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Ph.D Thesis

Product life cycle in financial decisions

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Introduction

Companies need to carefully balance their product portfolios and actions to survive, stay competitive, and maximize shareholders' value. One way to study a company's product portfolio is through its life cycle, a well-established concept that products move through life cycle stages. First, the product is introduced on the market. Then, the unit sales begin to increase. Third, the product reaches a plateau. Finally, the product gets obsolete, and the company discontinues its production (Utterback and Abernathy, 1975; Rink and Swan, 1979; Klepper, 1996). Despite the concept's importance, the finance literature has only recently started recognizing its value.[1] This doctoral thesis contributes to this literature by exploring different aspects of the product life cycle and its importance for companies' investment and financing decisions. The three essays composing the thesis cover three different but important companies' decisions: mergers and acquisitions (M&A), initial public offerings (IPO), and stock repurchases.

The first essay of the thesis is titled "Competitive approaches in mergers and acquisitions". The competitive approach is the top management's decision that influences the company's product life cycle curves. Two companies producing a similar product can choose different life cycle curves. On one side of the spectrum are companies aiming to be the first on the market with new products and innovations, while on the other side are companies specializing in cheaper versions when the products are already standardized and their demand well established (Klepper, 1996). Hence, competitive approach has direct implications for firms' investment decisions. Yet financial economists have largely ignored this relationship. This paper fills the gap by studying whether firm competitive approaches affect their M&A decisions. Comparing the product life cycles of similar companies to determine

[1] Hoberg and Maksimovic (2022), Chen et al. (2020), and Hajda and Nikolov (2021) are among papers exploring its relevance in finance decisions.

a company's competitive approach, the analysis reveals three central findings. First, both acquirers and targets are scattered through all the competitive groups. The result highlights that companies do not exhaust all their internal investment opportunities before acquiring other companies, but they continuously weigh all the viable alternatives. Additionally, the presence of targets across all the groups demonstrates that all acquirers are not driven by one acquisition motive; they pursue different goals through M&A. Second, the odds of a transaction for companies with the same competitive traits are twice as large as the odds for companies that belong to dissimilar competitive approaches. This acquirer-target pair pattern reveals that managers lack knowledge and experience to manage companies (divisions) organized with a different resource allocation (Harrison et al., 2017); the same market threat can differently impact an innovating firm starting the product life cycle early and a firm entering the market when the product is already standardized and their optimal market responses. Third, deals with competitive overlap earn, on average, 87 basis points higher combined announcement returns, and the acquirer's assets and sales increase significantly after the acquisition compared with the companies that bought a target with a different competitive approach. Therefore, the main contribution of the paper is to show that competitive approach affects firms' investment decisions.

The second essay of the thesis, titled "Product life cycle and initial public offerings", is joint work with Jiajie Xu (University of Iowa). It examines how firms' product life cycle influences the trade-off between the benefits and costs of going public. Firms decide to go public due to the IPO benefits, such as raising relatively cheaper capital from the public market than the private market for their internal investment projects, increasing visibility and grabbing market shares, raising capital for acquisitions. Nevertheless, these benefits come with non-negligible costs, such as leaking innovation information to the competitors, underpricing due to the information asymmetry towards investors, losing confidentiality and increasing financial transparency, reducing exploratory innovation, less control and more board of directors' influence(Hertzel and Smith, 1993; Chemmanur et al., 2010; Maksimovic and Pichler, 2001; Ferreira et al., 2014). However, not all the firms aim for all the benefits, nor do they equally face all the costs. Based on theoretical models, such as Hajda and Nikolov (2021), product life cycle relates to firms' investment and financing decisions. However, no empirical research so far analyzes this relationship. We fill the gap by constructing the product life cycle measure using textual analysis of S-1 registration statements for IPOs. The analysis shows that firms with a more innovative products are more likely to complete the IPO despite higher underpricing and a lower fraction of equity offered at IPO. These firms conduct more seasoned equity offerings, payout fewer dividends, and conduct fewer acquisitions after IPO. The findings demonstrate that firms with diverging product life cycles differently weigh the importance of raising capital through IPO, information asymmetry with investors, and revealing information to competitors. To establish causality, we use an instrumental variable and a difference-in-differences approach around the American Investors Protection Act. The main contribution of the paper is to show that firms with different product life cycles face different trade-offs between IPO benefits and costs.

The third essay of the thesis, "The Impact of Firm Life Cycle on Stock Repurchases and Firms' Post-Repurchase Performance", is joint work with Yuxin Wu (Boston College). It asks whether firms consider their life cycles when making share repurchase decisions. Stock repurchases have become an increasingly popular payout method in the last three decades and one of the most debated areas for regulation (Jagannathan et al., 2000; Wang et al., 2021). Proponents of regulating open market stock repurchases advocate that firms need to satisfy minimum investment standards before gaining eligibility for stock repurchases. They claim that firms sacrifice other investment opportunities that can otherwise benefit the firms and their employees when they repurchase stocks. However, the academic literature has not empirically investigated this claim's validity on a broad sample of stock repurchases. In this paper, we answer whether such proposed regulations benefit the firms and the economy. We find that mature firms with limited investment opportunities but excessive cash repurchase more shares than innovative firms with numerous profitable investment projects but limited funding. Moreover, firms adapt their financing and stock repurchase strategies according to their dynamic life cycles such that firms switching from the mature to the innovation stage of their life cycles change from repurchasing shares to seasoned equity offerings. In line with the agency theory, repurchasing mature firms outperform non-repurchasing mature firms in the post-repurchase period. Using an instrumental variable approach and a difference in differences analysis around the Energy Independence and Security Act of 2007, we draw causal inferences between firms' life cycles and their stock repurchase decisions. The main contribution of the paper is to shed new light on the popularly debated policy proposals as they indicate firms do not sacrifice corporate investments, employment, and other future prospects for the stock repurchase payouts.

References

Chemmanur, T. J., S. He, and D. K. Nandy (2010). The going-public decision and the product market. *The Review of Financial Studies 23*(5), 1855–1908.

Chen, A., G. Hoberg, and V. Maksimovic (2020). Life cycles of firm disclosures. *Unpublished working paper*.

Ferreira, D., G. Manso, and A. C. Silva (2014). Incentives to innovate and the decision to go public or private. *The Review of Financial Studies 27*(1), 256–300.

Hajda, J. and B. Nikolov (2021). Product market strategy and corporate policies. *Swiss Finance Institute Research Paper No. 21-02*.

Harrison, J. S., E. H. Hall Jr, and R. Nargundkar (2017). Resource allocation as an outcropping of strategic consistency: Performance implications. *Academy of Management Journal*.

Hertzel, M. and R. L. Smith (1993). Market discounts and shareholder gains for placing equity privately. *The Journal of Finance 48*(2), 459–485.

Hoberg, G. and V. Maksimovic (2022). Product life cycles in corporate finance. *The Review of Financial Studies*.

Jagannathan, M., C. P. Stephens, and M. S. Weisbach (2000). Financial flexibility and the choice between dividends and stock repurchases. *Journal of Financial Economics 57*(3), 355–384.

Klepper, S. (1996). Entry, exit, growth, and innovation over the product life cycle. *The American economic review*, 562–583.

Maksimovic, V. and P. Pichler (2001). Technological innovation and initial public offerings. *The Review of Financial Studies 14*(2), 459–494.

Rink, D. R. and J. E. Swan (1979). Product life cycle research: A literature review. *Journal of Business Research 7*(3), 219–242.

Utterback, J. M. and W. J. Abernathy (1975). A dynamic model of process and product innovation. *Omega 3*(6), 639–656.

Wang, Z., Q. E. Yin, and L. Yu (2021). Real effects of share repurchases legalization on corporate behaviors. *Journal of Financial Economics 140*(1), 197–219.

Competitive Approaches in Mergers and Acquisitions

Tina Oreski*

Abstract

This paper uses mergers and acquisitions (M&A) and textual analysis of firms' financial filings to show that competitive approach constitutes an important determinant of firms' investment decisions. The analysis reveals that becoming an acquirer or a target depends on the competitive approach. Moreover, M&A deals are more likely between companies implementing the same competitive approach. Those deals yield higher combined announcement returns, asset and sales growth. The same approach effect is stronger in a highly competitive environment and within an industry, suggesting that acquirer and target misalignment in competitive approaches constraints the optimal response to investment opportunities and market threats.

Keywords: mergers and acquisitions, strategy, synergies, product life cycle, competition, textual analysis

JEL code: G30, G34, L10, L21

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1 Introduction

Products move through life cycles.[1] Nevertheless, two companies can choose different life cycle curves for a similar product. On the one side of the spectrum are companies aiming to be the first on the market with new products and innovations, while on the other side are companies specializing in cheaper versions when the products are already standardized and their demand well established (Klepper, 1996). Hence, one firm's product life cycle can begin before and have a differently shaped curve than the other firm's product life cycle. I refer to these differences in the companies' product life cycles as competitive approaches or strategies.[2] Competitive approaches have direct implications for firms' resource allocation, cash flows, and investments. Yet, financial economists have largely ignored this relation. This paper eliminates the gap by empirically examining whether firms' competitive approaches affect one of their biggest investment decisions: mergers and acquisitions (M&A).

In M&A, the transaction incidence and the deal performance depend on both the acquirer and the target company. The finance literature has shown the positive impact of the overlap in the product, technology, human capital, and culture dimension (Hoberg and Phillips, 2010; Bena and Li, 2014; Lee et al., 2018; Bereskin et al., 2018; Li et al., 2020). However, none of these studies explores how M&A deals depend on acquirers' and target firms' competitive approaches and their similarity. In the Prahalad and Bettis (1986) model, companies with similar competitive approaches respond to entrant threats and make investment decisions similarly. Managers interpret market conditions and events through the experience gained in the core business of their firms, and they lack the knowledge and experience to manage companies (divisions) organized with a different resource allocation (Prahalad and Bettis, 1986; Harrison et al., 2017); the same market threat or an investment opportunity can differently impact an innovating firm starting the product life cycle early and a firm entering the market when the product is already standardized and their optimal market responses. Therefore, the main hypothesis of the paper is that misalignment between target and bidder competitive approaches constrains the merged company's optimal response to investment

[1]See, e.g., Abernathy and Utterback (1978); Hoberg and Maksimovic (2022); Hajda and Nikolov (2020)
[2]Following Caves (1980); Gimeno and Woo (1996); Utterback and Abernathy (1975), among others.

opportunities and market threats and diminishes potential M&A synergies.

To test the hypothesis, I require an estimate of companies' competitive approaches. The literature categorizes companies into four competitive approaches. Performance-maximizing firms attempt to be the first to introduce innovative products or services; sales-maximizing companies observe the innovations on the market and are prompt to quickly adapt and offer new product variations and features; cost-minimizing companies emphasize efficiency in cost production and enter the market later with simpler and less expensive versions; stuck-in-the-middle companies try to compete on multiple of the previous approaches, but they do not manage to apply any of them consistently (Utterback and Abernathy, 1975; Kim and Lim, 1988).[3]

To illustrate the concept, imagine an automotive industry with three companies, as depicted in Figure 1. Company A introduces an innovative car with parking sensors at time 0. Its innovation is unique on the market until time 2 when Company B offers a car with parking sensors. Company C enters the market at a later stage, at time 5. Its advantage compared to Company A and B lies in a cheaper production of cars with parking sensors. When the sales of the car with parking sensors drop sufficiently at time 6, Company A launches another innovation: a car with parking cameras. Again, it is the only company in the industry with the new product until Company B introduces a car with parking cameras at time 8. Competitive approaches can be understood as the shift in time of the product life cycles- Company A applies the performance-maximizing approach, Company B applies the sales-maximizing approach, and Company C applies the cost-minimizing approach.[4]

[Insert Figure 1 about Here]

Thus, Utterback and Abernathy (1975) model the change in competitive approaches with firms' product life cycles. I build on their model and employ product life cycle as the starting point to measure competitive approach. Following Hoberg and Maksimovic (2022), I exploit

[3]The first three categories closely follow the classification of Utterback and Abernathy (1975). Following Kim and Lim (1988), Porter (1980), and Miles et al. (1978), I define an additional group, stuck-in-the-middle companies.

[4]Stuck-in-the-middle companies would be depicted as applying different approaches across different products.

the textual analysis of 10-K financial statements to calculate the product life cycle. The procedure maps each company to a four-element vector every year that sums up to one: product innovation, process innovation, stability, and product discontinuation. Every product life cycle expresses the proportion of a company's products in a particular stage, which varies significantly across approaches. Therefore, I propose an additional step to measure competitive approach: comparing a firm's product life cycle with its most similar firms and detecting the product life cycle that obtains the highest ranking within the matching industry. The intuition is that the strongest product life cycle emphasizes companies' competitive focus (on average, Company A prioritizes introducing innovative products compared to Companies B and C). This step embeds the proxy's relative aspect: a firm's competitive approach is measured in relation only to its similar firms. As a result, companies are flagged as applying performance-maximizing, sales-maximizing, cost-minimizing, or stuck-in-the-middle competitive approaches.

Companies oriented toward the performance-maximizing approach are the youngest, grow the fastest, and reserve the biggest part of their sales for research and development (R&D), while companies that do not consistently apply any of the first three approaches are the oldest, have the lowest growth rate, and the smallest market-to-book (MB) ratio. The combination of traditional life cycle proxies (asset size, company's age, retained earnings over assets) explains up to 0.05 of the variation in the companies' competitive orientation.[5] This result suggests that competitive approach carries different information not absorbed by the life cycle proxies, which can bolster our understanding of the companies' investment decisions.

With the proxy for companies' competitive approaches in hand, I report three central findings. First, I document that in US public M&A deals between 1995 and 2017, both target and acquirer firms spread through all the competitive groups. Nonetheless, performance-maximizing companies realize the highest probability of becoming both acquirers and targets. The result highlights that companies do not exhaust all their internal investment opportunities before acquiring other companies but continuously weigh all the viable alternatives.

[5] The results are presented in Appendix A.

Additionally, the presence of targets across all the groups demonstrates that all acquirers are not driven by one acquisition motive; they pursue different goals through M&A. Second, the odds of a transaction for companies with the same competitive traits are twice as large as the odds for companies that belong to dissimilar approaches. This acquirer-target pair pattern reveals that firms anticipate the obstacles stemming from a partner with a different competitive posture and opt for a one with the same approach, for which managers possess more knowledge and experience. Third, deals with competitive approach overlap earn, on average, 87 basis points higher combined announcement returns, and the acquirers' assets and sales increase significantly after the acquisition compared with the companies that bought a target with a different approach. The analysis supports that acquirers buying competitively related target firms outperform other acquirers.

Next, I test the driving force behind the results: the competitive approach misalignment induces a company's suboptimal response to investment and business opportunities because the manager lacks experience and knowledge in managing a company with a different resource allocation. Eliminating these potential difficulties and reacting promptly should be particularly relevant in a high-competition environment, as intense competition demands a company's swift response due to the predatory risk (Haushalter et al., 2007; Valta, 2012). The separation of the sample into low and highly competitive, using the TNIC Herfindahl-Hirschman index (HHI) by Hoberg and Phillips (2016) and the product fluidity measure by Hoberg et al. (2014), upholds that companies in highly competitive industries exhibit a higher likelihood of acquiring a company with the same competitive approach. Moreover, competitive differences between a target and a bidder in diversifying acquisitions might not be detrimental since such a merger could involve two different settings where the requirements for success vary (Ramaswamy, 1997). Therefore, I examine whether the negative impact of competitive dissimilarity is more pronounced in the same industry acquisitions. The results provide strong support for the claim. These findings corroborate that managers better understand investment opportunities and threats for companies implementing the same competitive approach, resulting in better deal performance.

I complement the analysis with several robustness tests. I explicitly consider whether the results are driven by the traditional life cycle proxies and variables used in previous studies to predict M&A participation and abnormal returns, including size, age, profitability, market-to-book (MB) ratio, debt, and R&D expenses. Additionally, I verify the combined announcement return results with the market and Fama and French (1993, 1996) three-factor models. I further present the results including product-market similarity (Hoberg and Phillips, 2010), innovation (Bena and Li, 2014), and organizational culture (Li et al., 2020) variables. The main findings withstand those robustness checks. In summary, the main contribution of the paper is to show that competitive approaches affect firm investment decisions.

2 Related literature

This paper speaks primarily to the literature studying similarities and synergies in M&A. Rhodes-Kropf and Robinson (2008) formulate the assortative matching concept in M&A: in economic terms, acquirers and targets are similar (i.e., like buys like). They provide evidence that most transactions involve high market-to-book (MB) valuation firms purchasing other high-valuation firms and low-valuation firms acquiring other low-valuation firms. Hoberg and Phillips (2010) examine whether firms harness product market synergies through asset complementarities in M&A. They demonstrate that firms with similar product market language reach higher transaction likelihood and higher stock returns. Bena and Li (2014) conclude that technological overlap between firm pairs positively relates to the transaction incidence and merger outcomes. Lee et al. (2018) find that merger returns and postmerger performance are higher when firms have related human capital. Bereskin et al. (2018) and Li et al. (2020) show that corporate culture relatedness contributes to both the likelihood and benefits of mergers. Chen et al. (2020b) emphasize that reducing search frictions increases the likelihood of complementary mergers and postmerger synergistic value. I document that synergies arising from similarity in competitive approaches constitute a strong determinant of public M&A decisions.

The paper also adds to the fast-growing research in finance that employs textual analysis for hypothesis testing. Hoberg and Phillips (2016) generate a new set of industries based on text-analysis of firm 10-K product descriptions. Buehlmaier and Whited (2018) construct a measure of financial constraints using textual analysis of firms' annual reports and conclude that excess returns are higher for financially constrained firms. Cohen et al. (2020) underline that changes to the language and construction of 10-Ks and 10-Qs predict future earnings, profitability, and future firm-level bankruptcies. Hoberg and Maksimovic (2022) generate a new proxy for the product life cycle based on the textual analysis of 10-K filings. Based on the same measure, Chen et al. (2020a) provide evidence that firms with more exposure to the mature life cycle stage disclose substantially more details. In contrast, firms in the early stage of the life cycle strongly favor secrecy, consistent with inward-focused organic investment and mitigation of competitive threats. I propose a new measure of competitive approach based on textual analysis of 10-K financial statements.

3 Data

I construct the sample from four data sources: Thomson One SDC for M&A, the Center for Research in Security Prices (CRSP) for price and return data, Compustat for the companies' balance sheet data, and US Securities and Exchange Commission Electronic Data Gathering, Analysis, and Retrieval (SEC EDGAR) database for financial statements.

In Compustat, I exclude all the companies located outside the US, corporations with missing assets, and financial companies and utilities (Standard Industrial Classification codes 4900–4999 and 6000–6999). I map Compustat data to machine-readable 10-K documents, which yields 89,069 firm-year observations from 1994 to 2017. I extract all completed M&A with the date announced between January 1st, 1995 and December 31st, 2017, and I impose the following criteria:

1. The acquirers are US public firms.

2. The targets are US public firms and their subsidiaries.

3. The deal is completed.

4. The acquirer holds less than 50% of the target before the transaction and more than 50% after the transaction.

5. Neither the acquirer nor the target belongs to the financial sector because their balance sheets are very different from other firms or the utility sector since they are heavily regulated.

6. Date effective, percentage of shares owned after the transaction, percentage of shares acquired, and announcement date are non missing.

7. A company did not acquire another firm 120 days before the announcement day to ensure the estimation window of cumulative abnormal returns does not include other acquisitions.

After merging M&A data with company-year observations and excluding companies with missings assets, EBITDA, debt, MB ratio, and competitive approach (both for the acquirers and the targets), the procedure leaves me with 3,104 acquirer-target pairs. Table 1 tabulates the acquisitions during the sample period into public or subsidiary and cash, stock, or mixed deals. The number of acquisitions varies substantially over time, with many in the second half of the 1990s. Subsidiary acquisitions are more common than the acquisitions of entire public companies. Cash-only deals dominate over stock-only deals, with an average of 40% of the total number of transactions.

[Insert Table 1 about Here]

Following the existing literature, the other variables used throughout the paper are constructed as follows. Assets is defined as a natural logarithm of book assets (Compustat item AT). Age is the natural logarithm of a firm's age, measured as the number of years in the Compustat database. Debt represents the ratio of long-term debt to assets (DLTT/AT). R&D are research and development costs (XRD/sale); missing values are set to 0. EBITDA is defined as a firm's profitability (EBITDA/AT). MB stands for market-to-book ratio, calculated as the market value of the firm to total book asset value ((AT-CEQ+PRCC_F*CSHO)/AT), where the market value is proxied as the book value of assets less book value of common equity plus the market value of equity (equal to the stock price at the fiscal year-close times the number of common shares outstanding).

Table 2 presents descriptive statistics for acquirers and targets in the sample. Both types of companies are large US firms, with a mean asset size of over five billion US dollars. Acquirers achieve higher profitability and higher MB ratio than the targets, while targets spend more on R&D.

[Insert Table 2 about Here]

4 The competitive approach measure

To find a competitive approach proxy applicable to a broader range of companies, I follow Utterback and Abernathy (1975). They model that products develop over time in a predictable manner (with initial emphasis on product performance, then the emphasis moves to product variety, and finally to product standardization and costs) and that one can distinguish competitive approaches from companies' products. Ergo, I apply the product life cycle as a starting point to measure firms' competitive approaches.

To measure firm's product life cycle, I build on a recent finance literature approach using textual analysis of firms' financial statements (Hoberg and Maksimovic, 2022; Chen et al., 2020a). Unlike the other proposed measures, this methodology reflects that companies contain multiple products in different life cycle stages. I start by calculating the product life cycle by Hoberg and Maksimovic (2022), which implements textual analysis on 10-K financial statements.[6] The first step of the calculation employs Web crawling and text parsing algorithms to construct a database of machine-readable SEC EDGAR 10-K annual fillings from 1994 to 2017. I search the EDGAR database for filings that appear as "10-K","10-K405","10KSB", "10KSB40", or "10-KT". Then, I implement anchor-phrase methods to extract paragraphs from 10-K filings related to a company's specific life cycle. Appendix B

[6] Public companies must file the annual report on Form 10-K, providing a comprehensive overview of the company's business and financial condition and including audited financial statements. Under the regulation S-K, Item 101, the companies are obliged to describe the business done, the principal products produced and services, and a description of the status of a product or segment.

describes the procedure in detail. I deviate from the exact Hoberg and Maksimovic (2022) procedure in two ways: first, I delete the names of the cities in the US starting with the word "new" (for example, New York, New Orleans), as these cities might interfere with the first product life cycle; second, I retain the paragraphs including phrases "research and development" and "capital expenditure" because those paragraphs can contain valuable life cycle information.[7] I normalize the product life cycle exposure vector with the four individual paragraph counts by dividing each number by the total paragraph counts.

The procedure gives a four-element vector for each company in each year that sums up to one, and the elements express the fraction of the firm's products allotted to each of the four stages by Abernathy and Utterback (1978): (1) product innovation (Life1), (2) process innovation (Life2), (3) stability and maturity (Life3), and (4) product discontinuation (Life4). To measure competitive approach, I calculate for each company-year the percentile ranking of every product life cycle within the industry[8] in a three-year period.[9] The product life cycle with the highest ranking denotes the company's competitive approach.[10] That way, a company's approach is determined with respect to its similar firms and not to the whole population of firms.

As an illustrative example, a company with three consecutive product life cycle vectors of [0.69 0.21 0.03 0.07] in 2006, [0.70 0.27 0.01 0.02] in 2007, and [0.71 0.24 0 0.06] in 2008, averages [0.70 0.24 0.01 0.05] for the three years. Based on the average, the company's corresponding percentiles for 2008 within its industry are [95 28 0 0], and it is assigned to the performance-maximizing group. Similarly, a company fits the cost minimization or sales-maximizing approach if the highest percentile accompanies the second or third product phase, respectively. I sort a firm as a stuck-in-the-middle whenever the firm's dominant product life cycle percentile is the fourth phase, as those companies do not manage to apply any of the first

[7]The correlation coefficients between the Hoberg and Maksimovic (2022) life cycles and the life cycles calculated in this paper range between 0.84 and 0.95

[8]Industry in the main results is defined as a 2-digit NAICS industry. However, the results hold by specifying the industry to be 3-digit NAICS, 2-digit or 3-digit SIC, and identifying the nearest rivals as in Hoberg and Phillips (2016).

[9]I set the product-phase with less than 15% to zero percentile to avoid classifying companies into stages that do not represent a relevant part of the portfolio of products.

[10]In the unreported results, I varied the percentage from 10 to 25, and the results remain similar.

three approaches consistently, and they end up with more obsolete products (Porter, 1980). Thereby, the competitive approach measure indicates the company's highest product life cycle percentile within its industry in a three-year period, and it designates companies into performance-maximizing, cost-minimizing, sales-maximizing, or stuck-in-the-middle groups.

Performance-maximizing approach is seen in the early stages of the product life cycle. These companies emphasize differentiated products and services based on R&D and innovations. They charge higher prices due to enhanced quality and performance. Sales-maximizing companies rely on greater diffusion of their current products or services and stable relationship with the customers and suppliers. They watch others innovate and are prompt to adapt and offer new product variations and features quickly. The emphasis is placed on expanding sales and gaining market share. As the product life cycle evolves, product variety tends to be reduced, and the product becomes standardized. Companies applying the cost-minimizing approach focus on process innovations and efficiency in manufacturing and distribution of products to reach low product prices. Finally, stuck-in-the-middle companies struggle to apply any of the first three approaches consistently and end up with more obsolete products.

Table 3 summarizes the average firms' characteristics in each competitive group. Performance-maximizing companies are the youngest, grow the fastest, maintain the lowest debt ratio, allocate the biggest part of their sales to R&D, and realize the highest average patent value.[11] Consistent with the findings of Kogan et al. (2017) that large firms tend to file more patents, sales-maximizing firms obtain the highest number of patents per year. Cost-minimizing companies hold the highest debt percentage and are slightly older than sales-maximizing firms. Stuck-in-the-middle firms are the oldest, have the lowest growth rate, and have the smallest MB ratio. In addition, product life cycle phases demonstrate that, on average, firms own products in all life phases. Still, performance-maximizing firms produce the highest percentage of innovative products, sales-maximizing companies load predominantly on the third product life cycle stage, while cost-minimizing companies focus on lowering the cost of production. The product life cycle vector for stuck-in-the-middle firms supports the idea that the new proxy identifies firm competitive position relative to the other companies

[11]Patent data come from Kogan et al. (2017) The dollar value of a patent is based on the stock market reaction on the patent issue date

in the same industry. Even though stuck-in-the-middle firms have the highest percentage of obsolete products among all firms, they own more cost-minimizing products in absolute terms.

[Insert Table 3 about Here]

4.1 Dynamics of competitive approaches

Figure 2 depicts the ratio of firm competitive approaches over the years for the entire sample of firms, including acquirers, targets, and firms that did not transact. The proportion of performance-maximizing firms is the lowest at the beginning of the sample and the highest at the end, reaching 34% in 2017. Part of the growth lies in the increasing fraction (9% to 43%) of high-tech companies in the sample.[12] In the same period, cost-minimizing corporations comprise between 26% and 37%, and sales-maximizing firms vary between 25% and 31%. Stuck-in-the-middle public companies are the least represented category, with a peak of 20% after the financial crisis.

[Insert Figure 2 about Here]

Table 4 discloses the other type of dynamics: the mobility between the approaches in a one-year horizon.[13] It outlines that firms primarily remain in the same competitive group. Still, the lack of zero loadings in all the transition matrices confirms that companies may progress from the current to any of the three remaining competitive approaches. One of the leading examples of the competitive approach changes is Apple in 1995. Twenty years after its foundation, Apple's market share stagnated, it incurred financial loss, and was forced to lay off some of its employees. Trying to solve the problems, the company hired Steve Jobs as the CEO, which led to a series of innovations (iMac, Mac OS, iPhone, etc.), and eventually positioned Apple as one of the world's most valuable companies.

[12] I use the official definition of high-tech industries offered by the United States Department of Commerce. High-tech companies are defined as firms with three-digit SIC industry codes: 283, 357, 366, 382, 384, and 737. The classification is also applied in Brown et al. (2009).

[13] The table does not include the delistings because of liquidations and dropped firms (CRSP codes 400-599). During the sample years, 3.6% of the performance-maximizing firms and 5% of the stuck-in-the-middle firms delisted in the following year for those reasons.

[Insert Table 4 about Here]

The changes from the performance-maximizing to the stuck-in-the-middle approaches and vice versa within one year form the smallest fraction of transitions. They mainly occur as a consequence of firm restructuring and selling the least profitable segments. For example, before 1999, the management team of Ultrak company (CIK:318259) emphasized acquisitions to obtain new products, integrated systems, experienced personnel, channels of distribution, and new geographic territories. However, in 2000, Ultrak replaced the management team and referred to the transformation from a distributorship to a technology-based company as challenging, generating losses and resulting in downsizing the workforce. This short description elucidates why, accounting for other industry participants in the same year, Ultrak company is labeled as a performance-maximizing firm in 1999, while it is flagged as a stuck-in-the-middle company from 2000 to 2004.

5 Results

The competitive approach determines the product life cycle curves of firms' products, with the ultimate goal of maximizing firms' values and creating a competitive advantage. Therefore, it has a direct bearing on firms' investment decisions. This section analyzes this hypothesis in several steps. The first two steps test whether the probability of becoming an acquirer or a target is related to companies' approaches, and if so, which companies become acquirers and which become targets? Do all acquirers and targets belong to one approach or are they dispersed across different approaches? The third step investigates the acquirers and the target competitive pairs to understand whether acquirers select targets that match their competitive approaches or all acquirers focus on the targets with one competitive type.

The driving mechanism is that the divergence between the competitive approaches in M&A deals acts as a constraint to a company's optimal response to business and investment opportunities because the acquiring firm's manager lacks knowledge and experience about the target's resource allocation and competitive conditions (Harrison et al., 2017). The results in line with the predictions should pinpoint that acquirers seek out targets with the same competitive approach and that those deals reap higher synergies. Hence, the fourth step turns to the performance of the same and different competitive approach deals. Furthermore, if the acquiring managers lack knowledge and experience to manage a firm with a different competitive approach, I expect the effect to be stronger in a high-competition environment compared to a low-competition environment, as the timely and optimal reactions to business threats and opportunities are more important with intense competition (Haushalter et al., 2007; Valta, 2012). Also, success in different industries depends on different requirements, which lessens the necessary fit in diversifying acquisitions (Ramaswamy, 1997). On this ground, I study the likelihood of acquiring a company with the same competitive approach in low and high-competition environments and in related and diversifying deals.

5.1 Acquirers' competitive approaches

I begin by inspecting the acquirers' competitive traits. Figure 3 illustrates the ratio of acquirers' competitive approaches over the years. Acquirers do not cluster in one competitive group but spread through all the groups. The result implies that companies continuously evaluate external investment opportunities and do not have to exhaust their internal projects before acquiring other companies.

[Insert Figure 3 about Here]

For a direct test, I run a conditional logistic regression, following Bena and Li (2014) for firm i, deal m, and year t:

$$\begin{aligned} AcquirerFirm_{i,m,t} = \alpha + \beta_1 Performance_{i,t-1} + \beta_2 Sales_{i,t-1} + \beta_3 Stuck_{i,t-1} + \\ \delta_1 X_{i,t-1} + \eta_m + \epsilon_{i,m,t}, \end{aligned} \tag{1}$$

where the dependent variable, $AcquirerFirm$, is an indicator variable equal to one if the firm acquires another company in a given year, and zero otherwise. Since a company fits only one of the four approaches, the cost-minimizing group acts as the reference category, and the coefficients should be interpreted in relation to the cost-minimizing group.[14] X is a

[14]Selecting the cost-minimizing group is arbitrary.

set of control variables known to predict probability of becoming a target or an acquirer firm: assets, age, debt, MB ratio, profitability, and R&D. η is the fixed effect for each acquirer (target firm) and its control acquirers (control target firms). All variables are measured at the fiscal year-end immediately prior to the acquisition announcement date. Column 1 includes only the indicator variables for the performance-maximizing ($Performance$), sales-maximizing ($Sales$), and stuck-in-the-middle ($Stuck$) firms, whereas Column 2 also incorporates the control variables.

[Insert Table 5 about Here]

For each deal, there is one observation for the acquirer and multiple observations for the control acquirer group. To form the control group for each acquirer, I find up to five firms within the same industry and in the same year that did not participate in the acquisitions (neither as an acquirer nor as a target firm) in the last three years and that are most similar based on the propensity-matching score. Table 5 Columns 1 and 2 match on firms' assets and Column 3 matches on firms' assets and age.

The first three columns report the coefficient estimates and imply that cost-minimizing companies have the lowest probability of becoming acquirers. After considering other explanatory variables in Columns 2 and 3, performance-maximizing and sales-maximizing companies are associated with the highest probability of becoming acquirers. The odds of becoming an acquirer for the performance-maximizing (sales-maximizing) companies are between 2.61 and 1.77 (1.25 and 1.12) times as large as the odds for the cost-minimizing companies. The likelihood of becoming an acquirer compared with the closest companies by propensity matching score is positively related to lower age, lower debt ratio, higher profitability, and higher R&D. In summary, this section substantiates that acquirers choose different competitive approaches, which hints that they should also aim for different target firms.

5.2 Target firms' competitive approaches

The paper is articulated around the idea that acquirers consider targets' competitive approaches in their M&A decisions. To test this hypothesis, Figure 4 plots the fraction of the target firms in distinct competitive groups over the years. Targets are also located in all the groups.

[Insert Figure 4 about Here]

In the next step, I repeat the conditional logistic regression in Equation 1 for firm i, deal m, and year t:

$$\begin{aligned} TargetFirm_{i,m,t} = \alpha + \beta_1 Performance_{i,t-1} + \beta_2 Sales_{i,t-1} + \beta_3 Stuck_{i,t-1} + \\ \delta_2 X_{i,t-1} + \eta_m + \epsilon_{i,m,t} \end{aligned} \tag{2}$$

where the dependent variable, $TargetFirm$, is a binary variable equal to one if the firm or one of its subsidiaries was acquired by another public company in that year, and zero otherwise. Cost-minimizing companies again serve as the reference category, and all other variables remain specified as in Equation 1. The procedure to determine the control target group follows the steps described for the acquirer groups. Table 5 Columns 4 and 5 match on firms' assets, and Column 6 matches on firms' assets and age.

The last three columns record coefficient estimates from the conditional logit regression. Across specifications, performance-maximizing companies are associated with the highest probability of becoming targets, significant at the 1% level. For the performance-maximizing companies, the odds of becoming a target are between 3.18 and 1.98 times as large as the odds for companies pursuing the cost-minimizing approach. The results support the hypothesis that the target firm's competitive approach shapes the acquiring firm's focus of the search, and it rules out that the bulk of target firms hoards in one group (for example, the performance-maximizing approach). Compared with the closest firms by the propensity score, younger, less profitable, with less debt, and higher R&D companies are positively related to the probability of becoming targets.

5.3 Competitive pairs

After demonstrating that both acquirers' and targets' competitive approaches matter in M&A deals, the next step analyzes the acquirer-target pairs. Table 6 partitions the deals on the acquirer and target competitive groups. It establishes that acquirers and targets cover all the groups, but one pattern stands out in the table: companies mainly acquire firms with the same approach; the percentage varies from 30% for stuck-in-the-middle firms to 48% for performance-maximizing firms. Table 7 presents deal examples for each acquirer-target competitive pair.[15]

[Insert Table 6 about Here]

[Insert Table 7 about Here]

As the number of companies in different approaches does not have to be equal, I investigate this pattern in a more formal setting. Table 8 shows coefficient estimates from the conditional logit regression for firms i and j, deal m, and year t:

$$RealPair_{i,j,m,t} = \alpha + \beta SameApproach_{i,j,t-1} + \delta_1 X_{i,t-1} + \delta_2 X_{j,t-1} + \eta_m + \epsilon_{i,j,m,t}, \quad (3)$$

where the dependent variable, $RealPair$, is a dummy variable equal to one if a given company pair is a true acquirer-target pair in a given year and zero otherwise. For each deal, there is one observation for the acquirer (target firm) and up to five observations for the control acquirers (target firms). I select the control sample based on the propensity-matching score within the same industry and the same year, as in Table 5. The coefficient of interest is related to *SameApproach*, a dummy variable equal to one if a company pair overlaps in the approach and zero otherwise. Table 8 Column 1 and 2 match on firm size, while Column 3 matches additionally on firm age. Column 1 includes only the variable *SameApproach* and Columns 2 and 3 saturate the model with control variables.

[15] The sample of target companies includes both public companies and their subsidiaries. Subsidiary companies are already organized according to the resource allocation of the parent company, which, in the same approach deals, is similar to the acquirers' resource allocation.

[Insert Table 8 about Here]

In all the columns, *SameApproach* exhibits a positive and significant coefficient at the 1% level, indicating the same competitive approach leads to merger pairing. For the companies that pursue the same approach, the odds of a transaction are more than two times as large as the odds for companies that belong to different groups. The other control variables show predictable signs. Table 8 lends strong support for the competitive approach synergies.

Collectively, I present a large body of evidence and tests that the target firm's competitive approach forms an important factor in M&A decisions. But what are the benefits of acquiring a company with the same competitive approach?

5.4 Ex-post outcomes

I examine the benefits of the same approach deals through financial and real ex-post outcomes. Table 9 tests the financial outcomes by estimating combined acquirer and target announcement return for acquirer i, target j, acquirer's industry z, year t:

$$\begin{aligned} CombinedReturn_{i,j,z,t} = \alpha + \beta SameApproach_{i,j,t-1} + \gamma DealCharateristics_{i,j} \\ + \delta_1 X_{i,t-1} + \delta_2 X_{j,t-1} + \mu_z + \theta_t, \end{aligned} \tag{4}$$

where Deal Characteristics include: a subsidiary target indicator, *Subsidiary*, as the long-standing literature attests different CAR based on the status of the target; dummies for stock-only and cash-only deals, *CashDeal* and *StockDeal*, to control for acquisitions of targets paid only with stocks or cash; relative deal size, *RelativeSize*, since target size affects the acquirer's returns; industry relatedness of the acquisition, $DiffInd$, to capture that diversifying acquisitions have been found to destroy value (Morck et al., 1990; Andrade et al., 2001; Travlos, 1987; Fuller et al., 2002).

[Insert Table 9 about Here]

I implement the Carhart (1997) four-factor model to calculate the 3-day cumulative abnormal return (CAR) for both acquirers and targets during the window encompassed by event dates [-1,1], where event day 0 is the acquisition announcement date. The estimation window covers 120-day period, from event day -130 to event day -11, as suggested in Campbell et al. (1997). Combined returns are weighted by their market capitalization of both participants ten days before the announcement day. The combined return and continuous control variables are winsorized at the 1st and 99th percentiles to alleviate the impact of outliers. I have downloaded the daily factor data from Kenneth R. French's website.

The average acquirers' and targets' CAR for the overall sample are 0.87% and 10.57%, respectively. The mean bidder CAR for public targets amounts to -0.42%, while for the targets equals 25.53%. The average bidder CAR for subsidiaries is 1.72%, while targets experience an increase of 1.48%. The combined return averages 1.24% for the entire sample, 2.29% for public, and 0.63% for subsidiary target firms. The estimates are consistent with prior work (Maksimovic et al. (2011), Alexandridis et al. (2017), Filipovic and Wagner (2019)).

Table 9 Column 1 includes only the variable of interest *SameApproach*, while Column 2 also builds in the deal characteristics and acquirer i and target j control variables. All the columns add industry and year fixed effects to account for the unobserved industry and time-specific shocks. The coefficient of *SameApproach* in both columns is positive and statistically significant at the 1% level, suggesting that deals where the acquirer and the target belong to the same competitive group yield, on average, 87 basis points higher combined announcement returns than the pairs with different stages. Control variables exhibit predictable signs. Thus, the combined return analysis authenticates the competitive approach synergies.

Next, I track whether the financial value creation of acquiring a company with the same competitive approach is accompanied by real post-acquisition gains, particularly asset and sales growth. The challenge is that asset and sales growth may be endogenously related to merger and acquisition decisions. To address these concerns, I exploit a quasi-experiment, following Seru (2014) and Bena and Li (2014), where I compare the firms that withdrew their acquisitions of companies in the same (different) competitive approach with the firms that acquired a target company with the same (different) competitive approach. In the withdrawn sample, both the acquirer and the target are publicly listed US firms, and neither the acquirer nor the target belongs to the financial sector or utilities. After merging both acquirers and targets of the withdrawn acquisitions with the competitive approach data, the procedure results in 801 withdrawn acquisitions. The withdrawn acquisitions occur during the same year as the matched effective acquisitions, and the acquirers of the two acquisitions have the same age.[16] An additional condition for the treatment group is that the companies did not buy another public company or a subsidiary of a public company three years before the focal acquisition attempt. This restriction shrinks the sample of effective acquisitions from 3104 to 2088 deals. After merging with the control sample, the final sample consists of 749 acquisition pairs, 557 pairs with the same approach, and 192 pairs with a different approach. I adopt the three-year period around the announcement to inspect the parallel trend assumption of the difference-in-differences analysis (DiD). This step helps mitigate concerns that differences between the treated and the control group are not constant before the acquisition.

