, the percentage reached 15.9%, which ignited deep concerns about zombie firms in Korea.

To identify industries with relatively lower zombie shares, we examined eight technological

Table 2. Descriptive statistics

Variable	Observation	Mean	Median	Inter-quartile range	Standard dev. (overall)	Standard dev. (bet.)	Standard dev. (within)
$\frac{R_{i,t}}{C_{i,t-1}}$[1)]	4,749	1.5	0.4	0.4	22.3	15.0	19.6
$\Delta y_{i,t}$	12,071	0.2	0.1	0.4	0.6	0.3	0.5
$c_{i,t-2} - y_{i,t-2}$	8,315	–2.7	–2.4	2.2	2.1	2.0	0.8
$y_{i,t-2}$	13,597	15.7	16.0	2.3	1.7	1.7	0.7
Zombie status (1/0)	8,185	0.11	0.0	0.0	0.31	0.25	0.22
Industry with lower zombie share (1/0)	16,071	0.36	0	1	0.48	0.48	0

[1)] R&D capital stock (C) was calculated by authors, which is detailed in Appendix 2.
R&D, research and development.

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fields, including Machine, Electronics, Information Technology, Chemical, Biomedical, Energy, Knowledge Service, and Ceramics, using our data set. Then, we compared the zombie shares of each technological field to the average zombie share across all fields. Based on this comparison, industries that demonstrated a below-average zombie share were categorized as possessing a low zombie share. Thus, among the eight technological fields, the Machine, Information Technology, and Knowledge fields were identified as industries with lower zombie shares.[4]

It is also important to mention that the percentage of missing data in the R/C variable is up to about 70%.[5] This matches findings by Hall & Oriani (2006), who report between 65% and 88% missing values for the R/C variable. Missing R&D data is known to come from one of two reasons: first, a firm's information service provider could not collect and supply the firm's financial information, and second, R&D information is originally blank on the firm's financial statements by intentional choice (Koh & Reeb, 2015).

Either case poses potential selection bias in the estimation. For this reason, we explored the randomness of the omission in our data according to a firm's zombie status or sales. First, the missing percentage of R&D data in zombie firms is not much different from that of non-zombie firms.[6] Second, the nullity correlation between R/C and the sales variable is found to be less than 0.2, which also confirms that the missingness of R&D data does not depend on the sales volume. Hence, we presume that the missingness of R&D data would be quite random, which will not severely cause sample selection bias in our estimation.

Data and variables for hypothesis 2a and 2b

To test the relationship between a firm's zombie status and project output, this study collected data on government-sponsored R&D projects from KEIT. The project-level data includes 1,066 projects that were implemented by private firms, not by other types of research organizations (e.g., universities, public research institutes, etc.), and were fully completed before the end of 2015. Each firm's financial information (2012–2014) is also merged.

This study uses two dependent variables for technological and commercial success: patent application and commercialization. All these are dichotomous indicators because the dataset does not contain detailed information on the number of patent applications. In Table 3, the mean of patent applications (*Patent*) is 0.65, which indicates that 65% of projects in our data reported that they applied for a patent produced from a government-sponsored R&D project. The mean of commercialization (*Comm*) is 0.56, lower than the mean of patent applications.

In Table 3, 16% of all principal firms in the projects belong to zombie status. The mean government fund is $1.514M, with a standard deviation of 1.467. The average project's total duration is 3.06 years, with a standard deviation of 1.54. Within each project, there are an average of 3.21 participating organizations besides the principal firm, and the average TRL upon the project completion is 6.7 (i.e., somewhere between the prototype stage and production stage).

In Fig. 2, we observe the simple mean difference in the two dependent variables according to

[4] Average zombie share across all field (0.26), Machine (0.22), Electronics (0.30), Information Technology (0.22), Chemical (0.27), Biomedical (0.37), Energy (0.30), Knowledge service (0.17), and Ceramics (0.28).
[5] The total number of observations in R/C variables is 16,071, among which the number of missing data is 11,322, or 70%.
[6] Missing percent: 51.68% in zombie firms, 56.75% in non-zombie firms.

Table 3. Descriptive statistics

Variable	Observation	Mean	Standard dev.	Median	Inter-quartile range
Patent (1/0)	1,066	0.65	0.48	1	1
Commercialization (1/0)	1,066	0.56	0.50	1	1
Zombie status (1/0)	962	0.16	0.37	0	0
Industry with lower zombie share	1,066	0.35	0.48	0	1
Government fund	1,066	15.14	14.67	12.6	14.56
Project duration	1,066	3.06	1.54	3	2
Partners	1,066	3.21	2.02	3	2
Technology readiness level	1,007	6.70	1.77	7	2

a firm's zombie status. A firm with a zombie status produces higher patent applications and lower commercialization than one without a zombie status. Contrary to the ordinary notion of zombie firms, firms with a zombie status in government-sponsored R&D projects are more aggressive in securing technological competitiveness. We might conjecture that a firm probably became a zombie status not because of losing competitiveness but because of persistently innovative investment. In the following section, we will provide more reliable results through our model that controls for other variables affecting patent and commercialization.

The strongest correlation among the exploratory variables is 0.49, and it lies between the government fund and project duration indicators. This suggests that there is no strong multicollinearity in the exploratory variables. A detailed description of the variables is shown in Table 4 below.

Results

Dynamic panel data analysis for hypothesis 1a and 1b

A two-step system GMM methodology is applied to test our hypotheses 1a and 1b. Both estimations (specifications 1 and 2) in Table 5 meet the requirement for validating the estimation results. The Hansen (1982) *J* test does not reject the validity of instrumental variables (i.e., the validity of over-identifying restriction) at the 5% statistical significance level. AR test also confirms

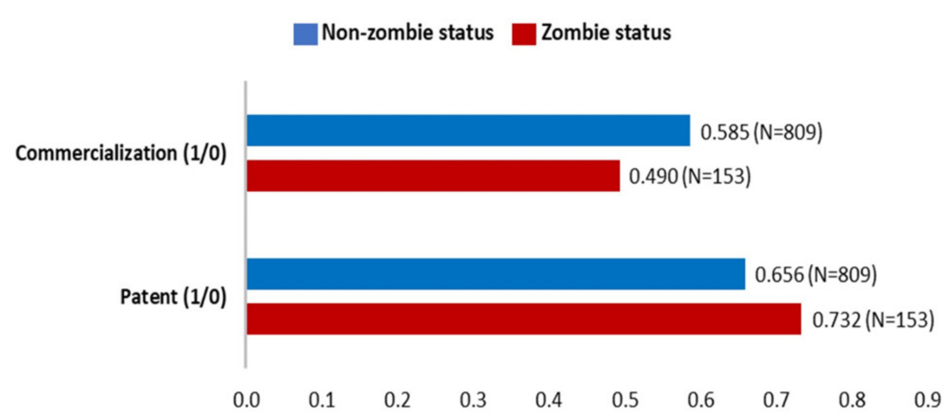

Fig. 2. The mean of patent (1/0) and commercialization (1/0) according to a firm's zombie status.