Figure 5 verifies the parallel trend assumption for assets, and Appendix C focuses on the parallel trend in sales. Panel A in Figure 5 plots the average asset size for the treatment and control subsample for the deals with the same approach, while Panel B plots the deals where the acquirer and the target have different approaches. The time spans from three years before the announcement to three years after the announcement. Prior to the deal announcement, the evolution of the two groups in both subsamples is largely parallel. The gray area on the graphs marks the year of acquisition. The surge in the assets of the effective acquisitions in that year is mostly mechanical (A+B>A); however, the analysis concentrates on the period after the acquisition. After the acquisition, the two lines separate in Panel A, and they remain parallel in Panel B. Companies that acquired a firm with the same approach experience a stronger asset growth than their control sample. In contrast, companies that acquired a target with a different competitive approach do not materialize such growth. The same conclusion also applies to sales in Appendix C. I conclude that the two samples satisfy

[16] I perform the analysis also with various combinations of industry, year, age, and asset size, and all the results are quantitatively similar.

the parallel trend assumption necessary for the DiD analysis.

[Insert Figure 5 about Here]

In the DiD analysis, I first estimate the following regression using a panel data set from three years prior to bid announcement to three years after the deal announcement separately for the subsample of deals that overlap in the competitive approach and on the subsample of deals without the overlap:

$$Assets_{i,j,t} = \alpha + \beta_1 After_{i,j,t} + \beta_2 After_{i,j,t} * Effective_{i,j} + \eta_{i,j} + \theta_t, \tag{5}$$

where the dependent variable, $Assets_{i,j,t}$, is the acquirer's assets of the deal i, j at time t. The dependent variable in Appendix D is $Sales_{i,j,t}$, the acquirer's sales of the deal i, j. The indicator variable *After* equals one for the postmerger time period and zero otherwise. The indicator variable *Effective* equals one for the treatment deals and zero for the withdrawn deals. The dummy variable *After**Effective* is the interaction term between *After* and *Effective*. I introduce deal and year fixed effects to difference away any time-invariant differences among deals and a common trend affecting deals in both the treatment and control samples.

Table 10 Columns 1 and 2 display coefficient estimates from the OLS regression in Equation 5 using a subsample of deals with and without competitive overlap. The coefficient on the interaction term *After**Effective* is positive and significant at the 1% level for deals with the competitive overlap, while negative and significant at the 5% level for deals without the competitive overlap. Completing a deal between firms with the same competitive approach generates asset growth, while buying a target with a different approach results in lower assets.

[Insert Table 10 about Here]

Next, I investigate the heterogeneity in the treatment effect of a merger on postmerger assets, estimating the following equation on the entire sample:

$$\begin{aligned} Assets_{i,j,t} = \alpha + \beta_1 After_{i,j,t} + \beta_2 After_{i,j,t} * Effective_{i,j} \\ + \beta_3 SameApproach_{i,j,t-1} * After_{i,j,t} \\ + \beta_4 SameApproach_{i,j,t-1} * After_{i,j,t} * Effective_{i,j} + \eta_{i,j} + \theta_t + \epsilon_{i,j,t}, \end{aligned} \tag{6}$$

where the dependent variable $Assets_{i,j,t}$, deal and year fixed effects, the indicator variables $After$, $Effective$, and $After * Effective$ are as specified in Equation 5. The dummy variable *SameApproach* equals one for the deals in which the acquirer and the target have the same competitive approach and zero otherwise. The coefficient of interest is β_4 for the interaction term between *SameApproach*, *After*, and *Effective*, which detects the effect on asset size of acquiring a target with the same competitive approach.

Table 10 Column 3 presents coefficient estimates from the OLS regression in Equation 6. The coefficient on the interaction term *SameApproach*After* is negative and significant at the 5% level. But this decline is reversed for the companies that acquire targets with the same approach; the coefficient on the triple interaction term *SameApproach*After*Effective* is positive and significant at the 1% level. The interaction term is also positive and significant at the 1% level in Appendix D Column 3.[17] The findings establish that the competitive synergies deliver real post-acquisition gains, supporting the paper's predictions.

I assess the robustness of the DiD analysis by conducting a placebo test, where I falsely assume that the companies acquired another company three years before the actual deal materialized. Table 10 Column 4 displays the estimates. The coefficient on the interaction term *SameApproach*After*Effective* is statistically indistinguishable from zero, certifying that the captured asset growth emanates from acquiring the company with the same competitive approach. The findings are the same for sales in Appendix D. The results in this section highlight that companies consider the target firm's competitive approach as an important factor in M&A deals because of the financial and real benefits emerging from the

[17] Eliminating the acquisition pairs without all 7 years (3 years before the announcement, the announcement year, and 3 years after the acquisition) shrinks the sample to 7302 observations, with 5273 observations with the same approach and 2029 observations with a different approach. The results also hold in this smaller sample. The interaction term is positive and significant at the 5% level.

competitive similarity.

5.5 The underlying mechanism

The hypothesis postulates that companies opt for a target with the same competitive approach because this selection leads to more informed decision-making during important business decisions, such as big investment opportunities or new entrant threats. This section examines the proposed mechanism in two different ways.

First, as taking the available investment and business opportunities is paramount with intense competition, selecting a target firm with the same approach should be more pronounced in highly competitive environments. Namely, if I repeat the analysis from Equation 3 and separate between companies with low competition and companies with high competition, I expect to observe a stronger impact for companies facing more competitive threats.

To separate the sample into low and high competition environments, I use two measures based on processing the text of 10-K annual filings, which acknowledge that each company is surrounded by a unique set of nearby competitors that changes over the years: Hoberg and Phillips (2016) TNIC HHI measure and Hoberg et al. (2014) product fluidity variable. The TNIC HHI measure is the sales-weighted HHI of firms in a firm's industry. The product fluidity variable is a measure of a firm's competitive threats in its product market that captures changes in rival firms' products relative to the firm. I follow Bharath and Hertzel (2019) and define $HighCompetition$ ($HighFluidity$) firms as those with the TNIC HHI (product fluidity) below (above) the sample median.

Table 11 Columns 1 and 2 present the conditional logistic regression results in Equation 3 separately for the subsample of low TNIC HHI industries and the subsample of high TNIC HHI industries. Columns 3 and 4 display the coefficient estimates on the subsamples of the product-fluidity measure. Columns 1 and 3 do not include the control variables, while Columns 2 and 4 also incorporate control variables, as specified in Table 8. The coefficients on $SameApproach$ are all positive and statistically significant at the 1% level, indicating that companies, in general, prefer targets with the same approach. However, positive and highly statistically significant interaction terms $SameApproach * HighCompetition$ and $SameApproach * HighFluidity$ show that the effect is more pronounced with vigorous competition. This result validates the prediction that managers' knowledge and experience are especially vital in intense competition.

[Insert Table 11 about Here]

Second, competitive differences between a target and a bidder in different industries might not be detrimental, as the requirements for success vary between industries (Ramaswamy, 1997). Therefore, I test whether the negative impact of competitive dissimilarity is stronger in the same industry mergers compared to diversifying acquisitions. Table 11 Columns 5 and 6 present the conditional logistic regression results in Equation 3 using the interaction term between the $SameApproach$ and $SameIndustry$ variables. $SameIndustry$ is an indicator variable equal to one if two companies operate in the same industry, as in Chen et al. (2020b). Column 5 does not include any control variables, while Column 6 implements the full set of control variables. The coefficient on $SameApproach * SameIndustry$ is positive and statistically significant at the 1% level in both the columns, implying that the competitive similarity is more important in the same industry deals, consistent with the predictions. The result substantiates that competitive dissimilarity acts as a constraint to the merged company's market response.

6 Additional evidence

To complete the analysis, this section explores three specific factors that influence M&A decisions: product market, innovation, and culture synergies. Using textual analysis of 10-K product descriptions, Hoberg and Phillips (2010) reveal that firms capitalize on product-market synergies through asset complementarities. They disclose that transactions are more likely between firms that use similar product market language. Also, transaction incidence is higher for firms more broadly similar to all firms in the economy (asset complementarity effect) because those firms have more opportunities for pairings that can generate synergies.

It is lower for firms that are more similar to their local rivals (competitive effect), as firms with very near rivals must compete for restructuring opportunities given that a potential partner can view its rivals as substitute partners. Conceptually, product similarity captures a different effect compared to competitive approach. While product similarity is high for two companies producing the same products (for example, cars), those two companies can be very different in competitive approach (a performance-maximizing and a cost-minimizing producer).

Table 12 Column 1 reestimates the conditional logit regression in Equation 2, where I add the similarity score between the acquirer and the target as a control variable. The coefficient estimates uphold that after including the similarity in the product language, the variable *SameApproach* is still positive and highly statistically significant. I also substantiate that product similarity alters the pairing decisions. Table 12 Column 2 further incorporates broad similarity and product similarity for targets as independent variables. Broad similarity is defined as the average similarity between firm i and all other firms in the sample. Product similarity is the average pairwise similarity between firm i and its ten most similar rivals. The closest rivals are the ten firms with the highest local similarity to i. These measures use the broad and local dictionary, described in Hoberg and Phillips (2010). The two measures do not subsume the effect of the same competitive approach variable. Firms with high local product market competition are less likely to be targets of restructuring transactions, given the existence of multiple substitute target firms. The coefficient on broad similarity for targets turns insignificant after including the control variables and the similarity score between the acquirer and the target. These results conform with the premise of Gimeno and Woo (1996), that companies can be competitively similar with little market overlap but also competitively different with substantial market overlap.

[Insert Table 12 about Here]

The second factor influencing M&A is the technological overlap. Bena and Li (2014) proclaim that its presence between two firms' innovation activities, as captured by the proximity of patent portfolios, shared knowledge bases, and mutual citations of patent portfolios, has a significant effect on the probability of a merger pair formation. They conclude that synergies obtained from combining innovation capabilities are important drivers of acquisitions. From the theoretical perspective, technological proximity should not eliminate the competitive similarity effect for two reasons. First, companies can apply similar competitive approaches even with marginally related technologies (for example, a car and a computer producer). Second, to apply their approaches, many companies do not rely on patents. Table 12 Column 3 mimics the conditional logit regression in Equation 2 with the technological proximity as the explanatory variable. Technological proximity measures the closeness of any two firms' innovation activities in the technology space using patent counts in different technology classes. Competitive approach and technological synergies disclose positive and highly statistically significant coefficients. Column 4 displays that the competitive approach significance persists after including both product market and technology variables.

Finally, the section explores whether the main findings are sensitive to the inclusion of the corporate culture variable. I rely on the data from Li et al. (2020), who propose a new proxy for the corporate culture using a semisupervised machine learning technique on earnings calls. They conclude that firms closer in cultural values are more likely to do a deal together. A priori, cultural and competitive similarities indicate different effects. For example, achieving the performance-maximizing approach goals can result from innovations developed by a few very talented people within a company with a strong organizational hierarchy or by teamwork and questioning colleagues' ideas. Thus, I expect that corporate culture does not fully explain the competitive approach variable. I follow the authors and define culture distance between two firms as the square root of the sum of squared differences between a firm pair across all five cultural values: innovation, integrity, quality, respect, and teamwork. Table 12 Column 5 presents the conditional logit regression analogous to Equation 2 with the cultural distance as the explanatory variable. The sample size is smaller than the first four columns because the culture variables data begin in 2001. The *SameApproach* coefficient is positive and statistically significant at the 1% level, in line with the predictions. The coefficient on corporate culture distance is negative and statistically significant at the 1% level, confirming the results of Li et al. (2020). Taken as a whole, this paper uncovers that competitive similarity represents a strong factor affecting M&A deals.

7 Conclusion

This paper provides evidence of the relation between competitive approaches and firms' investment decisions. It shows that firms consider their own and their target firm's competitive approach in M&A deals. Buying a target company with the same approach yields synergies, visible through financial and real ex-post benefits. The effect is magnified in a highly competitive environment and within the same industry, confirming that managers better understand the business of the same approach companies.

The paper also makes a methodological contribution. I propose a relative proxy to estimate competitive approach, relying on the life cycle theory and the textual analysis of corporate 10-K financial statements. The novelty is that the phases are not determined by the one-size-fits-all methodology; a company's portfolio of products is compared only with the portfolio of other firms within the same industry. That way, each industry can have companies applying different approaches.

Overall, the paper presents the first cut in understanding the importance of the firm competitive approach in investment decisions. One limitation of this study lies in the sample; it is restricted by the 10-K financial statements, available only for public companies. Future work could propose a method based on the company's products for both private and public firms. Finally, the analysis could also be extended to other related questions, like serial acquirers' approaches and their targets.

References

William J Abernathy and James M Utterback. Patterns of industrial innovation. *Technology Review*, 80(7):40–47, 1978.

George Alexandridis, Nikolaos Antypas, and Nickolaos Travlos. Value creation from m&as: New evidence. *Journal of Corporate Finance*, 45:632–650, 2017.

Gregor Andrade, Mark Mitchell, and Erik Stafford. New evidence and perspectives on mergers. *Journal of Economic Perspectives*, 15(2):103–120, 2001.

Jan Bena and Kai Li. Corporate innovations and mergers and acquisitions. *The Journal of Finance*, 69(5):1923–1960, 2014.

Frederick L Bereskin, Seong K Byun, Micah S Officer, and Jong-Min Oh. The effect of cultural similarity on mergers and acquisitions: Evidence from corporate social responsibility. *Journal of Financial and Quantitative Analysis (JFQA)*, 53(5):1995–2039, 2018.

Sreedhar T Bharath and Michael Hertzel. External governance and debt structure. *The Review of Financial Studies*, 32(9):3335–3365, 2019.

James R Brown, Steven M Fazzari, and Bruce C Petersen. Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom. *The Journal of Finance*, 64(1):151–185, 2009.

Matthias MM Buehlmaier and Toni M Whited. Are financial constraints priced? evidence from textual analysis. *The Review of Financial Studies*, 31(7):2693–2728, 2018.

John Y Campbell, John J Champbell, John W Campbell, Andrew W Lo, Andrew W Lo, and A Craig MacKinlay. *The Econometrics of Financial Markets*. Princeton University Press, 1997.

Mark M Carhart. On persistence in mutual fund performance. *The Journal of Finance*, 52 (1):57–82, 1997.

Richard E Caves. Industrial organization, corporate strategy and structure. In *Readings in Accounting for Management Control*, pages 335–370. Springer, 1980.

AJ Chen, Gerard Hoberg, and Vojislav Maksimovic. Life cycles of firm disclosures. *Unpublished working paper*, 2020a.

Jiakai Chen, Joon Ho Kim, and S Ghon Rhee. Do low search costs facilitate like-buys-like mergers? evidence from common bank networks. *Journal of Financial Economics*, 2020b.

Lauren Cohen, Christopher Malloy, and Quoc Nguyen. Lazy prices. *The Journal of Finance*, 75(3):1371–1415, 2020.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Eugene F Fama and Kenneth R French. Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1):55–84, 1996.

Zoran Filipovic and Alexander F. Wagner. The intangibles song in takeover announcements: Good tempo, hollow tune. *Unpublished working paper*, 2019.

Kathleen Fuller, Jeffry Netter, and Mike Stegemoller. What do returns to acquiring firms tell us? evidence from firms that make many acquisitions. *The Journal of Finance*, 57(4): 1763–1793, 2002.

Javier Gimeno and Carolyn Y Woo. Hypercompetition in a multimarket environment: The role of strategic similarity and multimarket contact in competitive de-escalation. *Organization Science*, 7(3):322–341, 1996.

Jakub Hajda and Boris Nikolov. Product market strategy and corporate policies. *Unpublished working paper*, 2020.

Jeffrey S Harrison, Ernest H Hall Jr, and Rajendra Nargundkar. Resource allocation as an outcropping of strategic consistency: Performance implications. *Academy of Management Journal*, 2017.

David Haushalter, Sandy Klasa, and William F Maxwell. The influence of product market dynamics on a firm's cash holdings and hedging behavior. *Journal of Financial Economics*, 84(3):797–825, 2007.

Gerard Hoberg and Vojislav Maksimovic. Product life cycles in corporate finance. *The Review of Financial Studies*, 2022. doi: 10.1093/rfs/hhab134.

Gerard Hoberg and Gordon Phillips. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10):3773–3811, 2010.

Gerard Hoberg and Gordon Phillips. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465, 2016.

Gerard Hoberg, Gordon Phillips, and Nagpurnanand Prabhala. Product market threats, payouts, and financial flexibility. *The Journal of Finance*, 69(1):293–324, 2014.

Linsu Kim and Yooncheol Lim. Environment, generic strategies, and performance in a rapidly developing country: A taxonomic approach. *Academy of Management Journal*, 31 (4):802–827, 1988.

Steven Klepper. Entry, exit, growth, and innovation over the product life cycle. *The American economic review*, pages 562–583, 1996.

Leonid Kogan, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2): 665–712, 2017.

Kyeong Hun Lee, David C Mauer, and Emma Qianying Xu. Human capital relatedness and mergers and acquisitions. *Journal of Financial Economics*, 129(1):111–135, 2018.

Kai Li, Feng Mai, Rui Shen, and Xinyan Yan. Measuring Corporate Culture Using Machine Learning. *The Review of Financial Studies*, 07 2020. ISSN 0893-9454. doi: 10.1093/rfs/hhaa079.

Vojislav Maksimovic, Gordon Phillips, and Nagpurnanand R Prabhala. Post-merger restructuring and the boundaries of the firm. *Journal of Financial Economics*, 102(2):317–343, 2011.

Raymond E Miles, Charles C Snow, Alan D Meyer, and Henry J Coleman Jr. Organizational strategy, structure, and process. *Academy of Management Review*, 3(3):546–562, 1978.

Randall Morck, Andrei Shleifer, and Robert W Vishny. Do managerial objectives drive bad acquisitions? *The Journal of Finance*, 45(1):31–48, 1990.

Michael Porter. Competitive strategy: techniques for analyzing industries and competitors. *Editorial Free Pr, ISBN*, 13:9780029253601, 1980.

Coimbatore K Prahalad and Richard A Bettis. The dominant logic: A new linkage between diversity and performance. *Strategic Management Journal*, 7(6):485–501, 1986.

Kannan Ramaswamy. The performance impact of strategic similarity in horizontal mergers: Evidence from the us banking industry. *Academy of Management Journal*, 40(3):697–715, 1997.

Matthew Rhodes-Kropf and David T Robinson. The market for mergers and the boundaries of the firm. *The Journal of Finance*, 63(3):1169–1211, 2008.

Amit Seru. Firm boundaries matter: Evidence from conglomerates and r&d activity. *Journal of Financial Economics*, 111(2):381–405, 2014.

Nickolaos G Travlos. Corporate takeover bids, methods of payment, and bidding firms' stock returns. *The Journal of Finance*, 42(4):943–963, 1987.

James M Utterback and William J Abernathy. A dynamic model of process and product innovation. *Omega*, 3(6):639–656, 1975.

Philip Valta. Competition and the cost of debt. *Journal of Financial Economics*, 105(3): 661–682, 2012.

Figure 1: Relation of product life cycle and competitive approach

The figure presents product life cycle of three car companies: Company A, B, and C. The three companies gradually introduce two product innovations: parking sensors and parking cameras. Competitive approaches can be interpreted as the shift in the product life cycle between the companies.

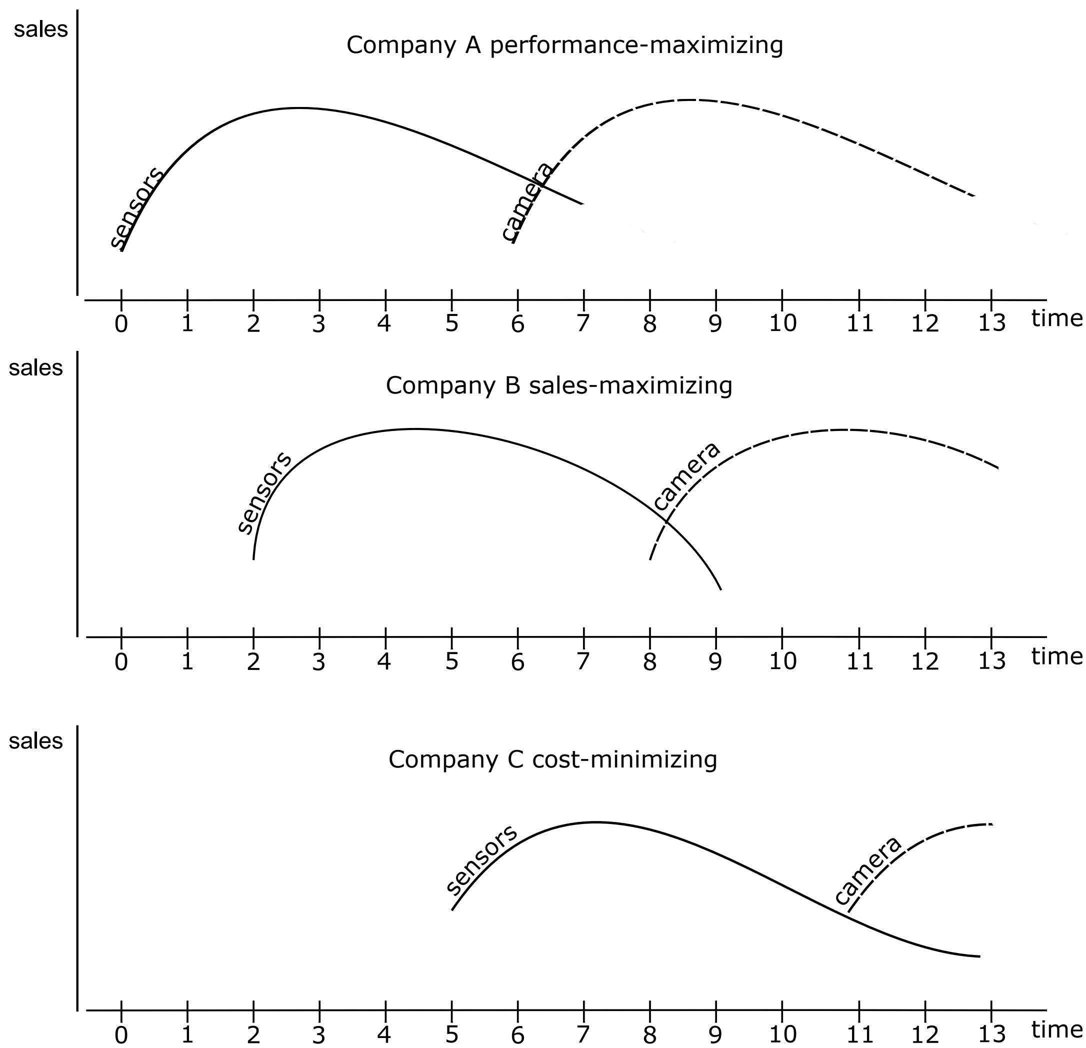


Figure 2: Firm competitive approaches over years
The figure shows the fractions of US firms' competitive approaches between 1994 and 2017. The solid line represents firms applying the performance-maximizing approach, the dashed line shows firms applying the cost-minimizing approach, and the dash-dot and dotted lines stand for the sales-maximizing and stuck-in-the-middle companies, respectively. The sample consists of US public firms with 89,049 firm-year observations. The detailed explanation of the sample is given in Section 3, and the calculation of firm loadings on different approaches is described in Section 4 and Appendix B.

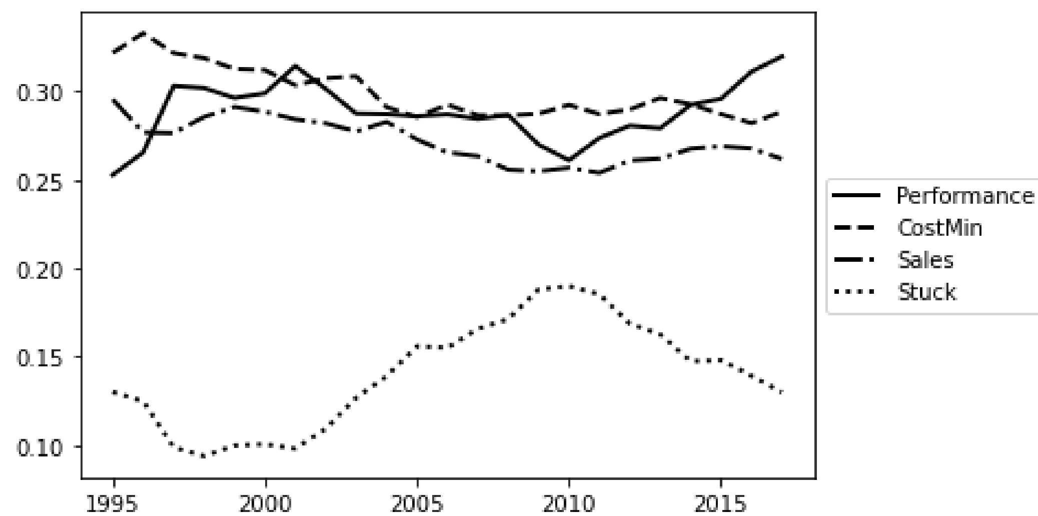


Figure 3: Acquirer competitive approaches over years

The figure shows the fractions of US acquirers' competitive approaches between 1995 and 2017. The solid line represents firms applying the performance-maximizing approach, the dashed line shows firms applying the cost-minimizing approach, and the dash-dot and dotted lines stand for the sales-maximizing and stuck-in-the-middle companies, respectively. The sample consists of 3,104 deals. The detailed explanation of the sample is given in Section 3, and the calculation of firm loadings on different approaches is described in Section 4 and Appendix B.

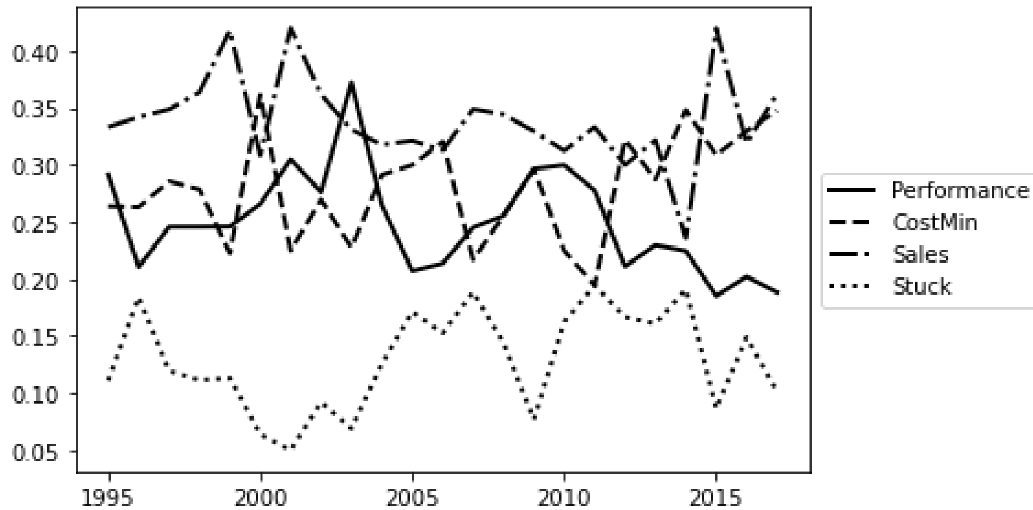


Figure 4: Target firms' competitive approaches over years

The figure shows the fractions of US target firms' competitive approaches between 1995 and 2017. The solid line represents firms applying the performance-maximizing approach, the dashed line shows firms applying the cost-minimizing approach, and the dash-dot and dotted lines stand for the sales-maximizing and stuck-in-the-middle companies, respectively. The sample consists of 3,104 deals. The detailed explanation of the sample is given in Section 3, and the calculation of firm loadings on different approaches is described in Section 4 and Appendix B.

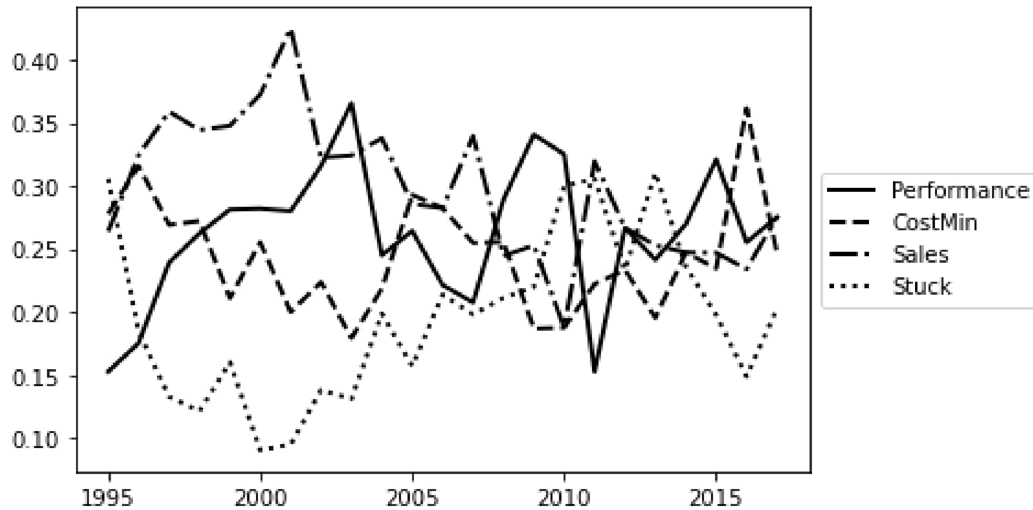


Figure 5: Asset size of acquirers and companies that withdrew their bid
The figure plots the average asset size of the acquirers and companies that announced a deal but withdrew their bid. I use panel data running from three years before the bid announcement to three years after the announcement. Panel A consists of the deals in which the acquirer and the target apply the same competitive approach, while Panel B displays the deals with the acquirer and the target with different approaches. The gray area on the graph marks the announcement year.

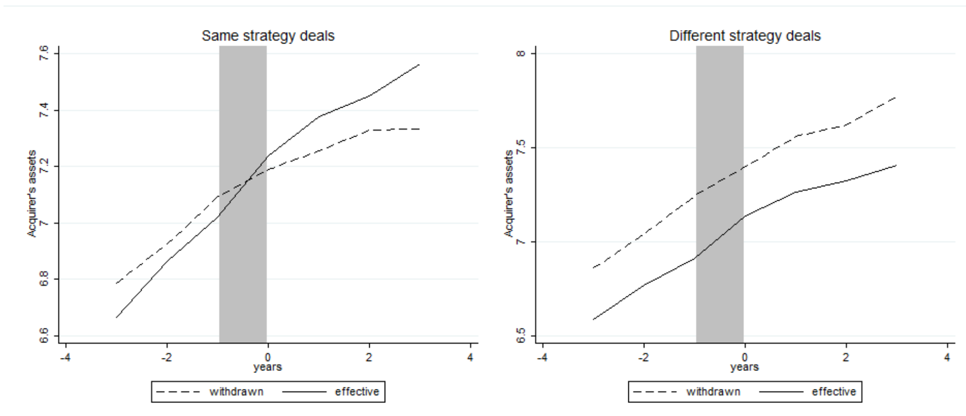


Table 1: Public corporate acquisitions over time, 1995-2017
The table reports the distribution of M&A sample of US public acquirers and targets together with their subsidiaries, announced and completed during the period 1995-2017. It shows the total number of M&A in the sample during a year, the ratio of public and subsidiary targets, the fraction of deals payed only with cash, only with stock, and other type of payment deals. The total number of M&A deals in the sample is 3,104. Sample criteria are described in detail in Section 3.

Year	Number	Public	Subsidiary	CashDeal	StockDeal	MixDeal
1995	72	0.24	0.76	0.17	0.14	0.69
1996	114	0.29	0.71	0.32	0.15	0.54
1997	301	0.40	0.60	0.34	0.18	0.49
1998	305	0.40	0.60	0.30	0.21	0.48
1999	256	0.48	0.52	0.30	0.21	0.48
2000	188	0.41	0.59	0.33	0.16	0.51
2001	200	0.42	0.57	0.32	0.16	0.52
2002	152	0.27	0.73	0.40	0.11	0.49
2003	145	0.39	0.61	0.36	0.10	0.54
2004	151	0.36	0.64	0.42	0.10	0.48
2005	140	0.42	0.58	0.48	0.08	0.44
2006	131	0.34	0.66	0.53	0.06	0.40
2007	106	0.42	0.58	0.62	0.01	0.37
2008	90	0.40	0.60	0.52	0.03	0.44
2009	91	0.40	0.60	0.46	0.05	0.48
2010	80	0.45	0.55	0.57	0.06	0.36
2011	72	0.29	0.71	0.44	0.03	0.53
2012	90	0.33	0.67	0.52	0.04	0.43
2013	87	0.36	0.64	0.51	0.06	0.44
2014	89	0.37	0.63	0.34	0.10	0.56
2015	81	0.54	0.46	0.43	0.05	0.52
2016	94	0.47	0.53	0.57	0.05	0.37
2017	69	0.43	0.57	0.42	0.09	0.49
Total	3104	0.39	0.61	0.40	0.12	0.48

Table 2: Summary statistics

The table reports summary statistics for the acquirers and the target firms. The sample consists of 3,104 US public deals, announced and completed during the period 1995-2017. Sample criteria are described in detail in Section 3. Definitions of the variables are provided in Section 3.

Variable	Mean	Std	25%	50%	75%
Acquirers					
Assets	6.98	2.00	5.60	6.99	8.42
Age	11.97	6.01	8.00	10.00	16.00
Debt	0.20	0.20	0.03	0.17	0.31
R&D	0.12	0.86	0.00	0.01	0.08
EBITDA	0.12	0.15	0.09	0.14	0.19
MB	2.30	2.30	1.32	1.73	2.51
Targets					
Assets	6.73	2.27	4.98	6.65	8.53
Age	11.36	5.79	7.00	10.00	15.00
Debt	0.20	0.21	0.02	0.17	0.31
R&D	0.20	1.23	0.00	0.02	0.10
EBITDA	0.07	0.23	0.05	0.11	0.17
MB	2.01	1.92	1.18	1.54	2.21

Table 3: Average firm characteristics by competitive group
The table reports average age, asset growth, market-to-book ratio, the ratio of research and development over sales, long term debt over assets, number of patents (#Pat), the ratio of patent value over assets ($Pat), and the average of the four product life-cycle phases (Life1-Life4). The sample consists of 89,069 firm-year observations between 1995 and 2017. Number of patents and value of patents are from Kogan et al (2017). The detailed explanation of the firm competitive approach and product life-cycle measures is given in Section 4. Definitions of the variables are provided in Section 3.

Competitive approach	Age	Growth	MB	R&D	Debt	$Pat	#Pat	Life1	Life2	Life3	Life4
Performance-max	9.70	1.25	3.21	0.93	0.15	0.06	6.60	0.42	0.32	0.22	0.04
CostMin	11.04	1.17	2.29	0.18	0.25	0.01	4.19	0.17	0.58	0.21	0.04
Sales-max	10.65	1.22	2.45	0.14	0.22	0.01	8.47	0.22	0.34	0.39	0.04
Stuck	13.37	1.13	2.00	0.15	0.23	0.01	6.55	0.16	0.36	0.20	0.27

Table 4: Transition matrix of competitive approach in one year horizon.
The table reports the transition matrix of firm competitive approaches for US public firms during the period 1994-2017. The detailed explanation of competitive approach is given in Section 4.

	Approach in the following year			
Approach	Performance-max	CostMin	Sales-max	Stuck
Performance-max	83%	6%	8%	3%
CostMin	5%	84%	6%	4%
Sales-max	7%	8%	81%	4%
Stuck	4%	8%	6%	81%

Table 5: Likelihood of becoming a target or an acquirer
The table reports the coefficient estimates of the conditional logistic regression, where the dependent variable is a dummy variable equal to 1, if a firm becomes an acquirer (target) in a given year and zero otherwise. Cost-minimizing group serves as the reference category in all the columns. The independent variables are measured at the fiscal year-end immediately prior to acquisition announcement date. Definitions of the variables are provided in Section 3. The detailed explanation for the control sample is given in Section 5.3. Control sample in Columns 1, 2, 4, and 5 is based on firm size. Control sample in Columns 3 and 6 is based on firm size and age. Standard errors clustered at the deal level are reported in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Acquirer	(2) Acquirer	(3) Acquirer	(4) Target	(5) Target	(6) Target
Perform-max	0.961***	0.570***	0.676***	1.158***	0.681***	0.963***
	(0.059)	(0.076)	(0.060)	(0.061)	(0.074)	(0.064)
Sales-max	0.222***	0.117**	0.172***	0.262***	0.278***	0.256***
	(0.052)	(0.055)	(0.053)	(0.054)	(0.059)	(0.056)
Stuck	-0.147**	-0.136*	-0.151**	0.334***	0.349***	0.296***
	(0.071)	(0.071)	(0.071)	(0.067)	(0.068)	(0.067)
Age		-0.103***			-0.061***	
		(0.006)			(0.005)	
MB		0.108***	-0.009***		0.093***	-0.045***
		(0.014)	(0.002)		(0.022)	(0.013)
EBITDA		1.220***	1.433***		-3.529***	-0.178***
		(0.171)	(0.196)		(0.380)	(0.062)
Debt		-0.664***	-0.794***		-0.346**	-0.663***
		(0.155)	(0.156)		(0.169)	(0.171)
R&D		1.820***	0.211***		2.948***	0.159***
		(0.577)	(0.052)		(0.405)	(0.048)
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.03	0.09	0.04	0.04	0.12	0.04
Observations	18620	18620	18620	18621	18621	18621

Table 6: Acquirer-target competitive approach pairs
The table shows the number of acquirer-target matched competitive approach pairs. The calculation of competitive approach is provided in Section 4. The explanation of the sample is given in Section 3.

	Targets' approach				
Acquirers' approach	Performance-max	CostMin	Sales-max	Stuck	Total
Performance-max	374	110	205	98	787
CostMin	141	348	212	161	862
Sales-max	238	203	474	162	1,077
Stuck	69	100	94	115	378
Total	822	761	985	536	3,104

Table 7: Example deals of mergers and acquisitions in each acquirer-target competitive group
The detailed explanation of the competitive approach measure is given in Section 4.

Acquiror approach	Target approach	Acquirer name	Target name	Year announced	Transaction value
Performance-max	Performance-max	Tesla motors	Solarcity	2016	$2.6bil
Performance-max	CostMin	Boston Scientific	Celsion	2007	$60mil
Performance-max	Sales-max	Ebay	Paypal	2002	$1.4bil
Performance-max	Stuck	Pfizer	Encysive Pharm	2008	$186mil
CostMin	Performance-max	Johnson&Johnson	Innotech	1997	$135mil
CostMin	CostMin	Delta Airlines	Northwest Airlines	2008	$2.9bil
CostMin	Sales-max	Alaska Air	Virgin America	2016	$4.2bil
CostMin	Stuck	New York Times	About.Com	2005	$410mil
Sales-max	Performance-max	Coca-Cola	Monster Beverage	2014	$2.1bil
Sales-max	CostMin	3M Co	Cogent Systems	2010	$932mil
Sales-max	Sales-max	Amazon	Whole foods	2017	$13.6bil
Sales-max	Stuck	AT&T	Dobson Commun	2007	$5.4bil
Stuck	Performance-max	3M Co	Robinson Nugent	2000	$123mil
Stuck	CostMin	Chiquita	Stokely	1997	$43mil
Stuck	Sales-max	Pepsi	Quaker Oats	2000	$14.4bil
Stuck	Stuck	Occidental Petroleum	Vintage Petroleum	2005	$3.6bil

Table 8: Acquirer-target firm pairing
The table shows the coefficient estimates from conditional logit model, where the dependent variable is a dummy variable equal to one if a given company pair is the true acquirer-target pair in a given year and zero otherwise. For each deal, there is one observation for the acquirer (target firm), and up to five observations of the control acquirers (target firms). The control sample is based on the propensity-matching score within the same industry and the same year. The first two columns match additionally on assets, while the last column matched additionally on assets and age. The calculation of competitive approach is given in Section 4. Definitions of the variables are provided in Section 3. Standard errors clustered at the deal level are given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) RealPair	(2) RealPair	(3) RealPair
SameApproach	0.739***	0.705***	0.738***
	(0.043)	(0.043)	(0.042)
Age_acq		-0.080***	
		(0.005)	
MB_acq		0.108***	-0.003**
		(0.011)	(0.002)
EBITDA_acq		1.064***	0.959***
		(0.149)	(0.129)
Debt_acq		-0.752***	-0.760***
		(0.124)	(0.105)
R&D_acq		1.617**	0.160***
		(0.632)	(0.031)
Age_tar		-0.052***	
		(0.004)	
MB_tar		0.117***	-0.020***
		(0.021)	(0.003)
EBITDA_tar		-2.298***	-0.079***
		(0.376)	(0.024)
Debt_tar		-0.480***	-0.701***
		(0.123)	(0.112)
R&D_tar		2.763***	0.145***
		(0.404)	(0.028)
Pseudo R^2	0.02	0.08	0.03
Observations	34137	34137	34137

Table 9: Combined announcement returns

This table reports OLS regression results for the combined announcement returns, CAR (-1,1), measured using Carhart four-factor model returns. Combined returns are weighted by the market capitalization of acquirers and targets ten days before the announcement day. The detailed explanation of the competitive approach measure is given in Section 4. Definitions of the control variables are provided in Section 5.4. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) CombinedReturn	(2) CombinedReturn
SameApproach	0.725**	0.869***
	(0.271)	(0.286)
RelativeSize		0.726*
		(0.418)
CashDeal		1.745***
		(0.463)
StockDeal		-2.515***
		(0.654)
DiffInd		-0.994**
		(0.395)
Subsidiary		-2.360***
		(0.426)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Control variables	No	Yes
R^2	0.02	0.09
Observations	3104	2493

Table 10: Long-term assets of acquirers

The table presents the coefficient estimates of difference-in-differences regression, where the dependent variable is the logarithm of acquirer's asset size. Column 1 presents the coefficient estimates on a subsample of same competitive approach deals, Column 2 shows the coefficient estimates on a subsample of different competitive approach deals, Column 3 includes all deals, while Column 4 is the placebo test, where it is falsely assumed that the acquirers acquired a company three years before the actual acquisition on the entire sample of deals. The dependent variable is the acquirer's assets of the deal m. The indicator variable *After* equals one for the postmerger time period, and zero otherwise. The indicator variable *Effective* equals one for the treatment deals and zero for the withdrawn deals. The indicator variable *SameApproach* equals one for the deal where the acquirer and target overlap in the competitive approach, and zero otherwise. The interactions terms between different variables are marked with $\times$. The selection of withdrawn acquisitions is described in Section 5.4. All columns include deal and year fixed effects. Robust standard errors are reported in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Assets	(2) Assets	(3) Assets	(4) FalsificationTest
After	0.323*	-0.320	0.394**	-0.008
	(0.182)	(0.315)	(0.175)	(0.204)
After $\times$ Effective	0.128***	-0.207**	-0.213**	-0.242**
	(0.049)	(0.085)	(0.085)	(0.095)
SameApproach $\times$ After			-0.208**	-0.010
			(0.082)	(0.094)
SameApproach $\times$ After $\times$ Effective			0.340***	0.153
			(0.098)	(0.108)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	6.713***	6.728***	6.717***	6.836***
	(0.040)	(0.075)	(0.035)	(0.042)
R^2	0.65	0.62	0.64	0.60
Observations	7119	2526	9645	7718

Table 11: Economic mechanism testing

The table presents the coefficient estimates from conditional logit model, where the independent variable is an indicator variable equal to one if a given company pair is the true acquirer-target pair in a given year, and zero otherwise. For each deal, there is one observation for the acquirer (target firm) and up to five observations of the control acquirers (target firms). The control sample is based on the propensity matching score within the same industry and the same year. Columns 1 and 2 show the coefficient estimates of the HHI variable, Columns 3 and 4 show the coefficient estimates of the product fluidity variable, and Columns 5 and 6 estimate the difference between same industry acquisitions and different industry acquisitions. Standard errors clustered at the deal level are given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) RealPair TNIC-HHI	(2) RealPair TNIC-HHI	(3) RealPair Fluidity	(4) RealPair Fluidity	(5) RealPair Industry	(6) RealPair Industry
SameApproach	0.581^{***}	0.589^{***}	0.475^{***}	0.497^{***}	0.294^{***}	0.368^{***}
	(0.061)	(0.071)	(0.060)	(0.068)	(0.079)	(0.096)
HighCompetition	0.040	0.168^{***}				
	(0.044)	(0.064)				
SameApproach × HighCompetition	0.232^{***}	0.179^{*}				
	(0.084)	(0.096)				
HighFluidity			-0.076^{*}	-0.058		
			(0.045)	(0.064)		
SameApproach × HighFluidity			0.441^{***}	0.364^{***}		
			(0.084)	(0.096)		
SameApproach × SameIndustry					0.574^{***}	0.438^{***}
					(0.094)	(0.110)
Control variables	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.02	0.30	0.02	0.30	0.02	0.30
Observations	29233	29233	29233	29233	29233	29233

Table 12: Firm pairs with synergy variables
The table presents the coefficient estimates from conditional logit model, where the dependent variable in an indicator variable equal to one if a given company pair is the true acquirer-target pair in a given year and zero otherwise. For each deal, there is one observations for the acquirer (target firm) and up to five observations of the control acquirers (target firms). The control sample is based on the propensity matching score within the same industry and the same year. $TwoCompScore$ is the similarity score between the companies. $BroadSimilarity_{acq}$ and $BroadSimilarity_{tar}$ are the broad similarity of acquirers and targets. $ProductSimilarity_{acq}$ and $ProductSimilarity_{tar}$ are the product similarities of acquirers and targets. $TechProx$ is the technological proximity of the given firm pair. $CulturalDis$ is the cultural distance between the firm-pair. Definitions of the control variables are provided in Section 5.4. Standard errors clustered at the deal level are given in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) RealPair	(2) RealPair	(3) RealPair	(4) RealPair	(5) RealPair
SameApproach	0.643***	0.668***	0.649***	0.619***	0.638***
	(0.047)	(0.048)	(0.044)	(0.048)	(0.083)
TwoCompScore	0.153***	0.198***		0.194***	
	(0.005)	(0.006)		(0.006)	
BroadSimilarity_acq		0.078*		0.092**	
		(0.043)		(0.044)	
ProductSimilarity_acq		0.005		0.005	
		(0.006)		(0.006)	
BroadSimilarity_tar		-0.069		-0.060	
		(0.058)		(0.060)	
ProductSimilarity_tar		-0.097***		-0.098***	
		(0.007)		(0.007)	
TechProx			2.917***	2.335***	
			(0.156)	(0.156)	
CulturalDis					-0.133***
					(0.021)
Control variables	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.34	0.37	0.26	0.39	0.38
Observations	34137	34137	34137	34137	9661

A Appendix

Relation between competitive approach and life-cycle

The table shows the coefficient estimates from logit model, where the dependent variable $Perf$ in the first four columns is a dummy variable equal to one if a company belongs to the performance-maximizing group in a given year. The dependent variable in Columns 5 to 8 is $CostMin$, a dummy variable equal to one if a company belongs to the cost-minimizing group in a given year, and zero otherwise. Columns 9 to 12 focus on $Sales$, a dummy variable equal to one if a company belongs to the sales-maximizing group in a given year, and zero otherwise. The dependent variable in the last four columns is $Stuck$, a dummy variable equal to one if a company belongs to the stuck-in-the-middle group in a given year, and zero otherwise. The calculation of competitive approach is given in Section 4. Definitions of the variables are provided in Section 3. Standard errors clustered at the deal level are given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Perf	(2) Perf	(3) Perf	(4) Perf	(5) CostMin	(6) CostMin	(7) CostMin	(8) CostMin	(9) Sales	(10) Sales	(11) Sales	(12) Sales	(13) Stuck	(14) Stuck	(15) Stuck	(16) Stuck
Age	0.000			-0.015***	0.038***			0.050***	0.022***			0.028***	0.086***			0.106***
	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)			(0.002)
Assets	-0.000***			-0.000***	0.000***			0.000***	0.000***			0.000***	0.000***			0.000***
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)
ReAt	0.000			0.000	0.000***			0.000***	0.000***			0.000*	0.000			0.000
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)
Constant	-1.323***	-1.231***	-1.458***	-2.718***	-1.746***	-1.361***	-1.247***	-2.771***	-1.721***	-1.482***	-1.366***	-2.725***	-3.247***	-2.291***	-2.396***	-3.882***
	(0.013)	(0.037)	(0.109)	(0.136)	(0.014)	(0.038)	(0.102)	(0.132)	(0.014)	(0.040)	(0.106)	(0.135)	(0.021)	(0.054)	(0.154)	(0.178)
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
PseudoR^2	0.002	0.02	0.008	0.028	0.011	0.015	0.005	0.031	0.008	0.016	0.002	0.024	0.049	0.099	0.005	0.062

B Appendix

Following Hoberg and Maksimovic (2022), I measure the firm loadings on life-cycle stages based on all paragraphs in 10-K that contain at least one word from each of the following two lists.

Life1 List A: product OR products OR service OR services
Life1 List B: development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand

Life2 List A: cost OR costs OR expense OR expenses
Life2 List B: labor OR employee OR employees OR wage OR wages OR salary OR salaries OR inventories OR inventory OR warehouse OR warehouses OR warehousing OR transportation OR shipping OR freight OR materials OR overhead OR administrative OR manufacturing OR manufacture OR production OR equipment OR facilities OR

Life4 List A: product OR products OR service OR services OR inventory OR inventories OR operation OR operations
Life4 List B: obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing

To measure the loading on Life3, I require three word lists, instead of two used in the other LC. A firm's 10-K must contain at least one word from List A and List B, and must not contain any words from the List C.

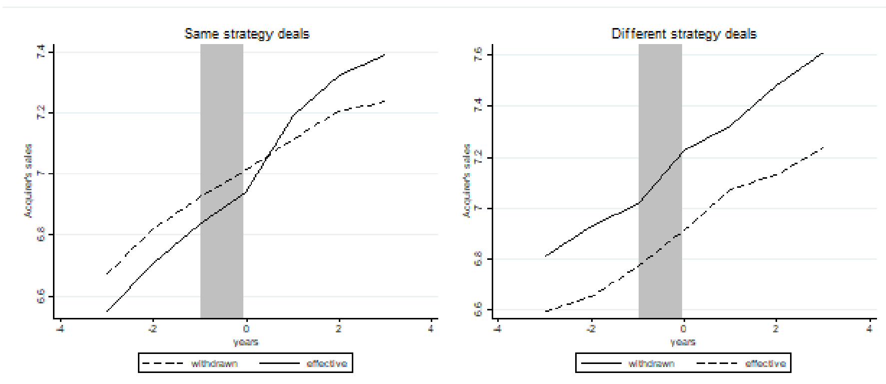
Life3 List A: product OR products OR service OR services

Life3 List B: line OR lines OR offerings OR mix OR existing OR portfolio OR current OR categories OR category OR continue OR group OR groups OR customer OR customers OR core OR consists OR continues OR provide OR providing OR provided OR providers OR includes OR continued OR consist

Life3 List C(exclusions): development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand OR future OR obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing OR cost OR costs OR expense OR expenses

C Appendix

Sales of acquirers and companies that withdrew their bid in the same competitive approach deals and different approach deals
The figure plots the average sale size of the acquirers and companies that announced a deal but withdrew their bid. Panel data runs from three years before the bid announcement to three years after the announcement. Panel A consists of the deal in which the acquirer and the target apply the same competitive approach, while Panel B displays the deals with non-overlapping approaches. The gray area on the graph marks the announcement year.



D Appendix

Long-term sales of acquirers

The table presents the coefficient estimates of difference-in-differences regression, where the dependent variable is the logarithm of acquirer's sales of the deal m. Column 1 presents the coefficient estimates on a subsample of same competitive approach deals, Column 2 on a subsample of different competitive approach deals, Column 3 includes all deals, while Column 4 is the placebo test, where it is falsely assumed that the acquirers acquired a company three years before the actual acquisition on the entire sample of deals. The indicator variable *After* equals one for the postmerger time period, and zero otherwise. The indicator variable *Effective* equals one for the treatment deals and zero for the withdrawn deals. The indicator variable *SameApproach* equals one for the deal where the firms overlap in the competitive approach, and zero otherwise. The interactions terms between different variables are marked with $\times$. All columns include deal and year fixed effects. Robust standard errors are reported in the parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Sales	(2) Sales	(3) Sales	(4) FalsificationTest
After	0.148	0.601**	0.366**	-0.124
	(0.205)	(0.266)	(0.187)	(0.221)
After × Effective	0.052	-0.250***	-0.248***	-0.141
	(0.049)	(0.083)	(0.083)	(0.101)
SameApproach × After			-0.172**	0.113
			(0.081)	(0.095)
SameApproach × After × Effective			0.301***	-0.082
			(0.096)	(0.114)
Constant	6.601***	6.694***	6.625***	6.729***
	(0.042)	(0.074)	(0.036)	(0.042)
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.666	0.604	0.650	0.625
Observations	7,066	2,516	9,582	7,677

Product Life Cycle and Initial Public Offerings *

Tina Oreski† Jiajie Xu ‡

Abstract

This paper examines how firms' product life cycle (PLC) influences the trade-off between the benefits and costs of going public. We construct the PLC measure by performing a textual analysis on S-1 registration statements for IPOs. Firms with a more product-innovative life cycle are more likely to complete the IPO despite higher underpricing and a lower fraction of equity offered at IPO. These firms conduct more seasoned equity offerings, payout fewer dividends, and conduct fewer acquisitions after IPO. The findings suggest that firms with diverging PLC differently weigh the importance of raising capital through IPO, information asymmetry with investors, and revealing information to competitors. To establish causality, we use an instrumental variable and a difference-in-differences approach. Our paper offers evidence on how PLC affects firms' going public trade-off.

Keywords: IPO, Product life cycle, Textual analysis, Competition, Information asymmetry

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1 Introduction

Going public is one of the most important corporate finance decisions (Zingales, 1995). A few benefits drive firms to conduct initial public offerings (IPOs), such as raising relatively cheaper capital from the public market compared to the private market (Hertzel & Smith, 1993), increasing visibility and grabbing market shares (Chemmanur, He, & Nandy, 2010). But these benefits come with non-negligible costs, such as losing confidentiality and increasing financial transparency (Bhattacharya & Ritter, 1983), reducing exploratory innovation (Ferreira, Manso, & Silva, 2014), and losing control (Brau & Fawcett, 2006). Given that product life cycle is one of the fundamental variables shaping firms' market opportunities, competitive challenges, and strategy responses (Abernathy & Utterback, 1978; Hajda & Nikolov, 2021; Hofer, 1975), the trade-off between the benefits and costs of going public naturally hinges on the life cycle (Chemmanur & Fulghieri, 1999). Despite its relevance, there is scarce empirical research on how life cycles shape the IPO decision and activity, mainly due to the challenge of measuring firms' life cycle.

This paper constructs a text-based measure of product life cycle at IPO by conducting a textual analysis on S-1 filings. We empirically study how product life cycle affects the trade-off between IPO benefits and costs. We argue that companies focusing on product innovations and early in the life cycle need the capital from the IPO for new investment projects, but at the same time, they encounter higher information asymmetry towards investors and they are more secretive about their proprietary product innovation (Ljungqvist, 2007; Ritter & Welch, 2002). On the other hand, companies with products with a stable market position (that have few internal projects) follow through the IPO to obtain funds to acquire other companies, they do not bear the cost of revealing information to rivals, and their information asymmetry towards investors is lower since their products and processes are well known (Celikyurt, Sevilir, & Shivdasani, 2010; Chen, Hoberg, & Maksimovic, 2020;

Hoberg & Maksimovic, 2022). Consequently, we test whether firms with different product life cycle weigh the benefits and costs of going public differently.

Specifically, we construct the product life cycle measure for IPO firms following Hoberg and Maksimovic (2022), where they conduct the textual analysis on public firms' 10-K filings. We apply the methodology on the S-1 filing, which is commonly known as the "Prospectus" and is a filing form for companies to complete the registration of securities with the Securities and Exchange Commission (SEC). The intuition of the proposed product life cycle measure is that many companies own various products, which do not necessarily belong to the same life cycle stage. That is why each company is modeled as a four-element vector of product life cycles, following Abernathy and Utterback (1978). The first element of the vector represents the proportion of products in the innovation stage, where the company emphasizes the development and introduction of a new product. The second element stands for the proportion of products in the process innovation stage, where the company focuses on improving the production process and lowering its costs. The third element incorporates all the products in the mature stage, where the attention turns to stability in products, suppliers, and customers. Finally, the last element of the vector indicates a company's exposure to the product discontinuation phase. Over time, each component might vary in response to shocks or product market competition, which is a novelty compared to the traditional life cycle variables, such as firm age.

Implementing the product life cycle measure on a sample of 3,297 IPO filings between 1994 and 2018, we first document several facts. First, on average, private companies filing the IPO registration possess products in all four product life cycle stages, not just in the earlier stages. Second, compared to the public firms, companies filing the registration statements load more on product innovation and products with stable markets, while public companies focus on process efficiency and own more obsolete products. Third, we compare the product life cycles for firms filing for an IPO in different sectors and show that they diverge significantly. For example, drugs and bio-tech companies focus on product innovations, while restaurants concentrate on process efficiency. Fourth, firms that follow through an IPO have slightly more products in the earliest product life cycle stage, while firms that withdraw an IPO have slightly more products in the mature stage.

Then, we explore how product life cycles relate to corporate finance decisions and performance during and after the IPO. We find that firms with a higher fraction of products in the stage of product innovation (i.e., a younger product life cycle) are more likely to complete their IPO process, but at the same time, experience higher underpricing and offer a lower fraction of equity to outside investors at IPO. Moreover, among firms that successfully conduct their IPO, firms with more products in the younger product life cycle are more likely to conduct seasoned equity offerings, less likely to pay out dividends, and less likely to acquire other firms after the IPO. These results suggest that companies with different product life cycles weigh the benefits and costs of IPO differently. Firms with more products in the product innovation stage need the capital for their internal investment projects, but they pay higher costs to overcome information asymmetry towards investors and perceive disclosing information to their competitors as more threatening than other firms (Brown & Martinsson, 2019). After the IPO, they require the capital to develop their products further, and that is why they pay fewer dividends, conduct more SEOs, and are not focused on acquisitions. On the contrary, firms with a more mature product market often perform IPO to acquire other companies.

After examining corporate finance behaviors during and after the IPO and establishing the relationship between firms' product life cycles and the trade-off between IPO benefits and costs, we undertake several tests to address concerns about our main findings. First, some may argue that a younger product life cycle (i.e., having more products in the product-innovation stage) represents another way of measuring corporate innovation and that our results are fully driven by the correlation between patenting activity and the IPO process

(Farre-Mensa, Hegde, & Ljungqvist, 2020). We test this argument by including additional variables, the total number of patents and the number of citations per patent of a firm before its IPO filing and their interaction with the youngest product life cycle, into our baseline regressions. Our results still hold even after controlling for these patent measures, implying that the product life cycles capture different economic forces than patents despite their overlaps.

The second concern is that the above relationship we documented may not be causal. Unobservable factors that both correlate with product life cycles and corporate finance decisions during and after IPO may drive our findings. To alleviate the concern, we perform an instrumental variable (IV) analysis with the average product life cycle of similar public firms in the same year as the instrument for the endogenous variable, an IPO firm's product life cycle. we follow Hoberg and Phillips (2010) and identify the similar public companies of an IPO firm by performing a textual analysis and calculating the similarity scores between 10-K filings of public companies and S-1 filings of the IPO firms. We show that the IV is highly correlated with the product life cycle of an IPO firm, suggesting that the IV satisfies the relevance condition. Also, we argue that the IV is likely to affect the outcome variables only through the endogenous variable. The results of the instrumental variable analysis indicate that product life cycle indeed affects how firms weigh the benefits and costs of going public.

Finally, to confirm the causality between product life cycles and IPO-related corporate decisions, we exploit the American Inventors Protection Act (AIPA). The AIPA provides an exogenous shock to the trade-off between benefits and costs of going public. Before the AIPA, U.S. patent applications were kept secret until the patent was granted, and firms could avoid revealing information about their intellectual property through patent applications. After the introduction of the AIPA, companies were obliged to disclose their patent applications 18 months after the filing date, irrespective of the patent granting decision. The passage of the AIPA significantly accelerated the revelation of patent information. We are able to employ this policy shock and conduct a difference-in-differences (DiD) analysis because the AIPA lowered the costs of revealing information to competitors and sending signals to investors during the IPO process for firms with more products in the early life cycle: These firms have already disclosed their information to competitors and future investors in patent applications published before the IPO registration, hence, the actual cost of overcoming information asymmetry and information revelation declines during IPO. The results of the DiD analysis confirm that the IPO-related decisions depend on how firms with different product life cycles perceive the benefits and costs of going public. Therefore, the paper's main contribution is to show that product life cycle is an important force in determining firms' trade-off between IPO benefits and costs.

We organize the rest of the paper as follows. Section 2 discusses how this paper contributes to the related literature. Section 3 describes the data source, sample selection, and the construction of our measures. Section 4 presents the baseline results. In Section 5, we conduct additional tests to provide evidence for the causal relationship and address additional concerns. We conclude our paper in Section 6.

2 Related literature

Our paper contributes to several strands of literature. First, our paper contributes to the broad literature on the going public decision. Previous theoretical studies show that IPO firms face a trade-off between benefits such as raising cheap capital from the public market (Hertzel & Smith, 1993), optimize the ownership of the insider of the company (Zingales, 1995), and costs including releasing confidential information to competitors (Bhattacharya & Ritter, 1983; Maksimovic & Pichler, 2001; Spiegel & Tookes, 2008). Our paper provides empirical evidence that product life cycle is an important underlying channel that influences the going public decision and firms' financing activity around IPO.[1] It also suggests that firms with different product life cycles are exposed to the cost of overcoming information asymmetry through IPO underpricing differently, and that firms with more products in the innovative life cycle experience more underpricing.[2] Our paper builds on this strand of literature and suggests that firms with more products in the innovative life cycle experience more underpricing. In addition, our paper is also related to the literature on IPO long-run performances and corporate finance decisions.[3] We show that the product life cycle at IPO has impact on firms' post-IPO activity such as seasoned equity offering, acquisitions, and dividend payments.

Second, our findings contribute to the literature on the importance of a company's life cycle in financial decision-making. DeAngelo, DeAngelo, and Stulz (2006) argue that firms early in the life cycle have ample investment opportunities and they retain all the funds because of their limited earned equity, while mature companies with fewer attractive investment opportunities and more internal capital pay out dividends. DeAngelo, DeAngelo, and Stulz (2010) conclude that life cycle and firm's market-timing opportunities affect the decision of seasoned equity offering. Arikan and Stulz (2016) demonstrate that acquisition

[1]There are other papers empirically examine the decision of going public (but not related to product life cycle). Pagano, Panetta, and Zingales (1998) use data in Italy and find that firms go public to rebalance their accounts after high investment and growth. Chemmanur et al. (2010) use the Longitudinal Research Database and find that a private firm's product market characteristics such as total factor productivity, sales growth, and market share significantly affect its likelihood of going public, which confirms the predictions from Bayar and Chemmanur (2011). Chemmanur and He (2011) provide theoretical and empirical analysis of the role of product market competition plays in the going public decision. Dambra, Field, and Gustafson (2015) studies the disclosure cost in the context of the JOBS and Lowry and Shu (2002) shows litigation risk is an important concern for IPO firms.

[2]Previous theoretical studies have provided several types of explanations: asymmetric information, litigation, control theories, and behavioral theories (Ljungqvist, 2007). The strand of literature related to asymmetric information assumes one of the parties has information advantages and argues that IPO underpricing could be due to agency conflict between the issuer and underwriters (Baron, 1982), the signaling of high-quality issuers (Allen, Faulhaber, et al., 1989; Welch, 1989), compensation for information production or revelation of outside investors (Benveniste & Spindt, 1989; Chemmanur, 1993), or reward for the participation in IPO of uninformed investors (Rock, 1986). Ritter and Welch (2002) and Ljungqvist (2007) provide literature reviews of empirical studies on IPO underpricing.

[3]The signaling models built by Welch (1989) and Allen et al. (1989) predict that firms with higher underpricing payout more dividend yields and they do more SEOs. Jegadeesh, Weinstein, and Welch (1993) empirically show that the likelihood of issuing seasoned equity is positively correlated with IPO underpricing.

decisions follow a U-shape pattern over firms' life cycle: the acquisition rate falls sharply after the IPO, stays relatively constant for a number of years, and then increases.[4] In this paper, we show that product life cycle also influences how firms trade-off the costs and benefits of going public, which is one of the most crucial firm decisions.

Third, our paper speaks to the growing literature that implements textual analysis of companies' documents to explain firm investment policies. Using 10-K product descriptions, Hoberg and Maksimovic (2022) show that conditioning on the product life cycle substantially improves the explanatory power of investment-Q models, while Chen et al. (2020) present evidence that the firm's and its rivals' disclosures are shaped by their exposure to their product life cycle. Analyzing initial public offering prospectuses, Hanley and Hoberg (2010) decompose information into standard and informative components and present evidence that greater informative content, as a proxy for premarket due diligence, results in more accurate offer prices and less underpricing. Hanley and Hoberg (2012) suggest that issuers trade-off underpricing and strategic disclosure as potential hedges against litigation risk. We analyze S-1 fillings and establish that companies differ in their product life cycle when conducting their IPO.

To our knowledge, our paper is the first in the literature to study how product life cycle affects firms' trade-off between IPO benefits and costs.

3 Data

[4]Previous studies have used age (Arikan & Stulz, 2016), dividends (Grullon, Michaely, & Swaminathan, 2002), retained earnings over assets (DeAngelo et al., 2006) and size (Klein & Marquardt, 2006) to measure firm life cycles. However, these measures suffer from criticisms that firms do not progress deterministically down the life cycle (Miller & Friesen, 1984) (e.g., old firms could still maintain a young product life cycle by researching and developing new products and services). In addition, the life cycle of a firm may change due to external forces such as regulations or technology breakthroughs.

3.1 Sample Selection

The data of this study are compiled from various sources. We gather machine-readable S-1 filings from Security and Exchange Commission (SEC) Edgar database. S-1 is the initial registration form for companies to register new securities under the Securities Act of 1933. In this form, companies offering securities are required, under the regulation S-K item 101, to disclose a description of the company's properties and business, key products and services, material product research and development to be performed during the period covered in the plan, etc. To construct product life cycle measures, we use S-1 filings, following the same procedure as described in Section 3.2.1 to identify, extract, and parse firm product and business descriptions. From SDC Platinum, we obtain other IPO information and only include IPOs offered in U.S. exchanges. We match S-1 with requests for a withdrawal of a previously filed IPO (RW forms) for the analysis of withdrawn IPOs. We use SDC Platinum also for domestic acquisition data from January 1, 1994 to November 30, 2020, where the acquirers are U.S. public firms. To measure the IPO issuer's innovation capacity, we obtain patent data from the United States Patent and Trademark Office (USPTO). We collect the data on firms' seasonal equity offerings (SEO) and dividend payout after their IPO from Compustat. To test the potential underlying channels, we download the summary file of analyst earnings forecast from the Institutional Brokers Estimate System (I/B/E/S) and the size of the total assets of public firms from Compustat.

Following existing literature studying IPOs (Hanley & Hoberg, 2010; Loughran & Ritter, 2004; Ritter, 1991), we exclude firms in the financial or energy industries (with SIC code 6000-6900 or 4900-4999) and exclude real estate investment trusts (REITs), spin-offs, unit offerings, American depositary receipts (ADRs), and IPOs with an offering price lower than \$5. Our sample period spans from 1994 to 2018 (the sample starts when the S-1 filings are available electronically). Our main sample contains 3,297 unique firms filing for IPOs, with

665 withdrawn IPOs.

3.2 Variable Construction

3.2.1 Measuring Product Life Cycle

The finance literature has predominantly used the firm's age as a proxy for the life cycle. Loderer, Stulz, and Waelchli (2017) argue that firms become optimally more rigid as they age to focus on managing assets in place efficiently rather than on finding new growth opportunities. Arikan and Stulz (2016) show that acquisition activity follows a U-shaped pattern with respect to age. However, companies of the same age can diverge significantly in their life cycle; some companies can be innovative and prosperous, while other companies with the same age can already face innovative and financial difficulties. Hence, these low dimensional constructs target one firm attribute (age) that evolves over the life cycle, but they neglect other important features that define an individual life-phase.

Therefore, we adopt a recently developed methodology by Hoberg and Maksimovic (2022) to characterize the product life cycle of each firm. This methodology performs textual analysis of the companies' financial statements. A key methodological contribution is that a company's life cycle is determined by the description of the company's present business and products, and not by an attribute that moves mechanically (every company is one year older today than it was a year ago). Hence, the life cycle reflects the current condition of the company. We implement the methodology on S-1 fillings. We specifically rely on the regulation S-K, item 101, which requires a company to describe the business, its products and services, and provide the explanation of material product research and development in the S-1 document.

In SEC Edgar database, we download S-1 documents from 1994 to 2018. We use textual queries to extract paragraphs from the documents that relate to one of the four states:

product innovation (Life 1), process innovation (Life 2), stability and maturity (Life 3), and product discontinuation (Life 4). The textual queries are based on the lists of words specified in Hoberg and Maksimovic (2022) and listed in the Appendix A. These paragraphs discuss product research and development, results from operations, continuation and market share, obsolescence and product discontinuation. We diverge from the exact Hoberg and Maksimovic (2022) procedure in two points: First, we eliminate the names of cities in the documents starting with the word *new* (for example New York) because they interfere with the first PLC list; Second, we take into account paragraphs containing words “research and development” and “capital expenditures” as those paragraphs can contain valuable information. Appendix B offers an example of a paragraph for each of the four product life cycle phases in Fitbit’s S-1. First, we count the number of paragraphs appertaining to each of the four phases. Next, we divide each of the four numbers by the sum of the four counts. This procedure yields a four-element vector [Life1, Life2, Life3, Life4], summing up to unity, with each number representing the exposure to a particular life cycle. For example, Fitbit with [0.36, 0.34, 0.23, 0.07] and Dole Foods with [0.11, 0.30, 0.16, 0.43], contain products in all the life cycles. The difference is that Fitbit is classified as earlier in the life cycle because it weights more on the first stage compared to Dole Foods, which has a higher percentage of obsolete products.

3.2.2 Construction of Dependent Variables and Control Variables

We construct several dependent variables related to the going public decision, the first-day IPO performance, and post-IPO corporate finance decisions. We first look at the relationship between product life cycle and whether firms withdraw their IPO. We construct a dummy variable, *1(Effective_IPO)*, which equals one if a firm follows through its registration with the SEC to IPO and zero if it withdraws the registration. We then examine the fraction of equity offering at IPO, defined as shares offered at IPO divided by the total number of shares after the IPO. Lastly in our baseline specification, we consider IPO underpricing (*Underpricing*), defined as the first day's closing price minus the offering price and divided by the offering price.

We also examine the relationship between firms' product life cycle at IPO and their later SEO, dividend payout, and acquisition decisions in the public market. We construct two variables to measure SEO, one dummy which equals one if a firm conducts an SEO within three years after its IPO (SEO_3yrs) and another dummy which equals one if a firm conducts an SEO within five years after its IPO (SEO_5yrs). The variables constructed to measure the dividend payout of a firm are: the natural logarithm of one plus the amount of total dividends paid out in millions within three years after the IPO (Div_3yrs) and five years after the IPO (Div_5yrs). We examine the acquisition decisions in one and three years after the IPO because newly public firms make acquisitions at a torrid pace (Celikyurt et al., 2010). We define (Acq_3yrs) as a dummy variable equal to one if a company acquires another firm within three years of its IPO, and (Acq_5yrs) as a dummy equal to one if a company acquires another firm within five years since its IPO.

To understand how innovation capacity plays a role in the relationship between an issuer's product life cycle and its IPO underpricing, we construct variables using patent data from the USPTO. We define the variable *lnpat* as the natural logarithm of one plus the number of patents applied prior to a firm's IPO. We also construct another variable *lnciteperpat* as the natural logarithm of one plus the number of citations per patent for the above patents. Both the number of patents and the number of citations are adjusted for potential truncation bias, following Hall, Jaffe, and Trajtenberg (2001).

We control for a number of factors in the regressions including the natural logarithm of the amount offering in the IPO (*lnamntoffer*), the natural logarithm of the age of a firm (*lnage*), whether a firm is VC-backed or not (*VC_back*), whether the IPO's underwriters have prestigious reputation (*underwriter_repu*), and Nasdaq two-month returns after a firm files for an IPO (*Nasdaq2MonthRet*). The information on the amount offering is collected from the SDC Platinum. We obtain the firms' age from SDC Platinum and Jay Ritter's website,[5] and we handcollect data for firms that remain with missing age. *VC_back* is a dummy which equals one if an IPO firm has VC-backing and the information on VC financing is collected from the VentureXpert data set and merged with our IPO sample using firm name and incorporation state. *underwriter_repu* is also a dummy which equals one if at least one of the IPO underwriters has been graded with a score of nine in a ranking from zero (least prestigious) to nine (most prestigious) from 1992 to 2015. We download the underwriter rankings from Jay Ritter's website. To control for the short-term market fluctuation that might affect the IPO completion decision (Bernstein, 2015), we control for the two-month NASDAQ returns from the date of the IPO filing ($Nasdaq2MonthRet$).

3.3 Summary Statistics

Table 1 reports summary statistics. We winsorize all variables at the 1st and 99th percentiles in the regressions to alleviate the concern that the results may be driven by outliers. The sample firms on average have 30.5% of their products in the earliest life cycle (*life1*), 37.5% of products belonging to the process-innovation stage (*life2*), 29.1% products in the stability and maturity phase (*life3*), while very small proportion of products (2.7%) in the discontinuation stage (*life4*). We note that most of the companies at the time of S-1 submission own products in all four product life cycle stages. 80.4% of the IPOs in our sample complete their IPO successfully. The companies that follow through the IPO on average experience 27.3% of underpricing in the first trading day and they on average offer 28.9% of their total number of shares after the IPO.

[Insert Table 1 about Here]

[5] The website that contains the IPO database of Jay Ritter is `https://site.warrington.ufl.edu/ritter/ipo-data/`.

Figure 1 displays the comparison between the average product life cycle of IPO firms and public companies over the sample years.[6] IPO firms are more exposed to products in the innovation and maturity phase, while public companies load more on process innovation and product discontinuation stage.[7]

[Insert Figure 1 about Here]

Figure 2 plots the comparison between the average product life cycle of effective and withdrawn IPO companies. Without taking into account industry and year effects, effective and withdrawn IPO companies exhibit similar product life cycles in the entire sample.

[Insert Figure 2 about Here]

Figure 3 presents the average product life cycle for firms in four sectors, drugs, medical instruments, and biotechnology (with three-digit SIC code 283 and 384 or four-digit SIC code 8731 and 8733), software (with three-digit SIC code 737), communications equipment (with three-digit SIC code 366), and restaurant (with three-digit SIC code 581). The average product life cycles in the four sectors diverges significantly. While pharmaceutical and biotech companies focus on developing new products, restaurants center on minimizing costs, and the software industry focuses on existing clients with regular updates and after-sale support. Moreover, companies in different sectors are subject to different shocks, which impact the product life cycle of the companies (e.g. changes in the regulation for data privacy in the software sector).

[Insert Figure 3 about Here]

[6] The average product life cycle of public companies is calculated using the textual analysis described in Section 3.2.1 of 10-K financial statements following Hoberg and Maksimovic (2022).

[7] We note that Figure 1 and Figure 2 present the average percentages over the entire sample of companies and they do not take into consideration industry or year effects.

4 Baseline Results

Having constructed the measures of firms' product life cycle during the IPO filing, we examine how firms exposed to different product life cycles trade-off the benefits and costs of going public by looking at firms' IPO withdrawal decision, the fraction of equity offering, and the underpricing at IPO. We also investigate how the product life cycle at IPO is associated with post-IPO corporate finance activity including seasoned equity offering (SEO), dividend payout, and acquisition decisions.

Specifically, we estimate the following models:

$$
\begin{aligned}
Y_{f,i,t} &= \alpha + \beta_1 life1_{f,i,t} + \Gamma X_{f,i,t} + \mu_t + \eta_i + \delta_{f,i,t} \\
Y_{f,i,t} &= \alpha + \beta_1 life1_{f,i,t} + \beta_3 life3_{f,i,t} + \beta_4 life4_{f,i,t} + \Gamma X_{f,i,t} + \mu_t + \eta_i + \delta_{f,i,t}
\end{aligned}
\tag{1}
$$

where f stands for a firm in industry i that files its IPO in year t. The dependent variables are: a dummy for IPO completion (*1(IPO_Effective)*), the fraction of equity offering at IPO (*SharesOffered/SharesAfter*), IPO underpricing (*Underpricing*), dummies for post-IPO SEO activity (*SEO_3yrs* and *SEO_5yrs*), the amount of post-IPO dividend payouts (*Div_3yrs* and *Div_5yrs*), and dummies for post-IPO acquisition activity (*Acq_3yrs* and *Acq_5yrs*). The key variables of interest are the fractions of products in different product life cycle stages: the stage of product innovation (*life1*), the stage of stability and maturity (*life3*), and the stage of product discontinuation (*life4*). In the first specification, we include only *life1* as the key left-hand side variable given that IPO firms have most of their products in $life1$ as shown in Figure 1. Hence, the coefficient estimate on this variable should be interpreted compared to other three product life cycles combined. In the second specification, we include other two product life cycle variables *life3* and *life4*, and we set the fraction of products in the stage of process innovation (*life2*) as the reference category in the regressions, to avoid the problem of multicollinearity. That is why the coefficient estimates on the product life cycle variables in the second specification should be interpreted with respect to the process innovation phase and keeping other two product life cycle variables constant. In both columns, we control for a vector of variables that might impact firms' IPO decision and performances suggested by previous literature (Bernstein, 2015; Carter & Manaster, 1990; Chambers & Dimson, 2009; Hoberg, 2003; Lee & Wahal, 2004; Loughran & Ritter, 2004). Particularly, we include the natural logarithm of the offering amount (*lnamntoffer*), the natural logarithm of the firm age at IPO (*lnage*), a dummy for VC-backing (*VC_back*), a dummy for prestigious underwriters (*underwriter_repu*), and the two-month Nasdaq returns after a firm files the IPO (*Nasdaq2MonthRet*). We include year and 2-digit primary SIC code fixed effects to account for time-specific shocks and time-invariant unobservable industry characteristics that may affect the relationship between product life cycle and corporate finance decisions. We report standard errors robust to heteroskedasticity.

4.1 Product Life Cycle and IPO Completion

We start by examining the relationship between product life cycle and the decision of whether to proceed with or withdraw the IPO after filing the S-1 Form with the SEC. We hypothesize that if firms with different product life cycles indeed weigh the costs and benefits of going public differently, we should expect that some or all of the product life cycle measures to be significantly correlated with IPO completion. Specifically, we estimate equation (1) when the dependent variable is *1(Effective_IPO)*, a dummy which equals one if firm f follows through its IPO filing, and zero if it withdraws its IPO filing.

[Insert Table 2 about Here]

Results are presented in Table 2. In column (1), the variable of interest is *life1*, the fraction of products in the life cycle stage of product innovation. The magnitude of estimate on *life1* is 0.178 and statistically significant at 5% level, suggesting that when the fraction of products in the stage of product innovation increases one standard deviation compared to other product life cycles, the likelihood of a firm to follow through with its IPO increases by 0.07 standard deviations. In column (2), we add *life3* and *life4*, and set *life2* as the reference category. The results are similar to those illustrated in column (1). The coefficient is positive and statistically significant at 5% significance level, implying that firm with a higher fraction of product in the product innovation stage are more likely to follow through its IPO filings (i.e., less likely to withdraw their IPO). The coefficient estimates on β_3 and β_4 are not statistically significant.

The above results reflect the trade-off faced by firms with a higher fraction of products in the stage of product innovation (hereafter, a firm with younger product life cycle): On the one hand, these firms need to raise cheap money from the public market (Hertzel & Smith, 1993) to fund the product innovation; on the other hand, these firms may leak product innovation information to the competitors when going public (Boone, Floros, & Johnson, 2016; Spiegel & Tookes, 2008) and that is why they are secretive, consistent with the feature of inward-focused organic investment and the need for mitigating competitive threats (Chen et al., 2020). In our context, a firm with a younger product life cycle has a higher cost disclosing its prospectus (or filing its IPO S-1) while at the same time a larger benefit of raising capital. Thus, when a firm has decided to disclose its prospectus, it is more likely to complete the IPO given the information has already been released to the public.