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Table 4. **Description of variables**

Variable		Description
Dependent variables	Patent (1 or 0)	For technological output, it indicates whether a principal firm had applied for over one patent from each R&D project until the end of 2015.
	Commercialization (1 or 0)	For commercial output, it indicates whether a principal firm had reported success in commercialization from the R&D project until the end of 2015.
Independent variables	Zombie status	1 if every interest-coverage ratio is below one over the past three years (2012–2014), otherwise 0.
	Industry with lower zombie share	1 if the zombie share of a technological field is less than the average zombie share across all fields, otherwise 0.
	Government fund	Project funding a firm receives from the government (in US 100 K dollars).
	Project duration	Duration of each R&D project (in years).
	Collaboration structure	Number of partners who participated in each R&D project.
	Technology readiness level	Technology Readiness Level (TRL) which consists of 9 stages; 1–2 (basic), 3–4 (experimental), 5–6 (prototype), 7–8 (production), 9 (commercialization).
	Technological field	1 (machine), 2 (electronics), 3 (information technology), 4 (chemical), 5 (bio), 6 (energy), 7 (knowledge service), 8 (ceramics).

R&D, research and development.

Table 5. **Estimation result (dependent variable: annual R&D investment per stock)**

Specification	GMM-SYS		Robust check			
			Fixed effect OLS		Pooled OLS	
	Spec. 1	Spec. 2	Spec. 3	Spec. 4.	Spec. 5	Spec. 6.
$\lambda_1 \dfrac{R_{i,t-1}}{C_{i,t-2}}$	−0.001*** (0.000)	−0.001*** (0.000)	−0.001*** (0.000)	−0.001*** (0.000)	−0.001*** (0.000)	−0.001*** (0.000)
$\lambda_2 \Delta y_{i,t}$	0.083*** (0.028)	0.079*** (0.027)	0.079** (0.030)	0.076*** (0.030)	0.110*** (0.026)	0.105*** (0.025)
$\lambda_3 \Delta y_{i,t-1}$	0.094*** (0.025)	0.100*** (0.025)	0.103*** (0.025)	0.107*** (0.025)	0.089*** (0.025)	0.098*** (0.024)
$\lambda_4 \left(c_{i,t-2} - y_{i,t-2}\right)$	−0.198*** (0.029)	−0.196*** (0.029)	−0.276*** (0.043)	−0.273*** (0.043)	−0.175*** (0.029)	−0.173*** (0.029)
$\lambda_5\ y_{i,t-2}$	−0.118*** (0.021)	−0.111*** (0.021)	−0.168*** (0.030)	−0.161*** (0.030)	−0.101*** (0.019)	−0.093*** (0.019)
$\phi_1 \dfrac{Zombie\ status_{\ i,t}}{C_{i,t-1}}$	5,158.9*** (468.97)	5,084.6** (468.56)	5,613.1*** (462.81)	5,503.0*** (442.04)	5,649.9** (460.71)	5,542.9** (433.46)
$\phi_2 \dfrac{Zombie_{\ i,t} \times ILZS_i}{C_{i,t-1}}$	-	149,409.3** (60,078.25)	-	139,443.4** (65,582.93)	-	155,759.3** (64,433.88)
Constant	0.000*** (0.000)	1.832*** (0.311)	2.492*** (0.427)	2.366*** (0.431)	1.728*** (0.317)	1.576*** (0.321)
Firm fixed	Yes	Yes	Yes	Yes	No	No
Tech. field fixed[1)]	-	-	-	-	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,981	2,981	2,981	2,981	2,337[2)]	2,337
R-squared	-	-	0.114	0.118	0.130	0.139
Number of firms	704	704	704	704	-	-
Number of instruments	21	22	-	-	-	-

Table 5. Continued

Specification	GMM-SYS		Robust check			
			Fixed effect OLS		Pooled OLS	
	Spec. 1	Spec. 2	Spec. 3	Spec. 4.	Spec. 5	Spec. 6.
F-statistic	264.28	190.32	1,752.65	3,728.93	84.10	201.35
P (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.0000
AR test (p-val) 1st order	0.109	0.106	-	-	-	-
2nd order	0.558	0.599	-	-	-	-
Hansen *J* test (p-val)	0.087	0.091	-	-	-	-

***, **, * are statistical significance at 1%, 5%, and 10% respectively; standard errors are also reported in parentheses; p-values are reported for AR test and Hansen *J* test.
1) Tech. field includes the followings: 1 (machine), 2 (electronics), 3 (information technology), 4 (chemical), 5 (bio), 6 (energy), 7 (knowledge service), 8 (ceramics).
2) In the pooled OLS estimation, the technology field is newly added unlike GMM-SYS and Fixed effect OLS estimation. Some missing data in technology field make difference in the number of total observations.
R&D, research and development; GMM-SYS, Generalized Method of Moments System; OLS, ordinary least squares; ILZS, industry with lower zombie share; AR, auto-regressive.

no second-order autocorrelation at the 5% statistical significance level.

The variable of the most interest in this study is a firm's zombie status. The coefficient of zombie status (ϕ_1) is revealed to be significantly positive in both specifications (specifications 1 and 2), which might indicate that a firm's zombie status has a positive association with its R&D investment. The coefficient (ϕ_1) is estimated to be 5,158.9 in specification 1, which means that a firm with a zombie status would invest $5,158.9 more than it would invest if it were a non-zombie status. This study finds evidence to support our hypothesis 1a that the zombie status of SMEs will not reduce their R&D investment.

This study also found a significantly positive coefficient (ϕ_2) in support of hypothesis Hypothesis 1b. It indicates that the effect of a firm's zombie status on its R&D investment is more pronounced in industries with a lower share of zombie firms. Specifically, firms with zombie status in industries with lower congestion are likely to invest more in R&D activities than those with higher congestion. This highlights the potential impact of zombie congestion on a firm's investment behavior. This finding is quite similar to previous research by McGowan et al. (2018), which suggests that the market congestion caused by zombie firms can crowd out non-zombie investments and hinder market expansion. This study also suggests that even firms with zombie status are influenced by the level of zombie congestion in their respective industries.

The coefficient (λ_1) of the lagged dependent variable is estimated to be negative, which is consistent with the findings of Cincera et al. (2016). It is natural that the speed of R&D stock accumulation (R/C value) follows a decreasing trend. The value (R/C) in a firm goes up only in cases where the firm makes R&D investments that are more than 1.4 times[7] that of the previous period. Regarding the change in log sales ($\triangle y_{i,t}$, $\triangle y_{i,t-1}$), all coefficients (λ_2 and λ_3) are revealed to be significantly positive. Given that the variables are indicative of either future expectations or investment opportunities, this study can interpret that a firm's positive outlook and opportunity would speed up its R&D stock accumulation.