4.2 Product Life Cycle and Fraction of Equity Offered at IPO

For firms that follow through their IPO, we examine the relationship between product life cycle and the fraction of equity being offered at IPO. We hypothesize that the key trade-off, which varies among firms with different product life cycles, when deciding how much to offer during an IPO is largely determined by the cost of overcoming the information asymmetry between the firm and investors by holding more equity by insiders (Leland & Pyle, 1977). Firms with products in an early life cycle are more obscure for outside investors to learn about their businesses, hence, insiders need to hold more equity to signal the quality of their firm when conducting an IPO. We test the above hypothesis by estimating equation (1) and replace the dependent variable with *SharesOffered/SharesAfter*, which is defined as the number of shares offered at IPO divided by the total number of shares after IPO.

[Insert Table 3 about Here]

Table 3 shows the results. Column (1) includes only *life1* as the variable of interest and column (2) adds *life3* and *life4*. The coefficient estimates on *life1* are both negative and statistically significant at 1% significance level. The economic magnitude is also sizable: when a firm has a 1% higher fraction of products in the stage of product innovation at IPO, it on average offers 0.14% less equity at IPO. The coefficient estimate on *life3* is negative and the estimate on *life4* positive, although both of them are statistically insignificant. The results provide evidence for our hypothesis that firms exposed to different product life cycles consider the cost of overcoming the information asymmetry between the issuing firm and investors differently.

4.3 Product Life Cycle and IPO Underpricing

Depending on a firm's product life cycles, it can offer different levels of underpricing to investors as a signal (Allen et al., 1989; Welch, 1989) or compensation for information production and participation of outside investors (Benveniste & Spindt, 1989; Chemmanur, 1993; Rock, 1986) to alleviate information asymmetry. We hypothesize that firms with a higher fraction of products in a younger life cycle are associated with higher IPO underpricing. Following the literature, we define the underpricing as the difference between the closing price and the opening price in the first trading day divided by the opening price in the first trading day.

[Insert Table 4 about Here]

Table 4 presents the results. When we include *life1* as the only product life cycle as shown in column (1), the coefficient estimate on *life1* is significantly positive at 10% significance level and the coefficient estimate is 0.148. In column (2) where we add also maturity and product discontinuation phase to the regression, the coefficient estimate on *life1* is positive and significant at 5% level, suggesting that when a firm has 1% higher fraction of products in the product innovation compared to the process innovation stage, it on average experiences 0.18% higher underpricing. This finding confirms our conjecture that firms with higher fraction of products in the stage of product innovation have higher information asymmetry between the firm and the outside investors, and therefore, these firms need to offer higher compensation (i.e., higher underpricing) to investors purchasing shares at the IPO.

4.4 Sub-Sample Analyses

So far, we have provided evidence that firms with different product life cycle weigh the costs (mainly overcoming information asymmetry towards investors and imparting confidential information to competitors) and benefits (mainly raising cheap capital) of going public differently. In this sub-section, we further corroborate our previous findings by conducting sub-sample analyses.

4.4.1 By Information Asymmetry

As discussed before, firms with a higher fraction of products in an earlier product life cycle may have higher information asymmetry. As these firms usually need more external funding to finance their product innovation, they would be more likely to follow through their IPO filings. At the same time, to successfully complete the IPO, these firms need to pay a higher cost of underpricing at IPO to signal their quality (Allen et al., 1989) or use the underpricing to attract outside investors to engage in information production (Chemmanur, 1993). Furthermore, insiders need to hold a higher fraction of equity to signal their quality

(Leland & Pyle, 1977). If overcoming information asymmetry indeed is a cost during the IPO that varies for firms with different product life cycle, we expect our results to be stronger for firms in industries with higher information asymmetry.

[Insert Table C1 about Here]

Table C1 shows the results when conducting a sub-sample test based on information asymmetry. Following (Leuz, 2003), we use data from the Institutional Brokers Estimate System and calculate the average analysts' earnings forecast dispersion for each 2-digit SIC industry each year and use it as a measure of information asymmetry. We then categorize our sample IPO firms into two groups every year based on the average forecast dispersion of their primary industry. We run the same regressions as specified in equation (1). Columns (1), (3), and (5) show the results on a sample where firms in industries with relatively low analyst forecast dispersion (i.e., low information asymmetry) are included, and columns (2), (4), and (6) present the results on a sample where firms in industries with relatively high information asymmetry are included. The dependent variable is $1(IPO\_Effective)$ in columns (1) and (2). We observe that the coefficient estimates on $life1$ in these two columns are both positive, which is consistent with our previous findings. The coefficient estimate in column (2) is statistically significant at 1% level in the sample with relatively high information asymmetry, but insignificant for the sample with low information asymmetry, as shown in column (1). The magnitude of the estimate in column (2) is also five times larger than the one in column (1). When examining the effects on IPO underpricing and the fraction of equity offered at IPO, we observe similar patterns: The signs of the coefficient estimates on $life1$ are consistent with those in the baseline results; the coefficient estimates are statistically significant in the sample with relatively high information asymmetry but insignificant in the sample with relatively low information asymmetry. The magnitude of coefficient estimates on $life1$ is larger in the high-information-asymmetry sample than in the low-information-asymmetry sample.

4.4.2 By Product Market Competition

Going public may leak information to a firm's competitors to copy their product innovation (Spiegel & Tookes, 2008). Therefore, we expect our previous findings to be more significant in industries with higher market concentration in the public market. IPO firms will attract more attention from their public rivals because these public incumbent firms enjoy larger oligopoly rents in these markets and fear more about losing market shares to the IPO firms. In other words, the cost of disclosing the prospectus for IPO firms is higher in markets with higher concentration. Therefore, once a firm facing high market concentration with more products in the phase of product innovation files an IPO, it is more likely to follow through its IPO, accept higher underpricing, and offer a lower fraction of equity.

[Insert Table C2 about Here]

Table C2 presents the results of the sub-sample test when we group firms based on the product market competition. Following the previous literature, we use the asset of public firms to calculate the Herfindahl-Hirschman Index (HHI) for each 2-digit SIC industry and divide our sample IPO firms into two groups every year based on the HHI of their primary industry. The empirical specification is the same as the baseline regressions. Columns (1), (3), and (5) show the results of the observations whose market concentration is relatively low and columns (2), (4), and (6) present the results of the observations whose market concentration is relatively high. The dependent variable in columns (1) and (2) is $1(IPO\_Effective)$. The coefficient estimates on $life1$ in these two columns are both positive, which is consistent with our previous findings. The coefficient estimate in column (2) is statistically significant at 1% level in the sample with high market concentration, but insignificant for the sample with low market concentration, as shown in column (1). The magnitude of the estimate in column (2) is also five times larger, compared to column (1). When examining the effects on IPO underpricing and the fraction of equity offered at IPO, we observe similar patterns: The signs of the coefficient estimates on $life1$ are consistent with those in the baseline results; the coefficient estimates are statistically significant in the sample with relatively high market concentration but insignificant in the sample with relatively low market concentration; and the magnitude of coefficient estimates on $life1$ is larger in the high-market-concentration sample than in the low-market-concentration sample.

4.5 Product Life Cycle and Post-IPO Corporate Finance Decisions

We extend our analysis to post-IPO corporate finance decisions and activity to provide further support for our hypothesis that product life cycle determines how firms trade-off the benefits and costs of going public. In particular, we examine the relationship between firms' product life cycle and their SEO, dividend payout, and acquisitions after the IPO. We argue that IPO firms with a younger product life cycle have larger needs for capital to conduct innovation and an IPO may not be able to satisfy all their capital requirement. Therefore, these firms are more likely to conduct an SEO and less likely to payout dividends (Boone et al., 2016; DeAngelo et al., 2006). Furthermore, IPO firms with a younger product life cycle are also less likely to acquire other firms while firms with more products in a mature stage are more likely to go public for acquisitions (Celikyurt et al., 2010).[8]

[Insert Table 5 about Here]

Table 5 shows the results of the analysis on SEO. In columns (1) and (3), dependent variable is the dummy, *SEO_3yrs*, which equals one if a firm has conducted an SEO within three years since its IPO and zero otherwise. The dependent variable is replaced in columns (2) and (4) with *SEO_5yrs*, which equals one if a firm has conducted a SEO within five years since its IPO and zero otherwise. As in previous tables, we show estimation results with

[8]The following findings in Tables 5, 6, and 7 also suggest that product life cycle at IPO should not be simply interpreted as a way for firms to signal, as the findings are not consistent with the predictions given by Allen et al. (1989) and Welch (1989).

life1 in the first two columns and add *life3* and *life4* in the last two columns. In all four columns, the coefficient estimates on *life1* are all positive and statistically significant at 1% level. The magnitude of the estimates in columns (1) and (2) suggest that when a firm has a 1% higher fraction of products in the stage of product innovation at the time of its IPO, it on average experiences 0.31% higher likelihood to conduct an SEO within three years and a 0.32% higher likelihood to conduct an SEO within five years after its IPO. The coefficient estimates on *life3* are all negative, but statistically insignificant. Finally, the coefficient estimates on *life4* are all negative and statistically significant at 1% level. The results in Table 5 show that the likelihood of a firm conducting an SEO after its IPO is positively correlated with the fraction of its products in the youngest stage and negatively correlated with the fraction of its products in the later stages of the product life cycle at the time of the IPO.

[Insert Table 6 about Here]

Table 6 presents the results of the analysis related to post-IPO dividend payout. In the first two columns, we include only IPO year and industry fixed effects. In the last two columns, we embed additional controls to the analysis. The dependent variable is the natural logarithm of one plus the total amount of dividend paid out in millions within three years after the IPO (Div_3yrs) in columns (1) and (3) and within five years after the IPO (Div_5yrs) in columns (2) and (4). The coefficient estimates on *life1* are negative and statistically significant at 1% level in all the columns, which presents that firms with a higher fraction of product in the product innovative stage pay out significantly fewer dividends after the IPO.

[Insert Table 7 about Here]

Table 7 presents the analysis on firms' post-IPO acquisitions. The empirical specification is similar as in the previous tables. The dependent variable is a dummy which equals one if a company conducts at least one acquisition within three years after its IPO (Acq_3yrs)

in columns (1) and (3) and within five years after the IPO (Acq_5yrs) in columns (2) and (4). The coefficient estimates on $life1$ are all negative and statistically significant at 1% significance level in all four columns, which suggests that firms with more products in the earliest life cycle are less likely to acquire other firms after IPO. When we include $life3$ and $life4$ into the regressions as shown in columns (3) and (4), the coefficient estimates on $life3$ are significantly positive and negative, but insignificant on $life4$. The result on $life3$ are consistent with Celikyurt et al. (2010) that firms with more mature products, which can generate stable cash flow, are more likely to conduct acquisitions. However, the above estimates also show that not all firms, especially not the firms with a large fraction of products in the innovation stage, go public to acquire.

5 Additional Tests

The previous section shows that a firm's product life cycle at IPO is correlated with its trade-off between the costs and benefits of going public, as reflected by the corporate finance decisions and activity during and post IPO. However, the possibility that the product innovation phase still encapsulates the same information provided by other innovation measures, nor did we exclude the potential endogeneity in our regressions. This section first demonstrates that product life cycle measures capture different meanings as patent-based measures. Then, we use an instrumental variable approach to show the relationship between product life cycle and corporate finance activity and decisions at and post-IPO is causal. Finally, we apply a difference-in-differences approach to cement the validity of our results.

5.1 Comparing Patent Measures and Product Life Cycle Measures

Some may question if product life cycle measures, especially the fraction of products in the phase of product innovation ($life1$), capture the same concept as other measures of innovation constructed using patent data.[9] Below we perform a test which includes both the patent-based measures and the interaction terms with the product life cycle measure $life1$. If we observe that the coefficient estimate on $life1$ is still significant after including patent-based measures and the interaction terms, the results would reveal that the product life cycle measure captures some aspect of corporate innovation that patent-based measures are not able to capture.

[Insert Table 8 about Here]

Table 8 presents the results of tests where we add patent-based measures to the baseline regressions as shown in equation (1). The dependent variables are *1(IPO_Effective)* in columns (1) and (2), *Underpricing* in columns (3) and (4), and *SharesOffered/SharesAfter* in columns (5) and (6). We include the natural logarithm of one plus the number of patents applied prior to a firm's IPO (*lnpat*) and its interaction term with the fraction of products in the first life cycle ($life1$#*lnpat*) in columns (1), (3), and (5). We include the natural logarithm of one plus the number of citations per patent for the patents that firms applied prior to filing their IPO (*lnciteperpat*) and its interaction term with the fraction of products in the first life cycle ($life1$#*lnciteperpat*) in columns (2), (4), and (6). We observe that in all columns, the coefficient estimates on $life1$ maintain the same signs as those in the baseline regressions shown in Tables 2, 3, and 4 and they are all statistically significant at least at 5% significance level. Besides, the magnitude of the estimates on $life1$ only decreases a small fraction compared to that shown in the baseline results (e.g., when the dependent variable

[9] Many papers have used the number of patents or the number of patent citations to measure the quantity and quality of innovation, some examples include Seru (2014), Tian and Wang (2014), and Bernstein (2015).

is *1(IPO_Effective)*, the magnitude is 0.176 and 0.178 in Table 8 columns (1) and (2) and is 0.181 Table 2 in column (2)). The above results support our hypothesis that product life cycle measures capture some aspects that patent-based measure is unable to do, such as novel technologies and innovative business practices (Bellstam, Bhagat, & Cookson, 2020).

5.2 Instrumental Variable Analysis

Our goal is to identify the causal effect of product life cycle on firms' trade off between IPO benefits and costs. The remaining challenge is that some unobservable firm characteristics could drive the relationship between its product life cycles and corporate finance decisions. For example, a firm that has a high fraction of products in the product innovation stage and follows through its IPO process could be due to the CEO's overconfidence (Galasso & Simcoe, 2011) or sensation-seeking (Sunder, Sunder, & Zhang, 2017). To alleviate this type of endogeneity concerns, we use the average product life cycles of similar public firms as the instrument for an IPO company's product life cycle. Specifically, following Hoberg and Phillips (2010), we identify an IPO firm's similar public companies by performing a textual analysis and calculating the similarity scores between 10-Ks of public companies and S-1 of the IPO companies.[10]

For machine readable S-1 and 10-K, we focus on the product description section. This section appears in "Prospectus Summary" in most S-1s or Item 1 and Item 1A in most 10-Ks. We collect all unique words in all S-1 and 10-K documents in a given year and we discard all common words, defined as words that appear in more than 5% of the combined filings. The resulting list of N words is the "main dictionary." We then represent each firm as an N-vector summarizing its usage of the N words, and we normalize each vector to unit length. The

[10] In the main instrumental variable analysis, we use 30 most similar companies. We base this number of most similar companies on the average number of competitors in a SIC-4 industry. The results remain similar if we take 15,20, or 50 (close to SIC-3 average number of competitors) closest companies in the product-space.

cosine similarity of these vectors is bounded in the range [0,1], and firms having descriptions with more words in common have a higher similarity. Combining both S-1 and 10-K word lists within a year allows us to compare firms that file their registration statements with their public rivals.

For an instrument to be valid, it needs to satisfy both the relevance condition (it must be a strong predictor of an IPO company's product life cycle) and the exclusion restriction (it should not affect the company's IPO through any channel other than the company's product life cycle). We argue that the average product life cycle of similar public companies to the IPO firm meets both requirements. First, the average product life cycle is likely to satisfy the relevance condition because similar public companies usually share correlated product life cycles to the IPO firm. In Figure 4, we compare the average product life cycle of public firms and firms filing for an IPO by sectors. Specifically, we categorizing firms into high-tech versus low-tech industries and manufacturing versus non-manufacturing industries.[11] One can observe that even though the product life cycles vary significantly across different sectors, the average product life cycles are very similar between public firms and firms filing for an IPO. Later in this section, we will present the first-stage results of our IV analysis which show that the instrument indeed satisfies the relevance condition. The average product life cycle of similar public firms is also likely to satisfy the exclusion restriction because it is not determined by the IPO firm's unobservable characteristics and is likely to affect an IPO firm's corporate finance decisions only through its product life cycle.

[Insert Figure 4 about Here]

To implement the instrumental variable approach, we estimate the following first-stage regression:

[11] we define high-tech industries as drugs (3-digit SIC code 283), medical instruments (3-digit SIC code 384), office and computing equipment(3-digit SIC code 357), communications equipment (3-digit SIC code 366), electronic components (3-digit SIC code 367), scientific instruments (SIC 382), software (3-digit SIC code 737), and biotech (4-digit SIC code 8371 and 8373) following Brown, Fazzari, and Petersen (2009). The manufacturing industries are those with SIC code 2000 to 3999.

$$
\begin{aligned}
Life1_{f,i,t} = \alpha + \beta_1 SimiPublic\_life1_{i,t} + \beta_2 SimiPublic\_life3_{i,t} \\
+\beta_3 SimiPublic\_life4_{i,t} + \gamma X_{f,i,t} + \mu_t + \eta_i + \epsilon_{f,i,t} \\
Life3_{f,i,t} = \alpha + \beta_1 SimiPublic\_life1_{i,t} + \beta_2 SimiPublic\_life3_{i,t} \\
+\beta_3 SimiPublic\_life4_{i,t} + \gamma X_{f,i,t} + \mu_t + \eta_i + \epsilon_{f,i,t} \\
Life4_{f,i,t} = \alpha + \beta_1 SimiPublic\_life1_{i,t} + \beta_2 SimiPublic\_life3_{i,t} \\
+\beta_3 SimiPublic\_life4_{i,t} + \gamma X_{f,i,t} + \mu_t + \eta_i + \epsilon_{f,i,t}
\end{aligned} \tag{2}
$$

where f stands for a firm in industry i that files its IPO in year t. The dependent variables in the three regressions are the three product life cycle variables of the IPO firm: *life1*, *life3*, and *life4*. The main independent variables are: the average fraction of products of an IPO firm's similar public firms in the innovation phase ($SimiPublic\_life1$), in the mature stage ($SimiPublic\_life3$), and in the discontinuation phase ($SimiPublic\_life4$). Again, to avoid the problem of multicollinearity, we set the fraction of products in the stage of process innovation of similar public firms ($SimiPublic\_life2_{i,t}$) as the reference category in all four regressions. We include other control variables, $lnamntoffer$, $lnage$, VC_back, *underwriter_repu*, and $Nasdaq2MonthRet$, which are defined in equation (1). We incorporate both the IPO year and 2-digit primary SIC code fixed effects. The standard errors are robust to heteroskedasticity.

In the second stage of the instrumental variable analysis, we estimate the following model:

$$
Y_{f,i,T} = \alpha + \theta_1 lif\hat{e1}_{f,i,t} + \theta_2 lif\hat{e3}_{f,i,t} + \theta_3 lif\hat{e4}_{f,i,t} + \gamma X_{f,i,t} + \mu_t + \eta_i + \delta_{f,i,t} \tag{3}
$$

The dependent variables remain the same as in the baseline regressions: a dummy for IPO completion (*1(IPO_Effective)*), fraction of equity offering at IPO (*SharesOffered/SharesAfter*), IPO underpricing (*Underpricing*), dummies for SEO within three or five years after IPO

(*SEO_3yrs* and *SEO_5yrs*), the natural logarithm of the amount of post-IPO dividend payouts (*Div_3yrs* and *Div_5yrs*), and dummies for post-IPO acquisition activity (*Acq_3yrs* and *Acq_5yrs*). The key variables of interest are the predicted values from the first stage: $li\hat{f}e1$, $li\hat{f}e3$, and $li\hat{f}e4$.

Table 9 presents the results of instrumental variable analysis on during-IPO decisions as the main outcome variable. The first three columns in the three panels of Table 9 report the first stage of the analysis, where the dependent variables are the endogenous variables, $life1$, $life3$, and $life4$ and the instruments are $SimiPublic\_life1$, $SimiPublic\_life3$, and $SimiPublic\_life4$ with other control variables. In Panel A, the dependent variable is the dummy variable of IPO follow-through. We observe that in all the first-stage regressions, at least one of the coefficient estimates on the instruments, $SimiPublic\_life1$, $SimiPublic\_life3$, and $SimiPublic\_life4$ is positive and highly statistically significant, suggesting that the average product life cycle measures of similar firms are positively correlated with the IPO firms' product life cycle measures, thus satisfying the relevance restriction necessary for a valid instrument. We report the Sanderson-Windmeijer F-statistics as a diagnostic for weak identification (Sanderson & Windmeijer, 2016), given that we have multiple endogenous variables and instruments in the estimation.[12] The Sanderson-Windmeijer F-statistics take values of 334.37, 65.67, and 5.60 in columns (1) to (3), respectively, with a p-value of less than 0.001 in the first two columns and 0.018 in the third column. The Sanderson-Windmeijer F-statistics suggest that we can reject the null-hypothesis that our first-stage regressions suffer from weak identification at a 0.1% and 5% significance levels. Column (4) in Table 9 shows the result of the second-stage analysis when the dependent variable is *1(IPO_Effective)*, which equals one if a company follows through its IPO filing and zero if it withdraws the IPO. The coefficient estimate on the predicted value of the endogenous variable, $li\hat{f}e1$, in the last column captures the causal effect of the IPO firm's

[12]Kleibergen-Paap rk Wald statistic would be used when there is a single endogenous regressor and when standard errors are not i.i.d.

product innovation stage on the decision to follow through the IPO. The coefficient is both positive and statistically significant at 5% level, indicating that when companies have a higher fraction of products in the stage of product innovation, they are significantly more likely to follow through with their IPO. This result corresponds to our finding in the baseline regressions, shown in Table 2.

Panel B of Table 9 repeats the instrumental analysis with the replacement of the dependent variable in the second stage with the fraction of equity offered at IPO (*SharesOffered/SharesAfter*). The results of the first-stage analysis are shown in columns (1) to (3). The instruments and the endogenous variables are highly correlated and the analysis passes the weak identification test. Column (4) shows the second-stage estimation in which the coefficient estimate on $li\hat{f}e1$ is both negative and statistically significant at 1% level. Therefore, the results of the instrumental analysis continue to support the finding in Table 3 that firms with a younger product life cycle at IPO offer lower fraction of equity. The coefficient estimate on $li\hat{f}e3$ implies that companies with a stable market position also offer a lower fraction of equity at IPO.[13]

Panel C of Table 9 adopts the same specification with IPO underpricing as the dependent variable. The coefficient on $li\hat{f}e1$ in the last column is positive and highly statistically significant, corroborating the findings from Table 4 that firms with higher fraction of products in the product innovation stage offer higher compensation to purchase shares at the IPO. Similarly to the previous table, the pattern is visible also with the companies with a stable product position.

[Insert Table 9 about Here]

Table 10 focuses on post-IPO corporate finance decisions. The first-three columns present the results of first-stage regressions. Columns (4) and (5) present the coefficient

[13]The first-stage estimates are different from Panel A of Table9 due to different number of observations in each panel.

estimates when the dependent variable is the dummy, *SEO_3yrs* or *SEO_5yrs*, respectively. Coefficients on $li\hat{f}e1$ are positive and statistically significant at 1% level, further substantiating our baseline findings that the likelihood of a firm conducting an SEO is positively correlated with the fraction of the company's products in the youngest product life cycle stage. In columns (6) and (7), the dependent variables are related to dividend payout, Div_3yrs and Div_5yrs, respectively. We observe that the coefficient on $li\hat{f}e1$ is negative and statistically significant at 1% level, showing that the negative relation between the product innovation phase and dividends is robust under the IV setting. Finally, columns (8) and (9) display the second-stage results when the dependent variable is the acquisition dummy, Acq_3yrs or Acq_5yrs, respectively. The coefficient on $li\hat{f}e1$ is negative and statistically significant at 1% level in both columns, demonstrating that the negative relation between the product innovation phase and post-IPO acquisitions persists also in the IV setting. The table also corroborates the different relationships between the companies exposure to young versus stable product life cycles and after-IPO equity offerings and acquisitions.

[Insert Table 10 about Here]

Overall, the instrumental variable approach helps us rule out potential endogeneity concerns about our baseline results, supporting the causal interpretation of our findings regarding the relationship between the product life cycle of an IPO firm and its corporate finance decisions during and post IPO.

5.3 Responses to Changing Costs of Going Public

To further confirm our findings, our last step exploits a policy shock to firms' disclosure of patent information to competitors and potential investors, the American Inventor's Protection Act (AIPA). We argue that the Act affected the costs of going public.

Historically, U.S. patent applications were kept secret until the final patent was granted.

Firms could avoid revealing the content of their patents publicly without losing intellectual property protection. The AIPA became effective on November 29, 2000, and it required mandatory disclosure of patent applications 18 months after the filing date, even if the patent is not granted eventually (Hegde & Luo, 2018; Saidi & Žaldokas, 2021). Kim and Valentine (2021) show that U.S. Patent disclosure accelerate by 31% after the enactment of the AIPA.

Therefore, we predict that the AIPA impacts firms' IPO and post-IPO corporate decisions in two ways. First, the mandatory disclosure of patent applications lowers the concern of candidate firms for IPO on revealing information related to their product research and development because companies are obliged to reveal them already after the patent application. In other words, the cost of leaking information (Spiegel & Tookes, 2008) to competitors during IPO declines more for firms with more product innovation after the AIPA. Second, the AIPA alleviates the information friction between potential investors for the IPO and the firm because investors can learn the details of a firm's product innovation through their patent applications. Therefore, the cost of signaling to investors also decreases and the effect is more pronounced for firms with more product innovation after the AIPA. Below we test our predictions using a difference-in-differences approach by estimating the following model:

$$Y_{f,i,t} = \alpha + \gamma life1_{f,i,t} * Post + \beta_1 life1_{f,i,t} + \beta_3 life3_{f,i,t} + \beta_4 life4_{f,i,t} + \Gamma X_{f,i,t} + \mu_t + \eta_i + \delta_{f,i,t} \tag{4}$$

where *Post* is an indicator variable that takes a value one after 2000. The other variables are defined as in equation (1). γ is the DiD estimator of interest.

Table 11 shows the results of testing the changes in IPO follow-through, underpricing, and equity offered around the AIPA introduction. In Column (1), the dependent variable is the IPO follow-though dummy. The coefficient estimate on $life1_{f,i,t} * Post$ is negative, suggesting that firms with more product in the innovation stage are less likely to follow through the IPO after the AIPA. AIPA made some confidential information of a firm released before IPO, and hence, firms have less concern on revealing information to competitors at IPO and would be more likely to withdraw after they have disclosed their IPO prospectus. We observe that the coefficient estimate on $life1_{f,i,t} * Post$ is both negative and statistically significant at 1% significance level. The negative sign confirms our prediction that the AIPA lowers the information friction between investors and insiders in the firm by mandatory disclosure of patent applications, which results with lower IPO underpricing. In Column (3) when the dependent variable is the fraction of equity offered at IPO, the coefficient estimate on $life1_{f,i,t} * Post$ is positive and statistically significant at the 5% level. This result indicates that after the AIPA mandatory disclosure of patent applications, insiders/entrepreneurs at the IPO firm need to hold a lower fraction of firm equity to signal the firm quality, consistent with our prediction.

Table 12 shows the results of changes in post-IPO corporate finance decisions around the introduction of the AIPA. In Columns (1) and (2), we find that IPO firms with more products in the innovation stage conduct more SEOs after the AIPA. This result shows that the AIPA reduces the costs due to information asymmetry both at IPO and at SEO, and firms that need more capital to develop products offer more equity. Columns (3) and (4) show that firms with more products in the innovation stage issued fewer dividends after the AIPA. This result, again, illustrates that firms with more product innovation are more likely to be those with more financing needs, and when the costs of going public decline, these firms take the opportunity and seek capital from the public market and they are less likely to pay dividends. Columns (5) and (6) suggest that declining costs do not affect the decisions of firms with more products in the product innovation stage to acquire other companies. This section highlights the declining costs for firms with more products in the product innovation stage after the AIPA, which results with a different trade-off of IPO costs and benefits. To summarize, the IV analysis and the difference-in-differences approach confirm the causal relationship of the firm's product life cycle and the trade-off between IPO benefits and costs.

6 Conclusion

This paper examines the role of product life cycle in determining firms' trade-off between the benefits and costs of going public. We measure the product life cycle by performing textual analysis on companies' S-1 filings and categorize products into four stages: product innovation, process innovation, stability, and product discontinuation, following the literature. The findings show that companies owning more products in the product innovation phase are more likely to complete (instead of withdrawing) the IPO, even if they face higher underpricing and offer a lower fraction of equity. Moreover, these firms conduct more seasoned equity offerings, pay lower dividends, and conduct fewer acquisitions after the IPO. These results suggest that firms with diverging product life cycles put different weights on benefits and costs of going public such as raising capital through IPO, information asymmetry with investors, and revealing information to competitors. To establish causality, we first conduct an instrumental variable analysis by instrumenting an IPO firm's product life cycle using the average product life cycle of its similar public firm peers. We also conduct a difference-in-differences analysis by using the variation generated by the American Inventor Protection Act to the cost of going public in terms of revealing information to competitors and information asymmetry towards investors. Both analyses suggest that the product life cycle plays an important role in determining how firms make corporate finance decisions during and after the IPO.

References

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of industrial innovation. Technology Review, 80(7), 40–47.

Allen, F., Faulhaber, G. R., et al. (1989). Signaling by underpricing in the IPO market. Journal of Financial Economics, 23(2), 303–323.

Arikan, A. M., & Stulz, R. M. (2016). Corporate acquisitions, diversification, and the firm's life cycle. The Journal of Finance, 71(1), 139–194.

Baron, D. P. (1982). A model of the demand for investment banking advising and distribution services for new issues. The Journal of Finance, 37(4), 955–976.

Bayar, O., & Chemmanur, T. J. (2011). IPOs versus acquisitions and the valuation premium puzzle: A theory of exit choice by entrepreneurs and venture capitalists. Journal of Financial and Quantitative Analysis, 1755–1793.

Bellstam, G., Bhagat, S., & Cookson, J. A. (2020). A text-based analysis of corporate innovation. Management Science.

Benveniste, L. M., & Spindt, P. A. (1989). How investment bankers determine the offer price and allocation of new issues. Journal of Financial Economics, 24(2), 343–361.

Bernstein, S. (2015). Does going public affect innovation? The Journal of Finance, 70(4), 1365–1403.

Bhattacharya, S., & Ritter, J. R. (1983). Innovation and communication: Signalling with partial disclosure. The Review of Economic Studies, 50(2), 331–346.

Boone, A. L., Floros, I. V., & Johnson, S. A. (2016). Redacting proprietary information at the initial public offering. Journal of Financial Economics, 120(1), 102–123.

Brau, J. C., & Fawcett, S. E. (2006). Initial public offerings: An analysis of theory and practice. The Journal of Finance, 61(1), 399–436.

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. The Journal of Finance, 64(1), 151–185.

Brown, J. R., & Martinsson, G. (2019). Does transparency stifle or facilitate innovation? Management Science, 65(4), 1600–1623.

Carter, R., & Manaster, S. (1990). Initial public offerings and underwriter reputation. the Journal of Finance, 45(4), 1045–1067.

Celikyurt, U., Sevilir, M., & Shivdasani, A. (2010). Going public to acquire? the acquisition motive in IPOs. Journal of Financial Economics, 96(3), 345–363.

Chambers, D., & Dimson, E. (2009). IPO underpricing over the very long run. The Journal of Finance, 64(3), 1407–1443.

Chemmanur, T. J. (1993). The pricing of initial public offerings: A dynamic model with information production. The Journal of Finance, 48(1), 285–304.

Chemmanur, T. J., & Fulghieri, P. (1999). A theory of the going-public decision. The Review of Financial Studies, 12(2), 249–279.

Chemmanur, T. J., & He, J. (2011). IPO waves, product market competition, and the going public decision: Theory and evidence. Journal of Financial Economics, 101(2), 382–412.

Chemmanur, T. J., He, S., & Nandy, D. K. (2010). The going-public decision and the product market. The Review of Financial Studies, 23(5), 1855–1908.

Chen, A., Hoberg, G., & Maksimovic, V. (2020). Life cycles of firm disclosures. Available at SSRN 3703931.

Dambra, M., Field, L. C., & Gustafson, M. T. (2015). The JOBS ACT and IPO volume: Evidence that disclosure costs affect the IPO decision. Journal of Financial Economics, 116(1), 121–143.

DeAngelo, H., DeAngelo, L., & Stulz, R. M. (2006). Dividend policy and the earned/contributed capital mix: a test of the life-cycle theory. Journal of Financial Economics, 81(2), 227–254.

DeAngelo, H., DeAngelo, L., & Stulz, R. M. (2010). Seasoned equity offerings, market timing, and the corporate lifecycle. Journal of Financial Economics, 95(3), 275–295.

Farre-Mensa, J., Hegde, D., & Ljungqvist, A. (2020). What is a patent worth? evidence from the us patent "lottery". The Journal of Finance, 75(2), 639–682.

Ferreira, D., Manso, G., & Silva, A. C. (2014). Incentives to innovate and the decision to go public or private. The Review of Financial Studies, 27(1), 256–300.

Galasso, A., & Simcoe, T. S. (2011). Ceo overconfidence and innovation. Management Science, 57(8), 1469–1484.

Grullon, G., Michaely, R., & Swaminathan, B. (2002). Are dividend changes a sign of firm maturity? The Journal of Business, 75(3), 387–424.

Hajda, J., & Nikolov, B. (2021). Product market strategy and corporate policies. Swiss Finance Institute Research Paper No. 21-02.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools. National Bureau of Economic Research Working Paper.

Hanley, K. W., & Hoberg, G. (2010). The information content of IPO prospectuses. The Review of Financial Studies, 23(7), 2821–2864.

Hanley, K. W., & Hoberg, G. (2012). Litigation risk, strategic disclosure and the underpricing of initial public offerings. Journal of Financial Economics, 103(2), 235–254.

Hegde, D., & Luo, H. (2018). Patent publication and the market for ideas. Management Science, 64(2), 652–672.

Hertzel, M., & Smith, R. L. (1993). Market discounts and shareholder gains for placing equity privately. The Journal of Finance, 48(2), 459–485.

Hoberg, G. (2003). Strategic underwriting in initial public offerings. Yale University Working.

Hoberg, G., & Maksimovic, V. (2022). Product life cycles in corporate finance. The Review of Financial Studies.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. The Review of Financial Studies, 23(10), 3773–3811.

Hofer, C. W. (1975). Toward a contingency theory of business strategy. The Academy of Management Journal, 18(4), 784–810.

Jegadeesh, N., Weinstein, M., & Welch, I. (1993). An empirical investigation of IPO returns and subsequent equity offerings. Journal of Financial Economics, 34(2), 153–175.

Kim, J., & Valentine, K. (2021). The innovation consequences of mandatory patent disclosures. Journal of Accounting and Economics, 71(2-3), 101381.

Klein, A., & Marquardt, C. A. (2006). Fundamentals of accounting losses. The Accounting Review, 81(1), 179–206.

Lee, P. M., & Wahal, S. (2004). Grandstanding, certification and the underpricing of venture capital backed ipos. Journal of Financial Economics, 73(2), 375–407.

Leland, H. E., & Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. The Journal of Finance, 32(2), 371–387.

Leuz, C. (2003). IAS versus US GAAP: information asymmetry–based evidence from germany's new market. Journal of Accounting Research, 41(3), 445–472.

Ljungqvist, A. (2007). IPO underpricing. In Handbook of empirical corporate finance (pp. 375–422). Elsevier.

Loderer, C., Stulz, R., & Waelchli, U. (2017). Firm rigidities and the decline in growth opportunities. Management Science, 63(9), 3000–3020.

Loughran, T., & Ritter, J. (2004). Why has IPO underpricing changed over time? Financial

Management, 5–37.

Lowry, M., & Shu, S. (2002). Litigation risk and IPO underpricing. Journal of Financial Economics, 65(3), 309–335.

Maksimovic, V., & Pichler, P. (2001). Technological innovation and initial public offerings. The Review of Financial Studies, 14(2), 459–494.

Miller, D., & Friesen, P. H. (1984). A longitudinal study of the corporate life cycle. Management science, 30(10), 1161–1183.

Pagano, M., Panetta, F., & Zingales, L. (1998). Why do companies go public? an empirical analysis. The Journal of Finance, 53(1), 27–64.

Ritter, J. R. (1991). The long-run performance of initial public offerings. The Journal of Finance, 46(1), 3–27.

Ritter, J. R., & Welch, I. (2002). A review of IPO activity, pricing, and allocations. The Journal of Finance, 57(4), 1795–1828.

Rock, K. (1986). Why new issues are underpriced. Journal of Financial Economics, 15(1-2), 187–212.

Saidi, F., & Žaldokas, A. (2021). How does firms' innovation disclosure affect their banking relationships? Management Science, 67(2), 742–768.

Sanderson, E., & Windmeijer, F. (2016). A weak instrument f-test in linear iv models with multiple endogenous variables. Journal of Econometrics, 190(2), 212–221.

Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and r&d activity. Journal of Financial Economics, 111(2), 381–405.

Spiegel, M., & Tookes, H. (2008). Dynamic competition, innovation and strategic financing (Working Paper). Yale School of Management.

Sunder, J., Sunder, S. V., & Zhang, J. (2017). Pilot CEOs and corporate innovation. Journal of Financial Economics, 123(1), 209–224.

Tian, X., & Wang, T. Y. (2014). Tolerance for failure and corporate innovation. The Review of Financial Studies, 27(1), 211–255.

Welch, I. (1989). Seasoned offerings, imitation costs, and the underpricing of initial public offerings. The Journal of Finance, 44(2), 421–449.

Zingales, L. (1995). Insider ownership and the decision to go public. The Review of Economic Studies, 62(3), 425–448.

Figures and Tables

Figure 1. IPO Product Life-Cycle versus Public Company Product Life-Cycle
The figure shows the difference between average product life-cycle between IPO firms and public companies. life1 is the fraction of the products in the product innovation stage, life2 is the fraction of products in the process innovation stage, life3 is the fraction of products in the maturity phase, and life4 is the fraction of products in the product discontinuation stage. Section 3.2.2 provides the description of variable construction.

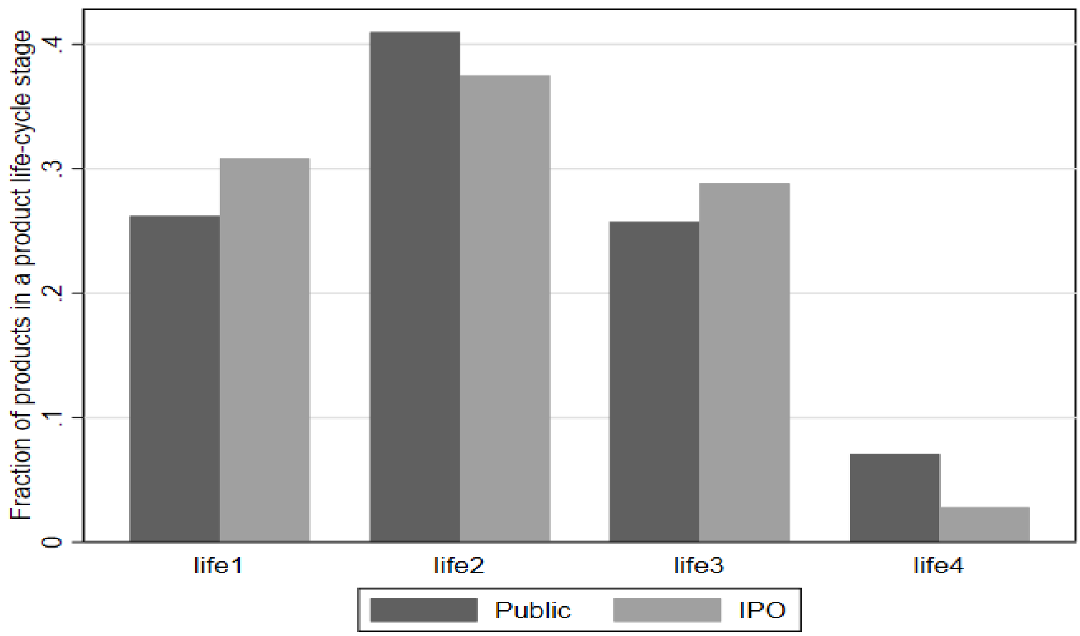

Figure 2. Successful IPO Product Life-Cycle versus Withdrawn IPO Product Life-Cycle

The figure shows the difference between average product life-cycle between IPO firms and firms that withdrew their IPO filings. life1 is the fraction of the products in the product innovation stage, life2 is the fraction of products in the process innovation stage, life3 is the fraction of products in the maturity phase, and life4 is the fraction of products in the product discontinuation stage. Section 3.2.2 provides the description of variable construction.

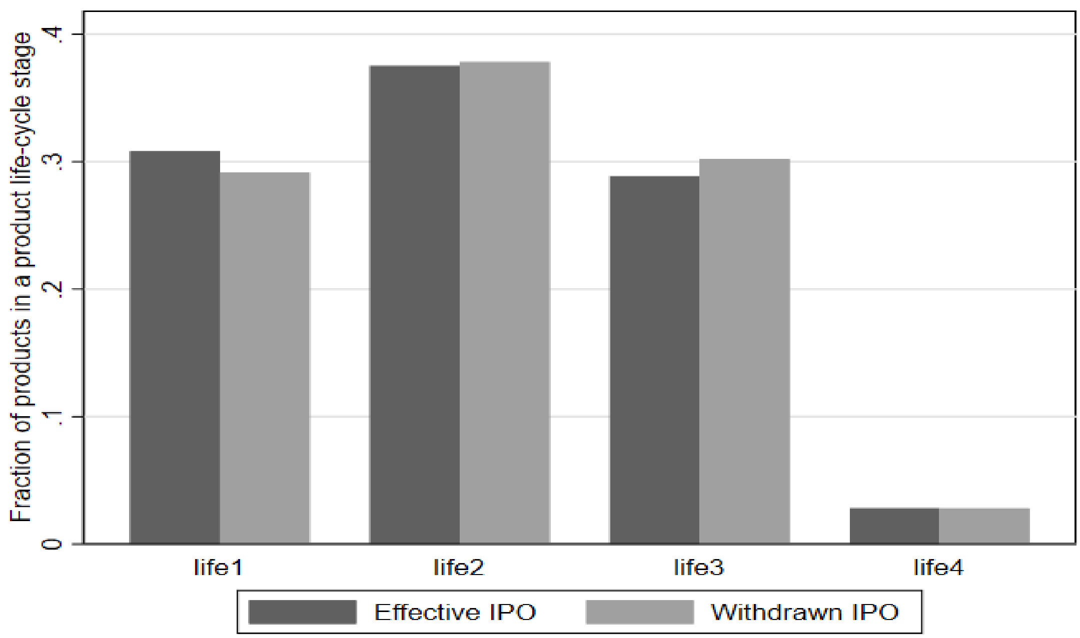

Figure 3. Product Life-Cycle at IPO by Sectors

The figure shows the difference between average product life-cycle between four sectors: drugs, software, communications equipment, and restaurants. Red bar is the fraction of the products in the product innovation stage, blue bar is the fraction of products in the process innovation stage, green bar is the fraction of products in the maturity phase, and yellow bar is the fraction of products in the product discontinuation stage. Section 3.2.2 provides the description of variable construction.

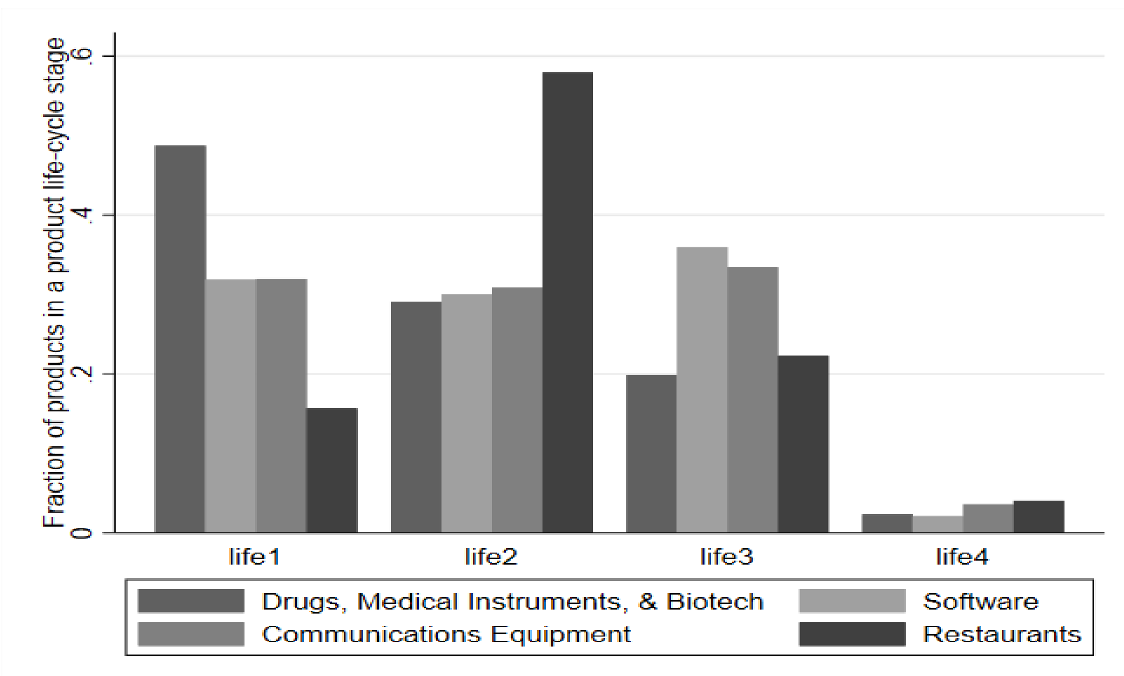

Figure 4. Comparing Product Life-Cycles of Public vs. IPO firms by Sector
The figure comparing the average product Life-Cycle of public and firms filing for an IPO of different sectors. The upper panel of the figure shows the comparison of public and IPO firms in low-tech and high-tech industries. Following Brown et al. (2009), we define high-tech industries as drugs (SIC 283), medical instruments (SIC 384), office and computing equipment(SIC 357), communications equipment (SIC 366), electronic components (SIC 367), scientific instruments (SIC 382), software (SIC 737), and biotech (SIC 8371 and 8373). The lower panel of the figure shows the comparison of public and IPO firms in manufacturing and non-manufacturing industries. life1 is the fraction of the products in the product innovation stage, life2 is the fraction of products in the process innovation stage, life3 is the fraction of products in the maturity phase, and life4 is the fraction of products in the product discontinuation stage. Section 3.2.2 provides the description of variable construction.

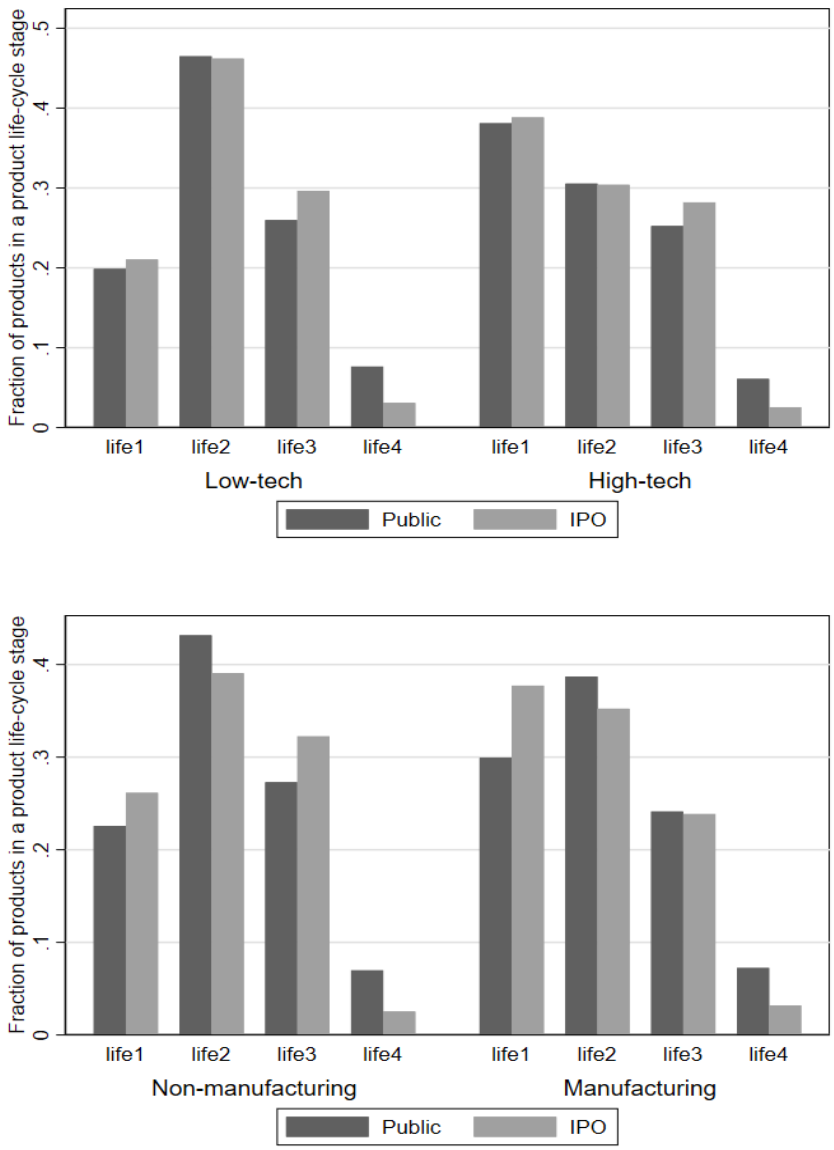

Table 1. Summary Statistics

This table displays the summary statistics for the variables used in this study. Definition of the variables and their sources are introduced in Section 3.

	N	mean	sd	min	p50	max
life1	3,297	0.305	0.149	0.045	0.289	0.670
life2	3,297	0.375	0.151	0.148	0.341	0.848
life3	3,297	0.291	0.116	0.049	0.287	0.591
life4	3,297	0.027	0.038	0.000	0.016	0.223
1(IPO_Effective)	3,297	0.804	0.397	0.000	1.000	1.000
Underprcing	2,577	0.273	0.500	-0.234	0.112	2.828
SharesOffered/SharesAfter	2,408	0.289	0.169	0.048	0.255	1.000
SEO_3yrs	2,651	0.307	0.462	0.000	0.000	1.000
SEO_5yrs	2,651	0.341	0.474	0.000	0.000	1.000
Div_3yrs	2,651	0.800	1.497	0.000	0.000	6.075
Div_5yr	2,651	0.906	1.615	0.000	0.000	6.410
Acq_3yrs	2,651	0.506	0.500	0.000	1.000	1.000
Acq_5yrs	2,651	0.564	0.496	0.000	1.000	1.000
lnpat	3,297	0.134	0.371	0.000	0.000	1.994
lnciteperpat	3,297	0.007	0.023	0.000	0.000	0.153
lnamntoffer	3,297	4.277	0.885	1.792	4.317	6.620
lnage	3,297	2.109	0.956	0.000	2.079	4.595
VC_back	3,297	0.559	0.497	0.000	1.000	1.000
underwriter_repu	3,297	0.521	0.500	0.000	1.000	1.000
NasdaqRet2Month	3,297	0.017	0.102	-0.384	0.030	0.419

Table 2. Product Life Cycle and IPO Follow-through

This table examines the relationship between product life cycle and the decision to follow through with the IPO. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable is *1(Effective_IPO)*, a dummy which equals one if a firm follows through its IPO filing, and zero if it withdraws its IPO filing. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *1(IPO_Effective)*	(2) *1(IPO_Effective)*
life1	0.178**	0.181**
	(0.069)	(0.074)
life3		0.044
		(0.081)
life4		-0.220
		(0.189)
lnamntoffer	0.044***	0.045***
	(0.010)	(0.010)
lnage	0.009	0.009
	(0.008)	(0.008)
VC_back	-0.033**	-0.035**
	(0.017)	(0.017)
underwriter_repu	0.014	0.013
	(0.016)	(0.016)
NasdaqRet2Month	0.467***	0.465***
	(0.078)	(0.078)
Constant	1.025***	1.046***
	(0.094)	(0.093)
Observations	3,297	3,297
R-squared	0.126	0.127
IPO Year	Controlled	Controlled
Industry	Controlled	Controlled

Table 3. Product Life Cycle and Fraction of Equity Offered at IPO

This table examines the relationship between product life cycle and the fraction of equity being offered at IPO. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable is *SharesOffered/SharesAfter*, defined as the the number of shares offered at IPO divided by the total number of shares after IPO. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects.The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *SharesOffered/SharesAfter*	(2) *SharesOffered/SharesAfter*
life1	-0.143***	-0.147***
	(0.031)	(0.034)
life3		-0.016
		(0.041)
life4		0.014
		(0.107)
lnamntoffer	0.010*	0.010*
	(0.006)	(0.006)
lnage	0.006	0.006
	(0.004)	(0.004)
VC_back	-0.017**	-0.016**
	(0.007)	(0.008)
underwriter_repu	-0.060***	-0.060***
	(0.007)	(0.007)
NasdaqRet2Month	0.067**	0.068**
	(0.032)	(0.032)
Constant	0.344***	0.346***
	(0.082)	(0.084)
Observations	2,408	2,408
R-squared	0.225	0.225
IPO Year	Controlled	Controlled
Industry	Controlled	Controlled

Table 4. Product Life Cycle and IPO Underpricing

This table examines the relationship between product life cycle and IPO underpricing. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable is *Underpricing*, defined as the difference between the closing price and the opening price in the first trading day divided by the opening price in the first trading day. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Underpricing*	(2) *Underpricing*
life1	0.148*	0.182**
	(0.082)	(0.085)
life3		0.133
		(0.101)
life4		-0.119
		(0.163)
lnamntoffer	-0.026**	-0.025**
	(0.012)	(0.012)
lnage	-0.034***	-0.034***
	(0.009)	(0.009)
VC_back	0.125***	0.121***
	(0.020)	(0.020)
underwriter_repu	0.127***	0.126***
	(0.022)	(0.022)
NasdaqRet2Month	0.523***	0.522***
	(0.136)	(0.137)
Constant	0.124*	0.111
	(0.070)	(0.080)
Observations	2,577	2,577
R-squared	0.271	0.272
IPO Year	Controlled	Controlled
Industry	Controlled	Controlled

Table 5. Product Life Cycle and Seasonal Equity Offerings

This table examines the relationship between product life cycle at IPO and SEO. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable in Columns 1 and 3 (2 and 4) is *SEO_3yrs* (*SEO_5yrs*), a dummy variable equal to one if a firm conducts an SEO within three (five) years since its IPO an zero otherwise. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *SEO_3yrs*	(2) *SEO_5yrs*	(3) *SEO_3yrs*	(4) *SEO_5yrs*
life1	0.313***	0.318***	0.261***	0.265***
	(0.090)	(0.092)	(0.096)	(0.098)
life3			-0.052	-0.045
			(0.105)	(0.107)
life4			-0.847***	-0.922***
			(0.222)	(0.227)
lnamntoffer	0.007	0.002	0.007	0.002
	(0.013)	(0.013)	(0.013)	(0.013)
lnage	0.001	0.001	0.003	0.003
	(0.010)	(0.010)	(0.010)	(0.010)
VC_back	0.036*	0.028	0.033	0.024
	(0.022)	(0.022)	(0.022)	(0.022)
underwriter_repu	-0.044**	-0.054**	-0.044**	-0.054**
	(0.021)	(0.022)	(0.021)	(0.022)
NasdaqRet2Month	-0.121	-0.134	-0.126	-0.140
	(0.095)	(0.098)	(0.095)	(0.098)
Constant	0.624*	0.597*	0.753***	0.734***
	(0.319)	(0.309)	(0.278)	(0.264)
Observations	2,651	2,651	2,651	2,651
R-squared	0.116	0.127	0.120	0.131
IPO Year	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled

Table 6. Product Life Cycle and Dividend Payout

This table examines the relationship between product life cycle at IPO and post-IPO dividend payout. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable in Columns 1 and 3 (2 and 4) is *Div_3years* (*Div_5years*), defined as the natural logarithm of one plus the total amount of dividend paid out in millions within three (five) years after the IPO. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Div_3yrs*	(2) *Div_5yrs*	(3) *Div_3yrs*	(4) *Div_5yrs*
life1	-1.147***	-1.249***	-1.156***	-1.246***
	(0.272)	(0.293)	(0.303)	(0.326)
life3			-0.205	-0.178
			(0.338)	(0.361)
life4			1.175	1.273
			(0.927)	(0.988)
lnamntoffer	0.363***	0.404***	0.360***	0.401***
	(0.045)	(0.048)	(0.045)	(0.048)
lnage	-0.015	-0.014	-0.017	-0.016
	(0.036)	(0.039)	(0.036)	(0.039)
VC_back	-0.467***	-0.522***	-0.456***	-0.511***
	(0.057)	(0.062)	(0.058)	(0.063)
underwriter_repu	0.049	0.067	0.050	0.068
	(0.061)	(0.065)	(0.061)	(0.065)
NasdaqRet2Month	-0.605**	-0.787**	-0.598**	-0.779**
	(0.296)	(0.314)	(0.296)	(0.314)
Constant	0.244	0.206	0.125	0.068
	(0.812)	(0.735)	(0.769)	(0.696)
Observations	2,651	2,651	2,651	2,651
R-squared	0.265	0.271	0.266	0.272
IPO Year	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled

Table 7. Product Life Cycle and Post-IPO Acquisitions

This table examines the relationship between product life cycle at IPO and SEO. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable in Columns 1 and 3 (2 and 4) is *Acq_3yrs* (*Acq_5yrs*), a dummy variable equal to one if a firm conducts an acquisition within three (five) years since its IPO an zero otherwise. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *Acq_3yrs*	(2) *Acq_5yrs*	(3) *Acq_3yrs*	(4) *Acq_5yrs*
life1	-0.508***	-0.481***	-0.461***	-0.423***
	(0.092)	(0.092)	(0.099)	(0.099)
life3			0.206*	0.219**
			(0.110)	(0.109)
life4			-0.314	-0.157
			(0.249)	(0.243)
lnamntoffer	0.043***	0.040***	0.045***	0.042***
	(0.014)	(0.014)	(0.014)	(0.014)
lnage	0.006	0.017*	0.006	0.016*
	(0.010)	(0.010)	(0.010)	(0.010)
VC_back	-0.033	-0.023	-0.040*	-0.029
	(0.022)	(0.022)	(0.022)	(0.022)
underwriter_repu	0.018	0.011	0.018	0.010
	(0.021)	(0.021)	(0.021)	(0.021)
NasdaqRet2Month	-0.059	-0.037	-0.062	-0.038
	(0.104)	(0.103)	(0.104)	(0.103)
Constant	1.105***	0.947***	1.103***	0.921***
	(0.125)	(0.170)	(0.126)	(0.165)
Observations	2,651	2,651	2,651	2,651
R-squared	0.203	0.191	0.205	0.193
IPO Year	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled

Table 8. Product Life Cycle, Innovation Capacity, and IPO Underpricing

This table displays the difference between product life cycle and patents. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable in Column 1 and 2 is *IPO_Effective*, defined in Table 2; in Column 3 and 4 is *Underpricing*, defined in Table 4 and in Column 5 and 6 is *SharesOffered/SharesAfter*, defined in Table 3. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)* is the natural logarithm of the amount offering in the IPO, *ln(age)* refers to the natural logarithm of the age of a firm, *VC_back* is defined as a dummy variable equal to one if a firm is VC-backed and zero otherwise, *underwriter_repu* is a dummy variable if the IPO's underwriters have prestigious reputation and zero otherwise, *Nasdaq2MonthRet* represents the two-month Nasdaq cumulative return after a firm files an IPO. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	1(IPO_Effective)		*Underpricing*		*SharesOffered/SharesAfter*	
life1	0.176**	0.178**	0.223**	0.196**	-0.147***	-0.143***
	(0.075)	(0.076)	(0.087)	(0.085)	(0.035)	(0.035)
life3	0.048	0.035	0.115	0.113	-0.019	-0.013
	(0.082)	(0.081)	(0.101)	(0.102)	(0.041)	(0.041)
life4	-0.215	-0.223	-0.111	-0.121	0.008	0.016
	(0.190)	(0.189)	(0.164)	(0.164)	(0.107)	(0.107)
lnpat	0.041		0.130**		-0.031*	
	(0.055)		(0.058)		(0.018)	
lnciteperpat		1.606		3.118*		-0.692**
		(1.218)		(1.684)		(0.321)
life1#lnpat	-0.027		-0.359***		0.033	
	(0.139)		(0.119)		(0.042)	
life1#lnciteperpat		-2.699		-6.682		0.932
		(3.366)		(4.251)		(0.856)
Controls	Yes	Yes	Yes	Yes		
Observations	3,297	3,297	2,577	2,577	2,408	2,408
R-squared	0.127	0.128	0.273	0.274	0.226	0.227
IPO Year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled

Table 9. IV Analysis: Product Life Cycle and IPO Follow-through, Underpricing, and Equity Offering

This table reports the instrumental variable (IV) regression results of the product life cycle and corporate finance decisions during the IPO: IPO follow-through, IPO underpricing, and IPO equity offering. The instruments *SimiPublic_life1*, *SimiPublic_life3*, and *SimiPublic_life4* are described in Section 5.2. The first three columns in each panel show the first stage regression results, regressing product life cycle variables *life1*, *life3*, and *life4* on the instruments, other controls, and year and industry fixed effects as in Equation 2. In Panel A, the last column shows the second stage regression results from Equation 3 with the dependent variable *1(Effective_IPO)*, a dummy which equals one if a firm follows through its IPO filing, and zero if it withdraws its IPO filing. In Panel B, the dependent variable in the last column is *SharesOffered/SharesAfter*, defined as the the number of shares offered at IPO divided by the total number of shares after IPO. In Panel C, the dependent variable in the last column is *Underpricing*, defined as the difference between the closing price and the opening price in the first trading day divided by the opening price in the first trading day. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. *ln(amntoffer)*, *ln(age)*, *VC_back*, *underwriter_repu*, *Nasdaq2MonthRet* are defined in Section 3.2.2. The continuous control variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The last row of the table reports the Sanderson-Windmeijer F-statistics for weak identification test with the p-val in parentheses. Standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. IV Analysis on IPO Follow-Through

	(1)	(2)	(3)	(4)
		1st-stage		2nd-stage
	life1	*life3*	*life4*	*1(IPO_Effective)*
SimiPublic_life1	0.778***	0.102**	0.023	
	(0.051)	(0.046)	(0.019)	
SimiPublic_life3	0.174***	0.655***	0.019	
	(0.064)	(0.060)	(0.024)	
SimiPublic_life4	-0.163	0.401***	0.171**	
	(0.168)	(0.153)	(0.072)	
life1				0.289**
				(0.143)
life3				0.041
				(0.259)
life4				0.134
				(3.518)
lnamntoffer	-0.019***	-0.003	0.002*	0.009
	(0.003)	(0.003)	(0.001)	(0.012)
lnage	0.001	0.001	0.002*	0.001
	(0.002)	(0.002)	(0.001)	(0.009)
VC_back	0.025***	0.013***	-0.007***	-0.042
	(0.004)	(0.004)	(0.002)	(0.031)
underwriter_repu	0.010**	-0.005	-0.001	0.024*
	(0.004)	(0.004)	(0.002)	(0.014)
NasdaqRet2Month	-0.049**	0.017	0.004	0.228***
	(0.020)	(0.020)	(0.007)	(0.072)
Constant	-0.007	-0.099**	0.109*	1.154**
	(0.048)	(0.044)	(0.062)	(0.461)
Observations	2,876	2,876	2,876	2,876
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
SW F-stat (p-val)	334.37 (0.000)	65.67 (0.000)	5.60 (0.018)	-

(Continued)

Panel B. IV Analysis on IPO Equity Offering

	(1)	(2)	(3)	(4)
	1st-stage			2nd-stage
	life1	*life3*	*life4*	*SharesOffered/SharesAfter*
SimiPublic_life1	0.760***	0.070	0.034	
	(0.058)	(0.051)	(0.022)	
SimiPublic_life3	0.154**	0.613***	0.031	
	(0.073)	(0.067)	(0.027)	
SimiPublic_life4	-0.156	0.358**	0.190**	
	(0.192)	(0.175)	(0.079)	
life1				-0.391***
				(0.142)
life3				-0.655***
				(0.253)
life4				4.171
				(2.671)
lnamntoffer	-0.018***	-0.003	0.002	-0.006
	(0.003)	(0.003)	(0.001)	(0.011)
lnage	0.001	0.004*	0.002*	-0.002
	(0.002)	(0.002)	(0.001)	(0.009)
VC_back	0.027***	0.011**	-0.008***	0.033
	(0.005)	(0.004)	(0.002)	(0.027)
underwriter_repu	0.011**	-0.005	-0.001	-0.056***
	(0.005)	(0.004)	(0.002)	(0.011)
NasdaqRet2Month	-0.055**	0.016	-0.007	0.098*
	(0.023)	(0.022)	(0.008)	(0.055)
Constant	-0.011	-0.081*	0.110*	-0.076
	(0.053)	(0.046)	(0.064)	(0.436)
Observations	2,348	2,348	2,348	2,348
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
SW F-stat (p-val)	91.47 (0.000)	40.70 (0.000)	5.70 (0.017)	-

(Continued)
Panel C. IV Analysis on IPO Underpricing

	(1)	(2)	(3)	(4)
		1st-stage		2nd-stage
	life1	*life3*	*life4*	*Underpricing*
SimiPublic_life1	0.765***	0.085*	0.020	
	(0.056)	(0.049)	(0.020)	
SimiPublic_life3	0.167**	0.637***	0.013	
	(0.069)	(0.064)	(0.025)	
SimiPublic_life4	-0.106	0.409**	0.163**	
	(0.188)	(0.172)	(0.076)	
life1				0.686***
				(0.265)
life3				2.459***
				(0.517)
life4				4.772
				(4.881)
lnamntoffer	-0.019***	-0.005	0.002	-0.008
	(0.003)	(0.003)	(0.001)	(0.020)
lnage	0.001	0.003	0.002**	-0.053***
	(0.002)	(0.002)	(0.001)	(0.017)
VC_back	0.025***	0.016***	-0.007***	0.114***
	(0.005)	(0.004)	(0.002)	(0.043)
underwriter_repu	0.011**	-0.004	-0.001	0.129***
	(0.004)	(0.004)	(0.002)	(0.025)
NasdaqRet2Month	-0.043**	0.012	-0.005	0.567***
	(0.021)	(0.021)	(0.008)	(0.155)
Constant	-0.009	-0.078*	0.109*	-1.078
	(0.050)	(0.045)	(0.062)	(0.669)
Observations	2,510	2,510	2,510	2,510
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
SW F-stat (p-val)	269.57 (0.000)	101.34 (0.000)	4.77 (0.029)	-

Table 10. IV Analysis: Product Life Cycle and Post-IPO Corporate Finance Decisions

This table reports the instrumental variable (IV) regression results of post-IPO corporate finance decisions on the product life cycle. The instruments *SimiPublic_life1*, *SimiPublic_life3*, and *SimiPublic_life4* are described in Section 5.2. The first three columns show the first stage regression results, regressing product life cycle variables *life1*, *life3*, and *life4* on the instruments, other controls, and year and industry fixed effects as in Equation 2. Columns (4) to (9) show the second stage regression results from Equation 3. The dependent variables in columns (4) and (5) are *SEO_3yrs* and *SEO_5yrs*, two dummy variables equal to one if a firm conducts an SEO within three and five years since its IPO an zero otherwise. The dependent variables in columns (6) and (7) are *Div_3years* and *Div_5years*, defined as the natural logarithm of one plus the total amount of dividend paid out in millions within three and five years after the IPO. The dependent variables in columns (8) and (9) are *Acq_3yrs* and *Acq_5yrs*, dummy variables which equal to one if a firm conducts an acquisition within three or five years since its IPO an zero otherwise. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. *ln(amntoffer)*, *ln(age)*, *VC_back*, *underwriter_repu*, *Nasdaq2MonthRet* are defined in Section 3.2.2. The continuous control variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects. The last row of the table reports the Sanderson-Windmeijer F-statistics for weak identification test with the p-val in parentheses. Standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1st-stage			2nd-stage					
	life1	*life3*	*life4*	*SEO_3yrs*	*SEO_5yrs*	*Div_3yrs*	*Div_5yrs*	*Acq_3yrs*	*Acq_5yrs*
SimiPublic_life1	0.758***	0.076	0.023						
	(0.055)	(0.048)	(0.020)						
SimiPublic_life3	0.165**	0.627***	0.016						
	(0.067)	(0.063)	(0.025)						
SimiPublic_life4	-0.135	0.342**	0.187**						
	(0.185)	(0.169)	(0.076)						
life1				0.960***	1.046***	-3.894***	-3.933***	-0.871***	-0.789***
				(0.252)	(0.244)	(0.956)	(0.948)	(0.277)	(0.266)
life3				-0.575	-0.722	-4.153***	-4.353***	1.468***	1.658***
				(0.479)	(0.470)	(1.606)	(1.639)	(0.512)	(0.496)
life4				3.499	0.299	17.963	11.875	-4.460	-1.461
				(5.025)	(4.778)	(16.299)	(16.190)	(4.983)	(4.795)
lnamntoffer	-0.018***	-0.004	0.002	0.015	0.016	0.257***	0.308***	0.053***	0.045**
	(0.003)	(0.003)	(0.001)	(0.018)	(0.017)	(0.063)	(0.063)	(0.019)	(0.019)
lnage	0.001	0.003	0.002**	-0.004	0.003	-0.046	-0.034	0.011	0.015
	(0.002)	(0.002)	(0.001)	(0.015)	(0.014)	(0.057)	(0.056)	(0.016)	(0.015)
VC_back	0.026***	0.015***	-0.007***	0.036	0.001	-0.165	-0.270*	-0.058	-0.030
	(0.005)	(0.004)	(0.002)	(0.046)	(0.045)	(0.140)	(0.141)	(0.046)	(0.045)
underwriter_repu	0.009**	-0.004	-0.000	-0.048**	-0.060***	0.078	0.094	0.011	0.007
	(0.004)	(0.004)	(0.002)	(0.023)	(0.023)	(0.072)	(0.072)	(0.023)	(0.023)
NasdaqRet2Month	-0.047**	0.013	-0.003	-0.036	-0.054	-0.593*	-0.801**	-0.145	-0.100
	(0.021)	(0.021)	(0.008)	(0.110)	(0.109)	(0.356)	(0.357)	(0.119)	(0.114)
Constant	-0.007	-0.070	0.108*	0.107	0.501	-0.568	0.144	1.510**	0.941
	(0.050)	(0.044)	(0.063)	(0.824)	(0.690)	(2.278)	(2.236)	(0.705)	(0.640)
Observations	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat (p-val)	272.81 (0.000)	110.19 (0.000)	6.33 (0.012)	-	-	-	-	-	-

Table 11. Changes Around the American Inventor Protection Act: IPO Follow-though, Underpricing, and Equity Offered

This table examines product market competition as an underlying channel of how product life cycle affects firms' corporate finance decisions during IPO. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable in columns 1 and 2 is *IPO_Effective*, in columns 3 and 4 *Underpricing*, and in columns 5 and 6 *SharesOffered/SharesAfter*, defined as in Table 2, 4, and 3 respectively. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)*, *ln(age)*, *VC_back*, *underwriter_repu*, and *Nasdaq2MonthRet* are defined in the previous tables. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects.The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) *1(IPO_Effective)*	(2) *Underpricing*	(3) *SharesOffered/SharesAfter*
*life1*Post*	-0.137	-0.349***	0.115**
	(0.108)	(0.127)	(0.057)
life1	0.261***	0.381***	-0.218***
	(0.093)	(0.131)	(0.051)
life3	0.046	0.133	-0.018
	(0.081)	(0.101)	(0.041)
life4	-0.236	-0.167	0.030
	(0.188)	(0.162)	(0.106)
lnamntoffer	0.044***	-0.026**	0.010*
	(0.010)	(0.012)	(0.006)
lnage	0.009	-0.034***	0.006
	(0.008)	(0.009)	(0.004)
VC_back	-0.034**	0.127***	-0.018**
	(0.017)	(0.020)	(0.008)
underwriter_repu	0.012	0.124***	-0.059***
	(0.016)	(0.022)	(0.007)
NasdaqRet2Month	0.485***	0.547***	0.067**
	(0.081)	(0.140)	(0.033)
Constant	1.026***	0.065	0.362***
	(0.094)	(0.085)	(0.085)
Observations	3,297	2,577	2,408
R-squared	0.127	0.273	0.227
Controls	YES	YES	YES
IPO Year	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled

Table 12. Changes Around the American Inventor Protection Act: Post-IPO Corporate Finance Decisions

This table examines product market competition as an underlying channel of how product life cycle affects firms' corporate finance decisions during IPO. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The dependent variable in columns 1 and 2 is *IPO_Effective*, in columns 3 and 4 *Underpricing*, and in columns 5 and 6 *SharesOffered/SharesAfter*, defined as in Table 2, 4, and 3 respectively. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)*, *ln(age)*, *VC_back*, *underwriter_repu*, and *Nasdaq2MonthRet* are defined in the previous tables. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects.The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	SEO_3yrs	*SEO_5yrs*	*Div_3yrs*	*Div_5yrs*	*Acq_3yrs*	*Acq_5yrs*
*life1*Post*	0.273*	0.292**	-2.084***	-2.405***	0.184	0.011
	(0.143)	(0.147)	(0.413)	(0.448)	(0.144)	(0.147)
life1	0.104	0.098	0.034	0.126	-0.567***	-0.430***
	(0.125)	(0.129)	(0.348)	(0.379)	(0.131)	(0.131)
life3	-0.054	-0.046	-0.207	-0.180	0.206*	0.219**
	(0.105)	(0.107)	(0.337)	(0.360)	(0.110)	(0.109)
life4	-0.806***	-0.876***	0.859	0.908	-0.284	-0.154
	(0.221)	(0.226)	(0.915)	(0.977)	(0.248)	(0.242)
lnamntoffer	0.008	0.003	0.351***	0.391***	0.046***	0.042***
	(0.013)	(0.013)	(0.045)	(0.048)	(0.014)	(0.014)
lnage	0.003	0.003	-0.017	-0.016	0.006	0.016*
	(0.010)	(0.010)	(0.036)	(0.038)	(0.010)	(0.010)
VC_back	0.028	0.019	-0.421***	-0.470***	-0.043*	-0.029
	(0.022)	(0.022)	(0.057)	(0.063)	(0.022)	(0.022)
underwriter_repu	-0.043**	-0.053**	0.039	0.055	0.019	0.010
	(0.021)	(0.022)	(0.061)	(0.065)	(0.021)	(0.021)
NasdaqRet2Month	-0.129	-0.141	-0.514*	-0.699**	-0.080	-0.047
	(0.100)	(0.102)	(0.307)	(0.326)	(0.108)	(0.107)
Constant	0.791***	0.774***	-0.153	-0.252	1.130***	0.924***
	(0.277)	(0.263)	(0.766)	(0.692)	(0.128)	(0.166)
Observations	2,651	2,651	2,651	2,651	2,651	2,651
R-squared	0.121	0.133	0.273	0.280	0.206	0.193
IPO Year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled

Appendix

A Constructing the Product Life Cycle Measures

Similar to Hoberg and Maksimovic (2022), we measure the firm product life cycle vector based on all paragraphs in S-1 that contain at least one word from each of the following two lists.

Life1 List A: product OR products OR service OR services

Life1 List B: development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand

Life2 List A: cost OR costs OR expense OR expenses

Life2 List B: labor OR employee OR employees OR wage OR wages OR salary OR salaries OR inventories OR inventory OR warehouse OR warehouses OR warehousing OR transportation OR shipping OR freight OR materials OR overhead OR administrative OR manufacturing OR manufacture OR production OR equipment OR facilities OR

Life4 List A: product OR products OR service OR services OR inventory OR inventories OR operation OR operations

Life4 List B: obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing

To measure Life3 weight, we require three word lists. A firm's S-1 must contain at least one word from List A and List B, and must not contain any words from the List C.

Life3 List A: product OR products OR service OR services

Life3 List B: line OR lines OR offerings OR mix OR existing OR portfolio OR current OR categories OR category OR continue OR group OR groups OR customer OR customers OR core OR consists OR continues OR provide OR providing OR provided OR providers OR includes OR continued OR consist

Life3 List C(exclusions): development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand OR future OR obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing OR cost OR costs OR expense OR expenses

B An Example

In general, S-1 documents contain multiple paragraphs in each of the four product life cycles. For example, Fitbit's S-1 has 76 paragraphs related to the product innovation phase, 71 paragraphs describing the process innovation phase, 48 paragraphs associated with the mature products, and 15 paragraphs for the declining phase. We categorize the paragraphs into the four product life-cycles based on the dictionary as detailed in Appendix A. Here we provide an example of one paragraph in Fitbit's S-1 for each of the four product life-cycles:

Life 1: Continue to introduce innovative products. We will continue to develop the world's most innovative and diverse connected health and fitness devices. Furthermore, we plan to continue to make significant investments in research and development to further strengthen our platform through both internally-developed and acquired technologies. In 2013 and 2014, we introduced five new connected health and fitness devices and added features including automatic sleep detection, heart rate tracking, call and text notifications, music control, and GPS tracking for speed, distance, and exercise routes.

Life2: We outsource the manufacturing of our products to several contract manufacturers, including Flextronics which is our primary contract manufacturer. These contract manufacturers produce our products in their facilities located in Asia. ... We believe that using outsourced manufacturing enables greater scale and flexibility at lower costs than establishing our own manufacturing facilities. We evaluate on an ongoing basis our current contract manufacturers and component suppliers, including, whether or not to utilize new or alternative contract manufacturers or component suppliers.

Life3: We rely on a limited number of suppliers, contract manufacturers, and logistics providers, and each of our products is manufactured by a single contract manufacturer.

Life4: During 2013, the Company recorded excess and obsolete Fitbit Force inventory-related amounts of \$10.3 million, included in the reserve, and wrote-off \$1.7 million for specialized Fitbit Force tooling and manufacturing equipment to cost of revenue as incurred in the consolidated statement of operations. During 2014, legal fees of \$2.9 million were recognized as incurred, in addition to legal settlement costs of \$0.5 million related to the Fitbit Force recall, which were included in general and administrative costs in the consolidated statement of operations. During the three months ended March 31, 2015, a benefit to legal expenses of \$0.1 million was recognized as incurred in general and administrative costs.