The error-correction term (λ_4) is found to be significantly negative, and this term captures the

[7] To maintain the same value (R/C) as the value of the previous period, the firm must invest at least 1.4 times its previous R&D investment. Rt/Ct−1 = Rt+1/Ct , Rt/Ct−1=α×Rt/(Ct−1+Rt), α=1+Rt/Ct−1. When we plug in the median value (0.4) into Rt/Ct−1 ,α approximately becomes 1.4 (=1+0.4).

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speed of adjustment from short-run dynamics into long-run equilibrium. The magnitude of the coefficients is estimated between −1 and 0, which shows that the model is converging to long-run equilibrium and the estimation is stable. The coefficient is estimated as −0.199 in specification 1, implying that 19.9% of disequilibrium between short-run and long-run equilibrium will be corrected before the next period.

The coefficient (λ_5) of the log sales ($y_{i,t-2}$) is found to be significantly negative. This term captures returns to scale. The negative coefficient can be interpreted as that firms, on average, exhibit decreasing returns to sales. Holding all other variables constant, the firm with a larger scale of sales would experience less increase in its R&D stock. It suggests that a firm with more sales would expect less return on its R&D stock increase. Thus, the firm will invest less in R&D than other firms with lower sales. This finding is also consistent with Kim(2018), which found diminishing returns to R&D investment in Korean manufacturing SMEs.

As a robust check of GMM estimation, the study implemented a fixed effect and pooled ordinary least squares (OLS) regression results. Table 5 shows that the coefficient of zombie status (ϕ) is still found to be significantly positive in all specifications. In addition, the coefficient (λ_1) of the lagged dependent variable in GMM estimation lies between the lower-bound estimate of fixed-effect regression and the upper-bound estimate of pooled OLS regression.[8] This confirms the validity of our GMM estimation results. We also tested other specifications by adopting the revised indicator[9] of a firm's zombie status. It reveals an insignificant effect on a firm's R&D investment, which confirms that the finding still accepts our hypothesis. Furthermore, we tried to control the effect of the global financial crisis[10] in our model. This does not make any difference in the effect of a firm's zombie status on its R&D investment.

As an additional test for the validity of our results, we implemented GMM estimation, as shown in Table 6, for three subgroups: firms in industries with a lower proportion of zombie firms, firms in industries with a higher proportion of zombie firms, and firms that have experienced zombie status ever before. Consistent with the moderating effect of industry zombie share on R&D investment, we found that zombie status in an industry with a lower zombie share is strongly associated with R&D investment. The coefficient of zombie status (ϕ_1) is 156,423.6 in the subgroup of the industry with a lower zombie share, while the coefficient is only 5,328.1 in the industry with a higher zombie share. Furthermore, when we focused only on firms that have previously experienced zombie status more than once, we obtained quite interesting results that differed from those of the overall sample. The coefficients ($\lambda_1, \lambda_2,$ and λ_3) turn into all insignificant, indicating that neither the speed of R&D stock accumulation nor the change in sales had an impact on the firm's R&D investment. We conjecture that a different behavioral mechanism may exist for zombie firms that have engaged in R&D activity persistently. These firms may be more likely to actively pursue R&D investment to overcome their zombie status rather than relying on previous patterns of R&D investment or sales performance.

[8] Since the lagged dependent variable is included as a regressor in the model, the variable is positively correlated with the error terms in fixed effect regression, leading to a downward bias in the coefficient. The pooled OLS regression, however, is known to show an upward bias in the coefficient of lagged dependent variables (Bond, 2002).

[9] With regard to a zombie indicator, we replaced the time span of 3 years with 4 years (i.e., 1 if the firm's annual interest-coverage ratio keeps below one during previous 4 consecutive years, otherwise 0).

[10] We operationalized global financial crisis as a dummy variable; 1 if the observation is among 2007–2009, otherwise 0. The dummy variable of global financial crisis was found insignificant in our model.

Table 6. Additional estimation result (dependent variable: annual R&D investment per stock)

Specification	GMM-SYS		
	Industry with lower zombie share	Industry with higher zombie share	Firms only that have ever experienced zombie status
$\lambda_1 \frac{R_{i,t-1}}{C_{i,t-2}}$	–0.005** (0.002)	–0.001** (0.000)	–0.044 (0.029)
$\lambda_2 \Delta y_{i,t}$	0.089** (0.038)	0.068* (0.035)	0.039 (0.039)
$\lambda_3 \Delta y_{i,t-1}$	0.076 (0.049)	0.091*** (0.034)	0.033 (0.034)
$\lambda_4 \left(c_{i,t-2} - y_{i,t-2}\right)$	–0.190*** (0.038)	–0.179*** (0.039)	–0.242*** (0.057)
$\lambda_5 y_{i,t-2}$	–0.102*** (0.022)	–0.098*** (0.031)	–0.162*** (0.034)
$\phi_1 \frac{Zombie\ status_{\ i,t}}{C_{i,t-1}}$	156,423.6*** (59,056.56)	5,328.1** (613.35)	4,874.8** (886.46)
Constant	1.828*** (0.372)	0.000*** (0.000)	0.000*** (0.000)
Firm fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
Observations	1,014	1,967	971
R-squared	-	-	-
Number of firms	239	465	234
Number of instruments	21	21	21
F-statistic	18.58	309.60	159.57
P (F-statistic)	0.000	0.000	0.000
AR test (p-val) 1st order	0.038	0.176	0.011
2nd order	0.144	0.332	0.904
Hansen *J* test (p-val)	0.332	0.006	0.198

***, **, * are statistical significance at 1%, 5%, and 10% respectively; standard errors are also reported in parentheses; p-values are reported for AR test and Hansen *J* test. R&D, research and development; GMM-SYS, Generalized Method of Moments System; AR, auto-regressive.

Logit regression results for hypothesis 2a and 2b

This study applied logistic regression to test the relationship between a firm's zombie status and its technological and commercial output. Table 7 shows the results of zombie status on technological and commercial output, respectively.