C Sub-Sample Tests

Table C1. Sub-Sample Analysis by Information Asymmetry

This table examines corporate finance decisions during IPO and product life cycles by grouping firms based on their information asymmetry environment. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The information asymmetry measure is defined as the average analysts' earnings forecast dispersion for each 2-digit SIC industry. The sample of IPO firms is categorized into Low and High group based on the average forecast dispersion of a firms' primary industries. The dependent variable in columns 1 and 2 is *IPO_Effective*, in columns 3 and 4 *Underpricing*, and in columns 5 and 6 *SharesOffered/SharesAfter*, defined as in Table 2, 4, and 3 respectively. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)*, *ln(age)*, *VC_back*, *underwriter_repu*, and *Nasdaq2MonthRet* are defined in the previous tables. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects.The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Information Asymmetry	(1) **Low** *1(IPO_Effective)*	(2) **High**	(3) **Low** *Underpricing*	(4) **High**	(5) **Low** *SharesOffered/SharesAfter*	(6) **High**
life1	0.059	0.272***	0.169	0.218*	-0.130**	-0.166***
	(0.109)	(0.102)	(0.137)	(0.112)	(0.056)	(0.045)
life3	-0.027	0.031	0.153	0.122	-0.100*	0.080
	(0.114)	(0.114)	(0.160)	(0.140)	(0.060)	(0.056)
life4	-0.062	-0.356	-0.135	-0.110	-0.104	0.183
	(0.235)	(0.332)	(0.226)	(0.251)	(0.133)	(0.187)
lnamntoffer	0.036**	0.038**	-0.031*	-0.017	0.010	0.010
	(0.014)	(0.015)	(0.017)	(0.018)	(0.007)	(0.009)
lnage	0.014	0.005	-0.031**	-0.039***	0.009	-0.002
	(0.011)	(0.012)	(0.012)	(0.014)	(0.006)	(0.006)
VC_back	-0.024	-0.027	0.157***	0.088***	-0.016	-0.022*
	(0.023)	(0.024)	(0.029)	(0.030)	(0.010)	(0.012)
underwriter_repu	0.017	0.008	0.132***	0.121***	-0.066***	-0.054***
	(0.023)	(0.023)	(0.032)	(0.030)	(0.011)	(0.010)
NasdaqRet2Month	0.238**	0.726***	0.549**	0.494***	0.100**	0.059
	(0.114)	(0.100)	(0.220)	(0.173)	(0.043)	(0.049)
Constant	1.160***	0.940***	0.050	0.062	0.319***	0.281***
	(0.104)	(0.101)	(0.108)	(0.111)	(0.090)	(0.089)
Observations	1,627	1,660	1,300	1,270	1,204	1,197
R-squared	0.156	0.174	0.279	0.278	0.306	0.200
IPO Year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled

Table C2. Sub-Sample Analysis by Product Market Competition

This table examines corporate finance decisions during IPO and product life cycles by grouping firms based on their product market competition. The IPO sample includes IPOs from 1994 to 2018. The detailed description of the sample is provided in Section 3. The product market competition measure is defined as the Herfindahl-Hirchman Index (HHI) for each 2-digit SIC industry. The sample of IPO firms is categorized into Low and High group based on the HHI of firms' primary industries. The dependent variable in columns 1 and 2 is *IPO_Effective*, in columns 3 and 4 *Underpricing*, and in columns 5 and 6 *SharesOffered/SharesAfter*, defined as in Table 2, 4, and 3 respectively. *life1*, *life2*, *life3*, and *life4* are the product life cycle variables described in Section 3.2.1. *ln(amntoffer)*, *ln(age)*, *VC_back*, *underwriter_repu*, and *Nasdaq2MonthRet* are defined in the previous tables. The continuous independent variables are winsorized at 1% and 99% levels. All specifications include year and industry fixed effects.The standard errors are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Market Concentration	**Low**	**High**	**Low**	**High**	**Low**	**High**
	1(IPO_Effective)		*Underpricing*		*SharesOffered/SharesAfter*	
life1	0.052	0.310***	0.124	0.213*	-0.138***	-0.144**
	(0.101)	(0.113)	(0.116)	(0.126)	(0.042)	(0.057)
life3	-0.042	0.111	0.169	0.074	0.044	-0.086
	(0.113)	(0.118)	(0.155)	(0.132)	(0.052)	(0.062)
life4	-0.347	-0.067	-0.512	0.114	0.198	-0.071
	(0.330)	(0.233)	(0.318)	(0.184)	(0.159)	(0.144)
lnamntoffer	0.041***	0.047***	-0.054**	-0.008	0.007	0.014*
	(0.015)	(0.014)	(0.021)	(0.015)	(0.008)	(0.008)
lnage	0.017	0.002	-0.048***	-0.025**	0.010	0.002
	(0.013)	(0.011)	(0.016)	(0.011)	(0.007)	(0.006)
VC_back	0.011	-0.075***	0.085***	0.159***	-0.021**	-0.016
	(0.023)	(0.025)	(0.030)	(0.027)	(0.010)	(0.012)
underwriter_repu	-0.007	0.029	0.184***	0.071**	-0.056***	-0.061***
	(0.022)	(0.024)	(0.030)	(0.032)	(0.009)	(0.012)
NasdaqRet2Month	0.342***	0.587***	0.244	0.809***	0.066*	0.062
	(0.112)	(0.109)	(0.204)	(0.171)	(0.039)	(0.051)
Constant	0.633***	1.028***	0.288	-0.070	0.280***	0.430***
	(0.139)	(0.119)	(0.237)	(0.086)	(0.096)	(0.110)
Observations	1,626	1,668	1,296	1,279	1,222	1,184
R-squared	0.110	0.166	0.265	0.312	0.171	0.285
IPO Year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled

The Impact of Firm Life Cycle on Stock Repurchases and Firms' Post-Repurchase Performances *

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Abstract

This paper shows that firms consider their life cycles when making share repurchase decisions. Mature firms with limited investment opportunities but excessive cash repurchase more shares than innovative firms with numerous profitable investment projects but limited funding. Moreover, firms adapt their financing and stock repurchase strategies according to their dynamic life cycles such that firms switching from the mature to the innovation stage of their life cycles change from repurchasing shares to SEOs. In line with the agency theory, repurchasing mature firms outperform non-repurchasing mature firms in the post-repurchase period. Our instrument variable approach implies that firm life cycles directly affect firms' stock repurchases. Using the Energy Independence and Security Act of 2007 as an exogenous shock for firms' energy innovation, we draw causal inferences between firms' life cycles and their stock repurchase decisions. The findings shed new light on the popularly debated policy proposals as they indicate firms do not sacrifice corporate investments, employment, and other future prospects for the stock repurchase payouts.

Keywords: payout policy, share repurchases, buy-backs, corporate investment, real effects, employment, firm life cycles, product market, regulations, firm performance
JEL: G32, G35, G40

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1 Introduction

Stock repurchases have become an increasingly popular payout method in the last three decades and one of the most debated areas for regulation. Proponents of regulating open market stock repurchases advocate that firms need to satisfy minimum investment standards before gaining eligibility for stock repurchases. They claim that firms sacrifice other investment opportunities that can otherwise benefit the firms and their employees when they repurchase stocks. However, the academic literature has not empirically investigated this claim's validity on a broad sample of stock repurchases. In this paper, we answer whether such proposed regulations benefit the firms and the economy.

Agency theory postulates that firms with free cash flow and limited investment opportunities benefit from disbursing cash back to their shareholders to avoid negative consequences such as managers' perquisite consumptions or non-profitable investment projects (Jensen, 1986; Stulz, 1990; Grullon and Michaely, 2004). Meanwhile, firm life cycle theory suggests that internal fund flows of firms in the mature life cycle outpace their limited profitable investment opportunities (Mueller, 1972). Mature stage firms enjoy a stable inflow of income and likely sit on excessive cash while facing limited investment opportunities, and firms at the younger stage encounter many profitable investment projects but experience financial constraints to fund these projects. Combining the two strands of literature stipulates that mature firms are more likely subject to agency problems than firms in the early life cycle. In turn, mature firms can benefit by distributing the excess cash back to shareholders via stock repurchases, and firms in the early life cycle are better off raising external financing to invest in profitable projects and establish their grounds in the product market. This hypothesis argues against the rationale behind currently suggested regulations on stock repurchases. To shed more light on the importance of stock repurchases, this paper tests firms' stock repurchase behaviors in the open market conditional on their firm life cycles, as well as the corresponding consequences on firms' real effects.

Recent academic literature has developed novel textual-based methodologies to extract firms' life cycles based on the Abernathy and Utterback (1978) model, which classifies companies into four life stages: innovative, cost-minimizing, mature, and the declining stage. We follow the methodologies in Hoberg and Maksimovic (2019) and Chen et al. (2021) that use the content of firm 10-K filings to proxy for firms' product life cycles. We then aggregate the product life cycles at the firm level to obtain a dynamic measure of firm life cycle, as in Oreski (2021). This dynamic measure enables a firm's life cycle to change from one year to another, depending on its exposure to the product market. This variation helps us examine how a firm repurchases shares at various stages of its life cycle.

We draw four main empirical conclusions. First, the results show that conditional on life cycles, mature firms are more likely to repurchase shares in the open market and spend more money buying back their shares than innovative firms. In terms of economic magnitude, an average mature firm is 6.7% more likely to conduct stock repurchases and spend 23.7% more than the unconditional mean on stock repurchases than innovative firms in a given year, both of which are sizable effects.

Second, we hypothesize that firms that experience life cycle transitions update their payout policy and financing decisions. In particular, firms that switch from the mature to the innovation stage from one year to the next are likely to revise their financial policy from stock repurchases to equity issuance from the prior year to the next. Our empirical findings strongly support this hypothesis: mature firms changing to the innovation stage are 3.1% more likely to switch from stock repurchases to seasoned equity offerings (SEOs). Therefore, we argue that firms make payout and financing decisions based on their life cycles. Specifically, as mature firms have limited profitable investment opportunities but stable cash income, they distribute the cash back to shareholders via stock repurchases. In contrast, innovative firms have limited funding but many profitable investment projects. Thus, firms whose life cycles change from mature to innovative adapt from distributing extra cash via stock repurchases to issuing SEOs to fund new profitable investments.

Third, we test an additional prediction of Bond and Zhong (2016): firms that repurchase shares before raising external financing are able to issue more equity later through SEOs. We analyze firms in the same life cycle that adopt different payout policies. We match firms by their life cycles, year, and two-digit industry and find the closest matched firm on seven different dimensions. The comparison of firms in the same life cycle reveals that the ones that repurchase shares are able to issue an average of $138.32 million more equity within the next five years. These results establish that conditional on firms' life cycles, stock repurchases enable firms to raise more funding when they need it later on, for instance, when they switch to the innovation stage and need financing for profitable investments.

Fourth, after providing evidence that firms consider their life cycles when repurchasing shares, we investigate the main argument for regulating share repurchases. Namely, firms trade off their future prospects with current share repurchases that only raise share prices in the short-term. We focus on mature firms that repurchase shares versus mature firms that do not repurchase shares in the same period. These sub-sample tests narrow the scope of analysis to firms with stable income but limited profitable investments. We find that mature firms that repurchase shares perform better in the future than those that do not repurchase shares. The better firm performances are reflected in terms of real effects such as higher future net income, total factor productivity (TFP), profitability, and in terms of financial effects such as higher long-run abnormal stock returns. The findings conform to the agency theory that profitable firms with limited investment opportunities (i.e., those facing more severe agency conflicts) should distribute the extra cash back to their shareholders to avoid agency problems that hurt their firm values.

To eliminate the endogeneity concerns in estimating the effect of firm life cycle on the decision of open market stock repurchases, we use two different identification strategies. First, we adopt an instrumental variable (I.V.) approach with firm age as the instrument for firm life cycles and find consistent results - mature firms repurchase more shares than innovative firms. The I.V. analyses delineate that firm life cycles are a key determinant that motivates firms whether or not to repurchase shares in the open market. Applying the same instrument to study post-repurchase real effects, we confirm that firms that repurchase shares conditional on their firm life cycles do not sacrifice their future performances for current stock repurchases.

Second, we exploit the Energy Independence and Security Act (EISA or the Act from here on) of 2007 as a quasi-natural experiment. The Act initiates a set of new energy standards that firms in energy intensive industries must satisfy and provides incentives for these firms to develop energy efficient products and processes. It specifies the list of industries that the U.S. government classifies as energy intensive and thus subject to the regulation imposed by the Act. This regulation forces firms in these energy intensive industries to innovate with respect to their energy consumption and products or they would face hefty penalties that can potentially outweigh the cost of developing energy innovation. For mature firms in the energy intensive industries, the Act moved their life cycles toward younger stages by imposing the new energy consumption standards, reducing their excessive cash, and thus decreasing their propensity to distribute cash via stock repurchases. On the other hand, the life cycles of innovative firms in the energy intensive industries were not affected because they were already innovating in other aspects. Any regulation that forces them to incur energy innovation would not change their life cycles. Thus, the affected mature firms will reduce their stock repurchases relative to innovative firms after the enactment of the Act. In other words, the affected mature firms should repurchase more than affected innovative firms before the Act, but such differences should dissipate after the Act came into effect. Utilizing this exogenous shock on firm life cycles, we find evidence that mature firms required by the Act for energy innovation repurchase less in the post-enactment period than in the pre-enactment period relative to innovative firms in the energy intensive industries. Hence, our difference-in-differences analysis confirms that firm life cycles directly influence firms' stock repurchase decisions.

Collectively, our results have crucial policy implications. First, firms appear to consider their life cycles and thus their available investment opportunities when making stock repurchase decisions: mature firms with abundant cash but few investment projects repurchase more shares than innovative firms with many investment opportunities but tight funding. Thus, regulations on stock repurchases should consider firms' life cycles. Second, profitable firms with limited investment projects that distribute money back to shareholders outperform their counterparts that do not repurchase while holding on to the excessive cash. Consequently, forcing a minimum investment standard on all firms can aggravate mature firms' agency conflicts. Third, firms that repurchase shares already take into account their investment opportunities and the effect of such repurchases on their future prospects. As the evidence does not point to forgone future prospects, it is questionable to regulate open market stock repurchases by arguing that open market share repurchases inhibit firms' growths.

Our paper is most closely related to the literature that uses the firm life cycle as an explanation for the observed dividend patterns, such as Grullon et al. (2002) and DeAngelo et al. (2006). But, those papers do not focus on share repurchases nor do they directly test the life cycle hypothesis. We directly test the firm life cycle impact on the share repurchase decisions building a textual analysis proxy for the firm life cycle. Furthermore, the general dividend pattern only explains the life cycle transition when firms shift from a young to a declining life cycle phase. Yet, the firm life cycle theory and Miller and Friesen (1984) postulate that firms can also transition from an older to a younger life cycle phase. Therefore, we acknowledge that firms do not progress inevitably down the life cycle and that their life cycle is dynamic.

This paper also adds to the strand of literature on open market repurchase programs. The traditional line of papers has analyzed the numerous reasons for open market share repurchases spanning from takeover deterrence (Dann, 1981), signaling firm value (Vermaelen, 1981; Ofer and Thakor, 1987), correcting undervaluation (Dittmar, 2000), adjusting shareholder disagreement with management (Huang and Thakor, 2013), and timing the market

(Dittmar and Field, 2015).[1] We highlight another important determinant of share repurchases, the life cycles of the repurchasing firms. Although the literature on share repurchases is rich, no papers study how dynamic firm life cycles affect firms' share repurchase decisions. This paper is the first to analyze and show that when firms consider their life cycles for share repurchase decisions, they sustain their post-repurchase firm performances. Further, our contribution also lies in the direct policy implications originated from our results that not only address the flaws in currently proposed regulations on open market share repurchases, but also on the rationale provided for such regulations.

This paper additionally complements the literature that studies firm life cycles. Abernathy and Utterback (1975) provides the seminal work on dynamic life cycles, and Hoberg and Maksimovic (2019) and Chen et al. (2021) apply textual analysis to empirically compute such life cycles. Other papers have attended to different proxies for firm life cycles and study their relationship with firm performance. For example, DeAngelo et al. (2006) use earned equity to common equity ratio as the proxy for firm life cycle, whereas DeAngelo et al. (2010) and Grullon et al. (2002) use dividend history and dividend increases respectively. Anthony and Ramesh (1992) and Kueng et al. (2014) measure firm life cycles with firm size, while Dickinson (2011) emphasizes on the trends of cash flow to estimate the life cycle of a firm. These papers use endogenous variables as the proxy for firm life cycles except for those using firm age (e.g., DeAngelo et al. (2010)). However, firm age is monotonic and cannot dynamically approximate changes in the life cycle within a firm (Hoberg and Maksimovic, 2019). Our paper distinguishes from the prior work as the first paper that uses an exogenous variable, firm age, as the instrument for dynamic life cycle measures to investigate its associated impact on open market stock repurchase programs. Our methodology retains the dynamic nature of firm life cycles while alleviating endogeneity issues, enabling us to draw more concrete and novel inferences. Further, our identification strategy using the EISA of 2007 as an exogenous shock firm life cycles and thus their corresponding share repurchase

[1] Please refer to Allen and Michaely (2003) for a detailed review of papers analyzing motivations for share repurchases.

decisions is also nascent to the literature.

Moreover, our paper is tangent to Allen et al. (2020), which, to our best knowledge, is the only paper that links firm life cycle with regulation. The critical distinction is that their paper focuses on the negative impact of financial regulation on young firms' innovation process ex-post, whereas our paper evaluates the rationale and ex-ante potential outcomes for regulating open market share repurchases. In addition, our paper not only emphasizes on firms at the mature stage of their life cycles but also speaks to firms in all life cycle stages. In sum, this paper is the first in the literature to analyze firms' stock repurchase activities while considering their life cycles. The finding that firms take into account their life cycles and investment opportunity sets before repurchasing shares is novel to the literature and carries a strong policy implication.

The rest of the paper is organized as follows. Section 2 presents hypothesis development. Section 3 describes the data construction and summary statistics. Section 4 focuses on the baseline and the changes in payout, and the financing decisions under dynamic firm life cycles. Section 5 displays the comparison between mature firms that repurchase shares and those that do not. Section 6 dives in with the instrumental variable analysis, which is used to further study firms' post-repurchase real effects in Section 7. We provide the details about the background and the analyses of our difference-in-differences identification strategy in Section 8. Section 9 addresses the policy debate on regulating open market repurchase programs and Section 10 concludes.

2 Hypothesis Development

Traditional corporate finance theory suggests that when a firm faces favorable prospects (i.e., investment projects with positive net present value), it should raise funds to finance these profitable projects (Modigliani and Miller, 1958; Myers and Majluf, 1984). On the other hand, if a firm has limited investment projects with positive net present value and it has extra cash on hand, it should distribute those cash back to its investors to avoid agency cost such as empire building, in line with its shareholders' interests (Jensen, 1986). Furthermore, Chen et al. (2021) demonstrate that firm insiders possess private information on the firm's future prospects and on the firm's life cycle. As firms later in the life cycle (i.e., mature firms) have fewer profitable investment projects but more steady income than firms earlier in the life cycles (i.e., innovative firms) (Arikan and Stulz, 2016; DeAngelo et al., 2006), it is natural to conjecture that mature firms will more likely repurchase shares than innovative firms. This leads to our first hypothesis:

H1: Firms at the mature stage of the life cycle are more likely to repurchase shares than firms at the innovation stage of the life cycle.

At the core of the life cycle models is that firms' financing and payout policies change according to the firms' life cycles. DeAngelo et al. (2010) and Hoberg and Maksimovic (2019) find that firms earlier in the life cycle are more likely to issue equity to fund their innovative projects, while DeAngelo et al. (2006) demonstrate that mature life cycle firms pay out dividends. Together with the H1 hypothesis, these findings suggest that when firms transition from the mature to the innovation phase, they will adjust their financing and payout policies accordingly, i.e., from distributing cash via stock repurchases to raising equity vis SEOs. In other words, the financing and payout policy of a given firm is dynamic and in accordance with its dynamic product life cycle exposure. Importantly, our dynamic firm life cycle measure is able to capture such a development. Firms at one particular stage of the life cycle in one year can change to a different stage of the life cycle in another year depending on their exposure to different levels of their product life cycles. Thus, our next hypotheses relates to the financing and payout policy of firms with dynamic life cycles:

H2: Firms whose life cycles change from the mature stage in the previous year to the innovation stage in the following year are likely to switch from repurchasing shares in the previous year to issuing equity in the following year.

Bond and Zhong (2016) provide theoretical background arguing that firms that repurchase shares prior to any equity issuance are able to raise more equity funding than similar firms that do not repurchase shares before the equity issuance. They attribute the reason to the positive signaling effect of share repurchases. Meanwhile, our hypotheses in H1 and H2 indicate that firm life cycles are likely determinants for the stock repurchase and equity issuance decisions. Thus, by combining with the theoretical argument from Bond and Zhong (2016), we conjecture that conditional on firm life cycles, mature firms that repurchase shares will raise more capital via SEOs later on when their life cycles shift to the innovation stage than mature firms that do not repurchase shares but issue equity later on when they are at the innovation stage. Thus, this generates our third hypothesis:

H3: Firms at the mature stage that repurchase shares are able to raise more equity financing later when their life cycles change to the innovation stage, in comparison to firms at the mature stage that do not repurchase shares but later issue equity when they are at the innovation stage.

Our previous hypotheses imply that a firm's life cycle affects its repurchase decisions. Meanwhile, corporate finance theories postulate that firms should return the money to shareholders to alleviate agency problems when they face limited profitable investments (e.g., Jensen (1986)). Therefore, firm values for those at a life cycle stage with few profitable investment opportunities would benefit from distributing extra cash to their shareholders. They exploit stock repurchases to avoid investing in negative net present value (NPV) projects and manager's perquisite consumptions that hurt the firm. This formalizes our next hypothesis:

H4: Firms at the mature stage that repurchase shares perform better in market valuation and in firms' real effects than firms at the mature stage that do not repurchase shares.

Upon establishing the positive association between the mature stage of firm life cycle and the decision of stock repurchases, we postulate this relationship has causal inference. The intuition is that mature firms have few profitable investments but they collect stable rents from their established product market positions. Under these circumstances, as firm managers' objective is to maximize shareholder value, the best option is to give the excessive cash back to shareholders rather than investing them in negative NPV projects. Thus, this mechanism should be causal. Companies can payout the excessive cash via dividends or stock repurchases. Current literature has established that firms prefer to payout through stock repurchases due to its flexibility (e.g., Jagannathan et al. (2000); Brav et al. (2005)). As firm life cycles are dynamic, firms would prefer to payout the excessive cash through stock repurchases than increased dividends due to the stickiness of dividend payments (more permanent commitments). In turn, firms would favor stock repurchases to pay out the transient extra cash inflow at the mature stage of their life cycles. This should result in a direct relationship between firm life cycle and the payout decision of stock repurchases in addition to their positive association. Thus, we hypothesize that:

H5: The relationship between firm cycle and stock repurchase decisions is causal.

We argue that mature firms repurchase shares when they do not have alternative profitable investment opportunities to spend the money earned from their established markets. In other words, mature firms conduct stock repurchases to maximize their firm values given the constraints they face. If this represents a better practice than investing in other projects for value maximization, it should increase or not hinder their firm value. Therefore, this practice should not occur at the cost of forgoing profitable projects, firing employees, or debilitating other firms' prospects. This leads to our final hypothesis:

H6: Firms that repurchase shares when they are at the mature stage will not sacrifice corporate investments, employment, firm value, and other firm level real effects.

3 Data, Variables, and Summary Statistics

3.1 Data

We obtain all 10-K filings for all publicly listed firms filed between 2003 to 2020 from the SEC EDGAR database. These filings provide the content for the text-based measure of product life cycles and thus our measure of firm life cycle. We describe the details of their construction in the next subsection. As the 10-K filings are annual financial reports, our sample constitutes a panel data at the firm-year level. We use the Compustat database for all accounting measures to calculate the control and outcome variables and the quarterly spending on actual stock repurchases by firms, which we aggregate at the firm-year level. All annual Compustat control variables are matched to the previous fiscal year-end except for annual actual repurchases, which are contemporaneous. We also lag firm life cycles by one year to alleviate endogeneity concerns where concurrent firm fundamentals drive both the life cycle and share repurchase decisions. The Center for Research in Security Prices (CRSP) provides stock prices and value-weighted CRSP market index to calculate stock returns and abnormal stock returns.

We refer to the SDC Platinum Merger and Acquisition database for the data on firms' equity issuance through SEOs. We only include seasoned equity offerings (SEOs) and exclude all initial public offerings (IPOs) because we analyze the impact of open market stock repurchases on firms' ability to issue equity, and such stock repurchases are only possible for publicly listed firms. We also exclude closed-end funds, unit types, mortgage-backed offerings, and non-U.S. dollar dominated issuance from the sample.

3.2 Product and Firm Life Cycles

To measure the firm life cycle, we adopt a textual analysis methodology by Hoberg and Maksimovic (2019) and its relative aspect as in Oreski (2021). The methodology acknowledges that companies do not progress deterministically down the life cycle, but they can shift to any phase in any given year, depending on the life cycle of their products and the relative positions among their competitors. The relative aspect compares a company's life cycle only to similar firms, and not public companies in general (a software company is different than a restaurant chain).

To calculate the product life cycles of a company, the methodology exploits the regulation S-K, under which public companies are legally obliged to describe their key products or services, material product research and development to be performed, and the status of development effort for new or enhanced products, etc. A detailed description of the life cycle calculation can be found in Hoberg and Maksimovic (2019) and Oreski (2021). The textual analysis of 10-K financial statements results in a four-element vector. The elements proxy for the percentage of products in each of the four product life cycle phases, described in Abernathy and Utterback (1975). The final step ranks the four-element vector among similar firms and classifies the companies into one of the four firm life cycle stages: innovative, cost-minimizing, stable, and declining in a given year.

3.3 Outcome Variables

Our outcome variables for stock repurchases are *Repurchase Indicator* and *Scaled Dollar Repurchase*. *Repurchase Indicator* is an indicator variable that equals one if a company actually repurchases its own shares in the open market in a given year, and zero otherwise. *Scaled Dollar Repurchase* measures the natural log of the dollar amount that a firm spends in a given year on repurchasing its shares in the open market scaled by its firm size, and it is denoted as *Scaled $Repurchase* in tables. In other words, the former measures the likelihood of actual repurchases while the latter measures the level of stock repurchases.

The variable *Employment* is the number of employees working at a firm in a given year, directly obtained from the Compustat Annual database. The outcome variables that proxy for the real effects in Section 7 are all in terms of percentage growth. *Sales Growth* for firm i in year t is the percentage increase in sales for firm i from year t-1 to t. Similar definitions apply to *Asset Growth*, *Investment Growth*, and *Employment Growth*.[2] *Profitability* refers

[2]Investment is calculated as the sum of R&D Expenses and Capital Expenditure scaled by the Total

to the operating income before depreciation divided by total assets of the firm. Total Factor Productivity (TFP) at the firm level follows the procedures described in Chemmanur et al. (2010, 2011, 2018).[3]

3.4 Summary Statistics

Table 1 presents the summary statistics of the sample. There are a total of 58,709 firm-year observations with 8,222 firms in 64 two-digit SIC industries. A given firm in our sample spends an average of $70.35 million repurchasing its shares in a year. In terms of the scaled dollar amount of repurchase, it has an average of 0.14 with a standard deviation of 0.24.

Firm size is calculated as the natural log of market capitalization of a firm in a given year. Our sample firms have sizes from 0.38 to 11.33, with similar mean and median, indicating firms with a large variation in sizes are incorporated in our sample. All growth measures have positive average values, suggesting that an average firm in our sample has positive growth in various aspects.

An average firm in the sample spends about $52.36 million on dividend payments in a given year. However, a median firm does not pay any dividends or repurchase any shares. Firms also have a mean of 9,820 for the number of employees working there. Companies in our sample have an age ranging from 2 years to 66 years with an average of 20 years. A median firm has an age of about 16 years.

4 Main Results

Assets of the firm.

[3]We do recognize there is one caveat embedded in our TFP measure. Since their TFP calculation starts at the plant level, obtained from the Longitudinal Research Database (LRD) from the U.S. Census Bureau, we do not have access to this data yet. Thus, we use all the variables from COMPUSTAT to proxy for output (revenue), labor (number of employees), capital stock (book value of equity), and cost (cost of goods sold adjusted for change in inventory). The regression of log-linear Cobb-Douglas production function produces the TFP we currently use. We are in the process of getting approval from the U.S. Census Bureau to have access to the plant level data, and will update the measure accordingly upon approval.

4.1 Baseline Regressions

Firms possess information about their investment sets, the risk of the available investment opportunities, and the cash they own. Since mature firms usually have established market power but limited profitable investment opportunities (e.g., DeAngelo et al. (2006), Chen et al. (2021)), they are likely to have excessive cash. This creates opportunities for mature firms to distribute the excessive cash back to their investors via stock repurchases instead of investing in non-profitable (negative NPV) projects. On the other hand, innovative firms have many more investment opportunities, but limited cash, which makes them have less, if at all, excessive cash. Therefore, our central argument hypothesizes that mature firms are likely to repurchase more shares than firms at the innovation stage of the firm life cycle (H1). We examine this hypothesis by running the following regression specification:

$$\begin{aligned} Repurchase_{i,j,t} = {} & \beta_1 CostMinimizing_{i,j,t-1} + \beta_2 Mature_{i,j,t-1} + \beta_3 Declining_{i,j,t-1} \\ & + \beta_4 X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \end{aligned} \tag{1}$$

where $Repurchase_{i,j,t}$ captures the actual repurchase behaviors of firm i of industry j in year t. $Repurchase_{i,j,t}$ takes in two forms: *Repurchase Indicator* and *Scaled Dollar Repurchase*. $CostMinimizing_{i,j,t-1}$ equals one if firm i in year *t-1* belongs to the cost-minimizing stage, and zero otherwise. Similarly, $Mature_{i,j,t-1}$ and $Declining_{i,j,t-1}$ equal one if firm i of industry j in year *t-1* pertains to the mature stage, and declining stage respectively, and zero otherwise. Coefficient of interest is β_2. The omitted variable is firm life cycle at the innovation stage, which serves as the reference group. Accordingly, all results with this specification should be interpreted relative to firms at the innovative stage of the firm life cycle. $X_{i,j,t}$ is the vector of firm level control variables that can potentially affect their repurchase behaviors. γ_j and δ_t represent industry and year fixed effects, respectively. $\epsilon_{i,j,t}$ represents the residuals. We cluster robust standard errors at the industry and year level. Table 2 presents the results.

Column (1) and (2) of Table 2 use *Repurchase Indicator* as the dependent variables, whereas column (3) and (4) use *Scaled Dollar Repurchase* as the dependent variables. Columns (1) and (3) do not include control variables, while columns (2) and (4) include the full set of control variables. The positive and significant coefficients on *Mature* across all four columns suggest that firms at the mature stage of their life cycles are more likely to repurchase and spend more money in repurchasing their own shares than firms at the innovation stage. For economic significance, an average mature firm is 6.7% more likely to repurchase shares in a given year than an innovative firm. In terms of dollar amount, the coefficient on *Mature* in column (4) regarding *Scaled Dollar Repurchase* is 0.03321, which is 23.72% of the unconditional mean.[4] In other words, an average mature firm will likely spend 23.72% more on stock repurchases than an innovative firm in a given year. This set of results have sizable economic effects and are consistent with our hypothesis H1.

We control for various alternative variables that can motivate a firm to repurchase its shares in the open market, such as firm size, age, profitability, and the amount of cash available to the firm. We also include the need for cash by using Altman Z-Score (Altman, 1968), since DeAngelo et al. (2010) argues that the need for cash drives firms to repurchase shares. We control for market pressure using market-to-book ratios (MTB) and dividend-price ratios (D/P). To test robustness, we also include product market competition and prior returns as two additional controls and present the results in Table A.1 for succinctness. The results still hold with these controls.

This baseline result demonstrates that the dynamic firm life cycle drives firms' actual stock repurchases in the open market. Hence, our findings suggest that a firm's life cycle is a key determinant for its subsequent actual repurchase behaviors.[5] This vividly reflects the reality of open market repurchase programs in which firms repurchase shares sporadically. One firm might repurchase a large sum of shares in one year while not repurchasing any

[4]The unconditional mean for *Scaled Dollar Repurchase* is 0.14. The difference between a mature firm and an innovative firm is $\frac{0.03321}{0.014} = 0.2372$, which is 23.72%.

[5]Firm size has also been used in the literature as a proxy for firm life cycle (e.g., Doyle et al. (2007)). We include it as a control variable and it does not change the results, as depicted in Table 2.

shares many years before or after. Our results suggest that the firm life cycle affects the repurchase decision-making process. In other words, firms consider their life cycles when repurchasing shares in the open market.

4.2 Change in Life Cycles

The life cycle theory postulates that firms' financing and payout policies evolve with their life cycles. The literature has documented that firms with many innovation projects are likely to issue equity (Arikan and Stulz, 2016), while Section 4.1 has established that firms at the mature stage are more likely to repurchase shares than firms at the innovation stage. Hoberg and Maksimovic (2019) argue that firm life cycles are dynamic, depending on firms' exposure in the product market. Thus, firms can transition between the different stages of the life cycle from one year to the other, and these transitions do not have to be adjacent. For example, declining firms can jump to the innovative stage in the next year and vice versa. Combining dynamic firm life cycles with the variation in equity issuance and stock repurchases within firm life cycles, we hypothesize that firms that switch from the mature stage to the innovation stage between two consecutive years are likely to adapt from repurchasing shares to equity issuance (via SEOs) in the same period (H2). We verify this hypothesis using the following regression specifications:

$$Repur\_to\_SEO_{i,j,t-1,t} = \beta_1 Mature\_to\_Innovation_{i,j,t-2,t-1} + \beta_2 X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \quad (2)$$

where $Repur\_to\_SEO_{i,j,t-1,t}$ is an indicator variable that equals one if firm i of industry j only repurchased shares in the open market in year *t-1* and only issued equity via SEOs in year t, and zero otherwise. $Mature\_to\_Innovation_{i,j,t-2,t-1}$ is an indicator variable that equals one if firm i of industry j belongs to the mature group in firm life cycle in year *t-2* but changes to the innovation stage of the firm life cycle in year *t-1*, and zero otherwise. The other variables are defined as in Equation 1 and robust standard errors are double clustered by industry and year. Table 3 displays the regression results.

Column (1) of Table 3 excludes the set of control variables, whereas column (2) includes the full set of control variables. The coefficient on β_1 is positive and statistically significant in both columns, suggesting that firms whose life cycles change from the mature stage to the innovative stage from one year to the next, switch from stock repurchases in the previous year to equity issuance via SEOs the following year. This is consistent with our hypothesis H2 that firms' financing and payout policies respond in accordance to dynamic firm life cycles. In terms of economic significance, if a firm's life cycle switches from the mature stage to the innovative stage in two consecutive years, it is 3.14% more likely to go from strictly repurchasing shares in the open market in the previous year to strictly raising external equity in the following year.

These results provide further evidence that firms consider their life cycles when making payout decisions. When firms are at the mature stage, they face limited investment opportunities while holding extra cash. Therefore, they will benefit from giving the extra cash back to their shareholders. Once their life cycle stage changes, firm insiders observe the newly available investment opportunities and direct all resources to take advantage of these new profitable investments. As the profitable investment opportunities now expand beyond what they had at the mature stage in which they had paid out the extra cash, they likely need to raise outside capital to finance some of these profitable investments. Our finding of such a dynamic change in firm life cycles, and the corresponding movement in corporate financing and payout policy is novel to the literature. The analyses also shed new light on the regulations regarding open market stock repurchases and seasoned equity offerings (SEOs). Relevant policies should also consider the importance of firm life cycles when regulating these activities.

4.3 Stock Repurchases and Subsequent Equity Issuance

Bond and Zhong (2016) provided theoretical analyses arguing that firms that conduct stock repurchases are able to issue more equity later.[6] In the context of firm life cycle, the previous subsection displays that firms whose life cycles change from the mature to innovation stage are likely to switch from stock repurchases as the payout policy to issue equity via SEOs to raise external financing. This provides a realistic setting to empirically validate the theory of Bond and Zhong (2016) with respect to the effect of prior open market stock repurchases on firms' subsequent equity issuance. Hence, we postulate that conditional on firm life cycles, firms that repurchase their shares are able to raise more equity later than similar firms that do not repurchase shares before equity issuance (H3). We test this hypothesis in two ways. First, we conduct an OLS regression analysis with the following specification:

$$Equity\_Raised_{i,j,t+1,t+5} = \beta_1 Repur\_before\_SEO_{i,j,t} + \beta_2 X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \quad (3)$$

where $Equity\_Raised_{i,j,t+1,t+5}$ measures the dollar amount of equity that firm i of industry j raises between year $t+1$ to $t+5$. $Repur\_before\_SEO_{i,j,t}$ is an indicator variable that equals one if firm i of industry j spends a positive amount of money repurchasing its shares in year t. All the other variables are defined as in Equation 1. Second, we investigate H3 by finding closest matches for firms with the same life cycle but different repurchase behaviors in the same year and conduct two-way t-tests on the amount of equity that they are able to raise within the subsequent five-year period.[7] Panel A of Table 4 pertains to the regression specified in Equation 3, whereas Panel B of Table 4 presents the results on the second strategy using two-way t-test.

Table 4 Column (1) does not include any controls, while column (2) includes the full set

[6] For details of the theory, please see Bond, Philip, and Hongda, Zhong, 2016, Buying High and Selling Low: Stock Repurchases and Persistent Asymmetric Information, *The Review of Financial Studies*, 29(6), 1409-1452.

[7] We repeat the same two tests using the amount of equity raised in a one-year and three-year window. The results are similar.

of control variables. Positive and statistically significant coefficients on *Repurchase Before Equity Issuance* imply that if a firm conducts open market stock repurchase in a given year, it is able to raise more money via SEOs within the next five years. For an average firm that has conducted stock repurchases within the five years prior to any equity issuance, it is able to raise $412.84 million more through the SEOs. Note that this regression does not take into account the life cycle of the firm. Thus, the results should be interpreted as the average effect of repurchases on firms' ability to raise equity subsequently.

Table 4 Panel B compares firms in the same life cycle and how stock repurchases affect their ability to issue equity. We extract mature firms in a given year that have spent a positive amount of money repurchasing their shares as the treated firms, and matures firms in the same year that have not spent any money repurchasing their shares as the control firms. Treated firms are matched to control firms by exact two-digit SIC industry and year. Control firms are then sorted by the proximity to each treated firm based on firm size, profitability, market-to-book ratios, cash holdings, the amount of dividends paid, earnings, and age. We choose the closest matched control firm for each treated firm.

The first (second) row of Table 4 Panel B represents the average amount of equity that treated (control) firms are able to raise via SEOs in a five-year period following a stock repurchase. The third row represents the difference in the amount of equity raised between the treatment and control groups. The positive and statistically significant results suggest that in a given year, mature firms that repurchase shares in the open market can raise an average of $138.32 million more equity via SEOs within the next five years than other mature firms that do not repurchase shares in the same year. This is the first empirical finding supporting the notion that firms who repurchase shares first are able to raise more equity subsequently, conditional on the life cycles of the repurchasing and issuing firms.

5 Mature Firms with Repurchases and without Repurchases

Traditional corporate finance theory states that when firms face few profitable investment opportunities, they should pay out the cash they have back to investors to avoid agency problems such as empire building (e.g., Jensen (1986)). This procedure increases firm values and improves the firms' prospects. As the life cycle theory argues that firms whose life cycles are at the mature stage have limited investment opportunities, these firms should benefit from distributing extra cash back to shareholders. In other words, mature firms that pay out excessive cash to their shareholders should at least preserve their firm values and perform better in other operating aspects than mature firms that do not pay out excessive cash, thus subject to higher agency costs (H4).

To test this hypothesis, we restrict the sample to firms whose life cycles are at the mature stage. We bifurcate the sub-sample into two groups: firms whose life cycles are at the mature stage in year *t-1* *and* spend a positive amount of money in stock repurchases in year *t*, versus those at the mature stage in year *t-1* but *do not repurchase* any shares in year *t*. We create an indicator variable, *Repurchase*, that equals one if a firm belongs to the former group and zero otherwise. We use lagged firm life cycles because revenue made and thus excess cash accrues through time during the mature life cycle. Thus, it might be till the next year that the firm sees all the leftover cash. The tests follow the regression specification:

$$y_{i,j,t+n} = \beta_1 Repurchase_{i,j,t} + \beta_2 X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \tag{4}$$

where all firms are at the mature stage in year *t-1*. n $\in$ {1, 2, 3} in years. Thus, $y_{i,j,t+n}$ represents the outcome variables for firm i of industry j in year *t+1*, *t+2*, and *t+3*. The outcome variables include *Net Income*, *Total Factor Productivity (TFP)*, *Profitability*, and *buy-and-hold abnormal stock returns (BHAR)*. We examine the impact of stock repurchases on both real effects as well as financial effects. Table 5 presents the results on real effects, while Table 6 presents the results on market valuations using BHAR as the proxy. The rest of the variables in Equation 4 follow the same definitions as in Equation 1 and we cluster standard errors at the industry and year level.

Columns (1) through (3) have future *Net Income* as the dependent variables, (4) through (6) have *TFP*, and columns (7) through (9) have *Profitability* as the dependent variables. The coefficients on *Repurchase* are positive and statistically significant across all columns. Thus, the results imply that mature firms that repurchase shares perform better at the firm level than their counterparts who do not repurchase shares.[8]

Table 6 pertains to the market valuations of mature firms that repurchase shares versus mature firms that do not repurchase shares. The dependent variables are always buy-and-hold abnormal stock returns (BHAR) in three months, six months, one year, and two years after the year *t*. The difference is that columns (1) through (4) use the Market Model to calculate BHAR, whereas columns (5) through (8) use the Fama-French Three Factor model (Fama and French, 1993), and columns (9) through (12) use the Fama-French-Carhart Four Factor model to calculate BHAR (Carhart, 1997).

The coefficients on *Repurchase* are positive and statistically significant in all columns, suggesting that mature firms that repurchase shares earn higher long-run abnormal stock returns than their counterparts who do not repurchase shares. The results are robust to the different asset pricing models applied to calculate abnormal stock returns. In terms of economic significance, as *Repurchase* is an indicator variable, its coefficients directly reflect the differences in abnormal stock returns. For instance, the results in columns (5) through (8) suggest that if a mature-staged firm i in year *t-1* repurchases shares in the following year t, it will earn an average of 2.95% higher BHAR using the Fama-French Three Factor model in three months than a mature-staged firm j in year *t-1*, which does not repurchase shares in year t. This difference widens to 134% in two years. In other words, mature firms that repurchase shares earn twice as much in abnormal stock returns over two years

[8]The independent variable for *Profitability* is omitted for columns (7) through (9) where future *Profitability* is the dependent variable.

than mature firms that do not repurchase shares, a rather large difference. Hence, empirical results displayed in Table 6 imply that the market also favors firms whose life cycles are at the mature stage to distribute excess cash by repurchasing shares and alleviate agency costs.

This set of findings bear quintessential importance for policy implications. Our results directly point out that mature firms, who face limited profitable investment projects, perform better when they distribute extra cash via stock repurchases both at the firm and the market level. At the firm level they generate higher income, productivity, and profitability in the next three years. At the market level they earn higher abnormal stock returns in the long-run for up to two years. Thus, when drafting regulatory policies on open market share repurchases, the investment opportunities that firms at different life cycles face should be carefully considered. Our results point clearly that forcing firms with limited investment opportunities to keep excess cash or use that cash for non-profitable investment projects can hurt the firm both in real and financial aspects.

6 Instrumental Variable (I.V.) Analysis

We have established that firms consider their life cycles when making stock repurchase decisions. Specifically, firms whose life cycles are at the mature stage and face limited profitable investments are more likely to repurchase shares than firms at the innovation stage who have many profitable investments but limited funding. Mature firms that do repurchase shares also perform better than mature firms that do not repurchase shares. However, there could remain an unobserved variable that affects both firm life cycle and share repurchases. For instance, receivables in the previous year might affect the one period lagged life cycle of the firm. At the same time, as firms know that they have receivable coming in, they might start repurchasing shares using the money in hand and replenish that money with receivables when they arrive. We address this potential endogeneity concern with two different empirical strategies, using an instrumental variable (I.V.) and difference in differences analysis.

In particular, in the I.V. analysis we use firm age as the instrument for firm life cycle. Firm age is defined as the number of years a firm has appeared in the Compustat database since the first record of Compustat in 1950. To be a valid instrument, firm age needs to satisfy both the relevance and the exclusion restrictions. The academic literature has long been using firm age as a proxy for firm life cycle (e.g., Arikan and Stulz (2016)). The first-stage results of our IV analysis in all the columns of Table 7 demonstrate that the instrument satisfies the relevance condition with respect to our dynamic firm life cycle measures. Furthermore, we contend that firm age is exogenous to firm management and operations (i.e., firms cannot change their age endogenously) and affects stock repurchases only through firms' life cycles.

Because our firm life cycle measure is a categorical variable, in Table 7 we separate the firm life cycle into four indicator variables (innovative, cost-minimizing, stable, and declining) and use Probit models to run the first stage regressions with firm age as the instrument (Wooldridge, 2010). We then use the predicted firm life cycles as independent variables in the second stage regressions to estimate the direct effect of firm life cycles on firms' subsequent actual repurchase decisions. Table 8 reports the results on the second stage regressions, which is specified as follows:

$$\begin{aligned} Y_{i,j,t} = {} & \beta_1 CostMini\hat{m}izing_{i,j,t-1} + \beta_2 Matu\hat{r}e_{i,j,t-1} + \beta_3 Declini\hat{n}g_{i,j,t-1} \\ & + \beta_4 X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \end{aligned} \tag{5}$$

where $Y_{i,j,t}$ represents the outcome variables: *Repurchase Indicator* and *Scaled Dollar Repurchase*. All predicted life cycles are lagged by one year. $CostMini\hat{m}izing_{i,j,t-1}$, $Matu\hat{r}e_{i,j,t-1}$, and $Declini\hat{n}g_{i,j,t-1}$ are predicted life cycles from the first stage regression. The omitted variable is the predicted life cycle at the innovation stage, which serves as the reference group. The rest of the variables follow the definitions in Equation 1 and we continue double clustering standard errors at the industry and year level. Column (1) of Table 8 uses *Repurchase Indicator* as the dependent variable, and column (2) uses *Scaled Dollar Repurchase* as the dependent variable.

The coefficients on $\hat{Mature}$, firms whose predicted life cycles are at the mature stage using firm age, are positive and statistically significant at the 1% level in both columns. It suggests that mature firms are more likely to repurchase shares in the open market, and they are likely to spend more money buying back shares than firms at the innovation stage. This instrumental variable approach allows us to draw more direct inference on the effect of firm life cycles on firms' subsequent repurchase behaviors. Specifically, mature firms, which face limited investment opportunities, will conduct more stock repurchases than innovative firms, which face many profitable investment projects but have limited funding.

7 The Impact of Firm Life Cycle and Stock Repurchases on Real Effects

One common argument against open market stock repurchases is that firms repurchase their own shares instead of investing that money in available projects, employees, or firms' assets.[9] This generic statement does not take into account that firm managers have private information about their firms, such as their life cycles and future prospects. Given that firm life cycles directly determine firms' repurchase behaviors, these firms very likely make optimal investment and payout decisions given the information set. Furthermore, Brav et al. (2005) find evidence that firms consider stock repurchases after considering all profitable investments. Thus, we argue that when firms consider their firm life cycles (i.e., the investment opportunities they have given the life cycles they are in) and make stock repurchases decisions accordingly, they have already assessed the implications on their real performance. These firms likely repurchase shares only if the stock repurchases do not hurt their real performance (H6). In this section, we analyze the impact of open market stock repurchases on firms' real effects conditional on the firms' life cycles at the time when stock repurchase deci-

[9] Clark, Brian, "Buyback blowback: Why politicians on the right and left are targeting stock repurchase," CNBC, 8, May, 2019. https://www.cnbc.com/2019/05/08/stock-buybacks-politicians-left-right-targetingthem.html

sions are made. We continue with firm age as the instrument for firm life cycles throughout the section.

7.1 Employment

To show that firms do not sacrifice future employees' prospects when deciding on stock repurchases conditional on life cycles, we run the following second stage regression specification with predicted firm life cycles, using firm age as the instrument:

$$
\begin{aligned}
Employ_{i,j,t+n} = {} & \beta_1 \widehat{Innovation}_{i,j,t-1} + \beta_2 \widehat{CostMinimizing}_{i,j,t-1} + \beta_3 \widehat{Mature}_{i,j,t-1} + \beta_4 \widehat{Declining}_{i,j,t-1} \\
& + \beta_5 Repurchase_{i,j,t} \times \widehat{Innovation}_{i,j,t-1} + \beta_6 Repurchase_{i,j,t} \times \widehat{CostMinimizing}_{i,j,t-1} \\
& + \beta_7 Repurchase_{i,j,t} \times \widehat{Mature}_{i,j,t-1} + \beta_8 Repurchase_{i,j,t} \times \widehat{Declining}_{i,j,t-1} \\
& + \beta_9 Repurchase_{i,j,t} + \beta_{10} X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t}
\end{aligned}
\tag{6}
$$

where n $\in \{1, 2, 3\}$ in years. $Employ_{i,j,t+n}$ takes two forms: $Employment_{i,j,t+n}$, which measures the level of employment for firm i of industry j in year $t+n$, and $EmploymentGrowth_{i,j,t+n}$, which measures the growth rate in employment for firm i of industry j in year $t+n$ from year $t+n-1$. The independent variable $Repurchase_{i,j,t}$ is an indicator variable that equals one if firm i repurchases its shares in the open market in year t, and zero otherwise. The coefficient of interest is β_7, which captures the marginal effect of firm i's actual repurchases in year t on its future employment conditional on its firm life cycle in year $t-1$. We focus particularly on β_7 because the potential cost of real effects in employment should be especially relevant for mature firms. Table 9 presents the results.

Table 9 columns (1) through (3) use the level of employment in one year, two years, and three years respectively as the dependent variables, whereas columns (4) through (6) use the growth rates in employment. The coefficients on $Repurchase \times \widehat{Mature}$ are positive and statistically insignificant in all columns, suggesting that mature firms do not sacrifice firm employment to repurchase shares. In fact, firms in all life cycles do not forgo employment to repurchase shares. We also conduct similar analyses *without* conditioning on firm life cycle, which are presented in the Appendix Table A.2. The unconditional results in Table A.2 with results conditioning on firm life cycle presented in Table 9 provide drastic contrast that once conditioning on the life cycle, firms will not forgo future employments. This is consistent with our hypothesis H6 regarding firms' employment such that conditional on firm life cycles, managers do not place stock repurchases as higher priority than their employees.

7.2 Tobin's Q and Productivity

Similarly, we test the effect of actual open market stock repurchases on firms' future *Tobin's Q* and *Total Factor Productivity (TFP)* conditional on repurchasing firms' life cycles before the stock repurchases. We follow the same regression specifications as in Equation 6 but change the dependent variables to firms' *Tobin's Q* and *TFP*. Table 10 delineates the results.

Columns (1), (2), and (3) focus on firms' *Tobin's Q* in one year, two years, and three years respectively. Columns (4), (5), and (6) set firms' *TFP* in one, two, and three years respectively as the dependent variables. The coefficients on $Repurchase \times \hat{Mature}$ are still statistically insignificant from zero. This finding extends to all interaction terms between the four predicted life cycle stages with the *Repurchase* indicator variable. We do not find evidence that firms sacrifice future firm values or future productivity to conduct stock repurchases once they consider their firm life cycles. Thus, consistent with H6 regarding firms' future value and productivity, firms repurchase stocks based on their life cycles and the availability of their investment opportunities, which does not come at the cost of future firm values or productivity levels.

7.3 Growths on Sales and Assets

We then turn to the real effects on the growth rates of two key firm performance measures: sales and total assets. Sales growth serves as the proxy that measures firms' performances in the product market, whereas the growth rate in total assets approximates the firm's general growth. We perform regressions similar to Equation 6 with the new dependent variables and present the results in Table 11. The first three columns in Table 11 pertain to the dependent variables of *Sales Growth* in one, two, and three years, whereas the remaining three columns pertain to the dependent variables of *Asset Growth* for the same subsequent years.

All the interaction terms between firm i's actual stock repurchases in year t and its predicted life cycles in year t-1 are statistically insignificant from zero, suggesting that once firms decide on stock repurchases based on their life cycles, and correspondingly, on their investment sets, they maintain their respective market shares in the product market and their general growth. As compared to the pooled regression results that do not condition on the life cycles of the firms (Table A.4), we demonstrate that firms do not sacrifice their growth opportunities to repurchase shares when they take their respective life cycles into account.

7.4 Investment

Finally, many critiques of open market stock repurchases argue that firms forgo investment opportunities to repurchase shares. Almeida et al. (2016) find that the probability of share repurchases that increase earnings per share (EPS) is sharply higher for firms that would have just missed the EPS forecast in the absence of the repurchase when compared with firms that narrowly beat the EPS forecast. On the other hand, our results underscore that on a large scale, firms decide on stock repurchases based on their life cycles and investment outlooks, and they do not forfeit profitable investments. In other words, when firms repurchase shares conditional on their life cycles, they have already exhausted all profitable investment projects and are left with non-profitable ones. This finding relates to H6 in terms of firms' future investments. We test this using Equation 6 but with $Investment_{i,j,t+n}$ and $Investment\,Growth_{i,j,t+n}$ as the dependent variables. Table 12 displays the results.

Table 12 columns (1) through (3) use *Investment* in one, two, and three years as the dependent variables respectively. Columns (4) through (6) use *Investment Growth* in one, two, and three years as the dependent variables. The coefficients on all interaction terms are statistically insignificant. The statistical insignificance implies that firms that repurchase shares based on their firm life cycles do not sacrifice future corporate investments, in contrast to the negative and significant coefficients for the pooled regressions in Table A.5. The finding is consistent with H6 that firms base their stock repurchase decisions on their life cycles and on alternative investment projects. When firms consider their life cycles while making stock repurchase decisions, they will not jeopardize their future investments. All evidence presented in this section align with the hypothesis H6. Firms do not trade off future prospects with current stock repurchases after taking into account their respective life cycles. Indeed, firms repurchase shares when they are at the mature life cycle stage, in which they face few profitable investments and maintain firm level performances.

8 Difference-in-Differences Analysis

The second strategy for mitigating the endogeneity concerns focuses on the difference-in-differences analysis around the Energy Independence and Security Act (EISA or the Act from here on) of 2007.[10] The Act was enacted by the one hundred and tenth congress of the United States (U.S.) on January 4th, 2007 and signed into law by President Bush on December 19th of the same year, making the law most likely to take effect in 2008. The Act aims to curtail energy consumption by U.S. corporations, improve their energy efficiency, and encourage them to develop more energy efficient products. The EISA sets more stringent standards for energy consumption that firms have to meet. In the meantime, it

[10]Energy Independence and Security Act of 2007, H.R.6, 110th Congress, 2007, https://www.congress.gov/bill/110th-congress/house-bill/6.

also rewards for energy innovation where generous grants and monetary rewards are available for firms in energy intensive industries to develop more efficient ways for energy usage or more energy efficient products. The Act classifies the information technology, electronics, consumer product manufacturing, food processing, and materials manufacturing industry as energy intensive. Thus, firms in these industries are subject to the rules required by the EISA.

We argue that the EISA exogenously changes the life cycles of mature firms in the energy intensive industries but not those of innovative firms in these industries. The reasons are in two folds. First, the shock is likely exogenous because energy consuming firms would not advocate for less energy consumption or higher energy efficiency. On the other hand, firms that do not consume much energy would probably not spend a large sum of money lobbying for more stringent energy regulations since they already meet the standards. Moreover, for the shock to be correlated with firm actions, it would take many firms across various of these listed industries to lobby for the Act together, making it even harder to believe (given the Act does not generally favor them).

Second, the Act practically forces firms in the energy intensive industries to develop better energy consumption mechanisms and innovate more energy efficient products. These firms either have to improve energy efficiency to stay in the specified energy consumption limit or want to improve energy efficiency (in both products and processes) to receive the grants and monetary rewards generously provided by the government (around $200 million per year). The caveat of the incentives provided by the Act, however, is that there must be cost-sharing between the firm and the Environmental Protection Agency or the U.S. Department of Energy, the two acting entities that ensure the implementation and enforcement of the Act. The Act requires the cost-sharing procedures to follow those specified in Section 988 of the Energy Policy Act of 2005, which states that firms have to pay at least 20% of the cost for most energy innovation programs and at least 50% for some special programs.Firms, of course, can achieve energy innovation in two ways: innovate in house or acquire technology developed by others to improve energy efficiency. Either of these two methods would require firms to spend money and thus reduce the amount of cash they have for other purposes, including stock repurchases. Consequently, the Act induces firms in the energy intensive industries to allocate money for energy innovation.

This re-allocation of monetary resources has a differential impact on the life cycles of energy intensive firms at various life stages when the Act was enacted. The most salient differential effects exist between innovative firms and mature firms, which will be the focus of our argument. For firms in the energy intensive industries who were at the mature stage of their life cycles when the Act came into effect, they were forced to develop energy innovation by the Act. The regulation effectively pushes these affected mature firms toward the younger stages of firm life cycle. On the other hand, for firms in the energy intensive industries who were already in the innovative phase of firm life cycle when the Act was implemented, the Act will only split their innovation focus between extant areas under development and energy-related aspects but it will not change their life cycles. Hence, the EISA influences the life cycles of only mature firms but not the innovative firms in the specified energy intensive industries.

By affecting the life cycles of only mature firms in the energy intensive industries but not those of the innovative firms in the same industries, the Act creates a treatment effect of our interest. We take the former as the treated group and the latter as the control group, and exclude firms at other stages of firm life cycle upon the enactment of the Act for a clearer comparison. As the treated group would generally move toward the younger stages of firm life cycles, they would face less excessive cash but more profitable investment opportunities, especially in energy innovation. In turn, they would have to reduce the cash distribution to shareholders through stock repurchases. Firms in the control group would still be in the innovative stage of firm life cycle and their reluctance and inability to repurchase shares should persist. As compared to the period prior to the implementation of the Act, the treatment effect can be estimated using a standard difference-in-differences approach.

In particular, in the pre-Act (pre-treatment) period, mature firms and innovative firms in the affected industries have different life cycles where the mature ones should have higher probability to repurchase shares and would spend more money on repurchasing shares than innovative firms for rationale mentioned in the previous sections. After the implementation of the Act (post-treatment), mature firms in the energy intensive industries were forced to younger stages of firm life cycle and moved closer to the innovative firms' life cycles which were not affected by the Act. Thus, the differences in their share repurchase behaviors should dissipate. This explanation implies a negative treatment effect.

To test this direct impact of firm life cycle exogenously imposed by the Act on firms' stock repurchase decisions, we run a difference-in-difference analysis. The treated group are mature firms in the energy intensive industries listed by the Act, which we isolate using their corresponding two- or three-digit SIC industries.[11] Innovative firms in these energy intensive industries in 2008, which is the year that the Act came into effect, belong to the control group. The treatment year is 2008 since the Act was only signed into law on December 19, 2007. We include three years before 2008 (from 2005 to 2007) as the pre-treatment period, and three years starting in 2008 (from 2008 to 2010) as the post-treatment period. Table 13 displays the regression results with the following specification:

$$Y_{i,j,t} = \beta_1 Treated + \beta_2 Treated \times Post + \beta_3 X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \tag{7}$$

where $Y_{i,j,t}$ represents the outcome variables: *Repurchase Indicator* and *Scaled Dollar Repurchase*. $Treated \times Post_{i,j,t}$ is the independent variable of interest, which equals one in a post-treatment period for companies at the mature stage in the energy intensive industries during 2008. The sample is restricted to only mature firms and innovative firms in the energy intensive industries specified by the Act in 2008. γ_j and δ_t stand for the industry and year fixed effects, respectively. The rest of the variables follow the definitions in Equation 1 and

[11] For a detailed description of each SIC code and its classification, please refer to: https://www.osha.gov/data/sic-manual.

we continue double clustering standard errors at the industry and year level. We omit the *Post* indicator variable because the year fixed effect absorbs the *Post* indicator.[12] Columns (1) and (2) of Table 13 use the *Repurchase Indicator* as the dependent variable, and columns (3) and (4) use *Scaled Dollar Repurchase.*

The coefficients on $Treated \times Post_{i,j,t}$ are negative and statistically significant in all columns, implying that mature firms forced to innovate will repurchase less relative to innovative firms whose life cycles did not change after the treatment. In other words, the differences in stock repurchase behaviors between mature firms and innovative firms affected by the act decrease after the implementation of the Act. Mature firms who migrate toward the younger stages of firm life cycle because of the Act will repurchase less often and fewer shares than before treatment with respect to innovative firms whose life cycles are not subject to change due to the shock. The evidence demonstrates that the life cycle of a firm will deterministically drive firms' share repurchase decisions.

To ensure the robustness of the results, we conduct placebo tests by assuming different implementation year of the Act (i.e., by assuming different treatment years). Table 14 displays the results. Columns (1) and (2) assumes 2006 as the treatment year, while columns (3) and (4) assumes 2011, and columns (5) and (6) assumes 2015 as the treatment year.[13] None of these placebo tests yield statistical significance on the treatment effect, validating our identification strategy.

We test for the parallel trend assumption and present the graphical results in Figure 1 and Figure 2. Figure 1 plots the treatment effect between the treated mature firms and innovative firms in the control group regarding the propensity for a firm to repurchase shares for each period relative to the treatment year, whereas Figure 2 plots that for *Scaled Dollar*

[12] *Post* takes on the same value in a given year, which will be absorbed by year fixed effect.

[13] We use 2006 because our sample starts in 2003, and we want to ensure a balanced horizon of three years before and after the treatment to estimate the effect. Thus, the earliest placebo year is 2006. The rationale behind choosing 2011 is that we do not want any of the three years immediately after the actual treatment in 2008 to contaminate the placebo tests. Thus, the earliest starting year for this placebo after the actual treatment is 2011 since the actual treatment effect was estimated from 2008 to 2010. We adopt an additional placebo test in 2015 to provide more robustness. Changing 2015 to 2014 or 2016 does not change the results of the placebo tests.

Repurchase, which is the natural log of the dollar amount a firm spends on repurchasing shares in a given year scaled by its firm size. Both graphs depict that mature firms in the energy intensive industries repurchase more than innovative firms in the same industries before the Act but such differences disappear after the passage of the Act. The two figures also show no obvious trends in the pre-treatment period, suggesting that the parallel trend assumption holds in our setting. We argue this treatment effect occurs because treated mature firms' life cycles moved away from the mature stage to the younger stages due to the Act, while controlled innovative firms' life cycles persisted at the innovative stage after the Act. As the life cycles between the treated firms and control firms converge, their share repurchase behaviors converge as well. Importantly, such convergence only took place after the Act became effective but not before.

The graphical and tabulated findings are in line with mature companies having less profitable investment opportunities and using the excess cash to fund stock repurchases while innovative firms having limited funding but many profitable investment opportunities. This set of results, together with the I.V. analysis, solidifies our hypothesis that firm life cycle strongly determines firms' stock repurchase decisions. The joint results also strengthen our argument that any policies regulating firms' stock repurchases should consider the firms' life cycles because they play a direct and paramount role in deciding whether and how many shares firms will repurchase in the open market.

9 Policy Implications

The findings of this paper point directly to policy implications. Regulating firms' open market repurchase programs has become a popular topic of discussion among politicians. Advocates for restricting firms' stock repurchases argue that companies repurchase shares to benefit their wealthy shareholders, at the cost of firm future prospects, their employees, and alternative corporate investments.[14] In turn, many proposed regulations hinge on imposing a minimum corporate investment level such that companies need to invest at least the government pre-determined amount in corporate projects, employee hiring and training, and other aspects before they are allowed to repurchase shares in the open market.[15] Our results show the potential damages of such policies.

The findings in Section 4.1, Section 6, and Section 8 indicate that firms actively consider their life cycles when repurchasing shares in the open market. In other words, they repurchase shares after considering other available investment opportunities. For mature firms with limited profitable projects, stock repurchases bear higher NPV than alternative projects. Further, the empirical evidence in Section 5 explicitly shows that mature firms who repurchase shares in the open market perform better than similar mature firms that do not repurchase shares. These combined results suggest that a regulatory policy that imposes minimum investment requirements before share repurchases creates situations in which mature firms are coerced to invest in value-destroying projects.

In addition, the results throughout Section 7 directly demonstrate that when firms repurchase shares conditional on their respective life cycles, they do not sacrifice their future firm prospects. The findings provide evidence against policymakers' arguments where firms purposely forgo investments beneficial to the firms to distribute wealth back to the shareholders. Our evidence supports the notion that firms repurchase shares on a large scale in the open market while considering the impact of such stock repurchases on their future performances. This is crucial given that firm insiders have private information about firm prospects, making it more difficult for outsiders to decide when and at what level companies should be allowed to conduct stock repurchases. Thus, if regulators intend to restrict companies from buying back shares, they should consider firms' life cycles and the firms' alternative use of cash.

[14] Mui, Ylan, Sen Marco Rubio takes aim at stock buybacks, an issue under attack by Democrats," CNBC, 12, February, 2019. https://www.cnbc.com/2019/02/12/rubio-backs-new-proposal-to-tackle-stockbuybacks.html

[15] "Schumer, Sanders, Socialism and Buybacks," Wall Street Journal, February, 12, 2019. https://www.wsj.com/articles/schumer-sanderssocialism-and-buybacks-11550003228

Simply forcing these firms to invest in projects does not necessarily benefit the firms and, consequently, the economy.

10 Conclusion

The agency theory asserts that firms with limited investment projects and substantial free cash flow should distribute those cash back to their shareholders to avoid agency conflicts. Moreover, the life cycle theory postulates that mature firms possess fewer profitable investment projects and a more steady income than firms in earlier life cycles. Based on the arguments from Chen et al. (2021) that firms understand their life cycle and future investment opportunities, this paper provides evidence that firms consider their life cycles when making payout decisions. Specifically, mature firms, who face limited investment opportunities and extra cash conduct more share repurchases than innovative firms with many profitable investment projects but limited funding. Importantly, the results underscore that firms do not trade off their prospects for share repurchases.

The paper speaks to a common argument among policymakers and politicians that stock repurchases hinder firms' investments because the money is not invested in profitable growth opportunities. On the contrary, our results indicate that firms actively consider their life cycles when deciding on the payout policy because they opt to repurchase shares only after they exhaust profitable investment projects. In conclusion, disregarding firms' life cycles in share repurchase regulations could hurt firms, their shareholders, and the economy.

References

Abernathy, W. J. and Utterback, J. M. (1975). A dynamic model of process and product innovation. *Omega*, 3(6):639–656.

Abernathy, W. J. and Utterback, J. M. (1978). Patterns of industrial innovation. *Technology Review*, 80(7):40–47.

Allen, A., Lewis-Western, M. F., and Valentine, K. (2020). The innovation consequences of financial regulation for young life-cycle firms. *Working Paper, available at SSRN 3184837.*

Allen, F. and Michaely, R. (2003). Payout policy. *Handbook of the Economics of Finance*, Chapter 7:337–429.

Almeida, H., Fos, V., and Kronlund, M. (2016). The real effects of share repurchases. *Journal of Financial Economics*, 119(1):168–185.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4):589–609.

Anthony, J. H. and Ramesh, K. (1992). Association between accounting performance measures and stock prices: A test of the life cycle hypothesis. *Journal of Accounting and Economics*, 15(2–3):203–227.

Arikan, A. M. and Stulz, R. M. (2016). Corporate acquisitions, diversification, and the firm's life cycle. *The Journal of Finance*, 71(1):139–194.

Bond, P. and Zhong, H. (2016). Buying high and selling low: Stock repurchases and persistent asymmetric information. *The Review of Financial Studies*, 29(6):1409–1452.

Brav, A., Graham, J., Harvey, C., and Michaely, R. (2005). Payout policy in the 21st century. *Journal of Financial Economics*, 77(3):483–527.

Brav, A., Jiang, W., Partnoy, F., and Thomas, R. (2008). Hedge fund activism, corporate governance, and firm performance. *The Journal of Finance*, 63(4):1729–1775.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82.

Chemmanur, T. J., He, J., He, S., , and Nandy, D. K. (2018). Product market characteristics and the choice between ipos and acquisitions. *Journal of Financial and Quantitative Analysis*, 53(2):681–721.

Chemmanur, T. J., He, S., and Nandy, D. K. (2010). The going-public decision and the product market. *The Review of Financial Studies*, 23(5):1855–1908.

Chemmanur, T. J., Krishnan, K., and Nandy, D. K. (2011). How does venture capital financing improve efficiency in private firms? a look beneath the surface. *The Review of Financial Studies*, 24(12):4037–4090.

Chen, A., Hoberg, G., and Maksimovic, V. (2021). Life cycles of firm disclosures. *Working Paper, available at SSRN 3703931.*

Dann, L. Y. (1981). Common stock repurchases: An analysis of returns to bondholders and stockholders. *Journal of Financial Economics*, 9(2):113–138.

DeAngelo, H., DeAngelo, L., and Stulz, R. (2006). Dividend policy and the earned/contributed capital mix: a test of the life-cycle theory. *Journal of Financial Economics*, 81(2):227–254.

DeAngelo, H., DeAngelo, L., and Stulz, R. (2010). Seasoned equity offerings, market timing, and the corporate lifecycle. *Journal of Financial Economics*, 95(3):275–295.

Dickinson, V. (2011). Cash flow patterns as a proxy for firm life cycle. *The Accounting Review*, 86(6):1969–1994.

Dittmar, A. K. (2000). Why do firms repurchase stock. *The Journal of Business*, 73(3):331–355.

Dittmar, A. K. and Field, L. C. (2015). Can managers time the market? evidence using repurchase price data. *Journal of Financial Economics*, 115(2):261–282.

Doyle, J., Ge, W., and McVay, S. (2007). Determinants of weaknesses in internal control over financial reporting. *Journal of Accounting and Economics*, 44(1-2):193–223.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56.

Grullon, G. and Michaely, R. (2004). The information content of share repurchase programs. *The Journal of Finance*, 59(2):651–680.

Grullon, G., Michaely, R., and Swaminathan, B. (2002). Are dividend changes a sign of firm maturity? *The Journal of Business*, 75(3):387–424.

Hoberg, G. and Maksimovic, V. (2019). Product life cycles in corporate finance. *Working Paper, available at SSRN 3182158.*

Huang, S. and Thakor, A. V. (2013). Investor heterogeneity, investor-management disagreement and share repurchases. *The Review of Financial Studies*, 26(10):2453–2491.

Jagannathan, M., Stephens, C. P., and Weisbach, M. S. (2000). Financial flexibility and the choice between dividends and stock repurchases. *Journal of Financial Economics*, 57(3):355–384.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2):323–329.

Kueng, L., Yang, M.-J., and Hong, B. (2014). Sources of firm life-cycle dynamics: Differentiating size vs. age effects. *NBER Working Paper 20621*, DOI 10.3386/w20621.

Lemmon, M. L., Roberts, M. R., and Zender, J. F. (2008). Back to the beginning: persistence and the cross-section of corporate capital structure. *The Journal of Finance*, 63(4):1575–1608.

Miller, D. and Friesen, P. H. (1984). A longitudinal study of the corporate life cycle. *Management science*, 30(10):1161–1183.

Modigliani, F. and Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, 48(3):261–297.

Mueller, D. C. (1972). A life cycle theory of the firm. *The Journal of Industrial Economics*, pages 199–219.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Ofer, A. R. and Thakor, A. V. (1987). A theory of stock price responses to alternative corporate cash disbursement methods: Stock repurchases and dividends. *The Journal of Finance*, 42(2):365–394.

Oreski, T. (2021). Strategic alignment in mergers and acquisitions. *Working paper, available at SSRN 3803420*.

Stulz, R. M. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics*, 26(1):3–27.

Vermaelen, T. (1981). Common stock repurchases and market signalling: An empirical study. *Journal of Financial Economics*, 9(2):139–183.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Table 1: Summary Statistics

This table presents the summary statistics of our sample. Altman Z-Score is computed based on Altman (1968). *Investment* follows Lemmon et al. (2008). All growth measures are computed relative to the previous year and are in decimals. *Tobin's Q* uses the methodology in Brav et al. (2008). Buy-and-hold abnormal stock returns (BHAR) are calculated using the Fama-French Three Factor model. *Total Factor Productivity (TFP)* follows Chemmanur et al. (2010, 2011, 2018). *Age* is defined as the number of years a firm has appeared in the Compustat database. There are a total of 58,709 firm-year observations with 8,222 unique firms from 64 different 2-digit SIC industries.

	Mean	St. Dev.	Median	Min	Max	Observations
Repurchase Dollar Amount ($ million)	70.35	293.71	0.00	0.00	2,244.81	58,738
Size	5.73	2.41	5.86	0.38	11.33	56,430
Scaled Dollar Repurchase	0.14	0.24	0.00	0.00	0.78	56,430
Profitability	-0.34	2.01	0.09	-16.56	0.41	58,298
Investment	0.19	0.30	0.09	0.00	2.14	36,678
Investment Growth	0.13	0.76	0.00	-0.93	4.85	35,433
Sales Growth	0.20	0.85	0.07	-0.99	6.48	54,243
Total Asset Growth	0.28	1.23	0.04	-0.79	9.81	57,841
Employee (thousands)	9.82	25.19	1.50	0.00	175.70	47,001
Employee Growth	0.08	0.35	0.02	-0.68	2.13	54,235
Altman Z-Score	-5.90	60.39	2.84	-508.60	65.03	53,549
Tobin's Q	2.32	9.94	1.81	-59.71	53.70	56,007
MTB (Market-to-Book ratio)	2.39	12.20	2.00	-71.58	61.36	56,219
D/P (Dividend Price ratio)	0.01	0.04	0.00	0.00	0.34	56,294
Earnings Per Share (EPS)	0.49	2.46	0.13	-9.03	10.29	57,104
P/E (Price Earnings ratio)	9.46	51.75	9.38	-228.61	270.00	55,263
Net Income ($ million)	137.11	591.07	2.35	-681.00	4,395.00	58,658
Cash ($ million)	289.12	849.83	38.92	0.00	6,258.00	58,733
Dividend Paid ($ million)	52.36	226.35	0.00	0.00	1,811.00	58,549
Age	20.04	15.65	15.00	2.00	66.00	58,738
Total Factor Productivity (TFP)	-0.01	0.66	0.03	-3.08	1.52	51,090
BHAR 3 Months	-0.01	0.37	-0.02	-1.23	1.33	35,263
BHAR 6 Months	-0.10	0.72	-0.06	-3.27	2.26	35,263
BHAR 1 Year	-0.52	2.32	-0.11	-16.24	3.13	35,263
BHAR 2 Year	-5.02	26.20	-0.19	-225.88	4.38	35,263
Last 6 Months' Return	0.05	0.44	0.01	-0.77	2.22	44,579
Firm					8,222	58,709
Industry (2-Digit SIC)					64	58,709

Table 2: Baseline Regressions
This table presents the baseline regression results. The dependent variables are *Repurchase Indicator* for the first two columns. *Repurchase Indicator* equals one if a firm spends a positive amount of money in repurchasing its shares in the open market in a given year, and zero otherwise. Columns (3) and (4) use *Scaled $Repurchase* as the dependent variable, which is the natural logarithm of the dollar amount that a firm spends on repurchasing its shares in the open market in a given year scaled by its firm size. The omitted independent variable is the firm life cycle indicator for innovative firms. Interpretations should be made in reference to firms at the innovation stage of their life cycles. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

VARIABLES	(1) Repurchase Indicator	(2) Repurchase Indicator	(3) Scaled $Repurchase	(4) Scaled $Repurchase
Cost Minimizing	0.09851***	0.05234***	0.04388***	0.01614**
	(4.34)	(3.19)	(3.79)	(2.26)
Mature	0.11017***	0.06684***	0.05932***	0.03321***
	(4.64)	(3.33)	(4.92)	(3.66)
Declining	0.16305***	0.07851***	0.07094***	0.03042***
	(5.45)	(4.35)	(4.75)	(3.93)
Size		0.07821***		0.04395***
		(11.04)		(9.23)
Profitability		0.01297***		0.00245***
		(5.77)		(3.00)
Altman Z-Score		-0.00039***		-0.00026***
		(-5.15)		(-6.57)
MTB		-0.00057***		-0.00013
		(-3.11)		(-1.38)
D/P		0.27408***		0.16172***
		(3.97)		(5.01)
Cash		-0.00000		0.00003***
		(-0.05)		(5.90)
Age		0.00405***		0.00188***
		(8.52)		(7.55)
Observations	58,707	53,291	56,399	53,291
Adjusted R-squared	0.120	0.307	0.109	0.384
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 3: Firm Life Cycles from Mature to Innovation

This table presents the result on dynamic firm life cycles and the corresponding changes in payout policy. The dependent variables are *Repurchase to Equity Issuance*, an indicator that equals one if a given firm repurchases shares in the open market in the previous *and* issues equity via SEOs in the following year, and zero otherwise. The independent variable of interest is *Mature to Innovation*, which equals one if a firm whose life cycle was at the mature stage in the prior year but changes to the innovation stage the next year, and zero otherwise. Column (1) does not include any control variables, while column (2) implements the full set of firm level control variables. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)
VARIABLES	Repurchase to Equity Issuance	Repurchase to Equity Issuance
Mature to Innovation	0.03216***	0.03141**
	(3.47)	(2.35)
Size		0.04257***
		(6.19)
Profitability		0.00057
		(0.24)
Altman Z-Score		-0.00008
		(-1.12)
MTB		0.00111***
		(13.01)
D/P		-0.54152***
		(-5.94)
Cash		-0.00007***
		(-7.01)
Age		0.00178***
		(4.04)
Observations	58,707	53,291
Adjusted R-squared	0.118	0.164
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 4: Repurchase and Post-Repurchase Equity Issuance
This table presents the results on the ability of raising equity after firms repurchase shares. Panel A presents the OLS regression results, whereas Panel B uses two sample t-tests. The dependent variables in Panel A are *Equity Raised*, which measures the dollar amount of equity issued by a firm via SEOs within five years of a given year. The independent variable of interest is *Repurchase Before Equity Issuance*, which equals one if a firm repurchases shares in the open market in a given year, and zero otherwise. In Panel B, we match firms in the same life cycle of the same industry in a given year, and find the closest match based on firm size, profitability, market-to-book ratios, cash holdings, the amount of dividends paid, earnings, and age. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Panel A: Regression of the amount of equity raised in five years after repurchases

	(1)	(2)
Variables	*Equity* $Raised_{[t+1,t+5]}$	*Equity* $Raised_{[t+1,t+5]}$
Repurchase Before Equity Issuance	463.91733***	412.84326***
	(7.92)	(7.09)
Size		18.39674***
		(4.89)
Profitability		1.01843
		(1.36)
Altman Z-Score		-0.10614**
		(-2.88)
MTB		0.14040*
		(2.06)
D/P		108.70724**
		(2.82)
Cash		-0.00563
		(-1.43)
Age		-1.12624**
		(-2.77)
Observations	50,487	45,921
Adjusted R-squared	0.096	0.129
Industry FE	Yes	Yes
Year FE	Yes	Yes

Panel B: Differences in the amount of equity raised by matched mature firms

	Mean Equity Raised

Table 5: Split Sample on Mature Firms - Subsequent Firm Level Outcomes

This table compares the real effects between mature firms that repurchase shares and those that do not repurchase shares. This is a sub-sample that is restricted only to firms at the mature stage of their life cycles. The dependent variables are *Net Income* in one, two, and three years for columns (1), (2), and (3) respectively; *Total Factor Productivity (TFP)* in one, two, and three years for columns (4), (5), and (6) respectively; and *Profitability* in one, two, and three years for columns (7), (8), and (9) respectively. The independent variable of interest is *Repurchase*, which equals one if a firm in a given year is at the mature stage of the life cycle *and* repurchases shares in the open market in that year, and zero otherwise. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Net Income			TFP			Profitability	
Variables	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
Repurchase	0.07663*	0.07621**	0.08627**	0.02863***	0.03063***	0.02826**	0.01781*	0.01454*	0.01212**
	(1.99)	(2.18)	(2.79)	(2.99)	(3.00)	(2.34)	(1.98)	(2.09)	(2.67)
Size	0.90339***	0.90237***	0.90110***	-0.02673***	-0.02813***	-0.03742***	0.02376***	0.02354***	0.02324***
	(57.27)	(52.94)	(50.47)	(-3.46)	(-3.64)	(-4.88)	(6.30)	(9.04)	(14.67)
Profitability	2.85872***	2.53452***	2.19420***	0.33239	0.40038	0.85062**			
	(8.32)	(7.46)	(6.03)	(0.98)	(1.09)	(2.15)			
Altman Z-Score	-0.01799***	-0.01799***	-0.01797***	0.00039	0.00078	0.00055	0.01248*	0.00900*	0.00422***
	(-4.91)	(-4.46)	(-4.15)	(0.20)	(0.39)	(0.30)	(1.85)	(1.97)	(4.64)
MTB	-0.01072***	-0.01086***	-0.01114***	0.01659***	0.01433***	0.01091***	-0.00082	-0.00036	0.00033
	(-3.67)	(-4.10)	(-4.67)	(5.85)	(4.81)	(3.61)	(-1.36)	(-0.78)	(0.73)
D/P	4.01456***	3.53162***	2.85506***	-0.30964	-0.36734	-0.58293	0.28062*	0.28485*	0.28136**
	(6.13)	(5.51)	(3.90)	(-0.87)	(-0.99)	(-1.37)	(1.95)	(2.06)	(2.34)
Cash	0.00008***	0.00008***	0.00008***	0.00005*	0.00006*	0.00006*	-0.00001***	-0.00001***	-0.00001***
	(6.87)	(6.80)	(6.27)	(1.85)	(1.86)	(2.04)	(-3.31)	(-5.28)	(-10.20)
Age	0.00542***	0.00518**	0.00481**	-0.00519***	-0.00555***	-0.00599***	0.00091***	0.00075***	0.00052***
	(2.94)	(2.68)	(2.39)	(-4.40)	(-4.42)	(-4.56)	(3.51)	(3.58)	(3.20)
Observations	18,186	16,870	15,615	22,567	20,811	19,185	23,276	21,449	19,756
Adjusted R-squared	0.850	0.841	0.834	0.223	0.229	0.248	0.334	0.285	0.282
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Split Sample on Mature Firms - Subsequent Long-run Abnormal Stock Returns