The zombie status (β_1) of SMEs is revealed to be a significant positive predictor of patent applications in specification 1. Specifically, if an SME with a zombie status implements a government-sponsored R&D project, the likelihood of producing a patent application is 1.55 times higher than that of a non-zombie firm. We confirm that an SME with the zombie status taking R&D activity persistently is more likely to achieve technological success. However, specification 3 shows that the effect of zombie status on the commercialization probability is insignificant. Both findings support our hypothesis 2a that the zombie status of SMEs will not have a negative association with their innovation output from government-sponsored R&D projects. Nevertheless, it should be noted that an SME with zombie status persistently engaging in R&D activity might face a limitation in achieving commercial success from the technology, as suggested by the negative coefficient (β_1),

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Table 7. Logit regression of patent application and commercialization

Dependent variables	Log odd ratio of the probability of patent application		Log odd ratio of the probability of commercialization	
Specification	Spec. 1	Spec. 2.	Spec. 3	Spec. 4.
β_1 Zombie status$_i$	0.437* (0.26)	0.278 (0.33)	–0.195 (0.22)	–0.255 (0.28)
β_2 Zombie status$_i$×*ILZS* $_i$		0.368 (0.51)		0.146 (0.45)
β_3 Government fund$_i$	0.064*** (0.02)	0.065*** (0.02)	–0.008 (0.01)	–0.008 (0.01)
β_4 Project duration$_i$	0.146 (0.09)	0.145 (0.09)	0.190*** (0.07)	0.190*** (0.07)
β_5 Partners$_i$	0.146** (0.06)	0.145** (0.06)	0.125** (0.06)	0.124*** (0.05)
β_6 Technological readiness level	-	-	0.205*** (0.05)	0.204*** (0.05)
Constant	–0.912*** (0.33)	–0.932** (0.33)	–2.392*** (0.44)	–2.397*** (0.43)
Observations	767	767	722	722
Tech. field Fixed 1)	Yes	Yes	Yes	Yes
Log likelihood	–413.530	–413.251	–443.424	–443.369

***, **, * are statistical significance at 1%, 5%, and 10%, respectively; standard errors are also reported in parentheses.
1) Tech. field includes the followings: 1 (machine), 2 (electronics), 3 (information technology), 4 (chemical), 5 (bio), 6 (energy), 7 (service), 8 (ceramics).
ILZS, industry with lower zombie share.

even though it is not statistically significant.

With regards to the moderation effect, the coefficient (β_2) is revealed as insignificant in all specifications (2 and 4). While the moderating effect of industry zombie share on the zombie firm's R&D investment is evident, the moderating effect disappears in the relationship between a zombie status and innovation output from government R&D funding. Regardless of whether firms belong to industries with a lower or higher zombie share, there may be no difference in the performance made by firms to produce innovation output from government R&D funding. Therefore, we reject hypothesis 2b, saying that the effect of a firm's zombie status on its innovation output will be stronger in industries with a lower share of zombie firms.

The estimated effect of the magnitude of government funding (β_3) on the probability of producing a patent application from an R&D project is significantly positive, but on the probability of fostering commercialization, it is close to 0. These results are consistent with the findings of Park (2014), which were drawn using 1,929 industrial government-sponsored R&D projects (2006–2010) in Korea. In contrast, the duration of the R&D project (β_4) is a strong and significant predictor of commercialization but has no effect on patent applications.

The number of partners involved in each R&D project (β_5) is found to influence both patent applications and commercialization significantly positively. Collaboration seems to matter more than any other factor in producing technological and commercial output. These results are consistent with previous findings in Park (2014), and Ma & Dwyer (2020) despite different measures of outcomes.

In addition, we need to mention the reverse causality of technological output and a firm's lack of finance. For example, suppose a firm evaluates that the technology becomes more promising during its development. In that case, it invests more in technological development (i.e., higher technological output), and accordingly, the firm might face a more serious lack of finance (i.e., zombie status). This would lead to biased estimation. However, we presume that severe reverse causality is not likely to happen in our estimation because there is some time lag between a firm's zombie status and its project output. As explained in Table 4, the zombie indicator captures a firm's financial condition from 2012 to 2014, while the firm's project output is measured on a cumulative basis by the end of 2015. Nevertheless, this study did not strictly control reverse causality using instrumental variables, which is the limitation of this study.

As an additional test, we first implement the same logistic regression for each subgroup of lower and higher zombie congestion industries, respectively. The lower zombie congestion industry includes the Machine, Information Technology, and Knowledge fields, among all eight technological fields. From the estimation results in Table 8, we found that the positive association between a firm's zombie status and the probability of producing a patent application still holds true, particularly in the lower zombie congestion industry, while there is no relationship in the higher zombie congestion industry. Regarding commercialization, there seems to be no association between a firm's zombie status and the probability of commercialization in both groups. All these results still do not reject our hypothesis 2a.

Second, we implement the same logistic regression for each subgroup of zombies and non-zombies, respectively. In Table 9, the effect of government funds on the probability of patent application is found to be significant in both zombie firm and non-zombie firm groups. However,

Table 8. Robust test on subgroups of low and high zombie congestion industry

Dependent variables	Log odd ratio of the probability of patent application		Log odd ratio of the probability of commercialization	
Subgroup	Lower congestion	Higher congestion	Lower congestion	Higher congestion
β_1 Zombie status$_i$	0.652^{*} (0.40)	0.281 (0.33)	−0.082 (0.35)	−0.261 (0.29)
β_3 Government fund$_i$	0.066^{***} (0.03)	0.063^{***} (0.03)	0.001 (0.01)	−0.014 (0.01)
β_4 Project duration$_i$	0.072 (0.13)	0.187 (0.13)	0.222^{**} (0.10)	0.177^{*} (0.10)
β_5 Partners$_i$	0.215^{*} (0.12)	0.121 (0.08)	0.020 (0.11)	0.168^{**} (0.07)
β_6 Technological readiness level	-	-	0.199^{***} (0.07)	0.204^{***} (0.06)
Constant	-0.909^{**} (0.46)	-0.925^{**} (0.39)	-2.313^{***} (0.65)	-1.549^{***} (0.53)
Observations	331	436	313	409
Tech. field fixed	Yes	Yes	Yes	Yes
Log likelihood	−183.405	−229.244	−197.930	−244.346

***, **, * are statistical significance at 1%, 5%, and 10%, respectively; standard errors are also reported in parentheses.

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Table 9. **Robust test on subgroups of zombies and non-zombies**

Dependent variables	Log odd ratio of the probability of patent application		Log odd ratio of the probability of commercialization	
Subgroup	Zombies	Non-zombies	Zombies	Non-zombies
β_3 Government fund$_i$	0.095** (0.04)	0.059*** (0.02)	0.001 (0.03)	−0.008 (0.01)
β_4 Project duration$_i$	−0.156 (0.23)	0.223** (0.10)	0.106 (0.19)	0.198** (0.08)
β_5 Partners$_i$	0.002 (0.15)	0.184** (0.07)	0.150 (0.13)	0.119* (0.06)
β_6 Technological readiness level	-	-	0.205 (0.13)	0.195*** (0.05)
Constant	0.389 (0.87)	−1.153*** (0.36)	−2.750** (1.16)	−2.304*** (0.47)
Observations	127	640	116	605
Tech. field fixed	Yes	Yes	Yes	Yes
Log likelihood	−61.658	−347.096	−70.975	−367.132

***, **, * are statistical significance at 1%, 5%, and 10%, respectively; standard errors are also reported in parentheses.

the magnitude of the effect is much stronger[11] in the zombie firm group than in the non-zombie firm group. It confirms that zombie firms better utilize government funds to produce technological output. Regarding commercialization, the effect of government funds is revealed to be insignificant. Remarkably, in all estimations, the zombie firms do not benefit from other project partners, unlike the non-zombie firms. It might also suggest that zombie firms lack networking capabilities to acquire external technological knowledge and business opportunities.

Table 10 summarizes the test results of all hypotheses. Hypotheses 1a, 1b and 2a are accepted, and on the contrary, hypothesis 2b is rejected.

Concluding Remarks

Our research question is whether the policy to restrict zombies in innovation funding is justifiable in terms of innovation. To address this question, this study aimed to explore the relationship between a firm's zombie status and its innovation, with a particular focus on the moderating effect of zombie congestion, by using the data from firms participating in government

Table 10. **Summary of hypotheses test**

Hypotheses		Results
Hypothesis 1a	A firm's zombie status will not reduce its R&D investment.	Accepted
Hypothesis 1b	The effect of a firm's zombie status on its R&D investment will be stronger in industries with a lower share of zombie firms.	Accepted
Hypothesis 2a	A firm's zombie status will not be negatively associated with its innovation output.	Accepted
Hypothesis 2b	The effect of a firm's zombie status on its innovation output will be stronger in industries with a lower share of zombie firms.	Rejected

R&D, research and development.

[11] Average marginal effect of government fund on the probability of patent application is estimated about 1.5% in the zombie group and about 1% in the non-zombie group.

R&D projects, which are representative of SMEs with R&D activity.

First, this study empirically tested the effect of a firm's zombie status on its innovation investment in SMEs through dynamic panel data analysis. It reveals that a firm with a zombie status invests an average of $5,158.9 more in R&D activities than a non-zombie firm when controlling for the effects of previous R&D investment and sales. It might reflect that SMEs with a zombie status taking R&D activity have a greater willingness to rebuild their competitiveness and ensure survival. Moreover, the study confirms the moderation effect of zombie congestion on a firm's investment. Specifically, the result indicates that firms with zombie status operating in industries with lower congestion tend to invest more in R&D than those with higher congestion. This may emphasize that policymakers need to adopt different policies for addressing zombie firms in each industry depending on the level of zombie share in that industry.

Second, the relationship between a firm's zombie status and innovation output is investigated. We confirm that firms in the zombie status that take R&D activity persistently are more likely to achieve technological success. However, the zombie status is not significantly associated with the probability of commercialization. All these support that a firm's zombie status will not negatively affect its innovation output from a government-sponsored R&D project. Nevertheless, firms with zombie status may encounter limitations in achieving commercial success due to financial constraints or weaker business capabilities. In addition, this study finds no evidence of any moderating effect of zombie congestion on the relationship between zombie status and innovation output from government R&D funding. Zombie congestion in a firm's industry does not seem to affect the firm's behavior in producing innovation output from government funding. Instead, project attributes such as project fund, duration, and partners appear to influence innovation output significantly.

At this point, we acknowledge that this study is subject to potential selection bias due to the specific nature of the data used. The dataset comprises SMEs that have received at least one government grant from the KEIT, the largest funding agency for industrial R&D in Korea. Consequently, our data exclude R&D-active SMEs that either have not participated in government-sponsored R&D projects or have participated in such projects funded by other agencies. These limitations necessitate caution when generalizing the empirical results to all SMEs, particularly those without government project participation. Focusing on KEIT-funded firms may skew the findings towards SMEs with higher transparency in information disclosure and a greater willingness to engage in innovation activities facilitated by government grants. Therefore, the results may not fully represent the broader spectrum of Korean SMEs.

In the remainder, we would like to discuss zombie firms, particularly R&D-active zombies, from two aspects: the danger of dichotomous indicators and the rationale for government funding. First, the dichotomy—zombie or non-zombie—can lead to bias. It is easy to carelessly apply the typical zombie image to any firm that has a zombie status. However, firms in our data seek desperately to escape from zombie status through more investment. This shows quite a considerable mismatch between the ordinary zombie images and those from our data on the Korean case. Ordinary zombie firms have been portrayed as sluggish businesses that completely lost their dynamic competitiveness and rely entirely on government subsidies or banks' low-interest rates for survival. This image seems to come from relatively big companies – listed firms (Caballero et al., 2008; Han et al., 2019; Liu

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et al., 2019; McGowan et al., 2018; Shaozhen et al., 2019). Our study, however, revealed a distinct image of zombie firms desperately striving for innovation, especially in R&D-active SMEs, although they somewhat lack commercialization capability.

Second, considering that the rationale of government intervention lies in inducing innovation, zombie firms contribute to achieving policy effectiveness. This study found that a firm's zombie status is associated with more aggressive R&D investment and higher technological output than those without a zombie status. A policy that excludes zombie firms in government-sponsored R&D funding may not realize the best outcomes. The uniform exclusion would lead to equity concerns in terms of singling out one class of firms that may warrant consideration. R&D-active firms with a zombie status, which continue to exhibit effort in innovation for their survival, need to get a fair chance to compete to win an innovation grant.

For better policymaking on zombie firms, it is crucial to accurately identify firms that are actual zombies. The identification method needs to be advanced by considering the firm's innovation activities. The use of a dichotomous indicator may be inadequate, so future studies need to explore more rigorous methods, such as categorical or continuous indicators, to better assess the level of zombie status. Furthermore, if long-term and rich data is available, it would be worthwhile to investigate the failure and death of innovative zombie firms in future research.

References

Acharya, V. V., Eisert, T., Eufinger, C., & Hirsch, C. (2019). Whatever it takes: The real effects of unconventional monetary policy. *The Review of Financial Studies*, *32*(9), 3366-3411. https://doi.org/10.1093/rfs/hhz005

Alfranseder, E., & Dzhamalova, V. (2014). The impact of the financial crisis on innovation and growth: Evidence from technology research and development. Lund University, Knut Wicksell Centre for Financial Studies.

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly*, *21*(6), 1086-1120. https://doi.org/10.1016/j.leaqua.2010.10.010

Baek, C., Jeong, M. W., Lee, H., Lee, Y. B., Noh, M., & Son, B. (2021). Empirical analysis of conversion of marginal companies in manufacturing to normal companies: Focusing on company's R&D activities and government's support effect. *Journal of Technology* & *Innovation*, *29*(2), 59-85. https://doi.org/10.14386/SIME.2021.29.2.59

Banerjee, R. N., & Hofmann, B. (2018). The rise of zombie firms: Causes and consequences. BIS Quarterly Review. https://ssrn.com/abstract=3288098

Bank of Korea. (2014). *Financial stability report*. Bank of Korea.

Bank of Korea. (2018). *Financial stability report*. Bank of Korea.

Bernstein, J. I., & Nadiri, M. I. (1989). Rates of return on physical and R&D capital and structure of the production process: Cross section and time series evidence. In B. Raj (Ed.), *Advances in econometrics and modelling* (pp. 169-187). Springer.

Blattner, L., Farinha, L., & Rebelo, F. (2019). *When losses turn into loans: The cost of undercapitalized* *banks*. European Central Bank.

Bond, S. R. (2002). Dynamic panel data models: A guide to micro data methods and practice. *Portuguese Economic Journal*, *1*(2), 141-162. https://doi.org/10.1007/s10258-002-0009-9

Bontempi, M. E. (2016). Investment–uncertainty relationship: Differences between intangible and physical capital. *Economics of Innovation and New Technology*, *25*(3), 240-268. https://doi.org/10.1080/10438599.2015.1076197

Borio, C. (2018). *A blind spot in today's macroeconomics*. Bank for International Settlements.

Brown, J. R., & Petersen, B. C. (2011). Cash holdings and R&D smoothing. *Journal of Corporate Finance*, *17*(3), 694-709. https://doi.org/10.1016/j.jcorpfin.2010.01.003

Caballero, R. J., Hoshi, T., & Kashyap, A. K. (2008). Zombie lending and depressed restructuring in Japan. *American Economic Review*, *98*(5), 1943-1977. https://doi.org/10.1257/aer.98.5.1943

Chang, Q., Zhou, Y., Liu, G., Wang, D., & Zhang, X. (2021). How does government intervention affect the formation of zombie firms? *Economic Modelling*, *94*, 768-779. https://doi.org/10.1016/j.econmod.2020.02.017

Cho, Y. (2004). R&D spillover effects in Korean manufacturing industries. *Korea Review of Applied Economics*, *6*(1), 209-232.

Cincera, M., Ravet, J., & Veugelers, R. (2016). The sensitivity of R&D investments to cash flows: Comparing young and old EU and US leading innovators. *Economics of Innovation and New Technology*, *25*(3), 304-320. https://doi.org/10.1080/10438599.2015.1076201

European Commission (Joint Research Centre). (2018). *Fear the walking dead?: Incidence and effects of zombie firms in Europe*. Publications Office.

General Operational Guideline for Industrial Technology Innovation Program. (2020). *Ministry of Trade, Industry, and Energy*. Ministry of Trade, Industry, and Energy.

Geng, Y., Liu, W., & Wu, Y. (2021). How do zombie firms affect China's industrial upgrading? *Economic Modelling*, *97*, 79-94. https://doi.org/10.1016/j.econmod.2021.01.010

Goldsmith, R. W. (1951). A perpetual inventory of national wealth. In Conference on Research in Income and Wealth (Ed.), *Studies in income and wealth* (pp. 5-73). National Bureau of Economic Research.

Goto, Y., & Wilbur, S. (2019). Unfinished business: Zombie firms among SME in Japan's lost decades. *Japan and the World Economy*, *49*, 105-112. https://doi.org/10.1016/j.japwor.2018.09.007

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, *10*(1), 92-116. https://doi.org/10.2307/3003321

Hall, B. H. (2002). The financing of research and development. *Oxford Review of Economic Policy*, *18*(1), 35-51. https://doi.org/10.1093/oxrep/18.1.35

Hall, B., Mulkay, B., & Mairesse, J. (2001). Investment and R&D in France and the United States. In D. Bundesbank (Ed.), *Investing today for the world of tomorrow: Studies on the investment process in Europe*. Springer.

Hall, B. H., & Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics*, *65*(1), 263-293. https://doi.org/10.1016/0304-4076(94)01604-X

Hall, B. H., & Oriani, R. (2006). Does the market value R&D investment by European firms?

Evidence from a panel of manufacturing firms in France, Germany, and Italy. *International Journal of Industrial Organization*, *24*(5), 971-993. https://doi.org/10.1016/j.ijindorg.2005.12.001

Han, S. (2016). The dall of growth and structural reform in Korea. *Economic Discussion, 55*. https://hdl.handle.net/10371/96774

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029-1054. https://doi.org/10.2307/1912775

Himmelberg, C. P., & Petersen, B. C. (1994). R&D and internal finance: A panel study of small firms in high-tech industries. *The Review of Economics and Statistics*, *76*(1), 38-51. https://doi.org/10.2307/2109824

Jorgenson, D. W. (1963). Capital theory and investment behavior. *The American Economic Review*, *53*(2), 247-259.

Kam, J., & Jung, T. (2018). Zombie firms and performance of R&D support programs for small and medium enterprises. *Journal of Korea Technology Innovation Society*, *21*(4), 1474-1492.

KIET. (2016). *Analysis of the status of marginal companies by industry and implications*. Korea Institute for Industrial Economics & Trade.

Kim, K. (2018). Diminishing returns to R&D investment on innovation in manufacturing SMEs: Do the technological intensity of industry matter? *International Journal of Innovation Management*, *22*(07), 1850056. https://doi.org/10.1142/S1363919618500561

Kim, S., Lim, C., Lee, S., Seo, J., & Hwang, J. (2014). *A study on the promotion of private R&D investment*. Science & Technology Policy Institute.

Kim, A., & Park, J. (2024). What type of fiscal rule promotes the fiscal soundness? *Journal of Policy Studies*, *39*(1), 1-15. https://doi.org/10.52372/jps39101

Kim, SJ. (2016). The fall of growth and structural reform in Korea. *Economic Discussion*, 55(1), 3-27.

Koh, P. S., & Reeb, D. M. (2015). Missing R&D. *Journal of Accounting and Economics*, *60*(1), 73-94. https://doi.org/10.1016/j.jacceco.2015.03.004

KOSIS. (2022). *Korean Statistical Information Service: Number of R&D active firms*. https://kosis.kr/

Lahr, H., & Mina, A. (2013). *Dynamic financial constraints and innovation: Evidence from the UK Innovation Surveys* [Conference presentation]. European Conference on Corporate R&D and Innovation CONCORDi-2013 Conference Paper, Seville, Spain.

Lee, B., Jang, P., & Oh, S. (2023). Study on the innovation activities and innovation performance on escaping the zombie firms: Focusing on the manufacturing industry. *Korea Society of Innovation*, *18*(3), 45-68. https://doi.org/10.46251/INNOS.2023.8.18.3.45

Liu, G., Zhang, X., Zhang, W., & Wang, D. (2019). The impact of government subsidies on the capacity utilization of zombie firms. *Economic Modelling*, *83*, 51-64. https://doi.org/10.1016/j.econmod.2019.09.034

Ma, H. R., & Dwyer, D. S. (2020). The effect of funding agency's choices: Empirical evidence from large-scale R&D projects in Korea's automotive industry. *International Journal of Technology, Policy and Management*, *20*(4), 273-298. https://doi.org/10.1504/IJTPM.2020.111492

Ma, H. R., Lee, C. J., & Oh, D. H. (2022). Identification of R&D paradox after the global financial crisis: Korean case focusing on the smart convergence and conventional industries. *Science, Technology and Society*, *27*(2), 213-232. https://doi.org/10.1177/09717218221075145

Malmberg, A., & Maskell, P. (1997). Towards an explanation of regional specialization and industry agglomeration. *European Planning Studies*, *5*(1), 25-41. https://doi.org/10.1080/09654319708720382

Martínez-Noya, A., & Narula, R. (2018). What more can we learn from R&D alliances? A review and research agenda. *BRQ Business Research Quarterly*, *21*(3), 195-212. https://doi.org/10.1016/j.brq.2018.04.001

McGowan, M. A., Andrews, D., & Millot, V. (2017). *Insolvency regimes, zombie firms and capital reallocation*. OECD.

McGowan, M. A., Andrews, D., & Millot, V. (2018). The walking dead? Zombie firms and productivity performance in OECD countries. *Economic Policy*, *33*(96), 685-736. https://doi.org/10.1093/epolic/eiy012

NABO. (2016). *Account settlement analysis (2015 fiscal year settlement)*. National Assembly Budget Office.

Narula, R. (2001). Choosing between internal and non-internal R&D activities: Some technological and economic factors. *Technology Analysis and Strategic Management*, *13*(3), 365-387. https://doi.org/10.1080/09537320120088183

Nurmi, S., Vanhala, J., & Viren, M. (2020). The life and death of zombies: Evidence from government subsidies to firms (Research Discussion Paper No. 8/2020). Bank of Finland.

Park, S. (2014). A methodological study of prediction model estimation for R&D performance creation success probability and design of experiments and analysis for sensitivity. *Management Consulting Research*, *14*(2), 287-311.

Pickup, M., & Evans, G. (2013). Addressing the endogeneity of economic evaluations in models of political choice. *Public Opinion Quarterly*, *77*(3), 735-754. https://doi.org/10.1093/poq/nft028

Qiao, L., & Fei, J. (2022). Government subsidies, enterprise operating efficiency, and "stiff but deathless" zombie firms. *Economic Modelling*, *107*, 105728. https://doi.org/10.1016/j.econmod.2021.105728

Qiao, X., Song, L., & Fan, X. (2022). How do zombie firms affect innovation: From the perspective of credit resources distortion. *Asian-Pacific Economic Literature*, *36*(1), 67-87. https://doi.org/10.1111/apel.12349

Roodman, D. (2009). How to do Xtabond2: An introduction to difference and system GMM in stata. *Stata Journal*, *9*(1), 86-136. https://doi.org/10.1177/1536867X0900900106

Schwartz, M., Peglow, F., Fritsch, M., & Günther, J. (2012). What drives innovation output from subsidized R&D cooperation?—Project-level evidence from Germany. *Technovation*, *32*(6), 358-369. https://doi.org/10.1016/j.technovation.2012.03.004

Shaozhen, H., You, W., & Nan, S. (2019). Zombie firms, external support and corporate environmental responsibility: Evidence from China. *Journal of Cleaner Production, 212*, 1499-1517. https://doi.org/10.1016/j.jclepro.2018.12.136

Ullah, S., Akhtar, P., & Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management*, *71*, 69-78. https://doi.org/10.1016/j.indmarman.2017.11.010

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the dynamics of internal corporate governance. *Journal of Financial Economics*, *105*(3), 581-606. https://doi.org/10.1016/

j.jfineco.2012.03.005

Wu, Y., & Pan, H. (2023). Zombie firms and corporate financialization: Evidence from China. *Review of Managerial Science, 18*(4), 1077-1099. https://doi.org/10.1007/s11846-023-00633-0

Yoon, J. W. (2014). Evolution of science and technology policy in Korea. *Journal of Policy Studies*, *29*(1), 147-172. https://doi.org/10.52372/kjps29107

Yu, X., Wu, F., Wan, K., & Chang, T. (2023). Zombie firms and corporate innovation: A double distortion effect—empirical evidence from China. *Applied Economics Letters*, *30*(4), 456-461. https://doi.org/10.1080/13504851.2021.1991563

Appendices

Appendix 1. R&D investment framework

The R&D error-correction framework was used by Cincera et al. (2016) to describe the relationship between a firm's sales and its R&D investment. The basic equation of the R&D error-correction framework is derived from the constant elasticity of substitution production function, which is transformed into an autoregressive distributed lag model (ADL) for dynamic adjustments of R&D capital.

The detailed derivation of this formula is summarized as follows: following the neo-classical approach in Jorgenson (1963), the desired amount of capital stock can be expressed as follows if the Cobb-Douglass production function is assumed:

$$\mathbf{K}^* = \gamma \frac{\mathbf{pQ}}{\mathbf{u}} \tag{A1}$$

where K* represents the desired amount of capital stock, Q is the quantity of output, p is the price of the output, u is the user cost of capital, and γ represents the elasticity of output concerning capital.

Equation (A1) can be rewritten in the following format:

$$\begin{aligned}\log\left(\mathbf{R}\ \&\ \mathbf{D}\ \text{stock}_{\mathbf{i,t}}\right) - \varepsilon_{\mathbf{i,t}} = \beta \log\left(\mathbf{Sales}_{\mathbf{i,t}}\right) \\ - \lambda \log\left(\mathbf{u}_{\mathbf{i,t}}\right)\end{aligned} \tag{A2}$$

where i represents an individual firm, t is a specific year, and εi,t is a random error term that is independent and identically distributed. Following Hall et al. (2001), the user cost of capital (u), which is latent and hard to measure, can be proxied with a time dummy (α_t) and specific firm fixed effects (α_i).

$$\begin{aligned}\log\left(\mathbf{R}\ \&\ \mathbf{D}\ \text{stock}_{\mathbf{i,t}}\right) = \beta \log\left(\mathbf{Sales}_{\mathbf{i,t}}\right) \\ + \alpha_{\mathbf{i}} + \alpha_{\mathbf{t}} + \varepsilon_{\mathbf{i,t}}\end{aligned} \tag{A3}$$

We add ADL(2,2)[12] into Equation (A3) in order to include both the effect of a firm's sales on its future R&D stock over the years and the effect of past R&D stock on subsequent R&D stock. The equation becomes:

$$\begin{aligned}\log\left(\text{R\&D stock}_{\text{i,t}}\right) = \rho_1 \log\left(\text{R\&D stock}_{\text{i,t}-1}\right) \\ + \rho_2 \log\left(\text{R\&D stock}_{\text{i,t}-2}\right) \\ \beta_0 \log\left(\text{Sales}_{\text{i,t}}\right) \\ + \beta_1 \log\left(\text{Sales}_{\text{i,t-1}}\right) \\ \beta_2 \log\left(\text{Sales}_{\text{i,t-2}}\right) \\ + \alpha_{\text{i}} + \alpha_{\text{t}} + \varepsilon_{\text{i,t}}\end{aligned} \tag{A4}$$

Equation (A4) can be converted to the following error-correction form through a simple linear transformation:

[12] Here, ADL (p, q) means that p is the number of lags of the dependent variable, and q is the number of lags of the regressor.

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$$
\begin{aligned}
\Delta\log\left(\text{R\&D stock}_{i,t}\right) = \alpha_{\mathbf{i}} + \alpha_{\mathbf{t}} \\
&+ \lambda_1 \Delta\log\left(\text{R\&D stock}_{i,t-1}\right) \\
&+ \lambda_2 \Delta\log\left(\text{Sales}_{i,t}\right) \\
&+ \lambda_3 \Delta\log\left(\text{Sales}_{i,t\text{-}1}\right) \\
&+ \lambda_4 \left(\log\left(\text{R\&D stock}_{i,t\text{-}2}\right)\right. \\
&\left.-\log\left(\text{Sales}_{i,t-2}\right)\right) \\
&+ \lambda_5 \log\left(\text{Sales}_{i,t-2}\right) + \varepsilon_{i,t}, \qquad \text{(A5)}
\end{aligned}
$$

Substituting $\Delta\log\ (R\,\&\,D\ stock_{\ i,t})$[13] into $\frac{R\,\&\,D\ \text{investment}_{\ i,t}}{R\,\&\,D\ \text{stock}_{\ i,t}} - \delta$ in equation (A5), the R&D error-correction framework is drawn into the equation (A6).

$$
\begin{aligned}
\frac{\mathbf{R}_{\mathbf{i,t}}}{\mathbf{C}_{\mathbf{i,t}-1}} = \alpha_{\mathbf{i}} + \alpha_{\mathbf{t}} + \lambda_1 \frac{\mathbf{R}_{\mathbf{i,t}-1}}{\mathbf{C}_{\mathbf{i,t}-2}} \\
&+ \lambda_2 \Delta\mathbf{y}_{\mathbf{i,t}} + \lambda_3 \Delta\mathbf{y}_{\mathbf{i,t}-1} \\
&+ \lambda_4 \left(\mathbf{c}_{\mathbf{i,t}-2} - \mathbf{y}_{\mathbf{i,t}-2}\right) + \lambda_5 \mathbf{y}_{\mathbf{i,t}-2} + \varepsilon_{\mathbf{i,t}} \qquad \text{(A6)}
\end{aligned}
$$

where R is a firm's own annual R&D investment, C is R&D stock, c and y are the natural logarithm of R&D stock and sales, respectively. This describes the relationship between an individual firm's sales increase and its R&D stock increase in the error-correction framework. This approach is useful in that it integrates the short-run dynamics with the long-run equilibrium. The first three variables (i.e., λ_1, λ_2, and λ_3) on the right-hand side of the equation capture the short-run effects, while the last two variables (i.e., λ_4 and λ_5) indicate long-run equilibrium. The coefficient (λ_4) is the error-correction term that adjusts disequilibrium, and the coefficient (λ_5) imposes the constant return to scale assumption (Hall et al., 2001).

Appendix 2. R&D capital stock estimation

Our research model for testing the relationship between a firm's zombie status and its R&D investment contains an R&D stock variable in its model. In order to estimate the model, an R&D stock must be calculated. A firm's R&D stock (C_t) can be expressed as the sum of its current R&D investment (R_t) and R&D stock in the previous period (Ct_{-1}).

$$
\begin{aligned}
\mathbf{C}_{\mathbf{t}} &= \mathbf{R}_t + (1-\delta)\mathbf{C}_{t-1} \\
&= \mathbf{R}_t + (1-\delta)\mathbf{R}_{t-1} + (1-\delta)^2 \mathbf{C}_{t-2} \\
&= \mathbf{R}_t + (1-\delta)\mathbf{R}_{\mathbf{t}-1} + (1-\delta)^2 \mathbf{R}_{t-2} \\
&\quad + \ldots + (1-\delta)^{\mathbf{t}-1}\mathbf{R}_1 \\
&\quad + (1-\delta)^{t}\mathbf{C}_0 \qquad \text{(A7)}
\end{aligned}
$$

13 $\Delta\log\left(\text{RDstock}_{i,t}\right) = \Delta\log\left(C_{i,t}\right) = \log\left(C_{i,t}\right) - \log\left(C_{i,t-1}\right) = \log\left(\frac{C_{i,t}}{C_{i,t-1}}\right) = \log\left(\frac{C_{i,t}}{C_{i,t-1}}\right) = \log\left(\frac{R_{i,t} + (1\text{-}\delta)C_{i,t-1}}{C_{i,t-1}}\right) = \log\left(1 + \left(\frac{R_{i,t}}{C_{i,t-1}} - \delta\right)\right) \approx \frac{R_{i,t}}{C_{i,t-1}} - \delta\left(\because \log(1+a) \fallingdotseq a, \text{ in Taylor expansion}\right)$, where δ is the depreciation rate.

where δ is the depreciation rate.

Goldsmith's perpetual inventory method is most used in the literature to estimate a firm's R&D stock (Goldsmith, 1951; Griliches, 1979). The perpetual inventory method assumes that a firm has invested in R&D with a constant growth rate (g) over infinite periods from the start until the reference time (t=0). This method is appropriate for firms that have gone a long time since their start date, as is the case with sample firms used in the Cincera et al. (2016). The age of the sample firms in Cincera et al. (2016) is between 50–100 years. The sample firms in this study started up in the year 2000 on average and are younger than those typical for the Goldsmith method.

So, this study will calculate R&D stock precisely using the information of a firm's start year instead of adopting the perpetual inventory method, which assumes that firms have invested in annual R&D capital infinite times. The method used in this study is expressed in equation (A8).

$$\mathbf{C}_0 = \mathbf{R}_{\mathrm{ref}} + \frac{\mathbf{R}_{\mathrm{ref}}(1-\delta)^1}{(1+\mathbf{g})^1} + \frac{\mathbf{R}_{\mathrm{ref}}(1-\delta)^2}{(1+\mathbf{g})^2} + \ldots + \frac{\mathbf{R}_{\mathrm{ref}}(1-\delta)^{\mathrm{ref-start}}}{(1+\mathbf{g})^{\mathrm{ref-start}}} \tag{A8}$$

For firms with missing information on their start year, the average year of the sample (i.e., the year 2000) was substituted, and the reference year was set as 2006 for R&D stock estimation.

Each firm's R&D investment in the reference year (Rref) is measured as follows in each case:

The case that a firm's R&D investment data in 2007 is available: $R_{2006} = R_{2007} / (1+g)$

The case that a firm's R&D investment data in 2007 is missing: R_{2006} = the firm's average R&D investment between 2007 and 2015.

The depreciation rate (δ) is set as 15% following Cincera et al. (2016). It is known that there is no significant change in the R&D capital effect, even if the depreciation rate changes (Hall & Mairesse, 1995). In addition, we set up a firm's annual growth rate in R&D investment with the average growth rate of all firms in the same industry sector (Cho, 2004). For firms that are missing industry sector data, the average growth rate across all industry sectors is applied.

Using R&D investment in the reference year (R_{ref}), together with the growth rate (g), depreciation rate (δ), and each firm's start year, this study calculates each firm's R&D stock until 2006 according to the equation (A8). Then, this study estimates each firm's annual stocks sequentially from 2007 to 2015, according to equation (A7).

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