This table compares the effects on long-run abnormal stock returns between mature firms that repurchase shares and those that do not repurchase shares. This is a sub-sample that is restricted only to firms at the mature stage of their life cycles. The dependent variables are *buy-and-hold abnormal stock returns (BHAR)* in three months, six months, one year, and two years. Columns (1) through (4) use market adjusted model to calculated BHAR; columns (5) through (8) use the Fama-French Three Factor model (Fama and French, 1993) to calculate BHAR; columns (9) through (12) use the Fama-French-Carhart Four Factor model (Carhart, 1997) to calculate BHAR. The independent variable of interest is *Repurchase*, which equals one if a firm in a given year is at the mature stage of the life cycle *and* repurchases shares in the open market in that year, and zero otherwise. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	BHAR											
	Market Model				Fama French Three Factor				Fama French Four Factor			
Variables	Three Months	Six Months	One Year	Two Years	Three Months	Six Months	One Year	Two Years	Three Months	Six Months	One Year	Two Years
Repurchase	0.03504***	0.06427***	0.20841***	1.43943**	0.02946***	0.05717***	0.19125***	1.33544**	0.02654***	0.05714***	0.21219***	1.22554**
	(3.92)	(4.50)	(5.60)	(2.29)	(3.35)	(3.89)	(4.99)	(2.40)	(3.19)	(4.15)	(4.33)	(2.68)
Size	-0.00664	-0.00445	0.05935	0.93710*	-0.00559	-0.00704	0.05089	0.80091*	-0.00444	-0.00525	0.05312	0.69340*
	(-0.63)	(-0.18)	(0.92)	(1.92)	(-0.50)	(-0.27)	(0.82)	(1.88)	(-0.41)	(-0.20)	(0.86)	(1.92)
Profitability	-0.08187	-0.23895*	-0.59992*	-4.93984	-0.09888*	-0.21964*	-0.54785	-4.25408	-0.05672	-0.19813	-0.63931	-4.56451
	(-1.38)	(-1.98)	(-1.81)	(-1.29)	(-2.18)	(-2.00)	(-1.70)	(-1.26)	(-1.17)	(-1.77)	(-1.62)	(-1.62)
Altman Z-Score	-0.00302***	-0.00547**	-0.00961*	-0.02567	-0.00283**	-0.00559**	-0.00986*	-0.02569	-0.00293**	-0.00558**	-0.00961*	-0.03611
	(-3.20)	(-2.72)	(-1.82)	(-0.52)	(-3.03)	(-2.88)	(-2.00)	(-0.61)	(-3.03)	(-2.74)	(-1.98)	(-1.15)
MTB	-0.00236**	-0.00270	-0.00489	0.00159	-0.00228**	-0.00277	-0.00542	-0.00487	-0.00215*	-0.00271	-0.00533	-0.00433
	(-2.39)	(-1.56)	(-1.12)	(0.05)	(-2.20)	(-1.56)	(-1.28)	(-0.20)	(-2.12)	(-1.60)	(-1.25)	(-0.18)
D/P	0.12473	0.11378	0.66904	4.33116	0.13601	0.24390	0.60263	6.22724	0.10955	0.32550	0.95816	6.26760
	(0.89)	(0.44)	(0.80)	(0.62)	(0.93)	(0.86)	(0.68)	(0.93)	(0.80)	(1.13)	(1.08)	(1.00)
Cash	0.00001	0.00001	-0.00002	-0.00050*	0.00001	0.00002	-0.00001	-0.00036	0.00000	0.00001	-0.00001	-0.00031
	(0.50)	(0.38)	(-0.46)	(-1.85)	(0.67)	(0.72)	(-0.11)	(-1.45)	(0.51)	(0.61)	(-0.23)	(-1.47)
Age	0.00014	0.00028	0.00081	0.02057*	0.00002	0.00030	0.00084	0.01575	0.00012	0.00044	0.00132	0.01853*
	(0.43)	(0.46)	(0.52)	(1.88)	(0.05)	(0.45)	(0.54)	(1.71)	(0.38)	(0.64)	(0.87)	(2.14)
Observations	18,766	18,766	18,766	18,766	18,766	18,766	18,766	18,766	18,766	18,766	18,766	18,766
Adjusted R-squared	0.055	0.063	0.055	0.048	0.052	0.048	0.053	0.052	0.029	0.032	0.043	0.048
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Instrumental Variable Analysis First Stage

This table presents the ordered Probit first stage regression of the IV analysis. The dependent variables are the four life cycle stages: *Innovative*, *Cost Minimizing*, *Mature*, and *Declining*. The independent variable is the instrument of firm age, which is the number of years a firm has appeared in the Compustat database in a given year. Control variables are as defined before. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

VARIABLES	(1) Innovative	(2) Cost Minimizing	(3) Mature	(4) Declining
Age	-0.01450***	0.00524***	0.00127***	0.01565***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.08432***	0.07649***	-0.00669**	0.04080***
	(0.003)	(0.003)	(0.003)	(0.004)
Profitability	0.00172	0.01039*	0.00022	0.03458***
	(0.005)	(0.006)	(0.005)	(0.007)
Altman Z-Score	0.00074***	-0.00085***	-0.00029*	-0.00114***
	(0.000)	(0.000)	(0.000)	(0.000)
MTB	0.00298***	-0.00165***	-0.00129***	-0.00180***
	(0.000)	(0.001)	(0.000)	(0.001)
D/P	-1.70639***	0.61128***	0.13484	0.82129***
	(0.156)	(0.144)	(0.147)	(0.161)
Cash	0.00015***	-0.00013***	0.00007***	-0.00014***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	53,293	53,293	53,293	53,293
LR χ^2	2879	1174	140.5	1952
Prob < χ^2	0.00	0.00	0.00	0.00

Table 8: Instrumental Variable (I.V.) Analysis - Second Stage

This table presents the second stage regressions using predicted firm life cycles. The dependent variables is *Repurchase Indicator* for column (1) and *Scaled $Repurchase* for column (2). *Repurchase Indicator* equals one if a firm spends a positive amount of money in repurchasing its shares in the open market in a given year, and zero otherwise. *Scaled $Repurchase* is the natural logarithm of the dollar amount that a firm spends on repurchasing its shares in the open market in a given year scaled by its firm size. The omitted independent variable is the predicted firm life cycle at the innovation stage. Interpretations should be made in reference to firms at the innovation stage of their life cycles. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

VARIABLES	(1) Repurchase Indicator	(2) Scaled Repurchase
$Cost\hat{Minimizing}$	-0.16598	-0.92650
	(-0.22)	(-1.24)
$Ma\hat{t}ure$	1.70987***	1.15936***
	(4.10)	(3.83)
$Decl\hat{i}ning$	0.82312***	0.58132*
	(2.89)	(1.93)
Size	0.08029***	0.05117***
	(11.36)	(7.20)
Profitability	0.01536***	0.00978**
	(3.24)	(2.48)
Altman Z-Score	-0.00026	-0.00031**
	(-1.44)	(-1.98)
MTB	0.00015	0.00013
	(0.47)	(0.42)
D/P	0.12769	0.12642
	(0.81)	(0.86)
Cash	-0.00003	-0.00000
	(-1.52)	(-0.11)
Observations	53,293	53,293
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 9: I.V. Analysis on Subsequent Employment

This table presents the second stage I.V. analysis on the real effects of firm employment after their life cycles based repurchase decisions. The dependent variables are *Employment*, which measures the number of employees of a firm, in one, two, and three years for columns (1) through (3). The measure changes to the growth rate of employment for columns (4) through (6). The independent variables of interest are the interaction terms between the predicted firm life cycles from the first stage regressions and *Repurchase*, an indicator that equals one if a firm repurchases shares in the open market in a given year after the life cycle was measure. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Employment_{t+1}$	(2) $Employment_{t+2}$	(3) $Employment_{t+3}$	(4) $Employment\ Growth_{t+1}$	(5) $Employment\ Growth_{t+2}$	(6) $Employment\ Growth_{t+3}$
$\hat{Innovation}$	-513.32526	-1,390.60596	-25033.50391	-1.41797	-1.07788	-2.89985
	(-1.18)	(-0.52)	(-0.02)	(-0.54)	(-0.49)	(-0.03)
$\hat{CostMinimizing}$	-396.18375	-1,099.75647	-20642.08594	-2.06079*	-1.02380	-1.70977
	(-0.70)	(-0.60)	(-0.02)	(-1.72)	(-0.97)	(-0.02)
$\hat{Mature}$	877.44611	2,211.92920	41,303.48047	-1.10980	-0.13768	2.04817
	(1.41)	(0.50)	(0.02)	(-0.28)	(-0.05)	(0.02)
$\hat{Declining}$	-587.00342	-1,758.82251	-33950.03516	-0.93003	-1.11522	-2.93582
	(-1.05)	(-0.46)	(-0.02)	(-0.28)	(-0.43)	(-0.03)
Repurchase * $\hat{Innovation}$	1,726.27881	4,644.66602	93,394.93750	6.87289	4.50067	16.44089
	(0.70)	(0.46)	(0.02)	(0.37)	(0.33)	(0.02)
Repurchase * $\hat{CostMinimizing}$	1,310.23853	3,001.31616	68,371.18750	7.77652	4.32424	16.35535
	(0.45)	(0.39)	(0.02)	(0.45)	(0.34)	(0.02)
Repurchase * $\hat{Mature}$	-228.32043	-611.89972	-7,086.71875	4.34538	1.82270	4.66320
	(-0.15)	(-0.15)	(-0.02)	(0.99)	(0.64)	(0.02)
Repurchase * $\hat{Old}$	1,755.75891	5,039.33057	100859.35156	4.84738	3.70027	14.21915
	(0.86)	(0.46)	(0.02)	(0.30)	(0.31)	(0.02)
Repurchase	-1,080.93909	-2,804.26685	-59880.50391	-5.87272	-3.46662	-12.52142
	(-0.51)	(-0.41)	(-0.02)	(-0.44)	(-0.36)	(-0.02)
Size	4.14832	1.10386	-72.45802	0.02370	0.01528	0.04407
	(0.59)	(0.05)	(-0.02)	(0.48)	(0.39)	(0.02)
Profitability	-80.14920	-170.66577	-2,479.68823	-0.01040	-0.01218	0.00287
	(-1.28)	(-0.51)	(-0.02)	(-0.64)	(-0.82)	(0.00)
Altman Z-Score	-0.09934	0.64985	22.56690	0.00017	0.00019	-0.00031
	(-0.13)	(0.25)	(0.02)	(0.47)	(0.77)	(-0.01)
MTB	0.88270	2.29713	33.09560	0.00067	0.00074	0.00135
	(1.20)	(0.47)	(0.02)	(0.24)	(0.34)	(0.02)
D/P	-293.86484	-596.95990	-10280.22363	-0.23250	-0.24899	-0.53201
	(-1.42)	(-0.51)	(-0.02)	(-0.38)	(-0.56)	(-0.03)
Cash	0.01194**	0.00908	-0.01288	-0.00001	-0.00001	0.00001
	(2.06)	(0.61)	(-0.01)	(-0.08)	(-0.21)	(0.01)
Observations	39,206	34,136	29,713	44,463	38,179	32,818
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: I.V. Analysis on Subsequent Valuation and Productivity

This table presents the second stage I.V. analysis on the real effects of firm value and productivity after their life cycles based repurchase decisions. The dependent variable is *Tobin's Q*, which measures firm value, in one, two, and three years for columns (1) through (3). The dependent variables are *Total Factor Productivity* in one, two, and three years for columns (4) through (6). The independent variables of interest are the interaction terms between the predicted firm life cycles from the first stage regressions and *Repurchase*, an indicator that equals one if a firm repurchases shares in the open market in a given year after the life cycle was measure. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Tobin'sQ_{t+1}$	(2) $Tobin'sQ_{t+2}$	(3) $Tobin'sQ_{t+3}$	(4) TFP_{t+1}	(5) TFP_{t+2}	(6) TFP_{t+3}
$\widehat{Innovation}$	-4.39744	0.77542	18.89214	0.72875	0.17128	0.85275
	(-0.02)	(0.01)	(0.04)	(0.04)	(0.01)	(0.04)
$\widehat{CostMinimizing}$	-101.98641	-33.11369	5.86542	6.91085	5.96829	5.64676
	(-0.78)	(-0.63)	(0.02)	(0.44)	(0.30)	(0.25)
$\widehat{Mature}$	-46.06530	-25.41761	-26.85803	1.00980	0.16568	-1.01371
	(-0.13)	(-0.21)	(-0.05)	(0.04)	(0.00)	(-0.03)
$\widehat{Declining}$	54.23642	18.10248	18.75929	-2.94868	-2.76394	-1.48641
	(0.25)	(0.18)	(0.04)	(-0.17)	(-0.12)	(-0.07)
Repurchase * $\widehat{Innovation}$	205.05545	70.50654	-107.66753	-22.59888	-15.55108	-13.09653
	(0.09)	(0.10)	(-0.03)	(-0.12)	(-0.08)	(-0.08)
Repurchase * $\widehat{CostMinimizing}$	366.62234	125.20683	-101.81363	-32.08408	-25.26867	-21.26863
	(0.16)	(0.17)	(-0.03)	(-0.17)	(-0.13)	(-0.12)
Repurchase * $\widehat{Mature}$	214.71341	98.14687	-5.11185	-13.61776	-9.10168	-5.28553
	(0.36)	(0.47)	(-0.01)	(-0.24)	(-0.21)	(-0.15)
Repurchase * $\widehat{Declining}$	76.37180	30.25953	-96.11056	-13.76555	-8.79639	-8.03303
	(0.04)	(0.05)	(-0.04)	(-0.09)	(-0.06)	(-0.06)
Repurchase	-223.10115	-83.05702	74.83932	20.73968	15.02671	12.22577
	(-0.14)	(-0.15)	(0.03)	(0.15)	(0.11)	(0.10)
Size	0.70264	0.32282	-0.19061	-0.06202	-0.06231	-0.06420
	(0.13)	(0.17)	(-0.02)	(-0.12)	(-0.11)	(-0.12)
Profitability	0.56283	0.17900	-0.08735	0.03694	0.03595	0.02244
	(0.25)	(0.17)	(-0.01)	(0.39)	(0.31)	(0.15)
Altman Z-Score	-0.00147	0.01059	0.01900	-0.00049	-0.00047	0.00048
	(-0.04)	(0.53)	(0.12)	(-0.10)	(-0.26)	(0.07)
MTB	0.06260	0.03384	0.03122	0.00319	0.00328	0.00163
	(0.30)	(0.84)	(0.17)	(0.22)	(0.18)	(0.07)
D/P	4.56844	3.84268	3.21109	-0.11449	0.01458	0.72387
	(0.16)	(0.29)	(0.06)	(-0.03)	(0.01)	(0.12)
Cash	-0.00018	-0.00026	-0.00026	-0.00004	-0.00001	-0.00000
	(-0.03)	(-0.20)	(-0.07)	(-0.09)	(-0.05)	(-0.00)
Observations	45,702	39,016	33,366	40,971	35,135	30,216
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: I.V. Analysis on Subsequent Growths

This table presents the second stage I.V. analysis on the real effects of sales and asset growth after their life cycles based repurchase decisions. The dependent variables are *Sales Growth*, in one, two, and three years for columns (1) through (3), and *Asset Growth* in one, two, and three years for columns (4) through (6). The independent variables of interest are the interaction terms between the predicted firm life cycles from the first stage regressions and *Repurchase*, an indicator that equals one if a firm repurchases shares in the open market in the year after the life cycle was measured. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) *Sales* $Growth_{t+1}$	(2) *Sales* $Growth_{t+2}$	(3) *Sales* $Growth_{t+3}$	(4) *Asset* $Growth_{t+1}$	(5) *Asset* $Growth_{t+2}$	(6) *Asset* $Growth_{t+3}$
$Inno\hat{v}ation$	-4.13389	0.30706	83.91257	-7.92566	-14.93126	16.19475
	(-0.08)	(0.01)	(0.00)	(-0.12)	(-0.09)	(0.04)
$CostMi\hat{n}imizing$	-7.35615	-5.15351	64.55823	-5.13834	-2.02764	11.18988
	(-0.25)	(-0.40)	(0.00)	(-0.21)	(-0.03)	(0.05)
$Ma\hat{t}ure$	5.17480	-2.43608	-99.56844	11.65655	24.13721	-18.18351
	(0.07)	(-0.07)	(-0.00)	(0.10)	(0.10)	(-0.04)
$Decl\hat{i}ning$	-2.31441	2.33647	81.80716	-7.28253	-19.58801	14.63828
	(-0.05)	(0.09)	(0.00)	(-0.10)	(-0.11)	(0.04)
Repurchase * $Inno\hat{v}ation$	40.50268	6.26373	-577.73553	66.93930	100.07230	-122.27319
	(0.10)	(0.03)	(-0.00)	(0.10)	(0.08)	(-0.04)
Repurchase * $CostMi\hat{n}imizing$	48.57841	14.78190	-603.36084	70.51141	87.09484	-128.98026
	(0.11)	(0.08)	(-0.00)	(0.11)	(0.07)	(-0.05)
Repurchase * $Ma\hat{t}ure$	10.71527	7.17974	-156.46404	14.57255	9.85539	-36.51804
	(0.10)	(0.18)	(-0.00)	(0.10)	(0.03)	(-0.06)
Repurchase * $Decl\hat{i}ning$	28.31303	1.00063	-497.34235	52.02480	91.31138	-104.02209
	(0.09)	(0.01)	(-0.00)	(0.10)	(0.08)	(-0.04)
Repurchase	-31.85693	-7.77928	446.19974	-49.96700	-68.83689	95.46291
	(-0.10)	(-0.06)	(0.00)	(-0.10)	(-0.07)	(0.05)
Size	0.14335	0.03063	-1.69593	0.20598	0.27527	-0.35266
	(0.12)	(0.06)	(-0.00)	(0.12)	(0.08)	(-0.05)
Profitability	-0.04108	-0.10266	-0.81242	-0.10946	0.03446	-0.30892
	(-0.07)	(-0.35)	(-0.00)	(-0.16)	(0.02)	(-0.06)
Altman Z-Score	0.00113	0.00129	0.01902	-0.00120	-0.00265	0.00492
	(0.12)	(0.24)	(0.00)	(-0.14)	(-0.08)	(0.04)
MTB	0.00458	-0.00101	-0.02804	0.00767	0.01094	-0.00512
	(0.10)	(-0.15)	(-0.00)	(0.10)	(0.13)	(-0.03)
D/P	-0.53490	0.26548	13.80651	-0.91300	-2.65549	1.60409
	(-0.06)	(0.05)	(0.00)	(-0.10)	(-0.11)	(0.03)
Cash	0.00010	-0.00001	-0.00049	0.00018	0.00018	-0.00016
	(0.08)	(-0.03)	(-0.00)	(0.09)	(0.08)	(-0.05)
Observations	43,592	37,614	32,411	45,918	39,218	33,579
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: I.V. Analysis on Subsequent Investment

This table presents the second stage I.V. analysis on the real effects of firm level investment after their life cycles based repurchase decisions. The dependent variables are *Investment*, which measures the level of corporate investment, in one, two, and three years for columns (1) through (3). The measure changes to the growth rate of corporate investment in one, two, and three years for columns (4) through (6). The independent variables of interest are the interaction terms between the predicted firm life cycles from the first stage regressions and *Repurchase*, an indicator that equals one if a firm repurchases shares in the open market in a given year after the life cycle was measure. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Investment_{t+1}$	(2) $Investment_{t+2}$	(3) $Investment_{t+3}$	(4) $Investment\ Growth_{t+1}$	(5) $Investment\ Growth_{t+2}$	(6) $Investment\ Growth_{t+3}$
$\widehat{Innovation}$	3.85751	3.39063	1.55691	5.41474	1.97674	0.78636
	(0.18)	(0.21)	(0.45)	(0.09)	(0.18)	(0.23)
$\widehat{CostMinimizing}$	4.50548	3.14186	1.05169	8.77312	1.64174	0.67833
	(0.18)	(0.21)	(0.40)	(0.07)	(0.11)	(0.31)
$\widehat{Mature}$	-6.73806	-4.41315	-1.81748	-14.59931	-3.87417	-0.91994
	(-0.12)	(-0.14)	(-0.24)	(-0.11)	(-0.19)	(-0.14)
$\widehat{Declining}$	3.90895	3.50220	1.56597	5.51746	2.50426	0.61729
	(0.12)	(0.15)	(0.23)	(0.10)	(0.17)	(0.10)
Repurchase * $\widehat{Innovation}$	-38.88396	-30.64224	-13.34793	-69.48856	-18.13384	-8.39580
	(-0.17)	(-0.20)	(-0.41)	(-0.10)	(-0.19)	(-0.30)
Repurchase * $\widehat{CostMinimizing}$	-43.26018	-34.13635	-14.62845	-84.20826	-20.56329	-10.89699
	(-0.17)	(-0.21)	(-0.48)	(-0.10)	(-0.19)	(-0.41)
Repurchase * $\widehat{Mature}$	-13.62424	-12.03585	-6.05433	-21.37226	-4.81315	-4.13175
	(-0.23)	(-0.27)	(-0.60)	(-0.09)	(-0.17)	(-0.45)
Repurchase * $\widehat{Declining}$	-30.44349	-24.41638	-11.00187	-51.38498	-14.33840	-5.79698
	(-0.16)	(-0.19)	(-0.35)	(-0.10)	(-0.18)	(-0.21)
Repurchase	30.84631	24.66661	10.95780	55.71487	14.12546	7.20918
	(0.17)	(0.21)	(0.44)	(0.10)	(0.18)	(0.33)
Size	-0.14661	-0.11510	-0.05466	-0.32153	-0.10996	-0.06622
	(-0.16)	(-0.22)	(-0.57)	(-0.11)	(-0.28)	(-0.79)
Profitability	-0.05503	-0.07635	-0.05441*	0.05323	-0.05676	-0.03551
	(-0.71)	(-0.57)	(-1.65)	(0.09)	(-0.71)	(-1.52)
Altman Z-Score	0.00080	0.00125	0.00032	0.00224	0.00111	0.00051
	(0.17)	(0.20)	(0.32)	(0.12)	(0.21)	(0.49)
MTB	-0.00651	-0.00265	-0.00082	-0.01379	-0.00207	-0.00078
	(-0.13)	(-0.13)	(-0.18)	(-0.11)	(-0.15)	(-0.19)
D/P	1.20204	0.90821	0.58901	1.69676	0.61610	0.54739
	(0.17)	(0.26)	(0.83)	(0.13)	(0.30)	(0.84)
Cash	-0.00000	0.00002	0.00003	0.00002	0.00003	0.00003
	(-0.01)	(0.16)	(0.38)	(0.04)	(0.20)	(0.46)
Observations	30,177	25,870	22,158	29,600	25,440	21,840
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 13: Difference-in-Differences Analysis on Firm Share Repurchases

This table presents the difference-in-differences regression results. The treatment shock is the enactment of the Energy Independence and Security Act of 2007, which was signed into law on December 19th, 2007, making 2008 as the effective treatment year. Years from 2005 to 2007 are the pre-treatment periods with *Post* equal to zero, and years from 2008 to 2010 are the post-treatment periods with *Post* equal to one. Mature firms in the energy intensive industries specified by the Act in 2008 reside in the *Treated* group, while innovative firms in these energy intensive industries in 2008 belong to the control group. The treatment effect is estimated by the interaction term $Treated \times Post$. *Repurchase Indicator* is the dependent variable for columns (1) and (2), while columns (3) and (4) focus on *Scaled $Repurchase* as the dependent variable. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

VARIABLES	(1) Repurchase Indicator	(2) Repurchase Indicator	(3) Scaled Repurchase	(4) Scaled Repurchase
Treated	0.18506**	0.10785**	0.11398**	0.05587*
	(2.81)	(2.53)	(3.05)	(2.25)
Treated × Post	-0.04021***	-0.03950**	-0.02828***	-0.02826**
	(-9.91)	(-3.45)	(-21.61)	(-2.81)
Size		0.09083***		0.05081***
		(14.35)		(11.89)
Profitability		0.02099**		0.00647
		(3.34)		(1.68)
Altman Z-Score		-0.00065**		-0.00044***
		(-2.99)		(-3.87)
MTB		-0.00029		0.00013
		(-0.97)		(0.61)
D/P		0.24251		0.20010
		(0.81)		(1.85)
Cash		0.00000		0.00003***
		(0.09)		(5.43)
Age		0.00385***		0.00282***
		(5.13)		(6.88)
Observations	4,236	4,076	4,172	4,076
Adjusted R-squared	0.091	0.323	0.088	0.447
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 14: Placebo Tests on the Difference-in-Differences Analysis

This table presents placebo tests for the difference-in-differences analysis. We change the treatment year to two years before, three, and five years after the actual treatment year of 2008. The treatment effect is estimated by the interaction term $Treated \times Post$. Columns (1) and (2) pertain to the placebo tests with 2006 as the treatment year, columns (3) and (4) have 2011 as the treatment year, and columns (5) and (6) use 2015 as the treatment year. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment Year = 2006		Treatment Year = 2011		Treatment Year = 2015	
VARIABLES	Repurchase Indicator	Scaled $Repurchase	Repurchase Indicator	Scaled $Repurchase	Repurchase Indicator	Scaled $Repurchase
Treated	0.03159	0.01116	0.11363	0.04305	0.14391***	0.04837**
	(0.98)	(0.80)	(1.88)	(1.36)	(5.15)	(2.78)
Treated × Post	0.03840	0.03348	-0.01417	-0.00174	0.00985	0.00062
	(0.92)	(1.75)	(-0.98)	(-0.20)	(0.84)	(0.04)
Size	0.06910***	0.03668***	0.08454***	0.04460***	0.06528***	0.03434***
	(5.58)	(5.12)	(14.05)	(8.22)	(11.75)	(6.96)
Profitability	0.00503	0.00053	0.01558***	0.00259	0.01929***	0.00226*
	(1.51)	(0.32)	(7.63)	(1.73)	(7.47)	(2.10)
Altman Z-Score	-0.00031**	-0.00021**	-0.00047***	-0.00024**	-0.00052***	-0.00022***
	(-2.71)	(-2.98)	(-5.30)	(-3.93)	(-5.12)	(-4.26)
MTB	0.00005	0.00007	-0.00076	-0.00014	-0.00086**	-0.00019
	(0.12)	(0.23)	(-1.71)	(-1.01)	(-3.17)	(-1.70)
D/P	0.20524*	0.12629	0.06191	0.12598	-0.09673	0.14800***
	(2.11)	(1.85)	(0.18)	(1.34)	(-1.00)	(5.14)
Cash	0.00001	0.00003***	0.00001	0.00004***	0.00002	0.00005***
	(1.51)	(4.90)	(1.16)	(7.63)	(1.68)	(12.68)
Age	0.00482**	0.00251**	0.00345***	0.00182***	0.00535***	0.00268***
	(3.67)	(3.88)	(4.56)	(4.55)	(5.36)	(6.98)
Observations	4,421	4,421	3,537	3,537	3,953	3,953
Adjusted R-squared	0.344	0.402	0.358	0.490	0.355	0.502
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Parallel Trend for Actual Repurchase Indicator

The Energy Independence and Security Act (EISA) was enacted in 2007 and signed into law on December 19, 2007, making 2008 the treatment year of our analysis. The figure shows the parallel trend for the sub-sample of mature and innovative firms in energy intensive industries in 2008. The y-axis refers to the propensity for a firm to repurchase shares in the open market in a given year. *Treated* equals one for firms at the mature stage of firm life cycle in energy intensive industries classified by the EISA in 2008, and zero otherwise. *Post* equals one for years starting in 2008, and zero otherwise. We include three years before and after the treatment to estimate the treatment effect. The green vertical line separates the pre-treatment period from the post-treatment period.

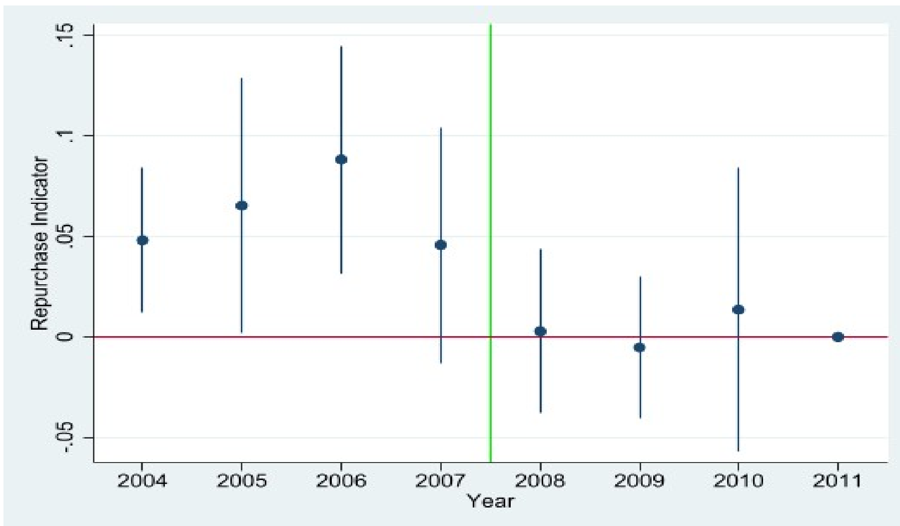
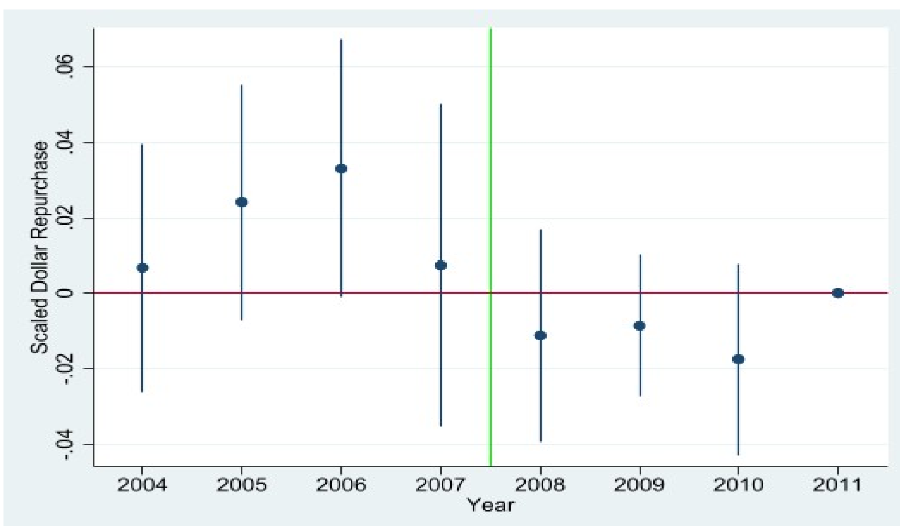


Figure 2: Parallel Trend for Scaled Dollar Repurchase

The Energy Independence and Security Act (EISA) was enacted in 2007 and signed into law on December 19, 2007, making 2008 the treatment year of our analysis. The figure shows the parallel trend for the sub-sample of mature and innovative firms in energy intensive industries in 2008. The y-axis refers to *Scaled $Repurchase*, which is the natural log of dollar amount of actual repurchases that a firm conducts in the open market in a given year scaled by its firm size. *Treated* equals one for firms at the mature stage of firm life cycle in energy intensive industries classified by the EISA in 2008, and zero otherwise. *Post* equals one for years starting in 2008, and zero otherwise. We include three years before and after the treatment to estimate the treatment effect. The green vertical line separates the pre-treatment period from the post-treatment period.



A Online Appendix

Table A.1: Robustness Test with Competition and Prior Returns

This table presents the robustness test for our main results. The dependent variables are similar to those in Table 2. The test includes the independent variables of *Competition* and *Last 6 Months' Returns* for additional controls and show consistent results. *Competition* denotes the competitive intensity in **??**. *Last 6 Months' Returns* measures the return on a firm's return for six months up to the first day of a given year. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

VARIABLES	(1) Repurchase Indicator	(2) Scaled $Repurchase
Cost Minimizing	0.02164	0.00195
	(1.19)	(0.26)
Mature	0.04825**	0.02136*
	(2.28)	(2.07)
Declining	0.05140**	0.01875**
	(2.74)	(2.28)
Competition	0.02631*	0.00729
	(1.90)	(0.87)
Last 6 Months' Returns	-0.04425***	-0.02114***
	(-3.76)	(-3.63)
Size	0.08374***	0.05532***
	(9.54)	(8.67)
Profitability	0.10176***	0.04597***
	(4.40)	(4.90)
Altman Z-Score	-0.00175**	-0.00150***
	(-2.79)	(-4.49)
MTB	-0.00083**	-0.00008
	(-2.29)	(-0.41)
D/P	0.34306***	0.18687***
	(3.77)	(4.08)
Cash	-0.00001	0.00002***
	(-0.85)	(3.87)
Age	0.00270***	0.00136***
	(5.35)	(5.56)
Observations	36,096	36,096
Adjusted R-squared	0.269	0.371
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table A.2: Employment After Share Repurchase - Pooled Regressions

This table presents the regression results of firm employment after repurchasing shares without conditional on their life cycles. The dependent variables are the same as those in Table 9. The independent variable *Repurchase* equals one if a firm spends a positive amount of money in repurchasing its shares in the open market in a given year and zero otherwise. No variables regarding firm life cycles are included. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Employment_{t+1}$	(2) $Employment_{t+2}$	(3) $Employment_{t+3}$	(4) $Employment\ Growth_{t+1}$	(5) $Employment\ Growth_{t+2}$	(6) $Employment\ Growth_{t+3}$
Repurchase	0.46638	0.35350	0.22442	-0.03109***	-0.01712***	-0.01105***
	(1.07)	(0.80)	(0.46)	(-4.01)	(-3.79)	(-3.40)
Size	3.16709***	3.36673***	3.54951***	0.01409***	0.00692***	0.00508**
	(5.07)	(5.25)	(5.41)	(5.54)	(3.14)	(2.87)
Profitability	-2.66367***	-2.25424***	-1.81287**	-0.02177***	-0.01881***	-0.02034***
	(-3.26)	(-3.30)	(-2.80)	(-4.27)	(-6.21)	(-4.19)
Altman Z-Score	-0.06767	-0.05509	-0.04137	0.00059***	0.00036***	0.00029*
	(-1.55)	(-1.26)	(-1.06)	(4.01)	(4.10)	(2.11)
MTB	-0.01605	-0.01162	-0.01468	0.00101***	0.00072***	0.00008
	(-1.08)	(-0.72)	(-0.91)	(6.21)	(6.20)	(0.35)
D/P	20.69332***	20.43909***	20.31672***	-0.14499***	-0.12422**	-0.12601
	(4.35)	(3.93)	(3.65)	(-3.94)	(-2.25)	(-1.49)
Cash	0.01016***	0.01018***	0.01030***	-0.00001***	-0.00000	-0.00000
	(8.60)	(8.71)	(8.85)	(-3.76)	(-1.54)	(-1.27)
Age	0.25223***	0.24777***	0.24385***	-0.00251***	-0.00178***	-0.00136***
	(4.79)	(4.65)	(4.55)	(-8.17)	(-8.49)	(-6.91)
Observations	39,206	34,136	29,713	44,463	38,178	32,818
Adjusted R-squared	0.491	0.494	0.497	0.041	0.030	0.028
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.3: Valuation and Productivity After Share Repurchase - Pooled Regressions

This table presents the regression results of firm valuation and productivity after repurchasing shares without conditional on their life cycles. The dependent variables are the same as those in Table 10. The independent variable *Repurchase* equals one if a firm spends a positive amount of money in repurchasing its shares in the open market in a given year and zero otherwise. No variables regarding firm life cycles are included. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. t-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Tobin'sQ_{t+1}$	(2) $Tobin'sQ_{t+2}$	(3) $Tobin'sQ_{t+3}$	(4) TFP_{t+1}	(5) TFP_{t+2}	(6) TFP_{t+3}
Repurchase	-0.22023**	-0.17766	-0.00579	0.08824	0.08162	0.08104
	(-2.44)	(-1.46)	(-0.04)	(1.47)	(1.50)	(1.54)
Size	0.20846***	0.22438***	0.18220***	0.00974	0.00772	0.00709
	(4.39)	(5.12)	(4.62)	(1.32)	(0.98)	(0.84)
Profitability	0.43069**	0.19662	0.18625	0.08481***	0.08744***	0.07978***
	(2.54)	(1.40)	(1.26)	(4.50)	(3.52)	(3.07)
Altman Z-Score	0.01049**	0.01406***	0.01285***	-0.00222***	-0.00212**	-0.00177*
	(2.52)	(4.23)	(3.16)	(-2.99)	(-2.30)	(-2.04)
MTB	0.09979***	0.05636***	0.04492***	0.00109	0.00085	0.00114
	(6.61)	(4.68)	(3.16)	(1.23)	(1.01)	(1.62)
D/P	-3.09995	0.36296	-0.36842	0.03047	0.13904	0.06204
	(-1.62)	(0.46)	(-0.35)	(0.16)	(0.92)	(0.31)
Cash	-0.00007	-0.00005	-0.00001	0.00001	0.00001	0.00001
	(-1.01)	(-0.65)	(-0.15)	(0.38)	(0.58)	(0.71)
Age	-0.01670***	-0.01127**	-0.01073**	-0.00009	-0.00053	-0.00081
	(-3.66)	(-2.32)	(-2.68)	(-0.04)	(-0.25)	(-0.42)
Observations	45,702	39,016	33,366	40,971	35,135	30,216
Adjusted R-squared	0.064	0.044	0.039	0.195	0.178	0.166
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4: Firm Growths After Share Repurchase - Pooled Regressions

This table presents the regression results of firm growths after repurchasing shares without conditional on their life cycles. The dependent variables are the same as those in Table 11. The independent variable *Repurchase* equals one if a firm spends a positive amount of money in repurchasing its shares in the open market in a given year and zero otherwise. No variables regarding firm life cycles are included. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Sales\ Growth_{t+1}$	(2) $Sales\ Growth_{t+2}$	(3) $Sales\ Growth_{t+3}$	(4) $Asset\ Growth_{t+1}$	(5) $Asset\ Growth_{t+2}$	(6) $Asset\ Growth_{t+3}$
Repurchase	-0.08523***	-0.05540**	-0.03924*	-0.02646	0.00146	-0.00318
	(-4.28)	(-2.35)	(-2.07)	(-1.54)	(0.11)	(-0.25)
Size	0.00248	-0.00077	-0.00368	0.01492*	-0.00863	-0.01168*
	(0.48)	(-0.16)	(-0.94)	(2.08)	(-1.04)	(-1.99)
Profitability	-0.11974***	-0.10597***	-0.08539***	-0.18991***	-0.13034***	-0.09260***
	(-14.98)	(-6.96)	(-4.37)	(-13.99)	(-6.40)	(-5.97)
Altman Z-Score	0.00280***	0.00153***	0.00094	0.00002	-0.00004	-0.00020
	(11.01)	(3.53)	(1.21)	(0.03)	(-0.08)	(-0.43)
MTB	0.00111	0.00082	0.00126	0.00078	0.00138	0.00058
	(1.44)	(1.75)	(1.34)	(0.78)	(1.60)	(0.50)
D/P	-0.09855	-0.20716	-0.45592**	0.05224	-0.00663	-0.21132
	(-0.76)	(-1.15)	(-2.49)	(0.28)	(-0.04)	(-1.43)
Cash	0.00000	0.00000	0.00000	-0.00001*	0.00001	0.00001
	(0.14)	(0.22)	(0.44)	(-1.82)	(1.00)	(1.63)
Age	-0.00457***	-0.00346***	-0.00276***	-0.00307***	-0.00223***	-0.00155***
	(-6.04)	(-4.45)	(-4.71)	(-5.45)	(-6.14)	(-4.00)
Observations	43,592	37,613	32,411	45,918	39,218	33,579
Adjusted R-squared	0.054	0.053	0.049	0.141	0.083	0.056
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5: Investment After Share Repurchase - Pooled Regressions

This table presents the regression results of firm investment after repurchasing shares without conditional on their life cycles. The dependent variables are the same as those in Table 12. The independent variable *Repurchase* equals one if a firm spends a positive amount of money in repurchasing its shares in the open market in a given year and zero otherwise. No variables regarding firm life cycles are included. All regressions include industry and year fixed effects. Standard errors are clustered at the industry and year level. *t*-statistics are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% level.

Variables	(1) $Investment_{t+1}$	(2) $Investment_{t+2}$	(3) $Investment_{t+3}$	(4) $Investment\ Growth_{t+1}$	(5) $Investment\ Growth_{t+2}$	(6) $Investment\ Growth_{t+3}$
Repurchase	-0.03374**	-0.03030**	-0.02673*	-0.02883**	-0.01483	-0.00438
	(-2.16)	(-2.18)	(-2.00)	(-2.67)	(-1.28)	(-0.56)
Size	-0.01503***	-0.01620***	-0.01745***	-0.04269***	-0.03855***	-0.03837***
	(-3.56)	(-3.83)	(-3.87)	(-10.82)	(-14.75)	(-11.51)
Profitability	-0.06111***	-0.06160***	-0.05349***	-0.00565	-0.04505***	-0.03405**
	(-5.14)	(-5.17)	(-4.72)	(-0.53)	(-5.06)	(-2.72)
Altman Z-Score	-0.00001	0.00005	-0.00015	0.00095*	0.00024	0.00009
	(-0.03)	(0.15)	(-0.61)	(1.86)	(0.54)	(0.17)
MTB	0.00040*	0.00052	0.00036	0.00017	0.00077	-0.00016
	(2.10)	(1.71)	(1.18)	(0.25)	(1.13)	(-0.16)
D/P	0.10176**	0.06175	0.17814*	0.21871	0.14261	0.28715**
	(2.67)	(1.18)	(1.96)	(1.00)	(1.29)	(2.23)
Cash	0.00001***	0.00001***	0.00001***	0.00003***	0.00003***	0.00002***
	(3.97)	(4.28)	(4.25)	(7.88)	(8.61)	(7.23)
Age	-0.00164***	-0.00163***	-0.00168***	-0.00189***	-0.00070***	-0.00061*
	(-4.33)	(-4.37)	(-4.28)	(-4.80)	(-4.29)	(-1.94)
Observations	30,176	25,870	22,158	29,596	25,439	21,839
Adjusted R-squared	0.300	0.290	0.273	0.033	0.040	0.038
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes