Two essays on the impact of automation on firms' operating performance and M&A decisions, and One essay on a comparative analysis in external financing between U.S. and Japan

by

Quoc Phan

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I.H. Asper School of Business

University of Manitoba

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Abstract

This thesis includes three topics on corporate finance: (1) Automation Exposure and Operating Performance, (2) Corporate Cash Shortfalls and External Financing: US vs Japan, and (3) Automation Exposure and M&A.

The first essay, "Automation Exposure and Operating Performance," finds empirical evidence that firms with increased automation exposure experience deteriorating operating performance in subsequent years. Further analysis shows that financially unconstrained firms are better positioned to mitigate this negative impact on their operating performance compared to financially constrained firms. However, unconstrained firms are drawn into an automation arms race, escalating their investments in capital, tangible assets, and R&D. This race, while aimed at maintaining a competitive edge, paradoxically leads to a greater deterioration in their financial health compared to their financially constrained counterparts.

In the second essay, "Corporate Cash Shortfalls and External Financing: US vs Japan," I find supporting evidence for the funding-horizon theory on external financing in both the US and Japan. I also find that repurchase and subnormal cash holding are important motives for debt issuance, while debt reduction is an important motive for equity issuance. Japanese firms are much less likely to issue debt and equity compared to US firms. The results suggest that this difference is due to the lower leverage used by Japanese firms and the fact that Japanese firms tend to be mature with fewer cash needs for growth.

In the third essay, “Automation Exposure and M&A,” I find evidence that firms with high automation exposure are more likely to be involved in M&A transactions. High automation exposure firms with high R&D, profitability, cash holding, market value, and low leverage tend to be acquirers, while firms with the reverse characteristics tend to be targets. I further find that

automation facilitates M&A transactions when product similarity is high. Consistent with the findings from my first essay on the automation arms race, acquisitions for automation purposes result in a "winner's curse," where the acquiring firms face greater financial constraints and lower operating profits in the following period.

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1 Chapter 1: General Introduction

This thesis includes three essays on corporate finance: (1) Automation Exposure and Financial Constraints, (2) Corporate Cash Shortfall and External Financing: International Evidence, and (3) Automation Exposure and M&A. In the first and third essays, I study the influence of automation on company performance and decisions. In the second essay, which is a different topic from automation, I run a comparative analysis between US and Japan on factors determine of external financing.

Chapter 2: Automation Exposure: Operating Performance & Automation Arm Race

Overview of Automation Technologies and Their Growing Significance in Industries

The Industrial Revolution, which began around 1760 and lasted until about 1840, marked a pivotal shift from manual craftsmanship to machine-based manufacturing, transforming economies and societies worldwide (Britannica, 2024[1]; National Geographic, 2024[2]). This period saw significant improvements in productivity, with innovations such as the steam engine and mechanized textile production fundamentally changing the nature of work and industry (History, 2024).s

Automation technologies have continued to evolve, significantly impacting firm performance. Modern automation encompasses a wide range of technologies, including robotics, artificial intelligence, and machine learning, all of which have become integral to industrial operations. These technologies enhance productivity, reduce labor costs, and improve quality and precision in

[1] https://www.britannica.com/event/Industrial-Revolution

[2] https://education.nationalgeographic.org/resource/resource-library-industrial-revolution/

manufacturing processes. For example, the adoption of industrial robots has been linked to increased productivity and efficiency in various sectors (History, 2024[3]).

The Motivation Behind Studying the Impact of Automation on Firm Performance

Understanding the impact of automation on firm performance is crucial due to its dual nature. On one hand, automation provides initial competitive advantages by reducing production costs and enabling firms to implement lower pricing strategies, thereby improving their market position. However, as automation becomes widespread, it transforms into an industry standard, leading to increased costs for all firms involved.

Research by Knesl (2024) highlights a critical aspect of the transition towards automation, illustrating how it forces firms into a game theory scenario. Firms must either adopt new automation technologies or risk obsolescence. This necessity turns automation into a compulsory investment, which can erode profit margins over time.

Is it true that automation has the same negative impact for all firms, or is there a difference? Since some firms are in better financial health to adopt automation while other firms are financially constrained, it is worth examining if there is a difference in the impact of automation between financially constrained and financially unconstrained firms.

Financially unconstrained firms initially benefit from improved operational performance due to reduced costs and enhanced competitive positioning. Because early automation adoption provides certain competitive advantages in cost and price, unconstrained firms will try to adopt new automation technologies as soon as possible to stay ahead of their rivals. This raises the question: will this lead to an automation arms race? If this leads to an automation arms race, what would be the consequences?

[3] https://www.history.com/topics/industrial-revolution

In chapter 2, I will explore the impact of new automation technologies on firm performance by examining 103,991 firm-year observations from 1976 to 2014 in the U.S. It is observed that new automation technologies, while initially providing competitive advantages, eventually evolve into an industry-wide standard. This ubiquity transforms automation into a necessary expenditure for firms, thereby becoming a standard cost that contributes to reduced profit margins. The research further indicates that financially unconstrained firms are more likely to embrace automation, initially experiencing enhanced operational performance due to decreased production costs and improved competitive positioning through lower pricing strategies. Conversely, financially constrained firms, hindered in their ability to adopt automation, are compelled to reduce prices and accept losses in order to maintain their market presence. However, a notable trend emerges among unconstrained firms: driven by peer pressure, they engage in an automation arms race, characterized by increased investments in automation and R&D. This race, while aimed at maintaining a competitive edge, paradoxically leads to a greater deterioration in their financial health comparing to their financially constrained counterparts.

Chapter 3: Corporate Cash Shortfalls and External Financing: US vs Japan

The dynamic trade-off model in DeAngelo et al. (2011) suggests a funding-horizon theory in which corporate cash needs and the nature of cash needs drive external financing decisions. Huang and Ritter (2021) find that firms running out of cash are likely to raise debt or equity. But is it too obvious that firms running out of cash will always resort to issuing debt or equity?

What are the other possible drivers for firms to issue debt and equity? If certain factors are the main drivers for debt and equity issuance, do these factors have the same impact across different countries? A comparison of these factors between the US and Japan would be insightful.

For instance, in the US, equity issuers tend to have long-lived cash needs while debt issuers usually have short-lived cash needs (Denis and McKeon, 2021; Liu et al., 2023). Does this pattern hold true in Japan as well? Additionally, how do capital restructuring motives, such as equity repurchase and debt reduction, influence financing decisions in both countries?

I test the funding-horizon theory about external financing and find evidence to support the theory in both the US and Japan. I also find that repurchase is an important motive for debt issuance and debt reduction is an important motive for equity issuance. Japanese firms are much less likely to issue debt and equity compared with US firms. The test results suggest that this difference is associated with the lower leverage used by Japanese firms and the fact that Japanese firms tend to be mature firms with less cash needs for growth.

Chapter 4: "Automation Exposure and M&A"

Mergers and acquisitions (M&A) play a crucial role in corporate strategy, facilitating growth, enhancing competitiveness, and driving innovation. They enable companies to quickly gain market share, diversify their product lines, and acquire new technologies or capabilities. Historical data shows that significant technological advancements, such as the development of new automation technologies, often correlate with increased M&A activity, see (Cassiman et al., 2005; Cefis, 2010; Micco, 2020).

As automation technologies become more advanced and widespread, their impact on industries is profound. Automation reduces production costs, improves product quality, and enhances flexibility in manufacturing processes, driving firms to adopt these technologies to remain competitive[4]. This drive for technological advancement often leads to an increase in M&A

[4] https://www.britannica.com/technology/automation/Modern-developments

activities, as firms seek to acquire not just automation capabilities but also the market share necessary to make these technologies economically viable, see (Bessen, 2016).

The hypothesis is that firms with high automation exposure are more likely to engage in M&A activities. This relationship can be attributed to several factors:

- Economic Viability of Automation: Automation requires significant investment, which becomes more economical with larger production volumes. Thus, acquiring firms can rapidly scale up production capabilities (Rhodes-Kropf & Robinson, 2008).
- Acquisition of Automation Patents: Instead of investing heavily in R&D, firms may prefer to acquire other companies with established automation technologies and patents, reducing risk and accelerating implementation (Phillips & Zhdanov, 2013).

Also, does the decision to pursue M&A for automation purposes depend on the similarity of the firm's products to its competitors? Kim & Mauborgne (2005) shows that product differentiation creates unique and competitive edge for firm in the firm. However, given in industry where product similarity is high, does this have an impact on automation and firm’s M&A?

Evidence indicates that automation is the second most significant factor driving M&A activity, following asset size. Firms exposed to higher levels of automation are more likely to pursue M&A. The automation factor remains the most impactful factor after controlling time, industry, size, and market-to-book value. Furthermore, the strategy of acquiring for automation purposes depends significantly on the current level of automation and the product similarity between the firm and its competitors. In industries with high automation and limited opportunities for product differentiation, firms are more likely to acquire others for automation purposes. Conversely, in industries with low automation levels, firms are less inclined to use acquisitions as a strategy, even if their products are very similar to those of their rivals. Consistent with the findings from my first essay on the automation arms race, acquisitions for automation purpose often result in a "winner's curse," where the acquiring firms face greater financial constraints and lower operating profits in the following period.

2 Chapter 2: Automation Exposure – Operating Peformance & Automation Arms Race

2.1 Introduction

The evolution from Industrial Revolution 1.0 through 4.0, now highlighted by the pervasive integration of artificial intelligence (AI) and robotics, underscores the increasing significance of automation in reshaping the global business landscape. The advancement in automation technology has significant effects on economic activities. The recent economics and finance literature on automation explore the effects of automation technology on labor market dynamics (Acemoglu & Restrepo, 2020), economic growth (Antony & Klarl, 2020), financial policy and capital structure (Bates et al., 2020; Liu Y. , 2021; Qiu et al., 2020), operating leverage (Bates et al., 2020; Cheng et al., 2022), investment (Benmelech & Zator, 2022), and asset pricing (Knesl J. , 2023; Zhang, 2019) and among others. A common perspective on automation is its capability in reducing the need for labor, lowering production costs and improving product quality. However, the real-world implications of automation technological shift on firm operations remain an open question. This essay seeks to address two critical aspects: (1) the influence of automation technology on firm operating performance, and (2) the existence and consequences of an automation arms race within the industry.

In recent years, we observe a rapid escalated investment in AI (a form of automation arm race) by tech giants such as Microsoft, Alphabet, Meta and Amazon. Microsoft substantially invested \$10 billion in OpenAI[5,6], together with the strategy to reduce its workforce by about 10,000 employees. Following the release of GPT, Google's CEO, Sundar Pichai, sent an email to

[5] https://finance.yahoo.com/news/microsoft-invests-10-billion-chatgpt-155459385.html
[6] https://www.reuters.com/technology/microsoft-emerges-big-winner-openai-turmoil-with-altman-board-2023-11-20/

all employees emphasizing developing Bard, Google's AI, is company's top priority. Pichai emphasized the urgency of addressing and integrating AI advancements, marking it as an urgent strategic matter that necessitates prompt and comprehensive action across all sectors of the organization. Other big techs, including Amazon and Meta, are also entering this AI race, signaling a widespread industry shift. Examining firms' perspectives on this AI arms race, the question arises: will this eventually benefit the firms, or will this race consume more resources and capital than the returns it generates?

In Knesl (2023), it is shown that companies initially gain an edge by adopting new automation technologies to cut costs and reduce prices; but as competitors follow suit, this advantage diminishes. Eventually, adopting these innovations becomes a necessity for survival, leading to industry standardization and generally lower profits for all firms. Building upon Knesl (2023) automation model, this essay introduces the variable of diverse initial financial constraints among firms. I find evidence that changes in new automation technology leave a negative impact on financial constrained firms while unconstrained firms can mitigate such negative impact. Furthermore, I find evidence of automation arms race among unconstrained firms, characterized by escalated investment and research and development spending. Ultimately, unconstrained firms involved in this automation race experience more significant financial health deterioration compared to their financially constrained counterparts.

My paper makes several contributions to the literature of automation. First, I find evidence to support the prediction of Knesl (2023) that automation leads to the reduction in profit of all firms. I further advance the model by demonstrating that the driver of the price war is initiated by financially unconstrained firms. To my knowledge, this is the first paper to show how automation trigger an automation arms race. My paper is different from (Ahmad et al., 2020), who also studies arms race but focusing on technology innovation in general and using change in barcode as proxy for product innovation. Second, I use the number of patents related to automation as the proxy for automation exposure rather than using traditional measures such as robots or probability of replacement.

The structure of this essay is organized as follows. In section 2, I develop conceptual frameworks and hypotheses. In section 3 I present data, sample, and model construction. Section 4 shows the regression result and section 5 concludes.

2.2 Conceptual Framework and Hypothesis Development

2.2.1 Automation Competition Hypothesis

Concerns surrounding automation predominantly revolve around its potential to displace jobs. Autor & Dorn (2013) showed that automation leads to a labor market polarization trend, where middle-skill jobs diminish, high-skill jobs proliferate, and low-skill jobs maintain relative stability, resulting in more employment at the high and low spectrum and a contraction in the middle. Acemoglu & Restrepo (2020) studied the impact of robots on the labor market, indicating the increase in the share of robots leading to the reduction in labor need and lower wage. This essay, I focus the analysis to firm's operating performance.

According to the technology adoption model in Knesl (2023), new automation technology lowers costs and firms in the industry have an incentive to adopt the new technology to stay competitive. Early adopters take advantage of automation cost to reduce price and to gain market share. This intangibly pushes more firms to adopt automation technology. Subsequently, the adopters lose the competitive advantage of lower costs. The cost of adoption become the necessity cost to stay in the market and thereby lower firm's profit. A similar idea is proposed in the innovation arms race theory in Ahmad et al. (2020). Knesl (2023) suggests that at equilibrium, automation innovations lead to lower profits.

Hypothesis 1: *"Firms with higher change in automation exposure have lower profit"*

2.2.2 Automation Adoption – Constrained vs Unconstrained Firms

While Knesl (2023) and Ahmad et al. (2020) predominantly consider competitive industries where all firms possess the capability to adopt new automation technology, this idealized scenario often doesn't hold true due to the substantial adoption costs associated with automation innovations. Consequently, firms grappling with financial constraints are at a disadvantage, unable to timely embrace such technologies. Hyytinen & Toivanen (2005) studied the effects of government funding on Finland’s small and medium-sized enterprises (SMEs), they suggest that financial constraints can hold back innovation. This scenario paves the way for financially unconstrained firms to capitalize on automation, thereby gaining a competitive edge. This disparity not only reduces the profits of non-adopting, constrained firms, but also exacerbates their financial limitations, making it increasingly challenging for them to bridge the technological gap. Hence, in this dynamic, automation innovations tend to depress profits for financially constrained firms, while those free from such constraints can effectively neutralize potential downsides. This notion is encapsulated in what I term the “Adoption Constraints Hypothesis.”

The fundamental distinction between “the Adoption Constraints Hypothesis” and the “Automation Competition Hypothesis” – or Knesl (2023) model – lies in the initial financial conditions of the firms. Knesl's model assumes a level playing field where all firms have equal chance to adopt new automation technologies. Conversely, the “Adoption Constraints Hypothesis” considers the fact that differences in initial financial conditions between constrained and unconstrained firms result in an uneven playing field where unconstrained firms possess the financial flexibility to adopt new automation technologies, while constrained firms face significant barriers to adoption. This divergence fundamentally alters the drivers of profit reduction. In Knesl’s model, the universal investment in automation erodes cost and price competitive advantages, making automation adoption a standard and competitive necessity, ultimately leading to reduced profits for all. In contrast, under the “Adoption Constraints Hypothesis” only financially unconstrained firms can afford to adopt automation, thereby securing both cost and price competitive advantages. These firms actively lower their prices to expand market share, compelling the financially constrained firms to follow suit despite such action leads to lower profit margin. This dynamic results in the same result of price reductions, but the underlying drivers differ: unconstrained firms reduce prices to leverage automation benefits, whereas constrained firms are compelled to reduce prices merely to remain viable in the market. Consequently, this leads to eroded profit margins for constrained firms, while unconstrained firms maintain, or even enhance, their profitability due to their adoption of automation.

Hypothesis 2: "*Given the same change in automation exposure, unconstrained firms should have better operating performance than constrained rivals*"

2.2.3 The Automation Arms Race

Following the "Adoption Constraints Hypothesis", I extend the analysis to show that automation arms race will likely take place among unconstrained firms. The nexus between innovation, competition, and real investment has been well-established in economic literature. The work of Richardson (1960), Arrow (1962), and recently Ahmad et al. (2020) showed how a highly innovative environment compels firms to consider competitive actions of their rivals in their investment strategies. This is especially pronounced for a new automation technology. The rationale is twofold. First, firms are compelled to vigilantly monitor and respond to their rivals' movements and investments in automation to not fall behind. Secondly, the first successful automation adopter gains significant cost and price advantages, creating a domino effect of "peer pressure" on its rivals, as in the example of Microsoft, Alphabet, Meta and Amazon. This domino effect compelling an automation arms race among firms which escalate spending in investment and RD among unconstrained firms. I propose automation arms race hypothesis:

Hypothesis 3: "*Unconstrained firms with significant exposure to automation technologies are likely to be pulled into the Automation Arms Race, characterized by escalated investments in automation and R&D*."

In the Richardson (1960) arms race model, depending on the initial setting, it is possible to have a perpetual climb up or reach zero eventually. Given our observations in recent technology arms race such as (1) Semiconductor (1960s-2000s), (2) CRISPR Gene Editing, (3) Autonomous Driving, (4) recent AI technology and many more. It is important to test the automation arms race hypothesis whether it will lead to better-off situation or value destroy.

Hypothesis 4: *"The automation arms race is costly; firms that are drawn into the race will subsequently end up with weakened financial strength."*

The Arms Race Hypothesis and the Automation Competition Hypothesis, as proposed in Knesl's model, exhibit similar outcomes but differ significantly in their driving factors and initial conditions. In Knesl's framework, all firms are assumed to have an equal opportunity to adopt automation technology. The observed reduction in profits stems from the new price equilibrium (lower) and the standardization of automation adoption costs. In the Arms Race hypothesis, firms have differences in initial setup, constrained vs unconstrained. Unconstrained firms have better financial flexibility to finance costly automation than constrained firms. Therefore, it is likely that unconstrained firms are early automation adopters and thereby gaining competitive edge to lower prices. As a consequence, constrained firms find themselves compelled to lower prices to remain viable, exacerbating their financial constraints due to their inability to invest in automation. This trend results in a lower profit margin and exacerbates financial strength (more financially constrained). In the other hand, unconstrained firms driven by "peer pressure", persist in substantial spending in automation investment and R&D. These costly expenditures, while aimed at maintaining a competitive lead, eventually erode their financial strength, ironically weakening these firms' financial strength over time.

Both scenarios of constrained and unconstrained firms lead to a decline in financial health. Constrained firms face increased financial constraints because they do not have the necessary capital to invest in automation; therefore, they have to follow the new lower price to survive in the market. This leads to a lower profit margin and higher financial constraints. For unconstrained firms, 'peer pressure' compels them to continuously spend on investment and R&D. These huge costs subsequently weaken the firms' financial health.

2.3 Data and Sample

2.3.1 Data and Sample

I use three datasets: the Fundamental Annual Compustat, the Compustat Historical Segment, and the Automation Patents of Mann & Puttmann (2023).

The Automation Patents dataset of Mann & Puttmann (2023) is constructed using machine learning algorithms to classify over 5 million patents on Google Patent Search from 1976 to 2014. Each patent is classified as (i) an automation patent, (ii) a pharmaceutical and chemical patent, or (iii) the rest. The Automation Patents dataset is available up to 4 digits of SIC code. I obtain the Automation Patents datasets from the authors' website on Nov 14th, 2021.

Financial data from the Fundamental Annual Compustat and the Compustat Historical Segment is selected from 1976 to 2014, matching time period of automation database. I remove: (1) all Utilities and Financial companies (SIC 4900-4999 and 6000-6999), (2) the total asset less than 25 million and sales less than 10 million, (3) companies with a total of employees less than 100. Firms also must have cash and equivalent less than total asset, and cost of good sold positive. To be included, firms must have at least 10 observations. The final sample size includes 103,991 firm-year observations with 6,017 unique firms.

2.3.2 The measure of Automation Exposure

In the literature, there are several approaches to measure automation: (1) probability of being lay-off, (2) text analysis from Dictionary of Occupational Titles (DOT), and (3) Number of robots shipped. It is also important to note that measuring the number of microprocessors used was a very popular proxy for research papers in the 1990s. However, due to the commonality of computers, this measure has been less used since the 2000s. The three common proxies for automation above has particular limitation in their coverage range for automation. The probability of being lay-off, (Frey & Osborne, 2017), and text analysis from DOT are limited because of their data update frequency[7] and the lack of completeness in firms' reports. The number of robots shipped[8][9] strongly assumes that automation must be in physical form and ignore the intangibility of automation such as Robotic Process Automation, a software that act like to human interacting with machines (see (Van der Aalst et al., 2018), and (Hofmann et al., 2020). I believe using the patent database is a better approach since it covers broader aspects of technological innovation, both tangible and intangible, and time-variant.

The automation database (Mann & Puttmann, 2023) is available up to 4 digits in the SIC industry. In theory, I could apply the same methodology to estimate the number of automation patents at the firm level. However, this is not the case for two reasons. First, (Mann & Puttmann, 2023) does not publish the machine learning algorithm (models, number of layers, and nodes) and training sample. I cannot replicate the paper at the firm scale level. Second, the spillover effect makes it less critical for firm-level data. In economics, any investment in technology by a company (via R&D) has two opposite spillover effects: (a) positive effect from knowledge spillover and (b) negative effect from product market rivals. The (a) positive spillover effect can be viewed as technology transferred or leaked out to all firms operating in the same industry sector. This transfer or leakage benefits all firms in the same industry sector. An example of a new technology transfer is the 5G technology, which benefits all computer and mobile industry firms. The (b) negative spillover effect is when rivals inherit the new technology and gain advantages over the company that invests in it.

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[7] Most paper using probability of being lay-off use the probability estimated in the paper of (Frey & Osborne, 2017). The drawback is time-invariant. There is only one probability value for each occupation in 2010. We believe this does not fully reflect the innovation in automation technology over time.

[8] Using the number of robots shipped as automation proxy is common and trendy in recent automation research papers: (Acemoglu & Restrepo, 2020), Graetz et Michaels (2018), , Dauth (2017) e.g.

[9] database is obtained from the International Federation of Robotics, IFR. https:ifr.org

For the two reasons above, the automation of a firm alone is less important because it does not account for the spillover effect. The objective is to calculate the automation variable which captures the aggregation of spillover effects. I call automation variable with the aggregation of spillover effect automation exposure.

According to spillover theory, if a technology spillover rate is θ, we can estimate the net of the positive and the negative effect of spillovers. The θ takes value from [0, 1]. On the two extreme sides, when θ = 0, there is no leak out, and when θ = 1, R&D is pure public good. We can model the spillover effect if we have information on R&D and θ for each company in each segment. Since automation is a sub-class of technology, modeling automation spillover effects is similar to technology spillover effects.

The first and most commonly used model for the spillover effect in technology is Jaffe (1986). The model first calculates the uncentered correlation P(i,j) between a firm (i) and its rivals (j) that operate in the same industry sector.

$$P(i,j) = \frac{F_i F_j^T}{(F_i F_i^T)^{12} \left(F_j F_j^T\right)^{12}} \tag{1}$$

F(·) is a vector measure of firm (i) investment in segment space. In (Jaffe, 1986), the leak-out rate θ is assumed to be constant for all firms. Then the net spillover S(i) for a firm (i) is:

$$S_i = \sum_{i \neq j}^{K} \left(P_{i,j} R_j\right) \tag{2}$$

Where R_j is the total investment in R&D of rival (j). The technology spillover model (the equation 1 and 2) was developed and used in (Bloom N. a., 2013). Then the spillover model is modified and applied in (Qiu et al., 2020) to calculate firm-level automation exposure. In this essay, I borrow the (Qiu et al., 2020) equation to calculate the automation exposure at the firm level.

$$\text{Auto}_{i,t} = Ln\left(\sum_{j=1}^{N} \text{SegSale}_{i,j,t} \cdot \text{AutoPatent}_{j,t} + 1\right) \tag{3}$$

Where:

- $\text{segsale}_{\text{i,j,t}}$: is the weight of segment sale of company i, in sector j, at time t
- $\text{autopatent}_{\text{j,t}}$ is the sum of all automation patents in sector j from time (t-5) to time t.

In equation (3) Segsale_(i,j,t) is the weight of segment sales of company i in sector j at year t. Autopatent_(j,t) is the sum of all automation patents (defined by (Mann & Puttmann, 2023)) in sector j from year t-4 to year t. The segment data are collected from Compustat Historical Segment database. The autoamtion data is collected from (Mann & Puttmann, 2023) website.

I see that it is essential to have a brief discussion about the proxies used in (Jaffe, 1986); (Bloom N. a., 2013), equations (1), and (2). The proxies used for F(·) in equation (1) are the number of scientists, the number of patents, or RD expense on each segment of a company (i). However, I cannot obtain any of the three proxies at the firm-level data. I have no data for the number of scientists. I also have no exact methodology from Mann & Puttmann (2023) to calculate each firm's automation patents. There is, indeed, RD expense for each segment at the firm level in Compustat; however, the missing rate is 86.01%. The substitution is to use segment sales with a very high availability rate. I acknowledge that using segment sales is equivalent to assuming that RD in each segment is proportional to segment sales.

2.3.3 Regression model

2.3.3.1 Automation Competition Hypothesis

To measure the effect of automation exposure on certain variables, I run regression on changes of automation exposure and changes in other dependent variables. For each firm year t, I measure the change in automation exposure relative to year t-5 as follows:

$$\Delta Auto_{i,t} = Auto_{i,t} - Auto_{i,t-5} \tag{4}$$

For dependent variables, calling Y, I either use change in Y, Δ(Y), or percentage change in Y, %Δ(Y). The formula for Δ(Y) and %Δ(Y) are calculated as follows:

$$\Delta Y_t = \frac{\sum_{t+1}^{t+5} Y}{5} - \frac{\sum_{t-4}^{t} Y}{5} \tag{5}$$

$$\%\Delta Y_t = \left(\frac{\sum_{t+1}^{t+5} Y}{5} \div \frac{\sum_{t-4}^{t} Y}{5}\right) - 1 \tag{6}$$

The baseline regression is the change of automation exposure (ΔAuto) on the change or percentage change in Y, Δ(Y) or %Δ(Y):

$$\Delta Y_{i,\ t}\ or\ \%\Delta Y_{i,\ t} = \alpha + \beta \Delta Auto_{i,t} + \sum_n \gamma_n C_{n,i,t} + \varphi_i + \mu_t + \varepsilon_{i,t} \tag{7}$$

In this model the control variables $C_{n,i,t}$ include log(Sale) or log(Asset), MtB (market value of assets to book value of assets), Leverage (total debt divided by total assets), and Firm Age (log of the number of years since the firm appear in Compustat). I also include firm fixed effects and year fixed effects in the model.

The impact of new automation technology on a firm's operational performance is further examined by regressing changes in automation exposure (ΔAuto) on various cost and profit measures, including: (1) COGS margin, (2) SG&A margin, (3) EBITDA margin, (4) EBIT margin, (5) Return on Assets (ROA), (6) Return on Equity (ROE), and (7) Profitability. Following Knesl's

(2023) model, the coefficient of ΔAuto is anticipated to be negative for the profitability margin, implying that new automation technology ultimately reduces firms' profits. For cost margins, no specific prediction is made, as firms may maintain a constant cost margin despite price reductions.

2.3.3.2 Automation Adoption Hypothesis

The adoption of new automation systems is costly, and firms with financial constraints are bound by their limited capital and resources, making them unable or barely able to implement automation. In contrast, unconstrained firms possess greater financial flexibility to invest in such costly automation. Consequently, automation exposure tends to negatively impact constrained firms, while unconstrained firms can more effectively mitigate such impacts.

For this analysis, long-term bond ratings serve as proxies to differentiate between unconstrained firms (those with a long-term rating) and constrained firms (those without a long-term rating record), following the methodology of Almeida et al. (2004). In equation (8), I add a rating indicator and the interaction of this indicator with changes in automation exposure to assess the impact of new automation technologies on firms' operating performance, conditioned on financial health. The baseline regression includes the added interaction and rating indicator as follows:

$$\Delta Y_{i,\ t} = \alpha + \beta \Delta Auto_{i,t} + \delta \Delta Auto_{i,t} \times R_{i,t} + \theta R_{i,t} + \sum_{n} \gamma_n \, C_{n,i,t} + \varphi_i + \mu_t + \varepsilon_{i,t} \tag{8}$$

I use the same dependent variables in Automation Competition Hypothesis. The sign of the coefficients β of ΔAuto is expected to remain unchanged. However, the coefficient of the interaction, δ, is expected to exhibit a sign opposite to that of β. An opposite sign to β indicates that unconstrained firms are capable of mitigating or experiencing a less negative impact of new automation technology changes on operating performance.

2.3.3.3 Automation Arms Race and the Consequences

For an individual firm, adopting new automation technology enables it to reduce production costs, thereby gaining a competitive edge in pricing. Consequently, a firm investing in automation can afford to lower its prices relative to its competitors, aiming to capture a larger market share. This competitive advantage compels all industry players to either embrace new automation technology or risk obsolescence. Hence, firms find themselves inevitably drawn into an automation arms race, characterized by increased capital expenditure and R&D investment.

In an automation arms race, unconstrained firms escalate their investments in automation, indicated by increased capital expenditures and intensified R&D efforts. This suggests that firms deeply engaged in an automation arms race possibly encounter increasing financial constraints over time. To quantify this escalation in investment and R&D, I use the percentage change in capital expenditure (%Δ(CapEx)) and RD (%Δ(RD)). Given the propensity of unconstrained firms to participate in this costly competition, the interaction coefficients (δ) are expected to be positive. I also include additional indicators, the percentage change in tangible assets and the change in the tangible asset ratio. To test financial constraints, the WW-index is chosen over the SA-index and KZ-index for its comprehensive analytical capacity and due to recent critiques of the KZ-index. As unconstrained firms are theoretically more likely to engage in the race, I expect a positive sign of the interaction (δ). Conversely, a negative or insignificant interaction (δ) would challenge the automation arms race hypothesis.

[Table 2-1]

Table 1 shows the descriptive statistics of all variables used.

2.4 Result and Discussion

2.4.1 Automation Competition Hypothesis

Table 2-2, I examine the effect of changes in automation exposure on various operating measures, including the cost of goods sold margin, selling, general and administration (SG&A) margin, EBIT margin, EBITDA margin, return on assets (ROA), return on equity (ROE), and profitability. For each of the seven profit and cost measures, I first run the regression with only the change in automation exposure (including firm-fixed and year-fixed effects) – these are the odd-numbered columns. Then, I run the regression with all control variables – these are the even-numbered columns. The results indicate that an increase in automation exposure leads to a higher cost of goods sold margin, with significant coefficients in both columns (1) and (2). This result contradicts to the Automation Competition Hypothesis; however, the next section will give a clear answer for such contradict result. For the SG&A margin, the coefficient is positive and significant only when not controlling for other variables, as shown in column (3). However, the insignificance in column (4) suggests that the effect is averaged out between constrained and unconstrained firms, which I will discuss in the next section. Contrary to the cost measures, all profit measures show a negative and significant relationship with changes in automation exposure, supporting the argument that an increase in automation technology leads to a subsequent deteriorate in profit.

[Table 2-2]

2.4.2 Adoption Constraints Hypothesis

In this section, I explore how changes in automation exposure affect constrained and unconstrained firms differently. In Table 2-3, I analyze the impact of changes in automation exposure and its interaction with the financial constraints indicator, Rated, on operating performance measures.

[Table 2-3]

Table 2-3 examines the impact of changes in automation exposure and its interaction with the financial constraints indicator on cost and profit measures. Similar to Table 2-2, odd-numbered columns report models without control variables, and even-numbered columns report full model with controlling variables. All models include firm fixed effect and year fixed effect. In terms of the COGS margin, there's only weak evidence that changes in automation exposure slightly increase COGS margin (0.03), while the coefficient for the interaction remaining insignificant (0.01). There are three possible reasons. First, regarding constrained firms, the inability to adopt new automation system while deploying old system at high cost and the pressure to lower price leads to the higher COGS margin. Second, regarding unconstrained firms, it might be the economies of scale not realized. Third, automation implementation takes time, and firms implementing automation may carries both old and new automation systems during the transition periods which increase cost of good sold margin.

However, the SG&A margin reveals a stark contrast between constrained and unconstrained firms. The overall effect of changes in automation exposure is positive and significant (0.04), whereas the interaction coefficient is negative and significant (-0.12). This indicates that unconstrained firms can more effectively leverage new automation technology to lower their SG&A expenses compared to their constrained counterparts. Recalling the earlier results for the SG&A margin in Table 2-2, where the coefficient β was found to be insignificant, the findings in Table 2-3 explain this outcome. The previous insignificance in the SG&A margin can be attributed to an averaging effect, which becomes evident when dissecting the data between constrained and unconstrained firms, as demonstrated in Table 2-3.

Regarding profit measures, from columns (5) to (12) and (15) and (16), the coefficients of changes in automation exposure are consistently negative (as in Table 2-2) and significant. The coefficients for the interaction are mostly positive and significant (except for ROE in columns 11 and 12), supporting the hypothesis that unconstrained firms can effectively adopt new automation technology and have better operating performance than constrained firms.

To understand why the interaction coefficients for ROE remain insignificant, it's worth noting that ROE is calculated as (Net Income/Equity). The observed insignificance in ROE might be attributed to substantial interest expenses incurred from debt financing for the costly automation arms race (further details will be addressed in the following section). To test and verify this conjecture – that interest expenses are diminishing the significance of ROE in our observations – I propose using (EBIT/Equity) as a supplementary measure. This measure is expected to isolate the impact of interest payments. If the interaction's insignificance in ROE is indeed influenced by interest expenses, then using (EBIT/Equity) should have negative (β) for changes in automation exposure (ΔAuto) and positive for the interaction (δ) when conducting the same regression as in Table 2-3. The results, displayed in columns (13) and (14), validate this conjecture. I observe a negative coefficient (β) for changes in automation exposure (ΔAuto) and a positive, significant coefficient (δ) for the interaction, aligning with the expectations and supporting the conjecture that interest payments are a significant factor in the observed insignificance of ROE.

2.4.3 Automation Arms Race

In this section, I test the hypothesis of an automation arms race, particularly among large and unconstrained firms. If the hypothesis holds, we should observe that firms with higher automation exposure demonstrate increased capital expenditure and R&D.

[Table 2-4]

Table 2-4 reports the regression analysis of the change in automation exposure against various investment metrics including: (1) percentage change in capital expenditure, (2) percentage change in tangible assets, and (3) percentage change in R&D investment. Columns (1), (3) and (5) present the regression results without control variables, while columns (2), (4), and (6) include full control variables. All models account for firm-fixed and year-fixed effects.

For the percentage change in capital expenditure, the coefficient of change in automation exposure is negative and significant (-1.25) in the model without control variables, as shown in column (1). However, this turns insignificant (-0.05) when full control variables are included. The interaction of change in automation exposure with the rating indicator shows a positive and significant coefficient (2.78). This finding has two implications. Firstly, under the influence of new automation technology, there is no clear evidence that constrained firms will likely increase their investment but rather maintain their pass investment levels. Secondly, the interaction provides evidence of an automation arms race in investment among unconstrained firms. This inference is further supported in columns (3) and (4), where the regression analysis includes changes in tangible assets. Here, the interaction coefficient of change in tangible assets is positive and significant (1.95). Moreover, evidence suggests that unconstrained firms also invest more in R&D, as shown in columns (5) and (6). The effect of change in automation exposure is insignificant (-

0.40 and -0.29), but the coefficient of the interaction is positive and significant (4.47 and 4.75) in both the simplified and full model.

[Table 2-5]

Table 2-5 reports the regression of changes in automation exposure on financial constraint indicators WW index. Columns (1) and (2) present coefficients for the simplified model and the full model concerning changes in the WW index. The results reveal some counterintuitive evidence. While a higher change in automation exposure leads to an increase in financial constraints (4.90 and 3.65) for all firms, the coefficient of the interaction is markedly positive and significant (4.55 and 3.73). This notably positive interaction coefficient (δ) suggests that unconstrained firms, despite their financial flexibility, having their financial health weaken at higher rate than financially constrained firms in the years following heightened automation exposure.

In examining the considerable decline in the financial health of unconstrained firms, I hypothesized that the expensive nature of the automation arms race might compel these firms to take on more debt. To investigate this, I run the regression on the change in the long-term debt-to-asset ratio. The result is shown in column (3) and (4) of Table 2-5. Column (3) presents results without controlling for other variables, while column (4) includes them. The significant interaction coefficient ($\delta = 0.20$) supports my hypothesis, indicating that unconstrained firms indeed show a notable increase in their long-term debt ratio. This increase is likely due to the high costs of automation arms race (investment and R&D), leading firms to issue bonds for financing. Consequently, this rise in long-term debt means higher interest expenses, which explains why the interaction effect on ROE isn't significant, recall earlier result in Table 2-3. This rise in debt suggests that firms are using up their borrowing capacity on automation arms race, leaving less room for funding other projects, and ultimately, this strains the firm's financial health. I also run the robust check where dependent variable is equity scaled by total asset. There is weak evidence (at 10% significant) that change in automation leads to an increase in Equity/Asset (0.06). However, there are strong evidences that unconstrained firms have a significant reduction in equity (as opposed to the increase in long-term liabilities shares).

This observation, when linking with the findings from Table 2-4, paints a complex picture. Unconstrained firms are evidently more inclined towards participating in the automation arms race, with an escalated amount in investment and R&D. Such significant investments put a strain on a company's finances, affecting budgets for other growth-related activities.

In summary, new automation technology have different impact on constrained and unconstrained firms. Analyzing the data from Table 2-2 through Table 2-5 paints a comprehensive picture. Unconstrained firms, with their financial flexibility and robust health, often lead the way in adopting new automation technologies. This early adoption grants them a competitive advantage in production costs, enabling them to reduce prices and capture more of the market share. On the other hand, financially constrained firms, limited in their ability to adopt new technologies, find themselves pressured to lower prices to remain competitive, as early adopters drive market prices down. This scenario leads to diminished profitability for these constrained firms. Meanwhile, unconstrained firms, as early adopters with a cost advantage, are better positioned to withstand these market pressures. This narrative is supported by various profitability measures presented in Table 2-3.

Despite their advantageous position, unconstrained firms also face their own set of challenges. The pressure to maintain a technological lead pushes them into an automation arms race, characterized by significant investment and R&D spending, as shown in Table 2-4. This intense competition, however, comes at a cost. Unconstrained firms see their financial health deteriorate more rapidly than their constrained counterparts, primarily due to the heavy debt taken on to finance these expensive automation initiatives, as evidenced in Table 2-5. The result is a reduced capacity for financing other growth opportunities, highlighting the complex trade-offs firms face in the race to automate.

2.5 Robustness check

It is possible that the result might be driven by technological innovations other than automation. I construct change in nonautomation exposure over the last 5 years using the same formula (3) and (4). Where nonautomation exposure are patents not related to automation or pharmaceutical-chemical. I re-run Table 2-3, Table 2-4, and Table 2-5 with the additional nonautomation exposure variable, ΔNonAuto. The result is showed in Table 2-6. All coefficient of change in automation exposure (β) and the interaction (δ) do not change sign and level of significant. Except, there is some minor differences with COGS, Table 2-6 – Panel A, column (1) and (2). However, this minor difference does not change the overall picture of automation arms race. To address endogeneity concerns, I run the two-stages regression using automation from university and government as instrument variables. The result remains robust with similar sign and significant.

[Table 2-6]

Other robust tests include: (1) using alternative measure for financial constraints – payoff, KZ-index and SA-index, (2) using alternative measure for automation exposure – number of automation patents produced at firm level, (3) testing with sub-samples of before and after internet boom 1994 and before and after economic crisis 2008, and (4) testing with sub-samples of manufacture firms and non-manufacture firms.

For alternative measure of financial constraints, the result shows the robust with pay-off and KZ-index but inconsistent with SA-index. My explanation for the different result with SA-index is due to the low dimension captured of SA-index with only asset size and age, while KZ-index and WW-index capture a richer dimension.

For alternative measure using number patent produced at firm level, I construct two measures, one is change in number of automation patent-count over the last five years, and the other is the change in the number of citation-weight automation patent over the last five years, following (Bena & Li, 2014). The result is consistent with citation-weight automation patent and have some slight differences with automation patent-count but still consistent with the main hypotheses.

For sub-samples before and after internet boom 1994 and before and after economic crisis 2008. The result is consistent with periods before and after 1994. For economic crisis 2008, the result is consistent with period before 2008 and is moderate with period after 2008

In conclusion, there is some slight differences; however, the general results of all robust tests are consistent with main hypotheses.

2.6 Conclusion

In this essay, I explore the impact of automation technology on firm operating performance. Validating the predictions of the Knesl model (the automation competition hypothesis), I uncover how automation negatively impact firm's operating performance and financial health. Regarding firm operations, the standardization of new automation technology across the industry diminishes its cost and price competitive advantage, ultimately reducing firm profits.

In addressing the automation adoption hypothesis, I deviate from the Knesl model's assumption that all firms have an equal opportunity to adopt automation. Instead, I categorize firms as either financially constrained or unconstrained. The empirical findings indicate that although automation negatively impacts firms' performance, unconstrained firms with financial flexibility can offset such risks, exhibiting better operating performance compared to their financially constrained rivals.

Nonetheless, the most pivotal insight arises from the hypothesis of the automation arms race. Unconstrained firms, influenced by peer pressure, are drawn into an automation arms race, with an escalate in investment and R&D. The result shows that unconstrained firms with greater automation exposure allocate more resources to investment (CapEx) and R&D, while constrained firms show no significant change. Such significant investments put a strain on a company's finances, affecting budgets for other growth-related activities. Further analysis reveals that although unconstrained firms initially possess better financial health, the consequence of the automation arms race leads to a more rapid deterioration of their financial strength compared to that of their constrained firms. This deterioration is likely driven by a significant debt financing for the costly automation. Evidence shows that change in automation leads to a significant debt issuance for unconstrained firms compared to constrained firms.

Variable	Definition
Auto(i,t)	Automation Exposure at time (t) $$Auto_{i,t} = \log\left(\sum_{s} WeightSegSale_{i,s,t} \times SegAuto_{s,t} + 1\right)$$ Where: - $WeightSegSale_{i,s,t}$ is firm (i) weight sale in industry segment (s) at time (t) - $SegAuto_{s,t}$ is the aggregation of automation patents in industry segment (s) at time (t) over the last 5 year
ΔAuto	Change in Automation Exposure over the last 5 year ΔAuto(i,t) = Auto(i,t) – Auto(i, t-5)
Ln(Sale)	Log of Sale
Ln(Age)	Log of Age Where Age = current year – first date data available on Compustat
MtB	Market to Book MtB = (CSHO*PRCC_F + DLTT + DLC) / (BKVLPS*CHSO + DLTT + DLC) Where: - CSHO: Compustat code for number of share outstanding - PRCC_F: Compustat code for ending fiscal year share price - BKVLPS: Compustat code for book value per share - DLTT: Compustat code for long term debt - DLC: Compustat code for short-term debt
Leverage	Leveragev = (DLTT + DLC) / AT Where: - DLTT: Compustat code for long term debt - DLC: Compustat code for short-term debt - AT: Compustat code for Total Asset -
ROA	ROA = EBIT/Total Asset EBIT: Earning Before Interest and Tax
Profit/Total Asset	Profit/Total Asset = OIBDP / AT Where: - AT: Compustat code for Total Asset - OIBDP: Compustat code for Operating Income Before Depreciation
CF/Book Equity	Cash Flow / Book Equity = (IB + DP) / CEQ Where: - IB: Compustat code for Income Before Extraordinary Items - DP: Compustat code for Depreciation and Amortization - CEQ: Compustat code for Common/Ordinary Equity – Total
Rate	Dummy variable, equal 1 if the firm has long-term bond rated ever rated. Detail calculation follows (Almeida et al., 2004)
CapEx	Capital Expenditure, Compustat code CAPX
Tangible	Tangible Asset, Compustat code PPENT

Emp	Number of employee used, Compustat code EMP
SG&A/Sale	Selling General & Administrative margin to Sale
EBITDA/Sale	EBITDA margin to Sale

2.7 Tables

Table 2-1

Descriptive Statistics of variables used.

	count	mean	std	min	25%	50%	75%	max
Ln(AT)	103,991	6.15	1.72	3.30	4.81	5.95	7.30	10.66
Ln(Sale)	103,991	6.27	1.68	2.92	4.99	6.12	7.39	10.52
Automation Exposure - Auto	103,991	4.29	3.52	0.00	0.40	4.24	7.23	11.43
Change Automation Exposure last 5yrs (ΔAuto)	80,739	0.83	2.17	-11.43	0.00	0.26	1.01	11.43
Market to Book - MtB	96,029	1.98	1.75	0.34	1.02	1.43	2.24	12.63
Leverage - Lev	103,635	0.26	0.22	0.00	0.08	0.23	0.38	1.08
Ln(Age)	103,991	2.76	0.75	0.00	2.30	2.83	3.33	4.19
Percentage Change in Sale, %Δ(Sale)	98,581	0.38	0.80	-0.64	-0.08	0.17	0.55	4.29
Change Employement/Capital - Δ(Emp/PPENT)	93,957	-0.02	0.06	-0.78	-0.03	-0.01	0.00	0.71
Change COGS Margin - Δ(COGS/Sale)	94,046	-0.07	0.34	-4.44	-0.19	-0.04	0.08	2.99
Change SG&A Margin - Δ(SG&A/Sale)	87,335	-0.02	0.11	-1.16	-0.05	-0.01	0.03	1.07
Change EBITDA Margin - Δ(EBITDA/Sale)	98,508	0.00	0.09	-1.06	-0.03	0.00	0.02	0.87
Change EBIT Margin - Δ(EBIT/Sale)	98,581	-0.01	0.10	-0.91	-0.04	0.00	0.02	1.06
Change Return on Asset - Δ(ROA)	98,581	-0.02	0.08	-0.60	-0.05	-0.01	0.02	0.53
Change EBIT to Equity - Δ(EBIT/Equity)	94,984	-0.03	0.29	-2.77	-0.12	-0.02	0.06	2.77
Change Return on Equity - Δ(ROE)	94,983	-0.04	0.33	-3.02	-0.11	-0.02	0.05	3.02
Change Profitability - Δ(Profit)	93,973	-0.02	0.09	-0.64	-0.07	-0.01	0.03	0.59
WW-index	96,403	0.08	2.29	-4.57	-1.31	-0.23	1.05	8.00
Change in WW-index - Δ(WW)	91,723	0.04	1.77	-12.58	-0.98	0.00	0.99	12.23
Change in Cash Flow to Asset - Δ(CF/AT)	98,508	-0.01	0.08	-0.61	-0.04	-0.01	0.02	0.69
Change in Long-term Debt ratio - Δ(LT Debt/AT)	98,464	0.00	0.13	-0.92	-0.05	0.00	0.06	0.92
Change in Sale Growth - Δ(Sale Growth)	95,923	-0.06	0.21	-1.71	-0.14	-0.04	0.04	1.43

Table 2-2

	Dependent variables													
	Δ(COGS/Sale)		Δ(SG&A/Sale)		Δ(EBITDA/Sale)		Δ(EBIT/Sale)		Δ(ROA)		Δ(ROE)		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ΔAuto	0.08***	0.03**	0.05***	0.01	-0.15***	-0.06***	-0.16***	-0.05***	-0.19***	-0.08***	-0.63***	-0.34***	-0.30***	-0.14***
ΔAuto	(5.71)	(2.45)	(4.76)	(0.85)	(-11.10)	(-4.37)	(-10.85)	(-3.57)	(-14.18)	(-5.72)	(-10.15)	(-5.51)	(-19.32)	(-9.10)
MtB		-0.25***		-0.12***		0.34***		0.29***		-0.02		2.46***		-0.09***
MtB		(-11.58)		(-7.07)		(15.99)		(11.92)		(-0.92)		(24.35)		(-3.74)
Ln(AT)		0.02***		0.01***		-0.03***		-0.03***		-0.03***		-0.10***		-0.05***
Ln(AT)		(31.53)		(34.30)		(-57.95)		(-64.15)		(-71.87)		(-46.25)		(-98.50)
Lev		-0.01***		-0.03***		0.04***		0.05***		0.07***		0.35***		0.06***
Lev		(-5.02)		(-17.31)		(19.70)		(23.23)		(36.11)		(36.51)		(28.04)
Ln(Age)		-0.01***		0.00		0.01***		0.02***		0.02***		0.05***		0.05***
Ln(Age)		(-3.09)		(-0.01)		(4.57)		(7.61)		(11.57)		(5.59)		(24.37)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	38.5%	40.1%	43.0%	44.6%	38.3%	41.7%	38.3%	42.4%	34.5%	40.0%	31.1%	35.3%	32.0%	40.9%
N-obs	76,099	72,210	70,919	68,039	76,039	72,154	76,099	72,210	76,099	72,210	73,704	70,365	76,039	72,154

This table reports the effect of change in automation technology (ΔAuto) on firm's operating performance (ΔOP). ΔOP is calculated as the difference between average OP from year t+1 to year t+5 and average OP from year t-4 to year t. Proxies for OP include: (1) change in COGS margin, (2) change in SG&A, (3) change in EBITDA, (4) change in EBIT, (5) change in ROA, (6) change in ROE and (7) change in Profitability (OIBDP/AT). Odd columns reports reduced model with change in automation exposure, and fixed-firm effect and year-fixed effect. Even columns reports full model. All variables are winsorized at 1-99. t values are reported in the parentheses. *, **, *** present significance at 10%, 5% and 1%, respectively.

Table 2-3

	Dependent variables															
	Δ(COGS/Sale)		Δ(SGA/Sale)		Δ(EBITDA/Sale)		Δ(EBIT/Sale)		Δ(ROA)		Δ(ROE)		Δ(EBIT/Eqty)		Δ(OIBDP/AT)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ΔAuto4	0.07***	0.03*	0.07***	0.04***	-0.17***	-0.08***	-0.18***	-0.08***	-0.23***	-0.12***	-0.67***	-0.36***	-0.66***	-0.44***	-0.32***	-0.16***
ΔAuto4	(4.88)	(1.72)	(6.43)	(3.41)	(-11.09)	(-5.20)	(-10.61)	(-4.34)	(-14.88)	(-7.65)	(-9.45)	(-5.22)	(-11.06)	(-7.39)	(-17.81)	(-9.22)
ΔAuto*Rate	0.01	0.01	-0.10***	-0.12***	0.08***	0.10***	0.08**	0.10***	0.16***	0.19***	0.18	0.18	0.59***	0.59***	0.06*	0.12***
ΔAuto*Rate	(0.18)	(0.31)	(-4.22)	(-5.08)	(2.65)	(3.09)	(2.18)	(2.91)	(5.14)	(6.14)	(1.21)	(1.24)	(4.70)	(4.81)	(1.70)	(3.34)
Rate	0.00	-0.01***	0.01***	0.00***	-0.01***	0.00***	0.00***	0.01***	0.00	0.01***	0.01	0.03***	-0.02***	0.00	-0.01***	0.01***
Rate	(-0.92)	(-6.74)	(7.82)	(5.56)	(-5.31)	(2.67)	(-3.65)	(4.63)	(-0.03)	(7.67)	(1.43)	(5.27)	(-3.71)	(-0.19)	(-5.37)	(8.61)
MtB		-0.24***		-0.12***		0.34***		0.29***		-0.02		2.46***		0.34***		-0.09***
MtB		(-11.57)		(-7.12)		(16.01)		(11.93)		(-0.90)		(24.37)		(4.01)		(-3.74)
Ln(AT)		0.02***		0.01***		-0.03***		-0.04***		-0.03***		-0.11***		-0.06***		-0.05***
Ln(AT)		(32.23)		(33.01)		(-57.62)		(-64.08)		(-72.36)		(-46.50)		(-32.80)		(-98.65)
Lev		-0.01***		-0.03***		0.04***		0.05***		0.07***		0.34***		0.22***		0.06***
Lev		(-3.94)		(-17.90)		(19.01)		(22.21)		(34.44)		(35.44)		(26.68)		(26.36)
Ln(Age)		-0.01***		0.00		0.01***		0.02***		0.02***		0.05***		0.05***		0.05***
Ln(Age)		(-3.67)		(0.33)		(4.89)		(8.08)		(12.41)		(6.09)		(6.70)		(25.16)
Fixed-firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	38.5%	40.1%	43.0%	44.6%	38.3%	41.8%	38.3%	42.4%	34.5%	40.1%	31.1%	35.3%	31.3%	33.4%	32.0%	41.0%
N-obs	76,099	72,210	70,919	68,039	76,039	72,154	76,099	72,210	76,099	72,210	73,704	70,365	73,704	70,365	76,039	72,154

This table reports the effect of change in automation technology (ΔAuto) on firm's operating performance (ΔOP), conditioning on firm's financial health, constrained vs unconstrained. Firms that has long-term credit rating is classified as unconstrained (Rate = 1, and 0 otherwise), this definition follow Almedia et al. (2004). ΔOP is calculated as the difference between average OP from year t+1 to year t+5 and average OP from year t-4 to year t. Proxies for OP include: (1) change in COGS margin, (2) change in SG&A, (3) change in EBITDA, (4) change in EBIT, (5) change in ROA, (6) change in ROE and (7) change in ratio of EBIT/Equity, (8) change in Profitability (OIBDP/AT). Odd columns reports the result of reduced model with change in automation exposure (ΔAuto), interaction (ΔAuto*Rate), and dummy variable if having rating (Rate). Even columns reports the full model. All models are included firm-fixed effect and year-fixed effect. All variables are winsorized at 1-99. t values are reported in the parentheses. *, **, *** present significance at 10%, 5% and 1%, respectively.

Table 2-4

	Dependent variables					
	% Change CAPEX		% Change PPENT		% Change RD	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAuto4	-1.25***	-0.05	-0.19	0.49***	-0.40	-0.29
ΔAuto4	(-5.37)	(-0.23)	(-1.08)	(2.84)	(-1.28)	(-0.92)
ΔAuto4*Rate	2.43***	2.78***	1.87***	1.95***	2.99***	3.13***
ΔAuto4*Rate	(5.03)	(5.83)	(5.23)	(5.55)	(4.47)	(4.75)
Rate	-0.30***	-0.08***	-0.34***	-0.23***	-0.27***	-0.24***
Rate	(-18.72)	(-5.04)	(-29.53)	(-19.46)	(-11.57)	(-10.20)
MtB		0.11***		0.12***		0.08***
MtB		(34.35)		(50.34)		(19.68)
Ln(AT)		-0.38***		-0.17***		-0.09***
Ln(AT)		(-51.64)		(-31.48)		(-8.13)
Lev		-0.86***		-0.69***		-0.48***
Lev		(-29.49)		(-32.26)		(-11.08)
Ln(Age)		-0.37***		-0.71***		-0.98***
Ln(Age)		(-13.32)		(-34.44)		(-24.71)
Fixed-year	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-firm	Yes	Yes	Yes	Yes	Yes	Yes
R-square	34.7%	40.6%	44.0%	49.7%	40.1%	43.0%
N-obs	75,680	71,816	76,042	72,157	34,552	33,651

This table reports how change in automation technology leads to the arms race among unconstrained firms. Dependent variables used are percentage change on capital expenditure, percentage change in tangible asset, percentage change in R&D, and the change in ratio of tangible asset. Percentage change Y is the growth the average leading Y from (t+1) to (t+5) with the average lagging Y from (t) to (t-4). Change in Y is the difference between the average leading Y from (t+1) to (t+5) and the average lagging Y from (t) to (t-4). Firms that has long-term credit rating is classified as unconstrained (Rate = 1, and 0 otherwise), this definition follow Almedia et al. (2004). Odd columns report reduced model with change in automation exposure (ΔAuto), interaction of change in automation exposure and rating indicator(ΔAuto*Rate), and indicator if has rating (Rate). Even columns report full model with controlling variables. All models include firm-fixed effect and year-fixed effect. All variables are winsorized at 1-99. t values are reported in the parentheses. *, **, *** present significance at 10%, 5% and 1%, respectively.
(*): Model with percentage change in R&D, I use the sub sample where observation has RD data since only 44.6% observation has R&D record.

Table 2-5

	Dependent variable					
	Δ(WW)		Δ(LT-Debt/AT)		Δ(Equity/AT)	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAuto4	4.90***	3.65***	-0.05*	-0.08***	-0.01	0.06*
ΔAuto4	(13.14)	(9.69)	(-1.94)	(-2.93)	(-0.46)	(1.71)
ΔAuto4*Rate	4.55***	3.73***	0.20***	0.20***	-0.17**	-0.20***
ΔAuto4*Rate	(6.00)	(4.90)	(3.68)	(3.59)	(-2.52)	(-2.99)
Rate	0.01	-0.16***	-0.04***	-0.03***	2.31***	2.64***
Rate	(0.54)	(-6.23)	(-19.70)	(-14.01)	(10.75)	(11.67)
MtB		-0.04***		0.00***		
MtB		(-8.01)		(-4.05)		
Ln(AT)		0.54***				-0.02***
Ln(AT)		(46.26)				(-13.98)
Ln(Sale)				0.01***		0.01***
Ln(Sale)				(10.25)		(25.23)
Lev		-0.65***		-0.12***		0.03***
Lev		(-13.89)		(-34.34)		(7.37)
Ln(Age)		-0.69***		-0.03***		0.00
Ln(Age)		(-15.36)		(-9.44)		(-1.04)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
R-square	34.0%	36.8%	32.3%	33.9%	36.9%	37.7%
N-obs	72,925	69,253	76,005	72,186	76,093	72,204

This table reports the consequences automation arms race on firm's financial constraints. Dependent variable measures for financial constraints (ΔFC): (1) change in WW-index (ΔWW), and (2) change in long-term debt ratio (ΔLT-Debt/AT). ΔFC is calculated as the difference between average FC from year t+1 to year t+5 and average FC from year t-4 to year t. Firms that has long-term credit rating is classified as unconstrained (Rate = 1, and 0 otherwise), this definition follow Almedia et al. (2004). Odd columns report reduced model with change in automation exposure (ΔAuto), interaction with financial constraints indicator (ΔAuto*Rate), and dummy variable indicator of having long-term debt rated (Rate). Even columns report full model with controlling variables. All models include firm-fixed effect and year-fixed effect. All variables are winsorized at 1-99. t values are reported in the parentheses. *, **, *** present significance at 10%, 5% and 1%, respectively.

Table 2-6

Robust-test, to confirm that the result is not driven by other innovations in technology, I re-run all model in **Error! Reference source not found.**, Table 2-3, Table 2-4, and Table 2-5 with the a dditional variable of change in nonautomation exposure, ΔNonAuto

Panel A: Re-run the Table 2 5 with additional variable of change in nonautomation exposure, ΔNonAuto

	Dependent Variables															
	Δ(COGS/Sale)		Δ(SGA/Sale)		Δ(EBITDA/Sale)		Δ(EBIT/Sale)		Δ(ROA)		Δ(ROE)		Δ(EBIT/Eqty)		Δ(OIBDP/AT)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ΔAuto4	0.05	0.00	0.21***	0.19***	-0.21***	-0.17***	-0.25***	-0.20***	-0.30***	-0.23***	-0.80***	-0.71***	-0.95***	-0.75***	-0.42***	-0.32***
ΔAuto4	(1.00)	(0.02)	(5.82)	(5.35)	(-4.34)	(-3.50)	(-4.73)	(-3.78)	(-6.25)	(-5.00)	(-3.65)	(-3.30)	(-5.16)	(-4.14)	(-7.65)	(-6.07)
ΔAuto*Rate	0.01	0.01	-0.11***	-0.13***	0.09***	0.10***	0.08**	0.11***	0.17***	0.20***	0.19	0.20	0.61***	0.61***	0.07*	0.13***
ΔAuto*Rate	(0.23)	(0.36)	(-4.51)	(-5.42)	(2.70)	(3.24)	(2.28)	(3.11)	(5.25)	(6.35)	(1.26)	(1.39)	(4.82)	(4.95)	(1.85)	(3.60)
Rate	0.00	-0.01***	0.01***	0.00***	-0.01***	0.00***	0.00***	0.01***	0.00	0.01***	0.01	0.03***	-0.02***	0.00	-0.01***	0.01***
Rate	(-0.93)	(-6.74)	(7.82)	(5.55)	(-5.31)	(2.68)	(-3.65)	(4.64)	(-0.04)	(7.67)	(1.43)	(5.28)	(-3.71)	(-0.19)	(-5.38)	(8.61)
ΔNonAuto	0.02	0.02	-0.12***	-0.14***	0.03	0.08*	0.06	0.12**	0.06	0.11***	0.12	0.31*	0.27*	0.29*	0.10**	0.15***
ΔNonAuto	(0.62)	(0.58)	(-3.94)	(-4.48)	(0.79)	(1.90)	(1.37)	(2.50)	(1.50)	(2.64)	(0.64)	(1.69)	(1.68)	(1.83)	(1.98)	(3.23)
MtB		0.00***		0.00***		0.00***		0.00***		0.00		0.02***		0.00***		0.00***
MtB		(-11.57)		(-7.13)		(16.01)		(11.94)		(-0.89)		(24.38)		(4.02)		(-3.73)
Ln(AT)		0.02***		0.01***		-0.03***		-0.04***		-0.03***		-0.11***		-0.06***		-0.05***
Ln(AT)		(32.21)		(33.06)		(-57.65)		(-64.11)		(-72.39)		(-46.52)		(-32.83)		(-98.70)
Lev		-0.01***		-0.03***		0.04***		0.05***		0.07***		0.34***		0.22***		0.06***
Lev		(-3.94)		(-17.89)		(19.01)		(22.20)		(34.44)		(35.44)		(26.68)		(26.36)
Ln(Age)		-0.01***		0.00		0.01***		0.02***		0.02***		0.05***		0.05***		0.05***
Ln(Age)		(-3.68)		(0.47)		(4.83)		(8.01)		(12.33)		(6.04)		(6.65)		(25.05)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	38.5%	40.1%	43.1%	44.6%	38.3%	41.8%	38.3%	42.4%	34.5%	40.1%	31.1%	35.3%	31.3%	33.4%	32.1%	41.0%
N-obs	76,099	72,210	70,919	68,039	76,039	72,154	76,099	72,210	76,099	72,210	73,704	70,365	73,704	70,365	76,039	72,154

Table 2.6 – Panel B. Re-run the Table 2-4 with additional variable of change in nonautomation exposure, ΔNonAuto

	Dependent variables							
	%ΔCapEx		%ΔPPENT		ΔPPENT/AT		%ΔRD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔAuto4	3.38***	3.98***	3.64***	3.42***	-0.02	-0.03	3.95*	3.36
ΔAuto4	(4.70)	(5.60)	(6.84)	(6.52)	(-0.38)	(-0.68)	(1.70)	(1.43)
ΔAuto4*Rate	2.16***	2.53***	1.65***	1.78***	-0.17***	-0.17***	-5.28***	-5.30***
ΔAuto4*Rate	(4.46)	(5.29)	(4.60)	(5.03)	(-5.00)	(-4.83)	(-3.40)	(-3.38)
Rate	-0.30***	-0.08***	-0.34***	-0.23***	0.00**	0.00	-0.33***	-0.29***
Rate	(-18.71)	(-5.04)	(-29.52)	(-19.47)	(-2.15)	(-1.51)	(-6.20)	(-5.25)
ΔNonAuto	-0.04***	-0.04***	-0.04***	-0.03***	0.00*	0.00	-0.05**	-0.05**
ΔNonAuto	(-6.80)	(-6.01)	(-7.61)	(-5.92)	(1.65)	(1.47)	(-2.51)	(-2.12)
MtB		0.11***		0.12***		0.00***		0.08***
MtB		(34.34)		(50.34)		(5.63)		(8.43)
Ln(AT)		-0.38***		-0.17***		0.00***		-0.12***
Ln(AT)		(-51.56)		(-31.39)		(7.46)		(-4.83)
Lev		-0.86***		-0.69***		-0.03***		-0.59***
Lev		(-29.49)		(-32.26)		(-14.82)		(-5.82)
Ln(Age)		-0.37***		-0.70***		-0.01***		-1.18***
Ln(Age)		(-13.14)		(-34.26)		(-6.49)		(-12.61)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	34.7%	40.6%	44.1%	49.7%	34.8%	35.2%	26.7%	27.6%
N-obs	75,680	71,816	76,042	72,157	76,042	72,157	34,552	33,651

Table 2.6 – Panel C. Re-run the Table 2-5 with additional variable of change in nonautomation exposure, ΔNonAuto

	Dependent variables					
	ΔWW		DebtLT/AT		Equity/AT	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAuto4	7.28***	5.42***	0.04	-0.02	0.03	0.08
ΔAuto4	(6.38)	(4.72)	(0.48)	(-0.19)	(0.36)	(0.77)
ΔAuto4*Rate	4.42***	3.64***	0.20***	0.19***	-0.17**	-0.20***
ΔAuto4*Rate	(5.82)	(4.76)	(3.57)	(3.51)	(-2.56)	(-3.00)
Rate	0.01	-0.16***	-0.04***	-0.03***	2.31***	2.64***
Rate	(0.55)	(-6.23)	(-19.70)	(-14.01)	(10.75)	(11.67)
ΔNonAuto	-0.02**	-0.02	0.00	0.00	0.00	0.00
ΔNonAuto	(-2.21)	(-1.63)	(-1.17)	(-0.82)	(-0.53)	(-0.23)
MtB		-0.04***		0.00***		
MtB		(-8.02)		(-4.05)		
Ln(AT)		0.54***				-0.02***
Ln(AT)		(46.28)				(-13.98)
Ln(Sale)				0.01***		0.01***
Ln(Sale)				(10.27)		(25.22)
Lev		-0.65***		-0.12***		0.03***
Lev		(-13.89)		(-34.34)		(7.37)
Ln(Age)		-0.68***		-0.03***		0.00
Ln(Age)		(-15.30)		(-9.41)		(-1.03)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
R-square	34.0%	36.8%	32.3%	33.9%	36.9%	37.7%
N-obs	72,925	69,253	76,005	72,186	76,093	72,204

2.8 Appendix – Variable Table

Order	Variable Name	Formula and WRDS code
1	Automation Exposure	$$\text{Auto}_{i,t} = Ln\left(\sum_{j=1}^{N} \text{SegSale}_{i,j,t} \cdot \text{AutoPatent}_{j,t}\right)$$ Where: - SegSale(i,j,t): weight of sale of company (i) in segment (j) at time (t) - AutoPatent(j,t): rolling 5 years sum of all automation related patents in sector (j)
2	Non-Automation Exposure	$$\text{NonAuto}_{i,t} = Ln\left(\sum_{j=1}^{N} \text{SegSale}_{i,j,t} \cdot \text{NonAutoPatent}_{j,t}\right)$$ Where: - SegSale(i,j,t): weight of sale of company (i) in segment (j) at time (t) - Non-Automation Patents(j,t): rolling 5 years sum of all Non-Automation related patents in sector (j)
3	Chemical-Pharmaceutical Exposure	$$\text{Chem}_{i,t} = Ln\left(\sum_{j=1}^{N} \text{SegSale}_{i,j,t} \cdot \text{ChemPatent}_{j,t}\right)$$ Where: - SegSale(i,j,t): weight of sale of company (i) in segment (j) at time (t)

		- ChemPatent(j,t): rolling 5 years sum of all chemical-pharmaceutical related patents in sector (j)
4	Cash Flow	(IB+DP)/AT
5	Cash flow standard Deviation	Standard Deviation (rolling 5 years) of cash flow Where cash flow = (IB + DP) /AT
6	Capital Expenditure	CAPX/AT
7	Change in Cash Holding	Δ cash holding = CHE(t)/AT(t) – CHE(t-1)/AT(t-1)
8	COGS	COGS/SALE
9	DIV	Dummy 1 if DVC+DVP >0, 0 otherwise
10	Financial constraint KZ index	KZ-index = – 1.001909*(IB+DP)/PPENT(t-1) + 0.2826389*(AT + CSHO*PRCC_F – CEQ – TXDB)/AT + 3.139193*(DLTT + DLC)/(DLTT + DLC + SEQ) – 39.3678*(DVC + DVP)/PPENT(t-1) -1.314759*(CHE)/PPENT(t-1)

11	Financial constraint SA index	SA-index = – 0.737*Ln(AT) + 0.043*Ln(AT)^2 – 0.040*AGE
12	Financial constraint WW index	WW-index = – 0.091*(IB+DP)/AT + 0.062*(DVC+DVP) + 0.021*DLTT/AT – 0.044*Ln(AT) + 0.102*ISG – 0.035*SG Where: - ISG: percentage change in sum of 3 digits segment sale of each year SG: firm level sale growth
13	Intangible Asset	INTAN / AT
14	Intangible Not Goodwill Asset	(INTAN – GDWL) / AT
15	Log(Asset)	Ln(AT)
16	Log of Employee	Log(EMP/AT +1)
17	Market-to-Book ratio	(CSHO*PRCC_F + DLTT + DLC) / (BKVLPS *CSHO + DLTT + DLC)
18	NCF (Net Cash Flow)	(OANCF- CAPX) / AT(t-1)
19	Operating Leverage	XSGA(t) / AT(t-1)
20	Profit	OIBDP/AT

21	ROA	EBIT/AT
22	R&D	XRD/AT
23	Tangible Asset	PPENT / AT
24	Tobin-Q	(AT + CSHO*PRCC_F – CEQ)/AT

3 Corporate Cash Shortfalls and External Financing: US vs JP

3.1 Introduction

The dynamic trade-off model in (DeAngelo et al., 2011) suggest a funding-horizon theory in which corporate cash needs and the nature of cash needs drive external financing decisions. Using US data, several studies find that most equity issuers (DeAngelo et al., Seasoned equity offerings, market timing, and the corporate lifecycle, 2010; Denis & McKeon, 2021; Huang & Ritter, 2021; Liu et al., 2023) and debt issuers (Huang & Ritter, 2021) would run out of cash soon without external financing. In addition, equity issuers tend to have long-lived cash needs (Denis & McKeon, 2021; Huang & Ritter, 2021; Liu et al., 2023) while debt issuers are more likely to have short-lived cash needs (Huang and Ritter, 2021) (henceforth HR). These results are consistent with the funding-horizon theory. However, it is not clear whether the funding-horizon theory also explains external financing decisions of firms in non-US countries. In this study, we attempt to answer this question by conducting a comparative study using data for companies from the US and Japan. We also explore additional factors that affect external financing decisions.

Using a sample that includes 80,176 firm year observations for US firms and 57,692 firm year observations for Japanese firms, we find that cash depletion plays a smaller role in explaining external financing decisions in Japan. About 21.7% of Japanese debt/equity issuers would run out of cash if they did not issue. In contrast, about 43.5% of US issuers in our sample would run out of cash if they did not raise external financing. In logit regressions the effects of cash depletion on external financing are sensitive to adjustments made to address endogeneity issues. Specifically, when we use fitted indicators of cash depletion in regressions, the results suggest that cash depletion is not a significant motive for equity issues in the US. In Japan the fitted cash depletion indicators does not have significant effects on either debt issues or equity issues. But we do find that the prospect of having subnormal cash ratio is associated with higher likelihood for debt issues in both the US and Japan when using actual or fitted values in logit regressions. Also consistent with the funding-horizon theory, we find evidence that firms tend to issue equity to meet persistent cash needs and issue debt to meet temporary cash needs in both the US and Japan.

We find that capital restructuring may be an important motive for external financing in both the US and Japan. In the US, on average the pure debt issuers use 41.2% of net debt issue proceeds to repurchase equity while the pure equity issuers use 32.7% of net equity issue proceeds to repay debt. The corresponding numbers for Japanese issuers are 30.7% and 49% respectively. In logit regressions equity repurchase and debt reduction consistently have strong correlations with external financing decisions in both the US and Japan.

Japanese firms seem much less likely to issue debt or equity than US firms. Japanese firms raise external financing in about 14.6% of the firm years while US firms do so in about 31.1% of the firm years. US firms are about 76% more likely to issue debt and 278% more likely to issue equity than Japanese firms. The first possible explanation is that Japanese firms are less likely to run out of cash. In our sample, only 3.6% of the Japanese firms face immediate cash depletion while 15.6% of the US firms do. However, even among firms that do not face cash depletion, those in Japan are also less inclined to raise external financing. About 11.8% of those Japanese firms issue debt or equity while about 20.8% of the corresponding US firms do so. US firms not running out of cash are about 32% more likely to issue debt and 225% more like to issue equity than their Japanese counterparts.

We try to explore other factors that may cause Japanese firms to raise external financing less frequently. We find that among firms not facing cash depletion, Japanese firms are less likely to have subnormal cash ratio if they do not raise external financing. In addition, when compared with US firms, a typical Japanese firm in our sample has lower leverage, lower R&D, lower Tobin's Q, and higher propensity to be dividend payers. In regressions these patterns are associated with lower chance to issue equity. These results suggest that Japanese firms are more likely to be mature companies with lower demand for equity capital and help explain why Japanese firms are less likely to issue equity. The lower likelihood to have subnormal cash ratio and lower leverage are also associated with lower chance to issue debt in regressions. Therefore, these two factors also help explain why Japanese firms are less likely to issue debt.

This essay contributes to the literature about the motives for external financing. The results in our paper suggest that the prospect of subnormal cash ratio may be a better measure for cash needs, which are predicted to be the motive for external financing in funding-horizon theory. Cash depletion has been used as the measure for cash needs in the literature (DeAngelo et al., 2010; Denis and McKeon, 2021; Huang and Ritter, 2021; Liu et al., 2023), but it may not survive in regression tests after adjustments to address endogeneity. We do find additional evidence from Japan to support the prediction that firms tend to issue equity to meet persistent cash needs and issue debt to meet temporary cash needs, further supporting the funding-horizon theory. We find evidence that the prospect of subnormal cash ratio, equity repurchase, and debt reduction may be important considerations for external financing decisions in both the US and Japan. This differs from the suggestion in HR that capital restructuring has limited importance as a motive for debt or equity issuance.

We also contribute to the literature about corporate financing in Japan. Much of the previous literature focuses on the effects of institutional features on corporate financing in Japan (Hirota, 1999; Hodder & Tschoegl, 1985; Jo et al., 1994; Kang & Stulz, 1996). We present evidence of significant differences in external financing between US and Japan and show that they are associated with differences in firm characteristics. This implies that there may be more room for applying finance theory to understanding corporate financial decisions in Japan.

The rest of the paper is organized as follows: in section 2 we describe the data and conduct univariate analysis; in section 3 we conduct regression analysis; section 4 concludes the paper.

3.2 Sample Description and Univariate Analysis

3.2.1 Data and sample

We collect the data for US companies from Compustat and the data for Japanese companies from Compustat Global. The sample period is from year 2000 to year 2022 because there are fewer than 25 Japanese firms each year in Compustat Global before 2000. We exclude small companies with total asset value of less than 10 million US dollars (adjusted to 2010 values). For firms in Japan, we convert Japanese Yen values to US dollar values using the average exchange rate during each year. We eliminate firms with SIC codes between 6000-6999 and 4900-4999. This excludes firms operating in regulated industries such as financial and utilities industries. We also exclude firms with negative sales. The final sample includes 80,176 firm year observations from the US and 57,692 firm year observations from Japan.

We define net debt issuance based on the change in the value of long-term debt and short-term debt. Net equity issuance is defined based on the difference between net cash flow from financing activities and net debt issuance. This is different from HR, who define debt and equity issuance based on net debt proceeds and net equity proceeds from cash flow statements. Unfortunately, we cannot use their method for Japanese firms in our sample because the value of the two net proceeds is missing for most of the observations. We do follow HR by including only cases when net debt issuance or net equity issuance is at least 5% of the book value of assets and 3% of the market value of equity at the beginning of the year. We also remove all firm years that involve mergers.

3.2.2 Summary statistics and univariate sorts

3.2.2.1 Likelihood of external financing and cash depletion

In Panel A of Table 1 we report the sample distribution by financing category. It seems Japanese firms are much less likely to raise external financing than US firms. In our sample, Japanese firms issue debt or equity in about 14.6% of the firm years while US firms do so in about 31.1% of the firm years. US firms are 113.3% more likely to raise external financing than Japanese firms. For the US firms in our sample, debt issues occur in 20.2% of the firm years while equity issues occur in 13.6% of the firm years[10]. The Japanese firms in our sample issue debt in 11.5% of the firm years and issue equity in 3.6% of the firm years. Based on these numbers, US firms are about 76% more likely to issue debt and 278% more likely to issue equity than Japanese firms.

(Insert Table 1 about here)

[10] These numbers are higher than the corresponding numbers in HR because of two factors: 1. we use different definitions for debt and equity issuance so that we can get enough observations for Japanese firms. 2. Our sample period of 2000 to 2022 is different from the sample period of 1972 to 2013 in HR.

In Panel B of Table 1 we report the likelihood of running out of cash based on whether the sample firms have net debt or equity issuance. Following HR, we estimate $Cash_{ex\ post}$ and $Cash_{ex\ ante}$ to measure the cash position firms would have if they did not raise external financing. $Cash_{ex\ post}$is defined as $Cash_{t-1} + NCF_t$, $Cash_{t-1}$ denotes cash holdings at the end of year t-1. NCF is the difference between the internal cash flow and the sum of investment, change in noncash networking capital, and dividends. $Cash_{ex\ post}$ is also equal to $Cash_{t-1} - \Delta D_t - \Delta E_t$. Here ΔD_t and ΔE_t denote net debt issuance and net equity issuance in year t respectively. $Cash_{ex\ ante}$ is defined as $Cash_{t-1} + NCF_{t-1}$ to alleviate the endogeneity concerns in the relation between NCF_t and net debt or equity issuance in t. Like in HR, we also report the likelihood of cash depletion for firm years with no net issuance of debt or equity, with the caveat that in these firm years most of the firms with $Cash_{ex\ post}$≤0 actually did some external financing, but not enough to meet the 5% book value threshold or the 3% market value thresholds.

Panel B shows that the US issuing firms in our sample would run out of cash in 43.5% of the firm years based on $Cash_{ex\ post}$. If we use $Cash_{ex\ ante}$, the likelihood of running out of cash will become 30% for US issuers. These values are lower than those reported in HR but still suggest that cash depletion is a dominant factor behind external financing decisions for US firms. For the Japanese issuers in our sample, the likelihood of cash depletion is much lower at 21.7% (12%) based on $Cash_{ex\ post}$ ($Cash_{ex\ ante}$), implying that Japanese issuers are about 50% (60%) less likely to run out of cash compared with US issuers. Not surprisingly, these differences are statistically significant. It seems cash depletion plays a much smaller role in explaining external financing decisions in Japan.

We further report the likelihood of cash depletion by financing type in Panel C of Table 1. In Japan, pure debt issuers would run out of cash 22% (9.2%) of the time while pure equity issuers would run out of cash 15.2% (19%) of the time based on $Cash_{ex\ post}$ ($Cash_{ex\ ante}$) if they did not issue. Compared with US issuers, both Japanese pure debt issuers and Japanese pure equity issuers are about 52% less likely to run out of cash. Japanese dual issues are most likely to be driven by cash depletion. Their likelihood of running out of cash is 58.1% (30.5%) based on $Cash_{ex\ post}$ ($Cash_{ex\ ante}$), only 22.8% (34.9%) lower than US dual issues. However, Japanese dual issues are relatively rare. They occur in only 0.5% of the firm years compared with 11% for pure debt issue and 3.1% for pure equity issue as reported in Panel A. Overall, the results suggest that cash depletion may still be an important driving force for debt or equity issues in Japan, but it may not be as dominant as in the US.

The much lower likelihood of cash depletion for Japanese firms reported in Panels B and C helps explain why Japanese firms are much less likely to raise external financing. Is it the sole explanation? We try to answer this question in Panel D of Table 1 by reporting the likelihood of financing, conditional on whether firms will run out of cash based on $Cash_{ex\ post}$ and $Cash_{ex\ ante}$. Because firms must raise external financing when they run out of cash, the likelihood of issuance for these firms only tells us the percentage of issues that meet the 5% threshold. Therefore, we focus on the likelihood of issuance for cases when firms do not expect to run out of cash without external financing. Based on $Cash_{ex\ post}$($Cash_{ex\ ante}$), the likelihood for US firms in our sample to raise external financing when they do not face cash depletion is 20.8% (26.8%). The corresponding value for Japanese firms not facing cash depletion is only 11.8% (13.5%). US firms not running out of cash are 75.8% (98.7%) more likely to raise external financing. This difference is more pronounced for equity financing. US firms not running out of cash are about 32% (65%)

more likely to issue debt and 225% (255%) more likely to issue equity than their Japanese counterparts.

The literature suggests that firms may try to reach an optimal cash ratio (Opler et al., 1999) and they may raise cash through external financing (McLean, 2011). Maybe Japanese firms are less likely to raise external financing because they are less likely to have subnormal cash level. To test this conjecture, in Panel E of Table 1 we report the likelihoods of having immediate subnormal cash ratio without external financing. Following HR, a firm's cash ratio is considered as subnormal if it is less than the median cash ratio of firms in the same industry, tercile of Tobin's Q, and tercile of total assets at the end of the same year. We estimate cash ratios based on $Cash_{ex\ post}$ and $Cash_{ex\ ante}$. Panel E shows that Japanese firms are less likely to have subnormal cash ratio. For example, based on $Cash_{ex\ post}$, Japanese firms will have subnormal cash ratio in 38.2% of the firm years while US firms will have subnormal cash ratio in 50.5% of the firm years. This is driven by the higher percentage of firms running out of cash in the US. After we exclude the firms that face cash depletion, only 34.9% of US firms will have subnormal cash ratio. The corresponding number for Japanese firms is very close at 34.6%. If we estimate cash ratios using $Cash_{ex\ ante}$, then Japanese firms are slightly more likely (35.3% vs 33%) to have subnormal cash ratio than US firms after we exclude the firms facing cash depletion. However, if we consider only firms not facing depletion, Japanese firms are indeed less likely (35.9% vs 41.4% based on $Cash_{ex\ post}$) to have subnormal cash ratio. This may have contributed to the lower likelihood of external financing for these Japanese firms.

Panel E also shows that in both US and Japan, pure debt issuers are more likely to have subnormal cash ratio if they did not do external financing. This is consistent with the idea that debt issues are more likely to be motivated by the desire to reach optimal cash ratio.

3.2.2.2 Type of external financing and nature of cash needs

Because firms usually have positive cash holdings to begin with, running out of cash means that a firm has significant negative internal cash flow (ICF). Panel F of Table 1 reports the sample distribution by financing type and whether internal cash flow (ICF) is negative. For US firms in our sample, Panel F shows following patterns: 1. When ICF is negative, firms are more likely to issue equity instead of debt; 2. When ICF is non-negative, firms are more likely to issue debt instead of equity. These results are consistent with those in HR. Japanese firms in our sample show a different pattern: firms are more likely to issue debt instead of equity whether ICF is negative or not.

In Panel G of Table 1 we group the observations based on cash depletion and report the distribution by financing type and whether ICF is negative. The results show the same patterns for the US firms regardless of whether firms are running out of cash: unprofitable firms are more likely to issue equity instead of debt while profitable firms are much more likely to issue debt instead of equity. These patterns hold whether we use $Cash_{ex\ post}$ or $Cash_{ex\ ante}$ to measure cash depletion. Again, the results are consistent with those in HR. Because negative ICF implies that at least part of the immediate cash needs is to cover operating loss, the results suggest that the nature of immediate cash needs may be important for the funding choice of US firms. In contrast, Japanese firms are more likely to issue equity only when both $Cash_{ex\ ante}$ and ICF are negative. In all other cases, Japanese firms are more likely to issue debt instead of equity. This result suggests that the funding choice of Japanese firms may not be as sensitive to profitability as US firms.

We report the summary statistics for the cash flow components for different financing groups, adjusted by $Asset_{t-1}$, in Panel A of Table 2. For pure debt issuers among the US firms in our sample, the mean $\Delta D_t/Asset_{t-1}$ ratio is 24.2% while the mean $\Delta E_t/Asset_{t-1}$ ratio is -10.1%. This implies that a significant portion of the debt issue proceeds may have been used to repurchase equity. Similarly, for pure equity issuers in the US, the mean $\Delta E_t/Asset_{t-1}$ ratio is 48.9% while the mean $\Delta D_t/Asset_{t-1}$ ratio is -9.3%, suggesting that a lot of equity issue proceeds may have been used to reduce debt. These results are different from those in HR and suggest that capital restructuring may be an important motive for debt or equity issuance in the US.

(Insert Table 2 about here)

Compared with US firms, Japanese firms issue less debt and equity as a proportion of their assets. Capital restructuring also seems to be an important motive for external financing in Japan. The Japanese pure debt issuers have mean $\Delta D_t/Asset_{t-1}$ ratio of 14.9% and mean $\Delta E_t/Asset_{t-1}$ ratio of -5.3%. The pure equity issuers have mean $\Delta E_t/Asset_{t-1}$ ratio of 24.7% and mean $\Delta E_t/Asset_{t-1}$ ratio of -10.2%. These results suggest that a significant portion of the external financing activities in Japan involves issuing debt to repurchase equity and issuing equity to reduce debt.

To measure the extent of capital restructuring, we estimate the percentage of debt (equity) proceeds used to repurchase equity (reduce debt) by pure debt (equity) issuers. The estimation is based on $-\Delta E_t/\Delta D_t$ ratio for pure debt issuers and $-\Delta D_t/\Delta E_t$ ratio for pure equity issuers. We winsorize the two ratios at 0 and 1[11]. The results are reported in Panel B of Table 2. They show that on average US pure debt (equity) issuers use 41.2% (32.7) of net debt (equity) issue proceeds to repurchase (repay) equity (debt). The corresponding numbers for Japanese pure debt (equity) issuers is 30.7% (49%). Japanese firms use less debt proceeds for repurchase but more equity proceeds to reduce debt. These results confirm that we should consider capital restructuring as one of the most important motives for external financing decisions in both the US and Japan.

For the rest of the cash flow components in Panel A, there are some common patterns. On average, equity issuers are much less profitable. Both debt and equity issuers have a higher average investment ratio than non-issuers, suggesting that immediate investment spending is an important motive for both debt and equity issuance. Equity issuers seem to retain more cash. Debt issuers seem to buy more non-cash assets. These patterns apply for both US firms and Japanese firms.

There are also some differences between US firms and Japanese firms. On average, US firms are more profitable than Japanese firms, but US equity issuers are less profitable than Japanese equity issuers. US firms invest much more than Japanese firms and have higher increase in non-cash assets. The debt issuers in the two countries have similar changes in cash level, but the US equity issuers see more increase in cash holdings than Japanese equity issuers. These features are consistent with the idea that Japanese firms in our sample are more likely to be mature companies while US firms are more likely to be growth firms. This helps explain why Japanese firms are less likely to issue equity.

[11] If a pure debt (equity) issuer also has net issue of equity (debt), then it is using 0% of new debt (equity) proceeds to repurchase equity (retire debt). If this pure debt (equity) issuer repurchases (repay) more equity (debt) than the debt (equity) it issued, then it is using 100% of debt (equity) proceeds to repurchase equity (retire debt).

To examine the persistence of cash needs, in Panel C of Table 2 we report the mean and change in cash holdings as of year t as well as ICF and NCF from t-1 to t+2 for issuers. Consistent with HR and Denis and McKeon (2021), for both the US and Japanese firms, Panel C shows that the losses and negative NCF for equity issuers seem to be more persistent than those for debt issuers. To measure persistency, we estimate the serial correlations in ICF, Loss (a dummy that equals 1 if ICF is negative and zero otherwise), NS (net spending as measured by Investments + ΔNoncash NWC + Cash Dividends), and NCF from t-1 to t+2 and report the results in Panel D of Table 2. Consistent with HR and Denis and McKeon (2021), in the US equity issuers have higher serial correlations for Loss and NCF than debt issuers from t-1 to t+2, implying that the equity issuers have more persistent losses and more persistent NCF than debt issuers during this period. In Japan the equity issuers have more persistent losses and more persistent NCF than debt issuers from t-1 to t+1, implying that equity issuers have persistent cash needs. These results are consistent with the funding-horizon theory and suggest that the nature of cash needs can also help explain the financing choice of Japanese firms.

3.2.2.3 Factors that affect the likelihood of external financing

We report the means and median of selected variables by country in Panel A of Table 3. US firms use more leverage than Japanese firms. If higher leverage more incentive to issue equity to repay debt, as suggested by the traditional trade-off theory of capital structure (see (Harris & Raviv, 1991) for an excellent review) then the lower leverage of Japanese firms does help explain why they are less likely to raise equity. At the same time, higher leverage may also be associated with higher likelihood to issue debt based on the pecking order theory of capital structure (Myers, 1984). Given the uncertainty of outcomes for R&D, firms with higher R&D are more likely to issue equity to fund R&D. This is consistent with the significantly higher R&D spending by US firms as reported in Panel A. Following HR, we estimate Industry Volatility to measure the risk of cash flow. Panel A shows that Japanese firms have significantly lower Industry Volatility than US firms. This helps explain why Japanese firms are less likely to run out of cash and less likely to have subnormal cash ratio despite holding less cash on average, thus helping explain why Japanese firms are less likely to seek external financing. The mean and median Tobin's Q ratio of US firms are much higher than those for Japanese firms. In addition, more than 87% of Japanese firms are dividend payers while less than 34% of the US firms pay dividends. These results are again consistent with the idea that Japanese firms are more likely to be mature firms with less cash needs while US firms are more likely to be growth firms with more needs for external financing.

(Insert Table 3 about here)

Japanese firms have lower mean cash holdings but higher median cash holdings, suggesting that difference in cash holding may not be very important in explain the lower likelihood of external financing by Japanese firms. US firms have higher stock returns than Japanese firms in the previous year and the next 3 years. Following HR, we define term spread as the percentage yield difference between 10- and one-year treasuries. Based on term spread, Japanese firms pay lower interest rate than US firms. This does not explain why Japanese firms are less likely to issue debt than US firms. Japanese firms are slightly larger and older based on log of sales and log of firm age. Given the small magnitude of the differences, we feel firm size and age probably are not very important explanations for the difference in likelihood of external financing between Japan and US.

We reported earlier that Japanese firms are less likely to seek external financing even when we only consider firms not running out of cash. Therefore, we report the means and median of the selected variables for observations with $Cash_{ex\ post} > 0$ in Panel B. We see similar patterns as in Panel A. Among firms not facing cash depletion, Japanese firms have lower leverage, lower R&D, lower cash flow volatility, lower Tobin's Q, and are much more likely to be dividend payers. All these differences may contribute to the lower likelihood of external financing for Japanese firms. We also estimate the results for observations with $Cash_{ex\ ante} > 0$ and see similar patterns[12].

3.3 Regression Tests

Our summary statistics and univariate sorts suggest at least the following patterns:

1. Cash depletion plays a smaller role in explaining external financing decisions in Japan.
2. The lower likelihood for external financing in Japan may also be associated with lower leverage and the fact that Japanese firms are more likely to be mature firms.
3. Capital restructuring may be an important motive for external financing in both the US and Japan.
4. The persistence of cash needs may help explain corporate financing choices in both the US and Japan.

Now we try to find out whether these patterns hold in regressions.

3.3.1 Cash depletion and external financing

Following HR, we first estimate multinomial logit regressions for the decision to issue only debt, only equity, both debt and equity, or neither debt nor equity (the base case) for both US and

[12] For observations with $Cash_{ex\ post} \leq 0$ or $Cash_{ex\ ante} \leq 0$, the results are largely similar. All these results are available upon request.

Japan. Among the explanatory variables we include three dummy variables about cash depletion: Immediate Depletion, Near Depletion, and Medium Depletion. Immediate Depletion equals 1 if $Cash_{t-1} + NCF_{t-1} \leq 0$, zero otherwise. Near Depletion equals 1 if $Cash_{t-1} + NCF_{t-1} > 0$ and $Cash_{t-1} + 2 \times NCF_{t-1} \leq 0$, zero otherwise. Medium Depletion equals 1 if $Cash_{t-1} + NCF_{t-1} > 0$ and $Cash_{t-1} + 2 \times NCF_{t-1} > 0$ and $Cash_{t-1} + 3 \times NCF_{t-1} \leq 0$, zero otherwise. These definitions are similar to those used in Table 7 of HR. We use these definitions instead of those based on NCF_t to alleviate concerns about endogeneity. We also include a Subnormal Cash dummy, which equals 1 if $(Cash_{t-1} + NCF_{t-1})/(Assets_{t-1} + (\Delta Assets_{t-1} - \Delta D_{t-1} - \Delta E_{t-1})) < Median\ Cash\ Ratio_{t-1}$ and $Cash_{t-1} + NCF_{t-1} > 0$, zero otherwise. Median cash ratio is for firms in the same industry, tercile of Tobin's Q, and tercile of total assets. The control variables we use are similar to those used in HR and include $Return_{t-1}$ (stock return in the previous year), $Return_{t+1,t+3}$ (stock return in the next 3 years), $Term\ Spread_{t-1}$, $Ln(Sales)_{t-1}$, $Ln(Age)_{t-1}$, $Leverage_{t-1}$, $R\&D_{t-1}$, $Industry\ Volatility_{t-1}$, Tobin's Q_{t-1}, and $Dividend\ Payer_{t-1}$. We control for industry fixed effects and year fixed effects. Following HR, we report the economic effects rather than the coefficients. The results for US firms are reported in Panel A of Table 4 and the results for Japanese firms are reported in Panel B.

(Insert Table 4 about here)

Consistent with HR and the funding-horizon theory, Panel A suggests that cash depletion has significant economic effects on debt and equity issuance in the US. The Z-statistics for Immediate Depletion, Near Depletion, and Medium Depletion are all significant at 1% level. Immediate Depletion has greater economic effect on debt issuance while Near Depletion and Medium Depletion have greater economic effects on equity issuance, suggesting that equity issues are more likely to have long-term cash needs. Also consistent with the funding-horizon theory, Panel B shows that the Z-statistics for Immediate Depletion and Near Depletion are significant at 1% level for debt and equity issuance in Japan. The economic effects of Immediate Depletion are 4.1 for debt issue and 0.9 for equity issue in Japan, lower than the corresponding economic effect of 7.7 and 5.9 in the US. This is consistent with the lower importance of cash depletion in external financing decision as reported in section 2.2. Unlike in the US, in Japan Medium Depletion has significant economic effects on debt issuance but not on equity issuance.

In both panels, the economic effects of Subnormal Cash are highly significant for debt issues, implying that the prospect of having a subnormal cash ratio significantly increases the likelihood of debt issuance, even if the firm does not expect to run out of cash. As shown earlier in Panel E of Table 1, among firms not facing cash depletion, Japanese firms are less likely to have subnormal cash ratio. This helps explain why Japanese firms are less likely to issue debt. For equity issues and dual issues, the Z-statistics of Subnormal Cash are significant in Panel A but not in Panel B.

3.3.2 Role of additional factors

As we reported earlier, Japanese firms have lower leverage and are more likely to be mature firms with lower R&D, lower cash flow volatility, lower Tobin's Q, and higher propensity to be dividend payers. In both panels of Table 4, the economic effects of leverage are positive and significant for both debt issues and equity issues, suggesting that the lower leverage Japanese firms use can help explain the lower likelihood of debt issuance and equity issuance in Japan. R&D has positive economic effect on equity issuance in both the US and Japan. This is consistent with the fund-horizon theory because R&D tend to be long-term spending. This also implies that the lower R&D in Japan can help explain the lower likelihood of equity issuance in Japan. The economic effects of industry volatility are positive and significant only for equity issues in the US and debt issues in Japan. Tobin's Q has positive economic effect on equity issuance in both the US and Japan. Therefore, the lower Q of Japanese firms can also help explain the lower likelihood of equity issuance in Japan. The economic effect of dividend payer dummy on equity issue is negative in both panels, suggesting that the higher propensity of Japanese firm to be dividend payers also contribute to the lower likelihood of equity issuance in Japan. Given that lower R&D, lower cash flow volatility, lower Tobin's Q, and higher propensity to be dividend payers are all features of mature firms, the regression results in Table 4 are consistent with the idea that Japanese firms are less likely to raise external financing because they use lower leverage and are more likely to be mature firms.

The economic effects of other independent variables are generally consistent with expectation. Consistent with the market timing theory of (Baker & Wurgler, 2002), the stock return in the next 3 years is negatively related to equity issuance in both the US and Japan. Term spread is negatively related to debt issuance in Japan. Large firms and older firms are less likely to issue equity in both the US and Japan.

3.3.3 Restructuring and external financing

It has been reported in Table 2 that firms in both the US and Japan use a significant portion of issue proceeds to repurchase equity or reduce debt. We test the relation between the likelihood of external financing and repurchase/debt reduction in Table 5 by including Repurchase and Debt Reduction among the independent variables. Repurchase is defined as $(-\frac{\Delta E_t}{Assets_{t-1}})$ if $(-\frac{\Delta E_t}{Assets_{t-1}}) > 0.01$, zero otherwise. Debt Reduction is defined as $(-\frac{\Delta D_t}{Assets_{t-1}})$ if $(-\frac{\Delta D_t}{Assets_{t-1}}) >$

0.01, zero otherwise. Because dual issues most likely do not involve repurchase and debt reduction, we focus on pure debt issues and pure equity issues only. In our sample repurchase is not applicable for equity issuers and debt reduction is not applicable for debt issuers, so we estimate separate logit regressions for debt issues and equity issues instead of multinominal logit regressions. The results are reported in Table 5.

(Insert Table 5 about here)

Consistent with the univariate results in Table 2, Panel A of Table 5 shows that in the US Repurchase has significant economic effects on debt issues and Debt Reduction has significant economic effects on equity issues. Panel B of Table 5 shows that Repurchase and Debt Reduction also have significant economic effects on external financing in Japan, although the magnitudes of the economic effects are smaller (11.3 vs 17.8 for Repurchase and 1.9 vs 8.5 for Debt Reduction). These results provide support to the idea that capital restructuring may be an important motive for external financing.

In Table 5 the cash depletion dummies and Subnormal Cash dummy still have significant effects on external financing. The economic effects of other independent variables are largely similar to those in Table 4. The only notable exception is the economic effect of Tobin's Q on debt issue. In Table 4 it is negative and marginally significant in the US and positive in Japan. In Table 5 it has become negative and highly significant in both the US and Japan. This change is consistent with the traditional wisdom that firms with higher Tobin's Q tend to be growth firms who are less likely to issue debt (Graham & Leary, 2011).

3.4. Endogeneity

A possible concern about the regressions in Table 4 and Table 5 is endogeneity. Investment decisions in year t may be jointly determined with external financing decisions. Although we use NCF_{t-1} to estimate the cash depletion dummies, NCF_{t-1} may still be correlated with investment decisions in year t. Repurchase decisions and debt reduction decisions may also be jointly determined with external financing decisions. To address this concern, following HR, we estimate NCF_{fitted}, the fitted value of NCF from a regression[13]. Then we re-estimate the cash depletion dummies and the Subnormal Cash dummy using NCF_{fitted} to replace NCF_{t-1}. After that we re-estimate the multinominal regressions using the fitted cash depletion dummies and fitted Subnormal Cash dummy. The results of the regressions are reported in Panels A and B of Table 6.

(Insert Table 6 about here)

Panel A of Table 6 reports the regression results for the US firms using fitted values for the depletion dummies and Subnormal Cash dummy. The economic effects of Immediate Depletion continue to be statistically significant for pure debt issues and dual issues but become insignificant for pure equity issues. In addition, the economic effects of Near Depletion are insignificant for both pure debt issue and pure equity issue. The economic effects of Medium Depletion are insignificant for pure debt issue. It seems using fitted values significantly weakens the explanatory power of cash depletion variables for US firms.

Panel B of Table 6 reports the multinomial logit regression results for the Japanese firms in our sample using fitted values. The economics effects of the cash depletion variables are either insignificant or negative, except the economic effect of Near Depletion on pure equity issue. These

[13] See Appendix B for descriptions about the fitted regressions used in this paper.

results can only be interpreted as not supporting an important role of cash depletion in external financing decisions in Japan.

However, in both the US and Japan, Subnormal Cash based on fitted value still has significant effects on debt issues and dual issues. In the US, the economic value of Subnormal Cash is also statistically significant. Combined with the results in Table 4 and Table 5, it seems avoiding subnormal cash level is an important motive for debt issues in both the US and Japan.

HR does not include Subnormal Cash in their multinomial logit regressions. To make sure that the differences in our results are not driven by this difference, we drop Subnormal Cash from the independent variables and re-estimate the multinomial logit regressions. The results are reported in Panel C and Panel D of Table 6. Panel C shows that the effects of Immediate Depletion become insignificant for all issues in the US. The effects of Near Depletion are insignificant for all issues. Only Medium Depletion see improvements in significance. In Panel D, the economics effects of the cash depletion variables are again either insignificant or negative, except the economic effect of Near Depletion on pure equity issue. It seems that the weak performance of fitted cash depletion dummies is not caused by the inclusion of Subnormal Cash.

If the effects of cash depletion on external financing are sensitive to adjustments made to address endogeneity issues, are the effects of repurchase and debt reduction also sensitive to the similar adjustments? To answer this question, we estimate the fitted values of Repurchase and Debt Reduction using regressions[14]. Then we re-estimate the logit regressions in Table 5 using the fitted values of Repurchase and Debt Reduction. The results are reported in Table 7.

[14] See Appendix B for descriptions about the fitted regressions used in this paper.

(Insert Table 7 about here)

Table 7 shows that Repurchase and Debt Reduction continue to have significant positive economic effects on financing decisions in both the US and Japan. Considering the results in Table 5, we conclude that the evidence supports the idea that firms are much more likely to issue debt (equity) if they intend to repurchase equity (reduce debt). Like in Table 6, there is only limited support for significant economic effects from cash depletion variables.

3.3.4 Persistence of cash needs

Panels C and D of Table 2 have provided some evidence that the cash needs for firms issuing equity are more persistent than those for firms issuing debt. Now we use multinominal logit regressions to examine the relation between cash needs persistency and financing choice. Following HR, we use $\mathrm{Investments_t}$, $\Delta\mathrm{Noncash\ NWC_t}$, and $\mathrm{Cash\ Dividends_t}$ as proxies for short-term cash needs. Investments, ΔNoncash NWC, and Cash Dividends in years t+1 and t+2 are used as proxies for long-term cash needs. We also add cash holding in year t-1 and ICF in years 5, t+1, and t+2 to control for the sources of cash. The results of the regressions are reported in Table 8.

(Insert Table 8 about here)

Panel A of Table 8 shows that $\mathrm{Investments_t}$ and $\Delta\mathrm{Noncash\ NWC_t}$ have large economic effects (32.8 and 17.6 respectively) on debt issue in the US. They also have statistically significant effects on equity issue, but the magnitudes are much smaller (5.9 and 1.4 respectively). In contrast, Investments in year t+1 and year t+2 are positively related to equity issue but negatively related to debt issue. ΔNoncash NWC in year t+1 is also positively related to equity issue but does not have statistically significant correlation with debt issue. These results are consistent with those in HR and support the funding-horizon theory, which predicts that firms tend to issue debt to finance short-term cash needs and issue equity to finance long-term cash needs.

Panel B of Table 8 shows similar pattern for Japan for investments cash needs. The economic effect of $\mathrm{Investments}_{\mathrm{t}}$ on debt issue is much larger than that on equity issue (17.1 vs 1.7). Probably because of the low frequency of equity issue in Japan, $\mathrm{Investments}_{\mathrm{t+1}}$ still has larger economic effect on debt issue than on equity issue, but the difference is much smaller (0.8 vs 0.3). $\mathrm{Investments}_{\mathrm{t+2}}$ does not have statistically significant economic effect on debt issue but has statistically significant effect on equity issue. $\Delta\mathrm{Noncash\ NWC}$ has positive relation with equity issue in all 3 years but tends to be negatively related to debt issue. These results also suggest that firms tend to issue debt to finance short-term cash needs and issue equity to finance persistent cash needs and are consistent with the funding-horizon theory.

3.4 Robustness checks

We conduct numerous robustness check for our tests. For all multinomial logit regressions, we also conduct separate logit regressions for debt issue and equity issue. The results are similar. The regressions in HR include the variable of default spread, which we do not include in our sample because it is not available for Japan. To make sure our results are not driven by the omission of this variable, we add default spread to the regressions for US firms. The results are also similar. We drop the Subnormal Cash dummy from the logit regressions for Table 5, Table 6, and Table 7. The results are still similar.

3.5 Conclusions

We test the funding-horizon theory about external financing through a comparative study on a sample including firms from the US and Japan. We find evidence to support the funding-horizon theory from both the US and Japan. We also find that a cash needs measure based on subnormal cash ratio performs better in empirical tests after fitted values are used to address endogeneity.

We test the effect of capital restructuring on external financing. The results suggest that firms in both the US and Japan use a substantial proportion of issue proceeds to repurchase equity or reduce debt. Regression tests show that repurchase is an important motive for debt issuance and debt reduction is an important motive for equity issuance.

We find that Japanese firms are much less likely to issue debt and equity compared with US firms. Our test results suggest that this difference is associated with the lower leverage used by Japanese firms and the fact that Japanese firms tend to be mature firms with less cash needs for growth.

Appendix A. Variable Definitions

Variable Names	Variable Definitions
$Cash_t$	Cash and Short-Term Investments (CHE) at the end of year t-1.
$\Delta Cash_t$	$Cash_t - Cash_{t-1}$
D_t	Debt outstanding at the end of year t, calculated as (Short term debt + Long term debt)
ΔD_t	Net debt issuance, calculated as $(D_t - D_{t-1})$
ΔE_t	Net equity issuance, calculated as the difference between net cash flow from financing activities and net debt issuance.
NCF_t	$\Delta Cash_t - \Delta D_t - \Delta E_t$
$Cash_{ex\ post}$	$Cash_{t-1} + NCF_t$. $Cash_{ex\ post}$ is also equal to $Cash_{t-1} - \Delta D_t - \Delta E_t$.
$Cash_{ex\ ante}$	$Cash_{t-1} + NCF_{t-1}$
ICF_t	Internal cash flow in year t. For firms reporting format codes 1–3, ICF = Income Before Extraordinary Items (IBC) + Extraordinary Items and Discontinued Operations (XIDOC) + Depreciation and Amortization (DPC) + Deferred Taxes (Changes)(TXDC) + Equity in Net Loss (Earnings) (ESUBC) + Sale of Property Plant and Equipment and Investments Gain (Loss) (SPPIV) + Funds from Operations Other (FOPO) + Sources of Funds Other (FSRCO). For firms reporting format code 7, ICF = IBC + XIDOC + DPC + TXDC + ESUBC + SPPIV + FOPO + Accounts Payable and Accrued Liabilities Increase (Decrease) (APALCH).
$Assets_t$	The book value of assets at the end of fiscal year t
$\Delta Assets_t$	$Assets_t - Assets_{t-1}$
$Investments_t$	For firms reporting format codes 1–3, Investments = Capital Expenditures (CAPX) + Increase in Investments (IVCH) + Acquisitions (AQC) + Uses of Funds Other (FUSEO) – Sale of Property (SPPE) – Sale of Investments (SIV). For firms reporting format code 7, investments = CAPX + IVCH + AQC – SPPE – SIV – Investing Activities Other (IVACO).
ΔNCW_t	Change in Net Working Capital. For firms reporting format codes 1–3, NWC = Working Capital Change Other (WCAPC) + Cash and Cash Equivalents Increase (Decrease) (CHECH). For firms reporting format code 7, NWC = – Accounts Receivable Decrease (Increase) (RECCH) – Inventory Decrease (Increase) (INVCH) – Accounts Payable and Accrued Liabilities Increase (Decrease) (APALCH) – Income Taxes Accrued Increase (Decrease) (TXACH) – Assets and Liabilities Other Net Change (AOLOCH) + Cash and Cash Equivalents Increase (Decrease) (CHECH) – Change in Short-Term Investments (IVSTCH) – Financing Activities Other (FIAO).
$\Delta Noncash\ NCW_t$	$\Delta NCW_t - \Delta Cash_t$
$\Delta Noncash_t$	$\Delta Assets_t - \Delta Cash_t$
$Loss_t$	a dummy that equals 1 if ICF is negative and zero otherwise
NS_t	Net spending as measured by Investments + ΔNoncash NWC + Cash Dividends

Leverage_t	The book value of debt (Total Liabilities [LT] + Minority Interest [MTB] – Deferred Taxes and Investment Tax Credit [TXDITC] + Liquidating Value of Preferred Stock [PSTKL] – Convertible Debt [DCVT]) ÷ the book value of total assets (AT) at the end of fiscal year t-1.
$\text{R\&D}_t$	Research and Development expenses (XRD) in year t scaled by beginning-of-year assets (AT). Firm-years for which this variable is missing are assigned a value of zero.
$\text{Industry Volatility}_t$	The average standard deviation of cash flow to assets of the firms with the same two-digit SIC code. Cash flow is defined as (Operating Income Before Depreciation [OIBDP] – Interest and Related Expense [XINT] – Income Taxes [TXT] – Common Dividends [DVC]) ÷ beginning-of-year assets. For each firm, the standard deviation of cash flow is computed for the 10 years until the end of year t, requiring at least three years of non-missing data.
Tobin's Q	Calculated as (Market value of equity + Total Assets – Book Value of Equity)/(Total Assets).
Dividend Payer_t	A dummy variable that equals one if the firm pays a common dividend in year t and zero otherwise.
Return_{t-1}	The total return on the firm's stock in fiscal year t-1.
$\text{Return}_{t+1,t+3}$	The total return on the firm's stock from fiscal year t+1 to fiscal year t+3. If the stock gets delisted before three years, the return until delisting is used.
Term Spread_t	The percentage yield difference between 10- and one-year constant fixed maturity treasuries on the last day of fiscal year t.
Ln(Sales)_t	The natural logarithm of net sales (SALE) during fiscal year t.
Ln(Age)_t	The natural logarithm of the number of years the firm has been listed on Compustat or Compustat Global
Immediate Depletion	A dummy that equals 1 if $\text{Cash}_{t-1} + \text{NCF}_{t-1} \leq 0$, zero otherwise.
Near Depletion	A dummy that equals 1 if $\text{Cash}_{t-1} + \text{NCF}_{t-1} > 0$ and $\text{Cash}_{t-1} + 2 \times \text{NCF}_{t-1} \leq 0$, zero otherwise.
Medium Depletion	A dummy that equals 1 if $\text{Cash}_{t-1} + \text{NCF}_{t-1} > 0$ and $\text{Cash}_{t-1} + 2 \times \text{NCF}_{t-1} > 0$ and $\text{Cash}_{t-1} + 3 \times \text{NCF}_{t-1} \leq 0$, zero otherwise.
Subnormal cash	A dummy that equals 1 if $(\text{Cash}_{t-1} + \text{NCF}_{t-1})/(\text{Assets}_{t-1} + (\Delta\text{Assets}_{t-1} - \Delta\text{D}_{t-1} - \Delta\text{E}_{t-1})) < \text{Median Cash Ratio}_{t-1}$ and $\text{Cash}_{t-1} + \text{NCF}_{t-1} > 0$, zero otherwise.
Repurchase	A dummy that is defined as $(-\frac{\Delta\text{E}_t}{\text{Assets}_{t-1}})$ if $(-\frac{\Delta\text{E}_t}{\text{Assets}_{t-1}}) > 0.01$, zero otherwise.
Debt Reduction	A dummy that is defined as $(-\frac{\Delta\text{D}_t}{\text{Assets}_{t-1}})$ if $(-\frac{\Delta\text{D}_t}{\text{Assets}_{t-1}}) > 0.01$, zero otherwise.
Net Debt Due_t	(Debt in current liabilities – Cash_t)/Assets_t
RF_t	Yield of one-year treasury bills
$\text{Interest Rate}_{t-1}$	(Interest expense)/(Total debt)

Appendix B. Independent variables used in regressions to estimate fitted values

Fitted NCF	Fitted Repurchase	Fitted Debt Reduction
Median of $\mathrm{NCF}_{t-1} \div \mathrm{Assets}_{t-1}$	Median of $\mathrm{NCF}_{t-1} \div \mathrm{Assets}_{t-1}$	Median of $\mathrm{NCF}_{t-1} \div \mathrm{Assets}_{t-1}$
Tobin's Q_{t-1}	Tobin's Q_{t-1}	Tobin's Q_{t-1}
Return_{t-1} (%)	Return_{t-1} (%)	Return_{t-1} (%)
$\mathrm{Return}_{t+1,t+3}$ (%)	$\mathrm{Return}_{t+1,t+3}$ (%)	$\mathrm{Return}_{t+1,t+3}$ (%)
Term Spread_{t-1} (%)	Term Spread_{t-1} (%)	Term Spread_{t-1} (%)
$\mathrm{Ln(Sales)}_{t-1}$	$\mathrm{Ln(Sales)}_{t-1}$	$\mathrm{Ln(Sales)}_{t-1}$
$\mathrm{Ln(Age)}_{t}$	$\mathrm{Ln(Age)}_{t}$	$\mathrm{Ln(Age)}_{t}$
$\mathrm{Leverage}_{t-1}$	$\mathrm{Leverage}_{t-1}$	$\mathrm{Leverage}_{t-1}$
$\mathrm{R\&D}_{t-1}$	$\mathrm{R\&D}_{t-1}$	$\mathrm{R\&D}_{t-1}$
Industry $\mathrm{Volatility}_{t-1}$	Industry $\mathrm{Volatility}_{t-1}$	Industry $\mathrm{Volatility}_{t-1}$
Dividend Payer_{t-1}	Dividend Payer_{t-1}	Dividend Payer_{t-1}
Constant	Constant	Net Debt Due_{t-1}
Industry dummies	Industry dummies	RF_{t-1}
Year dummies	Year dummies	Interest Rate_{t-1}
		Constant
		Industry dummies
		Year dummies

Table 3-1: Sample distribution

Panel A. Distribution by financing or not and financing type

	U.S.		Japan	
Type	N-Obs	Percentage	N-Obs	Percentage
All firm years	80,176	100.0%	57,692	100.0%
No External Financing	55,220	68.9%	49,272	85.4%
Pure Debt Issue	14,012	17.5%	6,334	11.0%
Dual Issue	2,172	2.7%	279	0.5%
Pure Equity Issue	8,772	10.9%	1,807	3.1%

Panel B. Distribution by cash depletion and financing or not

U.S.

	All firm-years		No issue		Net debt or equity issue	
Type	N	%	N	%	N	%
$\text{Cash}_{\text{ex post}} \leq 0$	12,474	15.6%	1,628	2.9%	10,846	43.5%
$\text{Cash}_{\text{ex post}} > 0$	67,702	84.4%	53,592	97.1%	14,110	56.5%
$\text{Cash}_{\text{ex ante}} \leq 0$	15,060	18.8%	7,561	13.7%	7,499	30.0%
$\text{Cash}_{\text{ex ante}} > 0$	65,116	81.2%	47,659	86.3%	17,457	70.0%

Japan

	All firm-years		No issue		Net debt or equity issue	
Type	N	%	N	%	N	%
$\text{Cash}_{\text{ex post}} \leq 0$	2,100	3.6%	270	0.5%	1,830	21.7%
$\text{Cash}_{\text{ex post}} > 0$	55,592	96.4%	49,002	99.5%	6,590	78.3%
$\text{Cash}_{\text{ex ante}} \leq 0$	2,780	4.8%	1,770	3.6%	1,010	12.0%
$\text{Cash}_{\text{ex ante}} > 0$	54,912	95.2%	47,502	96.4%	7,410	88.0%

Panel C. Distribution by cash depletion and financing type

U.S.

	Pure debt issue		Dual issue		Pure equity issue	
Type	N	%	N	%	N	%
All	14,012	100.0%	2,172	100.0%	8,772	100.0%
$\text{Cash}_{\text{ex post}} \leq 0$	6,429	45.9%	1,633	75.2%	2,784	31.7%
$\text{Cash}_{\text{ex post}} > 0$	7,583	54.1%	539	24.8%	5,988	68.3%
$\text{Cash}_{\text{ex ante}} \leq 0$	3,528	25.2%	1,016	46.8%	2,955	33.7%
$\text{Cash}_{\text{ex ante}} > 0$	10,484	74.8%	1,156	53.2%	5,817	66.3%

Japan

	Pure debt issue		Dual issue		Pure equity issue	
Type	N	%	N	%	N	%
All	6,334	100.0%	279	100.0%	1,807	100.0%
$\text{Cash}_{\text{ex post}} \leq 0$	1,393	22.0%	162	58.1%	275	15.2%
$\text{Cash}_{\text{ex post}} > 0$	4,941	78.0%	117	41.9%	1,532	84.8%
$\text{Cash}_{\text{ex ante}} \leq 0$	581	9.2%	85	30.5%	344	19.0%
$\text{Cash}_{\text{ex ante}} > 0$	5,753	90.8%	194	69.5%	1,463	81.0%

Panel D. Likelihood of financing, conditional on cash depletion

U.S.

	Net debt or equity issue	Debt issue	Equity issue
$\text{Cash}_{\text{ex post}} \leq 0$	10,846 : 12,474 = 87.0%	8,062:12,474 = 64.6%	4,417:13,659 = 35.4%
$\text{Cash}_{\text{ex post}} > 0$	14,110 : 67,702 = 20.8%	8,122:67,702 = 12.0%	6,527:67,702 = 9.6%
$\text{Cash}_{\text{ex ante}} \leq 0$	7,499 : 15,060 = 49.8%	4,544:15,060 = 30.2%	3,971:15,060 = 26.4%
$\text{Cash}_{\text{ex ante}} > 0$	17,457 : 65,116 = 26.8%	11,640:65,116 = 17.9%	6,973:65,116 = 10.7%

Japan

	Net debt or equity issue	Debt issue	Equity issue
$\text{Cash}_{\text{ex post}} \leq 0$	1,830 : 2,100 = 87.1%	1,555:2,100 = 74.0%	437:2,100 = 20.8%
$\text{Cash}_{\text{ex post}} > 0$	6,590 : 55,592 = 11.8%	5,058:55,592 = 9.1%	1,649:55,592 = 3.0%
$\text{Cash}_{\text{ex ante}} \leq 0$	1,010 : 2,780 = 36.3%	666:2,780 = 24.0%	429:2,780 = 15.4%
$\text{Cash}_{\text{ex ante}} > 0$	7,410 : 54,912 = 13.5%	5,947:54,912 = 10.8%	1,657:54,912 = 3.0%

Panel E. Likelihoods of having immediate subnormal cash ratio (< the median cash ratio):

U.S.

	All firm-years	No depletion	No Issue	Debt Issue	Equity Issue	Dual Issue
Subnormal cash based on $\text{Cash}_{\text{ex post}}$	50.5%	41.4%	40.6%	80.0%	63.9%	86.0%
Excluding $\text{Cash}_{\text{ex ante}} \leq 0$	34.9%	41.4%	37.6%	30.2%	23.5%	10.9%
Subnormal cash based on $\text{Cash}_{\text{ex ante}}$	51.8%	40.6%	47.2%	64.0%	60.0%	68.8%
Excluding $\text{Cash}_{\text{ex ante}} > 0$	33.0%	40.6%	33.6%	35.9%	23.7%	22.1%

Japan

	All firms	No depletion	No Issue	Debt Issue	Equity Issue	Dual Issue
Subnormal cash based on $\text{Cash}_{\text{ex post}}$	38.2%	35.9%	33.5%	70.6%	51.7%	81.4%
Excluding $\text{Cash}_{\text{ex ante}} \leq 0$	34.6%	35.9%	33.0%	47.1%	30.7%	23.3%
Subnormal cash based on $\text{Cash}_{\text{ex ante}}$	40.1%	37.0%	38.1%	52.1%	50.4%	54.8%
Excluding $\text{Cash}_{\text{ex ante}} \leq 0$	35.3%	37.0%	34.5%	42.1%	29.9%	24.4%

Panel F. Distribution by financing and internal cash flow

	U.S.								
	All	No issue		Dual issue		Equity issue		Debt issue	
	N	N	%	N	%	N	%	N	%
ICF < 0	16,078	8,272	51.4	1,001	6.2	5,590	34.8	3,217	20.0
ICF≥ 0	63,969	46,850	73.2	1,170	1.8	5,349	8.4	12,940	20.2
	Japan								
	All	No issue		Dual issue		Equity issue		Debt issue	
	N	N	%	N	%	N	%	N	%
ICF < 0	5,930	4,081	68.8	129	2.2	806	13.6	1,172	19.8
ICF≥ 0	51,757	45,187	87.3	150	0.3	1,280	2.5	5,440	10.5

Panel G. Distribution by financing, cash depletion, and internal cash flow

	U.S.							
	$\text{Cash}_{\text{ex post}} \leq 0$		$\text{Cash}_{\text{ex post}} > 0$		$\text{Cash}_{\text{ex ante}} \leq 0$		$\text{Cash}_{\text{ex ante}} > 0$	
	ICF < 0	ICF ≥ 0	ICF < 0	ICF ≥ 0	ICF < 0	ICF ≥ 0	ICF < 0	ICF ≥ 0
No issue N	387	1,240	7,885	45,610	1,467	6,089	6,805	40,761
No issue %	9.8	14.5	64.9	82.3	32.1	58.1	59.1	76.2
Debt issue N	1,739	6,317	1,478	6,623	1,323	3,217	1,894	9,723
Debt issue %	44.2	74.1	12.2	11.9	29.0	30.7	16.4	18.2
Equity issue N	2,507	1,909	3,083	3,440	2,278	1,691	3,312	3,658
Equity issue %	63.7	22.4	25.4	6.2	49.9	16.1	28.8	6.8
	Japan							
	$\text{Cash}_{\text{ex post}} \leq 0$		$\text{Cash}_{\text{ex post}} > 0$		$\text{Cash}_{\text{ex ante}} \leq 0$		$\text{Cash}_{\text{ex ante}} > 0$	
	ICF < 0	ICF ≥ 0	ICF < 0	ICF ≥ 0	ICF < 0	ICF ≥ 0	ICF < 0	ICF ≥ 0
No issue N	56	214	4,025	44,973	267	1,502	3,814	43,685
No issue %	8.6	14.8	76.2	89.4	39.5	71.4	72.6	88.0
Debt issue N	401	1,154	771	4,286	192	474	980	4,966
Debt issue %	61.7	79.6	14.6	8.5	28.4	22.5	18.7	10.0
Equity issue N	281	156	525	1,124	270	159	536	1,121
Equity issue %	43.2	10.8	9.9	2.2	39.9	7.6	10.2	2.3

This table reports the distribution of our sample of firms from US and Japan from 2000 to 2020, from Compustat North America and Compustat Global. Utility and financial firms are excluded. Panel A reports the distribution by financing or not and financing type. Panel B reports the distribution by cash depletion and financing or not. Panel C reports the distribution by cash depletion and financing type. Panel D reports the likelihood of financing, conditional on cash depletion. Panel E reports the likelihoods of having immediate subnormal cash ratio (< the median cash ratio). Panel F reports the distribution by financing and internal cash flow. Panel G reports the distribution by financing, cash depletion, and internal cash flow. A firm is defined as having pure equity issue if ($\Delta E_t \div Asset_t \geq 0.05$ and $\Delta E_t \div ME_{t-1} \geq 0.03$) and ($\Delta D_t \div Asset_{t-1} \leq 0.05$ or $\Delta D_t \div ME_{t-1} \leq 0.03$). A firm is defined as having pure debt issue if ($\Delta D_t \div Asset_t \geq 0.05$ and $\Delta D_t \div ME_{t-1} \geq 0.03$) and ($\Delta E_t \div Asset_{t-1} \leq 0.05$ or $\Delta E_t \div ME_{t-1} \leq 0.03$). A firm is defined as dual (both debt and equity issue) if ($\Delta E_t \div Asset_t \geq 0.05$ and $\Delta E_t \div ME_{t-1} \geq 0.03$) and ($\Delta D_t \div Asset_{t-1} \geq 0.05$ or $\Delta D_t \div ME_{t-1} \geq 0.03$). ΔD_t is the change in total debt ($DLTT_t + DLC_t - (DLTT_{t-1} + DLC_{t-1})$) where DLTT and DLC are long-term debt and short-term debt code in Compustat. ΔE_t is the change in equity, calculated by substract debt financing cash flow from financing cash flow, $FINCF_t - \Delta D_t$. $Asset_t$ and ME_t denote book value of assets and market value of equity at the end of time (t-1), respectively. Cash exposte is defined as $CH_{t-1} + NCF_t$ and cash exante is defined as $CH_{t-1} + NCF_{t-1}$ where NCF_t is Net Cash Flow at time (t). ICF denotes the Internal Cash Flow. Subnormal Cash (based on cash expost) take value one if $[((Cash_t - \Delta D_t - \Delta E_t) \div (Asset_t - \Delta D_t - \Delta E_t) <$ Median Cash $Ratio_t)$ or $(Cash_{t-1} + NCF_t \leq 0)]$ and immediate $depletion_{ex\text{-}post} = 0$, and zero otherwise. Subnormal cash (based on cash exante) is dummy variable take value one if $[((Cash_{t-1} + NCF_{t-1}) \div [Asset_{t-1} + (\Delta asset_{t-1} - \Delta D_{t-1} - \Delta E_{t-1})] <$ Median Cash $Ratio_{t-1})$ or $(Cash_{t-1} + NCF_{t-1} \leq 0)]$ and immediate $depletion_{ex\text{-}ante} = 0$, and zero otherwise. Immediate depletion (without subscript implies using cash exante) = 1 if $Cash_{t-1} + NCF_{t-1} < 0$ and 0 otherwise. Immediate $depletion_{ex\text{-}post} = 1$ if $Cash_{t-1} + NCF_t < 0$ and 0 otherwise. $Cash_{expost} = Cash_{t-1} + NCF_t$ and $Cash_{exante} = Cash_{t-1} + NCF_{t-1}$

Table 3-2: Cash and cash flow components (%)

Panel A. Mean of cash flow components (%) sorted by financing

U.S.

	No issue	Pure debt issue	Dual issue	Pure equity issue	Debt issue	Equity issue	All
$\Delta D_t/Asset_{t-1}$	-1.5	24.2	38.4	-9.3	26.1	0.1	3.2
$\Delta E_t/Asset_{t-1}$	-2.8	-10.1	42.9	48.9	-3.0	47.7	2.8
$ICF_t/Asset_{t-1}$	9.7	9.6	-8.1	-9.1	7.2	-8.9	7.2
$Investments_t/Asset_{t-1}$	9.7	21.9	52.4	17.2	26.0	24.2	13.8
$Cash\ Dividends_t/Asset_{t-1}$	1.3	1.6	0.7	0.3	1.5	0.3	1.3
$\Delta Noncash\ NWC_t/Asset_{t-1}$	0.7	3.2	0.1	-1.4	2.8	-1.1	0.9
$\Delta Cash_t/Asset_{t-1}$	-0.2	2.2	21.9	19.1	4.8	19.6	2.9
$\Delta Noncash_t/Asset_{t-1}$	2.0	31.8	66.6	9.7	36.5	21.0	9.8

Japan

	No issue	Pure debt issue	Dual issue	Pure equity issue	Debt issue	Equity issue	All
$\Delta D_t/Asset_{t-1}$	-1.3	14.9	24.7	-10.2	15.4	-5.5	0.4
$\Delta E_t/Asset_{t-1}$	-1.5	-5.3	27.2	24.7	-3.9	25.0	-0.9
$ICF_t/Asset_{t-1}$	6.7	5.6	-5.3	-0.4	5.1	-1.1	6.3
$Investments_t/Asset_{t-1}$	3.8	9.0	21.5	5.8	9.5	7.8	4.5
$Cash\ Dividends_t/Asset_{t-1}$	1.0	1.0	0.6	0.5	1.0	0.5	1.0
$\Delta Noncash\ NWC_t/Asset_{t-1}$	0.6	-2.9	-2.0	5.8	-2.8	4.8	0.4
$\Delta Cash_t/Asset_{t-1}$	0.5	3.8	16.7	8.3	4.3	9.4	1.2
$\Delta Noncash_t/Asset_{t-1}$	0.9	18.1	37.6	-0.5	18.9	4.6	3.0

Panel B. Percentage of debt (equity) proceeds used to repurchase equity (repay debt)

	U.S.		Japan	
	Mean	Median	Mean	Median
% of debt proceeds used to repurchase equity by pure debt issuers	41.2	28.1	30.7	17.2
% of equity proceeds used to reduce debt by pure equity issuers	32.7	7.6	49.0	44.1

Panel C. Mean cash and cash flow components (%) sorted by financing and cash depletion								
U.S.								
	Debt issue		Equity issue		Debt issue		Equity issue	
	$Cash_{ex\ post}$		$Cash_{ex\ post}$		$Cash_{ex\ ante}$		$Cash_{ex\ ante}$	
	>0	≤ 0	>0	≤ 0	>0	≤ 0	>0	≤ 0
$Cash_{t-1}$	20.9	9.6	36.0	19.2	18.3	7.5	36.7	16.1
$\Delta Cash_t$	7.1	2.6	20.6	18.1	4.5	5.5	20.3	18.5
ICF_{t-1}	7.4	5.7	-8.4	-15.3	8.9	-0.1	-5.5	-21.1
ICF_t	8.4	6.1	-4.2	-15.9	9.1	2.5	-5.2	-15.4
ICF_{t+1}	10.6	9.5	-2.9	-10.8	11.6	6.1	-3.2	-11.1
ICF_{t+2}	13.2	13.3	-1.5	-5.3	14.4	10.3	-1.2	-6.2
NCF_{t-1}	-1.2	-8.4	-14.2	-27.6	2.2	-22.8	-8.8	-38.7
NCF_t	-2.6	-34.1	-10.5	-54.3	-15.7	-24.8	-24.1	-35.4
NCF_{t+1}	-3.1	-10.5	-19.2	-40.5	-3.7	-14.8	-22.3	-37.5
NCF_{t+2}	-2.4	-11.2	-19.9	-42.5	-3.4	-15.4	-22.4	-40.3
Japan								
	Debt issue		Equity issue		Debt issue		Equity issue	
	$Cash_{ex\ post}$		$Cash_{ex\ post}$		$Cash_{ex\ ante}$		$Cash_{ex\ ante}$	
	>0	≤ 0	>0	≤ 0	>0	≤ 0	>0	≤ 0
$Cash_{t-1}$	19.6	10.4	23.2	18.9	18.4	9.1	24.2	15.0
$\Delta Cash_t$	5.0	2.0	9.9	7.9	4.1	5.9	9.4	9.5
ICF_{t-1}	6.5	4.4	-0.6	-14.7	6.6	0.2	1.1	-21.1
ICF_t	6.1	2.0	2.9	-16.0	5.6	1.0	1.8	-12.2
ICF_{t+1}	8.0	5.0	4.6	-9.8	7.8	3.1	4.2	-9.0
ICF_{t+2}	8.6	6.6	5.7	-10.3	8.5	4.6	4.5	-6.8
NCF_{t-1}	0.1	-3.7	-4.1	-21.1	1.1	-17.8	-0.6	-34.9
NCF_t	-2.8	-21.2	-1.3	-43.2	-6.4	-13.5	-7.4	-20.3
NCF_{t+1}	0.1	-4.1	-4.0	-26.6	-0.3	-5.8	-6.1	-18.9
NCF_{t+2}	1.0	-1.9	-4.8	-23.6	0.9	-4.3	-7.0	-16.2

Panel D. Persistence of internal cash flow, net spending, and net cash flow			
U.S.			
	All	Debt issue	Equity issue
Correlation between ICF_{t-1} and ICF_t	0.70	0.75	0.69
Correlation between ICF_t and ICF_{t+1}	0.68	0.72	0.68
Correlation between ICF_{t+1} and ICF_{t+2}	0.70	0.74	0.73
Correlation between $Loss_{t-1}$ and $Loss_t$	0.62	0.64	0.68
Correlation between $Loss_t$ and $Loss_{t+1}$	0.62	0.61	0.69
Correlation between $Loss_{t+1}$ and $Loss_{t+2}$	0.61	0.60	0.70
Correlation between NS_{t-1} and NS_t	0.39	0.24	0.23
Correlation between NS_t and NS_{t+1}	0.44	0.35	0.41
Correlation between NS_{t+1} and NS_{t+2}	0.51	0.51	0.53
Correlation between NCF_{t-1} and NCF_t	0.38	0.27	0.35
Correlation between NCF_t and NCF_{t+1}	0.30	0.20	0.32
Correlation between NCF_{t+1} and NCF_{t+2}	0.32	0.26	0.37
Japan			
	All	Debt issue	Equity issue
Correlation between ICF_{t-1} and ICF_t	0.53	0.48	0.56
Correlation between ICF_t and ICF_{t+1}	0.45	0.30	0.55
Correlation between ICF_{t+1} and ICF_{t+2}	0.48	0.56	0.55
Correlation between $Loss_{t-1}$ and $Loss_t$	0.35	0.34	0.50
Correlation between $Loss_t$ and $Loss_{t+1}$	0.35	0.35	0.49
Correlation between $Loss_{t+1}$ and $Loss_{t+2}$	0.36	0.34	0.49
Correlation between NS_{t-1} and NS_t	0.05	0.09	-0.05
Correlation between NS_t and NS_{t+1}	0.07	-0.01	0.20
Correlation between NS_{t+1} and NS_{t+2}	0.17	0.18	0.26
Correlation between NCF_{t-1} and NCF_t	0.20	0.13	0.36
Correlation between NCF_t and NCF_{t+1}	0.20	0.17	0.36
Correlation between NCF_{t+1} and NCF_{t+2}	0.26	0.32	0.31

This table reports Cash and Cash Flow components of our sample of firms from the U.S. and Japan from 2000 to 2020. Panel A reports the mean of cash flow components (%) sorted by financing. ΔD_t is change in total debt. ΔE_t is change in equity. ICF_t is internal cash flow. For firm reporting format code 1-3 or 10 (international), ICF = Income Before Extraodianary Items (IBC) + Extraodinary Items and Discontinued Operations (XIDOC) + Depreciation and Amortization (DPC) + Deferred Taxes (TXDC) + Sale of Property Plant and Equipment and Investment Gain Loss (SPPIV) + Fund from Operations Other (FOPO) + Source of Funds Other (FSRCO). For firm reporting format code 7, ICF = IBC + XIDOC + DPC + TXDC + SPPIV + FOPO +Account payable and accrued liabilities increase (decrease) APALCH. $Investment_t$ for firm reportin format code 1-3 or 10 = Capital Expenditure (CAPX) + Increase in Investment (IVCH) + Acquisitions (AQC) + Uses of Funds Others (FUSEO) – SPPIV. For firm reporting format code 7, $Investment_t$ = CAPX + IVCH + AQC – SPPIV – IVACO. Δnoncash $NWC_t = \Delta NWC_t - \Delta Cash_t$. $\Delta NonCasht_t = \Delta Asset_t - \Delta Cash_t$. Panel B reports the percentage of debt (equity) proceeds used to repurchase equity (repay debt). Debt proceeds to used to repurchase equity by pure debt issuer is 1 if (firm is pure debt issue) and ($\Delta E_t < 0$) and (abs(ΔE_t) > 1%*$Asset_{t-1}$). Equity proceeds used to reduce debt byt pure equity issuers is 1 if (firm is pure equity issue) and ($\Delta D_t < 0$) and (abs(ΔD_t) > 1%*$Asset_{t-1}$). Panel C reports mean cash and cash flow components (%) sorted by financing and cash depletion. Panel D reports the correlation between internal cash flow, net spending, and net cash flow. Net Spending (NS_t) = $Investment_t$ + ΔNoncash NWC_t + Cash $Dividends_t$. $Loss_t$ is a dummy variable that equals one if ICFt is negative and equals zero otherwise.

Table 3-3: Means and medians of key variables

Panel A. All firm-years	Means			Median		
	U.S.	Japan	Difference p-value	U.S.	Japan	Difference p-value
Leverage_{t-1} (%)	23.42	20.35	0.00	19.57	16.92	0.00
$\text{R\&D}_{t-1}$ (%)	4.64	1.29	0.00	0.21	0.41	0.00
$\text{Industry Volatility}_{t-1}$ (%)	20.27	2.57	0.00	214.83	2.79	0.00
Tobin's Q_{t-1}	2.02	1.18	0.00	1.51	0.99	0.00
$\text{Dividend Payer}_{t-1}$ (%)	33.97	87.21	0.00	0.00	100.00	0.00
$\text{Cash}_{t-1}/\text{Assets}_{t-1}$ (%)	19.84	18.82	0.00	11.78	15.21	0.00
Return_{t-1} (%)	15.20	10.63	0.00	5.59	3.40	0.06
$\text{Return}_{t+1,t+3}$ (%)	45.26	37.67	0.00	21.26	18.29	0.84
Term Spread_{t-1} (%)	1.36	0.76	0.00	1.40	0.74	0.00
Ln(Sales)_{t-1}	6.00	6.05	0.00	5.99	5.91	0.00
Ln(Age)_{t}	2.79	2.85	0.00	2.77	2.94	0.00

Panel B. Firm-years with $Cash_{ex\ \text{post}} > 0$	Means			Median		
	U.S.	Japan	Difference p-value	U.S.	Japan	Difference p-value
Leverage_{t-1} (%)	22.36	20.02	0.00	18.23	16.48	0.00
$\text{R\&D}_{t-1}$ (%)	4.74	1.30	0.00	0.46	0.42	0.00
$\text{Industry Volatility}_{t-1}$ (%)	19.99	2.57	0.00	19.42	2.53	0.00
Tobin's Q_{t-1}	2.01	1.17	0.00	1.51	0.98	0.00
$\text{Dividend Payer}_{t-1}$ (%)	35.67	87.65	0.00	0.00	100.00	0.00
$\text{Cash}_{t-1}/\text{Assets}_{t-1}$ (%)	22.08	19.21	0.00	13.83	15.66	0.00
Return_{t-1} (%)	14.25	10.67	0.00	4.97	3.53	0.00
$\text{Return}_{t+1,t+3}$ (%)	47.04	38.17	0.00	23.08	18.83	0.00
Term Spread_{t-1} (%)	1.37	0.76	0.00	1.40	0.74	0.00
Ln(Sales)_{t-1}	6.13	6.06	0.00	6.11	5.92	0.00
Ln(Age)_{t}	2.82	2.86	0.00	2.83	2.94	0.00

This table reports the means and medians of key variables for our sample of firms from the U.S. and Japan. Panel A reports mean and median and p-value for testing hypothesis of mean/median difference between the two samples (US and Japan). Panel B reports same to Panel A on subsample of Cash ex-post > 0. Hypothesis testing for mean difference assume variance difference between the two samples. Hypothesis testing for median using Mann–Whitney U test. $\text{Leverage}_{t-1} = (\text{DLC}_{t-1} + \text{DLTT}_{t-1}) / \text{Asset}_{t-1}$. $\text{R\&D}_{t-1} = \text{XRD}_{t-1} / \text{Asset}_{t-1}$. Industry volatility_t is the average standard deviation of cash flow to assets of the firms with the same two-digit SIC code. Cash flow is defined as (Operating Income Before Depreciation[OIBDP] – Interest and Related Expense [XINT] – Income Taxes [TXT] – Common Dividends [DVC]) ÷ beginning-of-year assets. For each firm, the standard deviation of cash flow is computed for the 10 years until the end of year t-1, requiring at least three years of nonmissing data. This definition follows Bates, Kahle, and Stulz (2009). Dividend payer_{t-1} equal one firm pay dividend and zero otherwise. Return_{t-1} is The total return on the firm's stock in fiscal year t-1. $\text{Return}_{t+1,\ t+3}$ is the total return on the firm's stock from fiscal year t+1 to fiscal year t+3. If the stockgets delisted before three years, the return until delisting is used. Term spread_{t-1} is the percentage yield difference between 10- and one-year constant fixed maturity treasuries on the day immediately prior to the beginning of fiscal year t. Ln(Sales)_{t-1} is log natural of sale in (USD value) expressing in purchasing power at 2010. Ln(Age)_t is firm age calcualted as the difference between current year (t) and year of IPO or first year of data avaiable (depend on which one is earlier).

Table 3-4: Cash depletion and financing decisions: multinomial logit regressions

Panel A. Multinomial logit model: U.S.									
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion	5.9	16.1	4.1	19.2	1.8	18.9	7.7	5.9
Near Depletion	1.0	3.5	2.0	9.8	0.6	7.3	1.7	2.6
Medium Depletion	0.8	2.6	1.1	6.2	0.2	2.6	1.0	1.3
Subnormal Cash	3.9	9.4	1.0	4.5	0.5	4.1	4.4	1.5
Leverage_{t-1}	4.1	11.5	5.2	22.2	0.7	8.3	4.8	5.9
$\text{R\&D}_{t-1}$	-4.7	-5.2	5.0	19.1	1.0	9.5	-3.7	6.0
$\text{Industry Volatility}_{t-1}$	-1.0	-1.4	1.1	3.0	0.2	1.5	-0.8	1.3
Tobin's Q_{t-1}	-1.1	-1.9	0.9	2.9	-0.2	-1.6	-1.3	0.7
$\text{Dividend Payer}_{t-1}$	-0.5	-0.9	-4.3	-12.1	-0.4	-3.7	-0.9	-4.7
Return_{t-1} (%)	3.9	9.5	1.6	8.3	0.8	9.1	4.7	2.4
$\text{Return}_{t+1,t+3}$ (%)	-0.2	-1.3	-1.8	-7.7	-0.4	-3.9	-0.5	-2.1
Term Spread_{t-1} (%)	-1.4	-1.0	-1.0	-1.1	0.6	1.3	-0.8	-0.4
Ln(Sales)_{t-1}	2.9	1.9	-9.0	-24.9	-1.5	-10.8	1.4	-10.5
Ln(Age)_{t}	-3.7	-9.7	-2.1	-8.4	-1.1	-9.8	-4.9	-3.2
Number of observations		40,534						
Pseudo R-squared		12.2%						

Panel B. Multinomial logit model: Japan									
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion	3.9	15.7	0.8	12.6	0.2	11.2	4.1	0.9
Near Depletion	2.1	8.2	0.4	4.7	0.1	2.5	2.1	0.4
Medium Depletion	1.7	6.7	0.1	1.6	0.0	1.7	1.7	0.1
Subnormal Cash	3.1	8.9	0.0	0.3	0.1	1.7	3.1	0.0
Leverage_{t-1}	5.0	15.7	1.6	15.9	0.1	2.7	5.0	1.6
$\text{R\&D}_{t-1}$	0.3	0.9	0.5	5.0	0.0	-0.1	0.3	0.5
$\text{Industry Volatility}_{t-1}$	1.8	4.6	0.1	1.4	0.0	-0.4	1.8	0.1
Tobin's Q_{t-1}	1.6	4.7	1.3	13.8	0.1	3.3	1.7	1.3
$\text{Dividend Payer}_{t-1}$	2.5	6.6	-1.6	-20.1	-0.1	-5.3	2.4	-1.8
Return_{t-1} (%)	0.4	1.1	-0.1	-0.5	0.1	4.0	0.5	0.0
$\text{Return}_{t+1,t+3}$ (%)	0.0	-0.1	-0.5	-4.0	0.0	-1.5	0.0	-0.5
Term Spread_{t-1} (%)	-8.2	-4.3	-0.4	-1.1	0.2	1.0	-8.1	-0.3
Ln(Sales)_{t-1}	-0.2	-0.9	-0.4	-3.3	-0.2	-5.4	-0.5	-0.6
Ln(Age)_{t}	-6.4	-16.2	-0.7	-6.5	-0.2	-6.1	-6.6	-0.9
Number of obs.		44,809						
Pseudo R-squared		11.0%						

This table reports the results of a multinomial logit model. The dependent variable takes four values, zero for no external financing, one for pure debt external financing, two for pure equity external financing, and three for dual issuance. Immediate depletion equals one if $Cash_{t-1} + NCF_{t-1} < 0$ and zeros otherwise. Near depletion equals one if $Cash_{t-1} + 2{*}NCF_{t-1} < 0$ and zero otherwise. Medium depletion equals one if $Cash_{t-1} + 3{*}NCF_{t-1} < 0$ and zero otherwise. Subnormal cash is dummy variable take value one if $[((Cash_{t-1} + NCF_{t-1}) \div [Asset_{t-1} + (\Delta asset_{t-1} - \Delta D_{t-1} - \Delta E_{t-1})] <$ Median Cash $Ratio_{t-1})$ or $(Cash_{t-1} + NCF_{t-1} \leq 0)]$ and immediate $depletion_{ex\text{-}ante} = 0$, and zero otherwise. We use NCF_{t-1} to address endogeneity issues since spending and financing may be jointly determined. We report economic effect rather than coefficient for interpretation purposes. Economic effect is calculated by allowing selected variables to varies by one standard deviation while keeping other variables at mean value. The difference in probability outcome is the economic effect. The industry and year dummy variables and the intercept are among the independent variables, but their economic effects and z-statistics are not reported. See Appendix A for detailed variable definitions.

Table 3-5: Cash depletion and capital restructuring: logit regressions

	U.S.				Japan			
	Pure debt issue		Pure equity issue		Pure debt issue		Pure equity issue	
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion	7.9	19.2	3.8	16.9	3.7	16.3	0.6	10.9
Near Depletion	1.5	3.8	2.1	10.9	2.0	8.4	0.2	3.3
Medium Depletion	1.3	3.5	1.3	7.4	1.7	7.7	0.1	0.9
Subnormal Cash	6.2	14.4	1.1	4.1	3.5	11.0	0.3	3.4
Repurchase	17.8	47.3			11.3	47.5		
Debt Reduction			8.5	40.2			1.9	32.5
Leverage_{t-1}	2.7	6.5	0.1	0.5	5.5	18.2	-0.1	-1.0
$\text{R\&D}_{t-1}$	-2.7	-4.3	4.3	19.8	0.6	1.8	0.4	5.6
$\text{Industry Volatility}_{t-1}$	-0.2	-0.3	0.8	2.5	0.7	2.1	-0.1	-0.5
Tobin's Q_{t-1}	-9.1	-15.6	1.0	4.3	-3.1	-8.6	1.0	12.3
$\text{Dividend Payer}_{t-1}$	-2.5	-6.2	-3.2	-10.1	1.6	4.8	-1.0	-15.7
Return_{t-1} (%)	4.7	10.9	1.5	6.9	0.8	2.3	0.0	0.4
$\text{Return}_{t+1,t+3}$ (%)	-0.5	-1.4	-1.6	-7.3	0.0	0.1	-0.5	-4.6
Term Spread_{t-1} (%)	-1.4	-1.0	-1.3	-1.5	-5.8	-3.3	-0.6	-1.2
Ln(Sales)_{t-1}	1.7	3.5	-6.6	-20.5	-1.0	-3.3	-0.3	-2.7
Ln(Age)_{t}	-3.1	-7.4	-2.3	-8.4	-5.4	-14.5	-0.6	-5.2
Number of obs.	40,519		40,519		44,809		44,809	
Pseudo R-squared	11.5%		28.9%		14.2%		30.3%	

This table reports the results of two logit regression models. For pure debt issue regressions, the dependent variable takes the value of one for pure debt external financing, zero otherwise. For pure equity issue regressions, the dependent variable takes the value of one for pure equity external financing, zero otherwise. Immediate depletion equals one if $Cash_{t-1} + NCF_{t-1} < 0$ and zeros otherwise. Near depletion equals one if $Cash_{t-1} + 2^{*}NCF_{t-1} < 0$ and zero otherwise. Medium depletion equals one if $Cash_{t-1} + 3^{*}NCF_{t-1} < 0$ and zero otherwise. Subnormal cash is dummy variable take value one if [$((Cash_{t-1} + NCF_{t-1}) \div [Asset_{t-1} + (\Delta asset_{t-1} - \Delta D_{t-1} - \Delta E_{t-1})] <$ Median Cash $Ratio_{t-1}$) or ($Cash_{t-1} + NCF_{t-1} \leq 0$)] and immediate $depletion_{ex\text{-}ante} = 0$, and zero otherwise. We use NCF_{t-1} to address endogeneity issues since spending and financing may be jointly determined. Repurchase is defined as $(-\frac{\Delta E_t}{Assets_{t-1}})$ if $(-\frac{\Delta E_t}{Assets_{t-1}}) > 0.01$, zero otherwise. Debt Reduction is defined as $(-\frac{\Delta D_t}{Assets_{t-1}})$ if $(-\frac{\Delta D_t}{Assets_{t-1}}) > 0.01$, zero otherwise. We report economic effect rather than coefficient for interpretation purposes. Economic effect is calculated by allowing selected variables to varies by one standard deviation while keeping other variables at mean value. The difference in probability outcome is the economic effect. The industry and year dummy variables and the intercept are among the independent variables, but their economic effects and z-statistics are not reported. See Appendix A for detailed variable definitions.

Table 3-6: Cash depletion and financing decisions: multinomial logit regressions using fitted value

Panel A. Multinomial logit model: U.S.								
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion$_{fitted}$	2.6	6.5	-0.1	0.7	0.3	3.7	2.9	0.2
Near Depletion$_{fitted}$	0.5	0.7	-0.2	-0.9	-0.2	-2.2	0.3	-0.5
Medium Depletion$_{fitted}$	-0.2	0.0	1.1	4.5	0.3	3.7	0.1	1.4
Subnormal Cash$_{fitted}$	4.2	12.8	0.4	3.0	0.5	5.1	4.7	0.9
Leverage$_{t-1}$	3.2	9.8	5.5	23.1	0.9	9.7	4.0	6.4
R&D$_{t-1}$	-4.0	-4.8	4.6	17.7	0.9	8.7	-3.0	5.5
Industry Volatility$_{t-1}$	-0.7	-0.9	1.1	3.4	0.3	1.9	-0.4	1.4
Tobin's Q$_{t-1}$	-0.9	-1.6	0.8	2.8	-0.2	-1.3	-1.1	0.6
Dividend Payer$_{t-1}$	0.2	-1.4	-4.2	-12.4	-0.5	-4.2	-0.2	-4.7
Return$_{t-1}$ (%)	2.9	7.7	1.1	5.9	0.6	6.8	3.5	1.7
Return$_{t+1,t+3}$ (%)	0.2	-0.4	-1.6	-7.2	-0.3	-3.6	-0.2	-2.0
Term Spread$_{t-1}$ (%)	-1.1	-0.9	-1.0	-1.1	0.6	1.3	-0.5	-0.4
Ln(Sales)$_{t-1}$	3.2	3.0	-9.3	-25.6	-1.6	-11.7	1.6	-10.9
Ln(Age)$_{t}$	-3.4	-9.7	-2.3	-9.2	-1.2	-10.8	-4.6	-3.5
Number of obs.	40,519							
Pseudo R-squared	11.3%							

Panel B. Multinomial logit model: Japan								
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion$_{fitted}$	-0.2	-0.5	-0.2	-2.1	0.1	0.0	-0.1	0.0
Near Depletion$_{fitted}$	0.3	0.5	0.2	3.0	-0.2	0.0	0.1	0.0
Medium Depletion$_{fitted}$	-1.1	-2.3	-0.1	-2.0	0.0	-0.9	-1.1	-0.1
Subnormal Cash$_{fitted}$	2.8	9.6	-0.1	-0.5	0.1	3.3	2.9	0.0
Leverage$_{t-1}$	5.8	18.6	1.8	17.5	0.1	3.5	5.9	1.9
R&D$_{t-1}$	0.3	1.0	0.5	5.1	0.0	0.1	0.3	0.5
Industry Volatility$_{t-1}$	1.9	5.0	0.1	1.2	0.0	-0.3	1.9	0.1
Tobin's Q$_{t-1}$	1.7	5.1	1.4	14.5	0.1	4.1	1.8	1.5
Dividend Payer$_{t-1}$	2.4	6.3	-1.7	-20.3	-0.1	-6.0	2.3	-1.8
Return$_{t-1}$ (%)	-0.2	-0.7	-0.2	-1.7	0.1	2.6	-0.2	-0.1
Return$_{t+1,t+3}$ (%)	0.0	-0.1	-0.5	-4.5	-0.1	-2.0	0.0	-0.6
Term Spread$_{t-1}$ (%)	-7.4	-3.9	-0.4	-1.0	0.3	1.6	-7.1	-0.2
Ln(Sales)$_{t-1}$	-0.3	-1.1	-0.5	-3.9	-0.3	-6.1	-0.6	-0.8
Ln(Age)$_{t}$	-6.8	-17.4	-0.8	-7.0	-0.2	-6.5	-7.0	-1.0
Number of obs.	44,809							
Pseudo R-squared	9.9%							

Panel C. Multinomial logit model: U.S. without Subnormal Cash								
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion$_{fitted}$	0.6	1.4	-0.3	-1.1	0.1	1.0	0.7	-0.2
Near Depletion$_{fitted}$	0.8	1.3	-0.2	-0.6	-0.2	-1.4	0.7	-0.4
Medium Depletion$_{fitted}$	0.9	2.1	1.2	5.5	0.5	5.2	1.4	1.7
Leverage_{t-1}	4.6	12.8	5.6	23.9	1.0	10.4	5.6	6.6
$\text{R\&D}_{t-1}$	-5.7	-7.0	4.6	17.5	0.9	7.6	-4.8	5.5
$\text{Industry Volatility}_{t-1}$	-1.0	-1.4	1.1	3.2	0.3	1.7	-0.7	1.4
Tobin's Q_{t-1}	-1.9	-3.4	0.8	2.4	-0.2	-1.9	-2.1	0.5
$\text{Dividend Payer}_{t-1}$	-0.5	-0.9	-4.3	-12.3	-0.5	-4.0	0.0	-4.7
Return_{t-1} (%)	3.3	8.2	1.1	6.0	0.6	6.8	3.9	1.7
$\text{Return}_{t+1,t+3}$ (%)	0.2	-0.4	-1.6	-7.1	-0.3	-3.4	-0.2	-2.0
Term Spread_{t-1} (%)	-1.3	-0.9	-1.0	-1.1	0.6	1.3	-0.6	-0.4
Ln(Sales)_{t-1}	3.7	3.3	-9.3	-25.7	-1.6	-11.2	2.0	-11.0
Ln(Age)_{t}	-3.4	-9.3	-2.2	-9.1	-1.3	-10.6	-4.7	-3.5
Number of obs.	40,519							
Pseudo R-squared	11.0%							

Panel D. Multinomial logit model: Japan without Subnormal Cash								
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion$_{fitted}$	-0.3	-0.8	-0.1	-2.0	0.1	0.0	-0.2	0.0
Near Depletion$_{fitted}$	0.3	0.6	0.2	3.0	-0.2	0.0	0.1	0.0
Medium Depletion$_{fitted}$	-1.0	-2.0	-0.1	-2.1	0.0	-0.6	-1.0	-0.1
Leverage_{t-1}	6.8	22.3	1.7	17.9	0.1	4.5	7.0	1.9
$\text{R\&D}_{t-1}$	0.2	0.8	0.5	5.2	0.0	0.0	0.2	0.5
$\text{Industry Volatility}_{t-1}$	1.5	3.9	0.1	1.3	0.0	-0.7	1.5	0.1
Tobin's Q_{t-1}	1.4	4.3	1.4	14.6	0.1	3.8	1.5	1.5
$\text{Dividend Payer}_{t-1}$	2.5	6.2	-1.7	-20.3	-0.2	-6.1	2.3	-1.8
Return_{t-1} (%)	-0.2	-0.5	-0.2	-1.7	0.1	2.6	-0.1	-0.1
$\text{Return}_{t+1,t+3}$ (%)	-0.2	-0.6	-0.5	-4.5	-0.1	-2.1	-0.2	-0.6
Term Spread_{t-1} (%)	-7.8	-4.0	-0.4	-1.0	0.3	1.5	-7.6	-0.1
Ln(Sales)_{t-1}	0.2	0.4	-0.5	-4.0	-0.3	-5.8	-0.1	-0.8
Ln(Age)_{t}	-6.8	-16.9	-0.8	-7.1	-0.2	-6.1	-7.0	-1.0
Number of obs.	44,809							
Pseudo R-squared	9.7%							

This table reports the results of a multinomial logit model. The dependent variable takes four values, zero for no external financing, one for pure debt external financing, two for pure equity external financing, and three for dual issuance. Immediate depletion equals one if $Cash_{t-1} + NCF_{t-1} < 0$ and zeros otherwise. The dummy variables of cash depletion are defined using fitted NCF. The regression to estimated fitted NCF is described in Appendix B. We report economic effect rather than coefficient for interpretation purposes. Economic effect is calculated by allowing selected variables to vary by one standard deviation while keeping other variables at mean value. The difference in probability outcome is the economic effect. The industry and year dummy variables and the intercept are among the independent variables, but their economic effects and z-statistics are not reported. See Appendix A for detailed variable definitions.

Table 3-7: Cash depletion and capital restructuring: logit regressions using fitted value

	U.S.				Japan			
	Pure debt issue		Pure equity issue		Pure debt issue		Pure equity issue	
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion$_{fitted}$	2.5	6.6	-1.3	-4.2	-0.1	-0.3	-0.2	-2.3
Near Depletion$_{fitted}$	0.6	1.0	-0.5	-1.5	0.2	0.3	0.3	3.3
Medium Depletion$_{fitted}$	-0.4	-0.7	0.8	2.5	-1.0	-2.1	-0.2	-1.8
Subnormal Cash$_{fitted}$	4.3	13.0	-1.6	-4.4	2.9	10.0	-0.4	-3.4
Repurchase$_{fitted}$	6.9	8.7			5.8	8.3		
Debt Reduction$_{fitted}$			8.5	6.8			17.0	6.2
Leverage$_{t-1}$	3.0	7.2	-1.6	-1.5	7.1	19.0	-6.4	-4.5
R&D$_{t-1}$	-3.5	-5.4	3.6	9.2	0.2	0.7	0.5	4.1
Industry Volatility$_{t-1}$	-0.2	-0.4	1.1	2.4	0.5	1.2	-0.5	-2.6
Tobin's Q$_{t-1}$	-4.8	-7.1	0.7	1.9	-1.0	-2.3	1.3	11.3
Dividend Payer$_{t-1}$	-3.2	-6.2	-3.6	-7.9	1.4	3.4	1.6	2.9
Return$_{t-1}$ (%)	2.9	7.2	1.6	4.7	-0.3	-1.0	-0.2	-1.9
Return$_{t+1,t+3}$ (%)	-0.1	-0.3	-2.2	-7.0	-0.1	-0.2	-1.1	-7.0
Term Spread$_{t-1}$ (%)	-0.9	-0.7	-0.9	-0.7	-5.4	-3.0	-1.5	-2.1
Ln(Sales)$_{t-1}$	1.5	2.8	-7.5	-12.0	-1.4	-3.9	0.6	2.8
Ln(Age)$_{t}$	-3.0	-7.5	-3.8	-9.0	-5.5	-14.0	-0.6	-3.7
Number of obs.	40,485		40,485		44,809		44,809	
Pseudo R-squared	4.3%		19.3%		5.3%		19.6%	

This table reports the results of two logit regression models. For pure debt issue regressions, the dependent variable takes the value of one for pure debt external financing, zero otherwise. For pure equity issue regressions, the dependent variable takes the value of one for pure equity external financing, zero otherwise. The dummy variables of cash depletion are defined using fitted NCF. Fitted values of Repurchase and Debt Reduction are used in the regressions. The regressions to estimated fitted NCF, fitted Repurchase, and fitted Debt Reduction are described in Appendix B. We report economic effect rather than coefficient for interpretation purposes. Economic effect is calculated by allowing selected variables to vary by one standard deviation while keeping other variables at mean value. The difference in probability outcome is the economic effect. The industry and year dummy variables and the intercept are among the independent variables, but their economic effects and z-statistics are not reported. See Appendix A for detailed variable definitions.

Table 3-8: Financing choice and persistence of cash needs

Panel A. Multinomial logit model: U.S.	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion	1.7	5.2	3.1	10.3	1.4	12.1	3.1	4.4
Near Depletion	1.4	4.0	1.6	7.1	0.5	6.4	1.9	2.1
Medium Depletion	1.0	3.1	0.9	4.5	0.2	2.2	1.2	1.0
Subnormal Cash	-0.1	0.0	0.4	1.0	0.3	2.2	0.2	0.7
$Cash_{t-1}$	-15.2	-18.5	-2.4	-8.6	-0.8	-6.5	-16.0	-3.3
ICF_t	-11.8	-13.1	-4.4	-12.4	-1.9	-14.9	-13.7	-6.3
$Investments_t$	30.3	41.9	3.4	15.6	2.5	34.7	32.8	5.9
$\Delta Noncash\ NWC_t$	16.4	20.4	0.3	4.8	1.1	11.8	17.6	1.4
$Cash\ Dividends_t$	3.7	5.8	0.5	1.8	0.0	0.7	3.7	0.6
ICF_{t+1}	3.5	2.9	-2.0	-3.4	0.2	1.8	3.7	-1.8
$Investments_{t+1}$	-7.6	-8.5	1.8	3.9	-0.3	-3.0	-7.9	1.5
$\Delta Noncash\ NWC_{t+1}$	-1.2	-0.8	1.9	4.1	0.2	1.4	-1.0	2.0
$Cash\ Dividends_{t+1}$	-2.1	-2.7	-0.2	-0.6	0.1	0.6	-2.0	0.0
ICF_{t+2}	7.7	7.5	-0.7	-0.2	0.3	3.1	8.0	-0.5
$Investments_{t+2}$	-3.4	-3.8	1.1	2.9	0.1	0.2	-3.3	1.1
$\Delta Noncash\ NWC_{t+2}$	-0.3	-0.1	0.6	1.5	0.1	1.6	-0.1	0.7
$Cash\ Dividends_{t+2}$	-4.3	-6.1	-0.8	-2.4	-0.1	-1.4	-4.5	-0.9
$Leverage_{t-1}$	3.1	9.3	5.3	20.1	0.5	6.8	3.7	5.9
$R\&D_{t-1}$	-1.8	-1.4	4.1	13.2	0.6	6.1	-1.2	4.8
$Industry\ Volatility_{t-1}$	-1.2	-1.8	1.2	3.0	0.2	1.5	-1.0	1.4
$Tobin's\ Q_{t-1}$	-1.4	-2.1	1.3	3.6	-0.4	-3.2	-1.8	0.9
$Dividend\ Payer_{t-1}$	1.5	1.5	-4.4	-9.8	-0.4	-3.2	1.1	-4.8
$Return_{t-1}$ (%)	2.8	7.2	2.0	8.5	0.7	8.9	3.5	2.7
$Return_{t+1,t+3}$ (%)	-0.6	-2.1	-1.6	-6.2	-0.3	-3.3	-0.9	-1.8
$Term\ Spread_{t-1}$ (%)	-1.2	-0.9	-1.1	-1.1	0.5	1.3	-0.6	-0.6
$Ln(Sales)_{t-1}$	1.6	0.2	-8.4	-20.4	-1.1	-8.6	0.6	-9.4
$Ln(Age)_t$	-3.6	-9.7	-2.5	-8.7	-0.9	-9.1	-4.5	-3.4
Number of obs.	40,289							
Pseudo R-squared	18.0%							

Panel B. Multinomial logit model: Japan								
	Pure debt issue		Pure equity issue		Dual issue		Debt issue	Equity issue
	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.	Econ. effect	Z-stat.
Immediate Depletion	1.6	6.4	0.5	6.8	0.1	5.3	1.7	0.7
Near Depletion	1.5	6.3	0.2	3.0	0.0	1.2	1.5	0.3
Medium Depletion	1.2	5.5	0.0	0.6	0.0	1.2	1.3	0.1
Subnormal Cash	0.3	0.7	0.0	0.1	0.0	0.3	0.3	0.0
Cash_{t-1}	-4.1	-8.3	-0.3	-2.4	-0.1	-2.0	-4.2	-0.4
ICF_{t}	-6.8	-16.9	-1.6	-13.9	-0.2	-10.4	-7.0	-1.8
$\mathrm{Investments}_{t}$	16.7	40.0	1.3	13.8	0.4	28.5	17.1	1.7
$\Delta\mathrm{Noncash\ NWC}_{t}$	-6.2	-17.8	1.0	10.2	0.0	-2.0	-6.2	0.9
$\mathrm{Cash\ Dividends}_{t}$	2.9	4.1	-1.9	-7.2	-0.2	-2.6	2.7	-2.2
ICF_{t+1}	1.8	4.2	0.0	-0.1	0.0	-0.9	1.8	-0.1
$\mathrm{Investments}_{t+1}$	0.7	1.9	0.3	3.2	0.0	2.5	0.8	0.3
$\Delta\mathrm{Noncash\ NWC}_{t+1}$	-0.6	-1.7	0.4	4.1	0.1	3.9	-0.5	0.4
$\mathrm{Cash\ Dividends}_{t+1}$	-5.2	-5.8	1.3	4.2	0.1	1.3	-5.1	1.4
ICF_{t+2}	1.5	3.0	-0.1	-0.4	0.0	1.4	1.5	0.0
$\mathrm{Investments}_{t+2}$	0.3	0.7	0.6	4.9	0.1	4.5	0.4	0.7
$\Delta\mathrm{Noncash\ NWC}_{t+2}$	-1.3	-4.1	0.4	4.5	0.0	2.0	-1.3	0.4
$\mathrm{Cash\ Dividends}_{t+2}$	-1.2	-1.7	0.5	2.3	0.0	0.1	-1.2	0.5
$\mathrm{Leverage}_{t-1}$	2.9	9.3	1.4	12.5	0.1	2.4	3.0	1.5
$\mathrm{R\&D}_{t-1}$	-0.1	-0.3	0.3	3.3	0.0	-0.3	-0.1	0.3
$\mathrm{Industry\ Volatility}_{t-1}$	1.6	4.4	0.4	2.8	0.0	0.6	1.6	0.4
$\mathrm{Tobin's\ Q}_{t-1}$	1.0	2.9	1.3	11.8	0.0	1.7	1.1	1.4
$\mathrm{Dividend\ Payer}_{t-1}$	2.7	7.0	-1.2	-12.2	0.0	-1.5	2.6	-1.3
Return_{t-1} (%)	0.4	1.2	0.1	0.7	0.1	3.2	0.5	0.2
$\mathrm{Return}_{t+1,t+3}$ (%)	0.0	-0.1	-0.5	-3.7	0.0	-0.7	0.0	-0.5
$\mathrm{Term\ Spread}_{t-1}$ (%)	-6.1	-3.5	-1.0	-1.8	0.2	1.1	-5.9	-0.8
$\mathrm{Ln(Sales)}_{t-1}$	-0.2	-0.8	-0.2	-1.3	-0.2	-3.5	-0.4	-0.3
$\mathrm{Ln(Age)}_{t}$	-5.6	-15.2	-1.0	-8.0	-0.2	-6.7	-5.8	-1.2
Number of obs.	44,090							
Pseudo R-squared	20.0%							

This table reports the results of a multinomial logit model. The dependent variable takes four values, zero for no external financing, one for pure debt external financing, two for pure equity external financing, and three for dual issuance. Immediate depletion equals one if $Cash_{t-1} + NCF_{t-1} < 0$ and zeros otherwise. Near depletion equals one if $Cash_{t-1} + 2^{*}NCF_{t-1} < 0$ and zero otherwise. Medium depletion equals one if $Cash_{t-1} + 3^{*}NCF_{t-1} < 0$ and zero otherwise. Subnormal cash is dummy variable take value one if $[((Cash_{t-1} + NCF_{t-1}) \div [Asset_{t-1} + (\Delta asset_{t-1} - \Delta D_{t-1} - \Delta E_{t-1})] <$ Median Cash $Ratio_{t-1}) \text{ or } (Cash_{t-1} + NCF_{t-1} \leq 0)]$ and immediate $depletion_{ex\text{-}ante} = 0$, and zero otherwise. We use NCF_{t-1} to address endogeneity issues since spending and financing may be jointly determined. We report economic effect rather than coefficient for interpretation purposes. Economic effect is calculated by allowing selected variables to varies by one standard deviation while keeping other variables at mean value. The difference in probability outcome is the economic effect. The industry and year dummy variables and the intercept are among the independent variables, but their economic effects and z-statistics are not reported. See Appendix A for detailed variable definitions.

4 Chapter 4: Automation and M&A

4.1 Introduction

This essay explores the potential role of New Automation Technology in shaping firm decisions to engage in M&A. By isolating automation from technological development, I uncover a transformative dimension that has long remained in the shadows of M&A research. Kaplan (2007) provided compelling evidence that a significant portion of M&A transactions are driven by technological shocks. Augmenting this perspective, Bena & Li (2014) found that technology overlaps serve not just as a catalyst for M&A activities but also as a precursor to an increase in post-merger patent production. In this essay, I investigate the relationship between new automation technology opportunities (referred to as automation exposure[15]) – a significant and influential branch of technology – and M&A activities, examining their impact on M&A decisions both pre-merger and post-merger.

In 2014, Google strategically acquired DeepMind, an AI company renowned for its capabilities in machine learning algorithms. This acquisition allowed Google to make transformative improvements in a myriad of sectors ranging from energy efficiency in data centers to search engine optimization. For instance, by applying machine learning to optimize energy consumption, Google achieved a 40%[16] reduction in its energy usage for cooling, resulting in both operational and environmental benefits. On the other hand, Yahoo, a contemporary of Google, refrained from making similar bold investments in automation technology. While Google actively sought to integrate cutting-edge automation technologies through the strategic acquisition of DeepMind, Yahoo remained largely inactive in incorporating such advancements into its

[15] The name automation exposure is to make it consistency with the name used in prior literature, (Qiu et al., 2020; Quoc et al., 2023)
[16] https://www.deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40

operational framework. This divergence in automation approaches, among with other key factors (see (Quora, 2016)),had tangible long-term effects: Yahoo's inertia contributed to its dwindling market relevance and ultimately led to its sale to Verizon in 2017 for a mere $4.48 billion, a fraction of its peak valuation of over $100 billion. In stark contrast, Google continues to stand as one of the world's most valuable companies, with a market capitalization exceeding $1 trillion as of 2021

In 2012, Amazon strategically acquired Kiva Systems for $775 million to revolutionize its warehouse logistics through advanced automation. The acquisition led to a reported 20% reduction in operating expenses and cut click-to-ship time by half, yielding not only cost savings but also faster customer service. Meanwhile, retail competitors like Macy's and Sears failed to make similar strategic investments in automation. Over the years, their hesitance resulted in declining market shares and financial troubles. Sears filed for bankruptcy in 2018, and Macy's closed around 125 stores, representing approximately a 15% drop in their retail footprint, see (Keuhnelian, 2023)

The two preceding examples underscore both the opportunities and imperatives of new automation technology presents for firms seeking a competitive advantage. Automation differs from invention; while invention aims to introduce new products, create uniqueness, and thus create a competitive advantage, automation focuses on improving the existing production systems. It seeks to boost productivity and thereby lowering costs, enhancing quality, and reducing defect rates.

Research on the intersection of Mergers and Acquisitions (M&A) and automation is sparse, likely due to the challenges of isolating automation-related patents from broader technological developments. Leveraging the breakthrough database presented by Mann (2021), which employs machine learning to classify over five million patents as automation-related or not, I construct a metric for automation exposure, an aggregation of automation-related patents, at the firm level.

The metric allows me to address several key questions. How does a firm's automation exposure influence its M&A decisions? Does high automation exposure predispose a firm to be an acquirer or a target? Given that automation is intrinsically linked to mass production and cost reduction, firms are inclined to pursue acquisitions that enhance these capabilities, particularly when product differentiation is minimal. Consequently, I investigate whether firms with high product similarity to their rivals are more motivated to undertake acquisitions for automation purposes (called automation-acquisition from now on), potentially to expand market reach or acquire essential automation technologies. Lastly, inspired by insights from (Liu et al., 2024), which posit that firms with heightened automation exposure are drawn into an 'automation arms race', a scenario that escalates investment and R&D, and thus deteriorates a firm's financial health, this research aspires to evaluate whether post automation-acqusition are associated with either an improvement or deterioration in a firm's financial health in subsequent periods.

Utilizing automation exposure metric and multiple logistic regression analyses, I discovered that automation exposure significantly influences a firm's M&A decisions. This impact remains robust even when controlling for year, industries, asset size, and market-to-book ratio factor. Notably, the marginal effect[17] of automation on a firm's likelihood of becoming an acquirer is two to three times greater than that of becoming a target. Additionally, the interaction between the level of automation exposure and the similarity of a firm's products to its rivals critically influences acquisition strategies. At high automation exposure, firms are more likely to acquire if there is a high product similarity to the rivals. When automation exposure are insufficient, the likelihood of pursuing an acquisition strategy remains low, regardless of product similarity to competitors. This insight builds on the observations by Hoberg & Phillips (2010), who found that

[17] The marginal effect (or economic effect) of a factor is a the probability from multinomial logistics model given the concerned factor to varies by one standard deviation while keeping other factors at mean level.

firms generally avoid acquiring businesses very similar to their own. Lastly, firms engaging in automation-driven acquisitions often experience the "winner's curse", facing increased financial constraints and reduced profitability in subsequent periods. This highlights the potential financial downsides of automation-acquisition strategies in the context of automation.

Given the fact that CERP[18] reports that automation could potentially elevate global GDP by at least 5%, the amount of research on automation is surprisingly limited in comparison to its potential impact. To bridge this research gap, this essay offers two key contributions. First, this study demonstrates the impact of new automation technology on firms' M&A decision-making, emphasizing that the current rapid pace of technological advancements, especially in machine learning algorithms and AI technology, could intensify the pressure for automation-driven M&A activities in the near future. Second, this essay enriches the existing literature in the M&A field regarding the impact of technology synergies.

My paper relates to and complements the research of Bena & Li (2014) and Sevilir & Tian (2012), examining the other aspect of technology, automation, on M&A decisions. Unlike their approach, which employs an aggregate of patents as an innovation measure, my study specifically targets patents related to automation. Regarding target selection, my research complements the findings of Hoberg & Phillips (2010) and Hoberg & Phillips (2016), who explore how asset and product similarities influence an acquirer's choice of targets. I concur with their conclusion and add on that another dimension of how automation and product similarity are interacting on M&A decision. When automation level is sufficiently high, and there is little room for product differentiation, firms are more likely to pursue acquisition strategies for automation purpose. Broadly, this finding contributes to the discourse on the importance of vertical mergers, as

[18]https://cepr.org/voxeu/columns/simulating-future-global-automation-its-consequences-and-evaluating-policy-options

emphasized by (Fan & Goyal, 2006) and (He & Tian, 2018). Of particular note, He & Tian (2018) identify “Related or Focus Acquisition” as a consistently reliable predictor of M&A success among 25 variables examined. My study finds that automation exposure is a crucial driver in a firm's likelihood to engage in M&A activities, given the same level of automation exposure, the marginal effect of a firm becoming an acquirer is two to three times as high as becoming a target. The result supports the findings of Phillips & Zhdanov (2013) regarding the role of firm size and R&D activity in determining these M&A roles, my research suggests that automation exposure, combined with firm size and R&D activity, provides a more detailed understanding of how firms decide to become acquirer or target. Lastly, my paper extends the finding of (Liu et al., 2024), indicating that automation-acquisition are likely to result in the 'winner's curse”.

This essay is organized as follows. Section II is literature review, conceptual framework and hypothesis development. Section III is Methodology, Key Variables and Samples. Section IV discusses the results. And Section V concludes.

4.2 Conceptual Framework and Hypothesis

4.2.1 Automation Exposure and transaction incidence

Kaplan (2007) and Pastor & Veronesi (2009) have observed that the majority of M&A waves are associated with technology shocks. Building on this, Bena & Li (2014) discovered that when firms share technological overlaps, it not only increases the likelihood of M&A transaction incidences pre-merger but also leads to patent synergies, with more patents being produced after the merger. In this essay, I argue that exposure to new automation technology, or automation exposure, serves as a catalyst for M&A transaction incidences.

Investing in automation is a costly endeavor, necessitating significant upfront fixed-cost investments and demanding mass production to realize economies of scale. Building on this fact, I identify three potential synergies driven by automation exposure. First, firms engage in M&A transactions to achieve operational synergies, which involves expanding their market to make the implementation of automation systems economically viable. This is essential as, without such expansion, the firm's market share would remain below the threshold necessary for new automation systems to reach economies of scale. Such strategic movements typically involve acquisitions among firms that possess similar or complementary assets or technologies, a notion supported by Rhodes-Kropf & Robinson (2008).

The second synergy is motivated by the pursuit of acquiring related automation patents to gain a competitive advantage, as illustrated by the examples of Google and Amazon highlighted in the Introduction. This rationale is consistent with the findings of (Phillips & Zhdanov, 2013). They discovered that larger firms prefer to allocate capital to acquire smaller firms that have successfully patented their R&D. On the other hand, smaller firms tend to follow a strategy of investing heavily in R&D with the aspiration of being acquired in the future. Bena & Li (2014) provided further evidence of these patent synergies, suggesting that firms with overlapping technologies are inclined to merge, which subsequently results in a patent synergy that boosts the patent production post-merger."

Liu et al. (2024) observed that firms with high automation exposure find themselves in an 'automation arms race', escalating their investments and R&D commitments. Drawing from the insights of Holmstrom & Roberts (1998), the motivation behind M&A often revolves around acquiring innovation to attain an information asymmetry advantage. This is because purchasing patents necessitates the revelation of information, making them less appealing to potential buyers. Building on these insights, firms with pronounced automation exposure are more inclined to pursue acquisitions of firms possessing beneficial automation patents. Thus, the first hypothesis can be stated as:

Hypothesis 1: "Firms with higher automation exposure are more likely to engage in M&A transactions.

4.2.2 Automation-Acquisition

If M&A is primarily driven by automation objectives (termed "automation-acquisition"), the primary motivations are likely rooted on achieving operational synergy or acquiring critical automation patents. For the purpose of this study, the focus is strictly on acquisition deals only. I do not consider target deals because the majority of target deals are classified as asset divestiture which often serve as financing rather than strategic motives, fall outside the scope of this analysis. Given these motivations, automation-acquisitions are likely to occur predominantly between firms that either possess similar assets or offer comparable products, facilitating strategic pairings that enhance productivity and provide a competitive edge. This observation aligns with the findings of Bloom & Van Reenen (2002), who emphasized the strategic influence of patents on firm-level productivity and market value. Moreover, Maksimovic et al. (2011) identify asset complementarity and productivity as critical factors influencing post-merger restructuring outcomes in M&A activities.

According to the Q-theory of mergers, Jovanovic & Rousseau (2002) propose that firms with high market-to-book (M/B) ratios tend to acquire firms with lower M/B ratios, providing the acquirer rapid access to the target's products and markets without the need for substantial new infrastructure. This framework suggests that firms pursuing an automation-acquisition strategy can quickly and cost-effectively expand their market share. However, subsequent empirical studies by Rhodes-Kropf & Viswanathan (2004), Rhodes-Kropf, Robinson, & Viswanathan (2005), and Rhodes-Kropf & Robinson (2008) challenge this theory, finding instead that high M/B firms often acquire targets with similar or slightly lower M/B ratios. Although exploring the interaction between automation and Q-theory could be valuable, I exclude this factor from my analysis due to sample bias, as approximately 60% of M&A deals lack essential target identifiers (gvkey).

The second aspect considers the impact of product similarity on decisions related to automation-acquisition. When products among firms are highly differentiated, these firms possess a broader spectrum of strategic options, see (Ramdas et al., 2010; Frambach et al., 2003; Jayaswal et al., 2011). However, in markets where products are highly similar, adopting cost and price strategies becomes a practical approach, see (Jain & Bala, 2018). Such environments encourage firms to pursue automation as a means to enhance efficiency and reduce costs. In their study, Hoberg & Phillips (2010) developed the broad and local similarity indices: Broad similarity measures a firm’s average pairwise similarity score compared to all other firms in the same industry[19], while local similarity measures it against the firm’s ten closest rivals. Their findings

[19] The industry here imply industry classified by product similarity, see (Hoberg & Phillips, 2016)

indicated that firms with high broad similarity are more inclined to engage in M&A due to asset complementarity. In contrast, local similarity reduces merger likelihood, attributed to the intense competition and antitrust law constraints faced by closely similar firms.

My critique focuses on their analysis of local similarity. Hoberg & Phillips (2010) employed a linear model to explore the relationship between local similarity and M&A activity, revealing a negative correlation. However, I propose a two-stage effect to better characterize this relationship. Initially, when local similarity is low, firms enjoy greater flexibility for product differentiation, allowing them to implement unique strategies that set their products apart from competitors. This phase of differentiation is supported by seminal works such as Porter (1980) and Kim & Mauborgne (2005), which highlight how firms leverage differentiation strategies to secure competitive advantages. At this stage, firms are generally less inclined to engage in costly M&As aimed at automation, given the broader array of strategic alternatives available.

In the second stage, where local similarity is high and the scope for product differentiation is limited, firms may adopt cost reduction strategies as a competitive tactic. This often propels them towards acquiring automation technologies to decrease costs and boost efficiency. This transition is supported by Grant (1991) and Henderson & Clark (1990), who note that when differentiation is constrained, firms tend to embrace low-cost strategies, frequently through technological innovations like automation. To more accurately depict this two-stage process, an upward quadratic model of local similarity is proposed[20], which offers a more precise representation than a linear model. The quadratic model illustrates that while M&A activity might be less frequent at lower levels of local similarity – where firms can still effectively differentiate – at higher levels, the drive towards cost leadership, including through automation, likely increases

[20] Model detail is discussed in Methodology section

M&A activities aimed at acquiring automation capabilities. This hypothesis challenge the linear approach by Hoberg & Phillips (2010), providing a deeper insight into how firms' strategic decisions evolve in response to product similarity among competitors.

Hypothesis 2a: "At low level of local similarity, firms are indifferent or less likely to pursue a costly acquisition for automation purpose."

Hypothesis 2b: "At high level of local similarity, firms have less room for product differentiation therefore firms would likely to end up in automation acquisitions strategy"

4.2.3 Automation Arm Race and M&A

Building on the preceding hypotheses, I narrow my focus to cases where automation is the primary catalyst for M&A transactions, automation-acquisition. An immediate follow-up question arises: Do these automation-driven mergers yield positive outcomes post-merger? The research conducted by Liu et al. (2024) offers valuable insights, indicating that firms with high automation exposure are drawn into an automation arm race. Such firms are observed to have escalated investment and R&D expenditures, thereby leading to a subsequent deterioration in financial health. If my initial hypothesis – that firms with higher automation exposure have a greater likelihood of engaging in M&A activities – is validated, then it's plausible that these automation-driven M&A transactions are part and parcel of the automation arms race. This lead to the question: Are these automation-driven M&A transactions successes or failures? This question paves the way for the exploration of two potential and testable post-merge hypothesis: success and failure.

For the channels through which automation-driven M&A can lead to success, there are a few considerations. Firstly, post-merger, combined firms might achieve economies of scale in automation implementation or they might acquire complementary automation patents. Either scenario could lead to positive synergies post-merger. Secondly, building upon the arguments from the previous two hypotheses, in the context of automation-driven M&A, firms are likely to pair with others that have similar assets or products. Drawing from the survey paper by (Renneboog & Vansteenkiste (2019), the authors reviewed twenty-five M&A predictors. Notably, they emphasized that related or focused acquisitions stand out as one of the three predictors that remain consistently significant across M&A literature. Given that automation-driven M&A transactions tend to pair firms with high similarity, it suggests a higher likelihood of positive outcomes post-merger. Such positive outcomes can bolster the merged entity's financial health by enhancing operational productivity, thereby alleviating financial constraints.

Exploring the channels through which automation-driven M&A might result in failure, the "winner's curse" emerges as a primary concern. A potential target holding valuable automation patents may attract multiple bidders, driving up the acquisition price. This intense competition might lead the winning bidder to overpay, to a degree where even post-merger synergies cannot offset the inflated acquisition cost, (Agrawal et al., 1992). Another perspective is drawn from the concept of "killer acquisitions," as highlighted by (Cunningham et al., 2021). While their study focuses on the pharmaceutical industry and identifies scenarios where acquiring companies purchase innovative targets merely to eliminate them and prevent future threats, a similar strategic killer-move could be at play in the automation arms race. For instance, a company might strategically acquire another firm with successful automation patents, not for integration or utilization, but to prevent a direct competitor from gaining these assets or even to stop the target from evolving into a threat itself. Such a killer-move could deplete the acquiring company's resources. However, adopting this strategy might be seen as a protective step to keep competitors from becoming stronger, adhering to the belief that it's better to spend a dime now than lose a quarter later.

In light of these considerations, I propose two contrasting hypotheses:

Hypothesis 3A: "Given automation-driven M&A, involvement in M&A will lessen the financial constraints in subsequent periods."

Hypothesis 3B: "Given automation-driven M&A, involvement in M&A will worsen the financial constraints in the subsequent periods."

4.3 Methodology, Key Variables, and Sample

4.3.1 Methodology

4.3.1.1 Hypothesis 1: Automation Exposure & M&A Transaction Incidence

The study aims to evaluate whether firms with a high level of automation exposure have a higher incidence of M&A transactions. The research design is based on the methodology from (Bena & Li, 2014) but incorporates a significant modification. While the original study employed binary logistic regression, this research adopts multiple logistic regression. The rationale for this choice includes the model's ability to manage multiple outcome categories, ease of interpretation, and a reduction in the risk of Type I errors compared to running multiple binary logistic regressions. The equation for the multiple logistic model is:

$$mlogit(Y_{t+\tau}) = \alpha + \beta_{1,t+\tau} Auto_t + \sum \theta_{t+\tau,k} C_{\{t+\tau,k\}} \quad (1)$$

Where:

- Auto(t): automation exposure at time t, defined in (Qiu J. a., 2020) and (Liu et al., 2024)
- Cs: control variables, consistent with those used in (Bena & Li, 2014)

The dependent variable Y can take one of three category values: zero for either control acquiror or control target, one for acquiror, and two for target. The primary independent variable is automation exposure (Auto). Time-fixed effect are incorporated to adjust for M&A waves.

Automation exposure is measured by aggregating all new automation-related patents filed within the last five years. Given that the implementation of automation technologies derived from patents may take several years, the study examines automation exposure at time t against M&A transaction incident and other variables at leading periods t+τ, where τ can be up to five years.

I use three types of control samples.

Random Control Sample: for each firm-observation identified as either an acquiror or a target, five corresponding observations are randomly chosen from the pool of firms that have not engaged in any M&A activities in the preceding three years. These selected firms must be from the same year.

SIC and Size Matched Control Sample: Each acquiror or target is matched with five firms drawn from the non-M&A pool. These selected firms must belong to the same industry, as determined by their SIC four-digit codes, have a similar size, and must have abstained from participating in any M&A activities in either the current year or the past three years. If the four-digit SIC industry has less than five observations, I move up to the three-digit SIC industry pool. The decision to control for industry and size is informed by existing literature, see (Andrade et al., 2001; Harford, 2005). These studies suggest that M&A activities are more likely to occur within the same industry, thereby justifying industry-based matching in the control sample. Furthermore, (Phillips & Zhdanov (2013) find that smaller firms tend to actively invest in R&D to become attractive targets, whereas larger firms are more inclined to allocate their capital for acquisitions, specifically targeting smaller firms with promising and potentially successful patents, rather than investing in R&D themselves

SIC, Size, and B/M Matched Control Sample: Acquirors or targets are paired with five firms that have the closest propensity scores, calculated based on size and the market to book ratio (M/B). These selected firms also must be from the same year and industry, following the SIC four-digit codes (move up to three digits if four digit pool has less than five observations), and have no M&A activity in the last three years.

4.3.1.2 Hypothesis 2: Automation-Acquisition

In the second hypothesis, I postulate that acquisitions for automation purposes are likely to occur when firms' products have low differentiation from their rivals'. I employ two multinomial logistic regression models formulated as:

$$mlogit(Y_{t+\tau}) = \alpha + \beta_{1,t}Auto_t + \gamma ProdSim_t + \delta Auto_t \times ProdSim_t + \phi BroadSim_t + \omega Auto_t \times BroadSim_t + \sum \theta_{t,k} C_{\{t,k\}} \quad (2)$$

$$mlogit(Y_{t+\tau}) = \alpha + \beta_{1,t}Auto_t + \gamma_1 ProdSim_t + \gamma_2 ProdSim_t^2 + \delta_1 Auto_t \times ProdSim_t + \delta_2 Auto_t \times ProdSim_t^2 + \phi BroadSim_t + \omega Auto_t \times BroadSim_t + \sum \theta_{t,k} C_{\{t,k\}} \quad (3)$$

In equations 2 and 3, the dependent variable takes three values: zero for non-M&A firms, one for acquirers, and two for targets. Following Hoberg & Phillips (2010), I include both local similarity (ProdSim) and broad similarity (BroadSim) and their interactions with the Auto variables (Auto×ProdSim and Auto×BroadSim). Local similarity is calculated as the mean of the ten highest product similarity pair indices, based on data retrieved from the Hoberg & Phillips website (TNIC3). Broad similarity is the mean of all firms excluding the top ten nearest firms.

In hypothesis 2b, I propose a two-stage effect of product similarity (local similarity). To model this in equation 3, I add the quadratic form $ProdSim^2$ and its interaction with Auto ($Auto \times ProdSim^2$). Our focus is equation 3.

To align with the conjecture, the quadratic form of ProdSim must be upward, equivalently ($Auto \times \delta_2 + \delta_1$) must be positive. This leads to two points. First, there exists a minimum turning point, $ProdSim^*$, at which when there is a high level of product similarity ($ProdSim \geq ProdSim^*$ equivalently when there is little opportunity for product differentiation), cost and price strategy become a viable option. As a result, firm is more likely to pursue the acquisition for automation purposes (cost reduction and price reduction afterward). Second, ProdSim* is a function of Auto, where $ProdSim^{*} = -\frac{1}{2}\frac{\delta_1 \times Auto + \gamma_1}{\delta_2 \times Auto + \gamma_2}$. This means the choice to pursue a costly acquisition is condition on the effect of automation technology. Or in simple words, only when automation is sufficient, and there is little difference in product offerings, then firm will pursue such costly acquisition for automation purposes.

I use the same method for sampling controlling samples as in hypothesis 1: Random Control Sample, SIC and Size Matched Control Sample, and SIC, Size and M/B Matched Control Sample.

4.3.1.3 Hypothesis 3: Automation M&A and Financial Constraints

To tell if auto-acquisition (to name for M&A incident that is driven by automation purpose) suffers from the "winning curse", I examine if those auto-acquisition firms will have higher financial constraints in the subsequent periods post merge/acquisition. If an M&A transaction incident is auto-acquisition then automation should be a critical factor. I propose two methods to assess the important of automation factor in M&A transaction incident.

The first method is identifying if automation factor is the most or the second most influential factors on M&A decision. Following (Phan, 2024), I calculate the probability contribution for each factor k, called PC(k), using the baseline equation (1). For each PC(i), the value shows how much probability each factor X(i) contribute to the total probability outcome. The advantage of probability contributions method is to express total probability outcomes into the linear sum of probabilities contribution, P = ΣPC(k) (where P: total probability outcomes).

Consider a simple logistics model: logit(y) = $\Sigma\beta X$, we can express as:

$$Logit(y) \ = \sum_{k=1}^{K} \beta_k X_k = \sum_{k=1}^{K} \mathfrak{f}_k = \sum_{k=1}^{K} \Delta\mathfrak{f}_k \times (K-k+1)$$

Where:

- $f(\mathrm{k}) = \beta(\mathrm{k})X(\mathrm{k})$
- $\Delta f(\mathrm{k}) = f(\mathrm{k}) - f(\mathrm{k}\text{-}1)$
- $\Delta f(1) = f(1) - f(0)$ where $f(0) = 0$
- For simplicity, I assume $f(\mathrm{k})$ is sorted in ascending order which mean $f(1)$ is the smallest value and $f(\mathrm{K})$ is the largest value.

Graphically, $\sum_{k=1}^{K} \Delta\mathfrak{f}_k \times (K-k+1)$ can be expressed as:

$$\begin{aligned}\sum_{k=1}^{K} \Delta\mathfrak{f}_k \times (K-k+1) \ = &+\Delta\mathfrak{f}(1) \\ &+\Delta\mathfrak{f}(1) \quad + \ \Delta\mathfrak{f}(2) \\ &+\Delta\mathfrak{f}(1) \quad + \ \Delta\mathfrak{f}(2) \qquad\quad +\Delta\mathfrak{f}(3) \\ &+\ldots\end{aligned}$$

$$\sum_{k=1}^{K} \Delta\mathfrak{f}_k \times (K-k+1) \ = \ \Delta\mathfrak{f}(1)\cdot K \ + \Delta\mathfrak{f}(2)\cdot(K-1) \ +\Delta\mathfrak{f}(3)\cdot(K-2) \ \ldots$$

The fundamental assumptions of probability contributions is: (1) decompose a factor $f(\mathrm{k}^*)$ into a sum of incremental $\Sigma\Delta f(\mathrm{k}\leq\mathrm{k}^*)$, and (2) all factors have the same $\Delta f(\mathrm{s})$ in the sum components should have the same marginal probability contribution in ΔP(k). Take an example of K=3 and all factor $f(\cdot)$ are sorted, we have:

$f(1) = \Delta f(1)$

$f(2) = \Delta f(1) + \Delta f(2)$

$f(3) = \Delta f(1) + \Delta f(2) + \Delta f(3)$

All three factor $f(\cdot)$ have the same incremental in $\Delta f(1)$ and therefore the marginal probability contribution ΔP(1) should be equally slitted among 3 factors. For $\Delta f(2)$, there are only two factors $f(2)$ and $f(3)$ that have $\Delta f(2)$; therefore the marginal probability contribution ΔP(2) should be equally split between two factors. And lastly, only factor 3 has $\Delta f(3)$ therefore the ΔP(3) will split for factor 3 only. The probability contribution for each factor are then:

PC(1) = ΔP(1)/3	P(1) = logit($\Delta f(1)\cdot 3$)	ΔP(1) = P(1)
PC(2) = ΔP(2)/2 + PC(1)	P(2) = logit($\Delta f(1)\cdot 3 + \Delta f(2)\cdot 2$)	ΔP(2) = P(2) – P(1)
PC(3) = ΔP(3)/1 + PC(2)	P(3) = logit($\Delta f(1)\cdot 3 + \Delta f(2)\cdot 2 + \Delta f(3)\cdot 1$)	ΔP(3) = P(3) – P(2)

Where logit(·) imply logistics function $e^{\Sigma\beta X} / (1+e^{\Sigma\beta X})$

Or we can generalize in formula as:

$$P(k=m) = logit\left(\sum_{k=1}^{m} \Delta f_k \times (K-k+1)\right)$$

$$\Delta P(k) = P(k) - P(k-1)$$

$$PC(k) = \frac{1}{(K-k+1)} \Delta P(k) + PC(k-1)$$

Following the Probability Contribution method, I calculate PC for each factor k. If PC(auto) is the second or the most probability contribution factor, then I assign that M&A deal to automation purpose. I allow PC(auto) to be at least the second most impact to control for firm size effect since large firm tend to do M&A more frequency.

The second method is to calculate the outcome probability with and without automation factors. If the probability outcome without automation is less than 50% (I choose 50% because it is a common threshold in logistics regression analysis), and the probability with automation is larger than 50%, then I consider that automation is a critical factor in merge/acquisition. Such merge/acquisition will be classified as Auto-acquisition.

For any M&A that meet one of the two methods above will be classified as Auto-acquisition. The rest M&A will be classified as nonautomation related.

To test for the financial constraints post-M&A driven by automation, I use the following equation:

$$\Delta Y_{i,t+\tau} = \alpha + \beta_1 Auto_{i,t} + \gamma D_{AA} + \delta D_{AA} Auto_{i,t} + \sum_{k \in N} \lambda_k^{\tau} C_{k+\tau} + firm_i + year_t \quad (4)$$

The effect of acquiring automation does not take effect immediately, therefore, I use the regression of change, where key dependent variables measure the average change. Dependent variables ΔY are the differences between the average of leading five years and lagging five years. Dependent variables are profitability measures and financial constraint WW-index. Profitability measures include: ROA, EBITDA scaled by Total Asset, and Operating profit. I only use the WW-index because the KZ-index, (Kaplan & Zingales, 1995), is problematic (see (Fazzari et al., 2000; Allayannis & Mozumdar, 2004)), and the SA-index (or also called HP, (Hadlock & Pierce, 2010)) accounts only for Age and Size.

Our key study coefficients are γ (D_{AA}) and its interaction with auto δ (Auto×D_{AA}). If firms acquiring for automation purpose suffer from the winning curse, we should observe γ or δ to be negative for operating profit variable and positive for financial constraints index. This is because the winner paid the price too high, such that benefit from such automation acquisition do not make the deal better off. However, if acquirer can enjoy the benefits from automation-acquisition, then we should observe a reverse sign for γ and δ. Other control variables are standard ones in (Rajan & Zingales, 1995), (Simintzi et al., 2015), and (Serfling, 2016)

4.3.2 Key Variables

4.3.2.1 Automation Exposure and Other Technological Exposure

To measure automation exposure, I use equation from (Qiu et al., 2020) and (Liu et al., 2024) to estimate exposure to new automation technology at firm level:

$$Auto_{i,t} = Ln\left(\sum_{j=1}^{N} SegSale_{i,j,t} * AutoPatent_{j,t}\right) \tag{4}$$

- $SegSale_{i,j,t}$: is the weight of segment sale of company i, in sector j, at year t
- $AutoPatent_{j,t}$: is the sum of all automation patents in sector j from year (t-5) to year (t)
- $Auto_{i,t}$: is the automation exposure of company i, at year t

Equation (4) offers two advantages over traditional measures of automation. First, measuring automation through patent classification allows for the capture of technological advancements in both tangible and intangible forms. Second, using the weighted sum of segment sales as a factor in the equation accounts for the technology spillover effect.

In addition to these, two other types of technological exposure are included as control variables: Non-automation exposure (referred to as NonAuto) and pharmaceutical-chemical exposure (referred to as Chem). These two control variables are measured using the same formula outlined in equation (4), but with AutoPatent replaced by NonAuto Patent and Chem Patent, respectively.

4.3.2.2 Product Similarity

The variable for product similarity, ProdSim, adheres to the definition of the “local similarity” variable as established in Hoberg & Phillips (2010) and Hoberg & Phillips (2016). For each firm-year, ProdSim is computed as the average of the ten highest pairwise product similarity scores between the focal firm and its closest competitors in terms of product offerings. This measure offers a targeted perspective, focusing specifically on firms that share the most similar product portfolios. Data for pairwise product similarity is sourced from the Hoberg and Phillips website. In this essay I use TNIC3 database

4.3.2.3 Broad Similarity

Broad similarity for a firm i at time t, following (Hoberg and Phillips, 2010), is defined as the average of pairwise similarity with all firms, except for the first 10 highest.

4.3.2.4 Samples

I obtain M&A data from SDC Platinum, covering all deals from 1980 to 2021. The sample ends in 2014 due to the availability of (Mann K. a., 2021) automation patent database up to that year. Deals are included if either the acquiror or target is based in the U.S. and fall into one of the following categories: Acquisition type, Merger type, Acquisition of Majority Interest, or Acquisition of Assets. For Acquisition type deals, the acquiror must own less than 50% of shares before the transaction and at least 90% afterward to be considered. Selected deals must be both announced and completed within one year. I also exclude smaller deals by setting a deal value floor of $2 million, adjusted to 2010 values. Deals involving companies in regulated industries (SIC codes 6000-6999 and 4900-4999) are also excluded. This narrowed the sample size to 41,299 deals. Each deal is linked to accounting variables in Compustat using the gvkey-link-map provided by (Phillips & Zhdanov, 2013) and (Ewens et al., 2018). My sample size is larger than those found in other studies, primarily because unlike other literature that mandates both the acquiror and target be U.S.-based, my study allows for inclusion where either the acquiror or the target is located in the U.S.

year	total deal	both acq & tar valid GVKEY	Acquiror valid GVKEY	Target valid GVKEY
1980	23	23	23	23
1981	74	74	74	74
1982	68	68	68	68
1983	75	75	75	75
1984	84	84	84	84
1985	82	82	82	82
1986	100	100	100	100
1987	94	94	94	94
1988	92	92	92	92
1989	71	71	71	71
1990	52	52	52	52
1991	63	63	63	63
1992	71	71	71	71
1993	111	111	111	111
1994	189	189	189	189
1995	222	222	222	222
1996	2325	421	2087	659
1997	3276	809	2893	1192
1998	3473	774	3022	1225
1999	2777	704	2301	1180
2000	2569	604	2158	1015
2001	1862	551	1503	910
2002	1759	495	1408	846
2003	1759	461	1369	851
2004	1912	444	1594	762
2005	2140	417	1737	820
2006	2167	393	1741	819
2007	1992	371	1604	759
2008	1370	266	1106	530
2009	1050	227	761	516
2010	1425	305	1136	594
2011	1505	249	1212	542
2012	1476	269	1177	568
2013	1298	185	986	497
2014	1483	211	1219	475

Table 1 – Panel A: show the number of deal distribution from 1980-2014. In order for a deal to be considered in the sample, the deal type must be either “Acquisition”, “Merger”, “Acquisition of Majority Interest”, or “Acquisition of Assets”. For acquisitions deals, the acquiror must own less than 50% of shares before the transaction and at least 90% afterward to be considered. Deals value less than 2 million dollars (in 2010 value) are excluded. A deal should complete within one year since the announcement. Deals involving companies in regulated industries (SIC codes 6000-6999 and 4900-4999) are also excluded. Colum “total deal” show the number of deals each year. Column “both acq & tar valid GVKEY” show the number of deals which both acquiror and target have valid Compustat GVKEY. The other two columns left show the number of deals where either the acquiror or the target has valid Compustat GVKEY.

Table 1 Panel B1 - Sample pool of acquirors								
	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
auto4	7,586	5.64	3.94	0.00	1.73	6.06	9.06	11.51
nonauto4	7,586	5.83	4.20	0.00	0.72	6.73	9.56	11.68
chem4	7,586	4.24	3.61	0.00	0.01	4.22	7.31	10.42
lnat2010	7,586	7.45	1.73	3.30	6.22	7.37	8.61	10.68
lnsale2010	7,586	7.35	1.73	2.93	6.11	7.25	8.57	10.56
xrd	7,586	0.04	0.06	0.00	0.00	0.01	0.05	0.33
xroa	7,586	0.10	0.09	-0.47	0.06	0.10	0.14	0.35
xebitda	7,580	0.14	0.09	-0.40	0.09	0.14	0.19	0.40
xprofit	7,580	0.14	0.09	-0.40	0.09	0.14	0.19	0.40
xlev	7,586	0.22	0.19	0.00	0.06	0.20	0.32	0.96
xch	7,586	0.15	0.16	0.00	0.03	0.08	0.22	0.77
xmb	7,586	2.57	2.03	0.34	1.41	1.96	2.92	12.63
xtobinq	7,405	2.01	1.28	0.56	1.25	1.63	2.28	7.96
ww	7,400	-0.42	2.04	-5.29	-1.57	-0.62	0.49	7.77

Table 1 Panel B2 - Sample pool of targets								
	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
auto4	6,269	5.35	3.80	0.00	1.64	5.74	8.47	11.51
nonauto4	6,269	5.67	4.04	0.00	1.48	6.42	9.16	11.68
chem4	6,269	4.11	3.54	0.00	0.02	3.99	7.05	10.42
lnat2010	6,269	7.07	2.08	3.30	5.39	6.85	8.80	10.68
lnsale2010	6,269	7.03	1.98	2.93	5.45	6.82	8.56	10.56
xrd	6,269	0.03	0.06	0.00	0.00	0.00	0.04	0.33
xroa	6,269	0.05	0.11	-0.47	0.02	0.07	0.11	0.35
xebitda	6,265	0.10	0.11	-0.40	0.07	0.11	0.16	0.40
xprofit	6,265	0.10	0.11	-0.40	0.07	0.11	0.16	0.40
xlev	6,269	0.28	0.21	0.00	0.12	0.26	0.39	0.96
xch	6,269	0.11	0.14	0.00	0.02	0.06	0.15	0.77
xmb	6,269	1.93	1.52	0.34	1.10	1.51	2.22	12.63
xtobinq	5,899	1.52	0.84	0.56	1.03	1.30	1.71	7.96
ww	6,080	0.27	2.27	-5.29	-1.11	-0.08	1.27	7.77

Table 1 Panel B3 - Sample pool of firm-years without M&A last 3 years								
	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
auto4	74,078	4.10	3.41	0.00	0.30	4.01	6.94	11.51
nonauto4	74,078	4.69	3.70	0.00	0.20	5.16	7.85	11.68
chem4	74,078	3.12	2.96	0.00	0.00	2.82	5.35	10.42
lnat2010	74,078	5.64	1.62	3.30	4.37	5.38	6.62	10.68
lnsale2010	74,078	5.77	1.64	2.93	4.51	5.55	6.81	10.56
xrd	74,078	0.03	0.06	0.00	0.00	0.00	0.03	0.33
xroa	74,078	0.07	0.13	-0.47	0.02	0.08	0.13	0.35
xebitda	73,981	0.11	0.12	-0.40	0.07	0.12	0.18	0.40
xprofit	73,981	0.11	0.12	-0.40	0.07	0.12	0.18	0.40
xlev	74,078	0.25	0.22	0.00	0.06	0.21	0.38	0.96
xch	74,078	0.14	0.17	0.00	0.02	0.07	0.20	0.77
xmb	74,078	2.06	1.90	0.34	1.03	1.44	2.31	12.63
xtobinq	70,812	1.67	1.19	0.56	0.99	1.27	1.88	7.96
ww	70,043	-0.03	2.31	-5.29	-1.41	-0.24	1.07	7.77

Table 1 – Panel B: descriptive statistics of key variables used. Panel B1 is descriptive for pool of acquiror. Panel B2 is descriptive for pool of targets. Panel B3 is descriptive for pool of firm-year without M&A during the last 3 years.

4.4 Result and Discussion

4.4.1 Hypothesis 1: Automation Exposure & M&A Transaction Incidence

Table 2 illustrates the outcomes of the multiple logistic regression analysis based on Equation (1). Panels A, B, and C present the results derived from three distinct types of random/control samples: Random Control Sample, SIC & Size Matched Control Sample, and SIC, Size, and M/B Matched Control Sample. Given the nonlinear nature of logistic regression, marginal effects are reported instead of coefficient values for clearer interpretation. These marginal effects are calculated by altering a selected variable by one standard deviation while maintaining other variables at their mean levels. The difference in probability outcomes indicates the marginal effect. For example, in Table 2, Sample A, column (3), under the "Auto" row, the marginal value is 7.03 with a z-statistic of 8.89. This suggests that a one standard deviation increase in automation exposure results in a 7.03% increase in the likelihood of becoming an acquiror. The Random Control Sample's reported coefficient is the median value obtained through bootstrapping 1,000 times, following the standard procedure suggested by Tibshirani & Efron (1993) and Bena & Li (2014). The marginal effect in the Random Control Sample represents the universal effect of a selected variable on the outcome, whereas the other two control samples assess whether the marginal effect persists after controlling for industry, size, and M/B factors.

For each sample, the analysis begins with a simple multinomial logistic model that includes only the automation variable, with results displayed in columns (1, 2, 5, 6, 9, 10). The marginal effects of automation ('Auto') are positive and strongly significant for both Target and Acquiror columns. In the full model (baseline equation (1)), shown in columns (3, 4, 7, 8, 11, 12), the marginal effect of the automation factor remains positive and significant. In Sample A, which uses random pooling, the marginal effects are 7.03% for acquirors and 3.69% for targets. This reveals two key insights: firstly, automation significantly impacts M&A decisions, with firms under high automation exposure more likely to become acquirors than targets. Secondly, among all factors, automation is the second most impact factor on M&A decisions, following the asset size factor, which shows effects of 12.57% for acquirors and 7.39% for targets. In Samples B and C, where industry, firm size, and book-to-market ratio are controlled, the marginal effects of automation remain highly significant, being the strongest impact factor. Specifically, the effect for acquirors is about three times that for targets, with Sample B reporting 14.61% for acquirors versus 5.45% for targets, and Sample C reporting 13.76% to 4.62%. These results strongly suggest that automation continues to be a key driver in M&A decisions across various control samples.

It is important to note that in the SDC deals database, transactions are classified as either 'merger', 'acquisition', 'acquisition of majority interest', or 'acquisition of assets'. Therefore, the marginal effect of the target should be interpreted as the likelihood of being fully acquired or divesting part of its assets. Notably, 'acquisition of assets' accounts for two-thirds of all deal forms, with 64.7% of transactions classified under this category.

For the two control variables related to patents: Non-Auto and Chem, the signs are consistently negative (positive) for Non-Auto (Chem) across all three samples. Since these variables are not the focus of this essay, I will not discuss about their results. In all samples, the signs of the controlling factors remain consistent with prior literature. The marginal effects of Size (only reported in Sample A) and R&D (reported in all samples) align with existing findings. Specifically, the positive and significant marginal effect of Size in Sample A is supported by prior research (Harford, 1999; Moeller et al., Firm size and the gains from acquisitions, 2004), which suggests that larger firms, with greater cash reserves and easier access to financial markets, are more likely to act as acquirers rather than targets. The difference of approximately 5.18% (12.57% - 7.39%) in the marginal effects between acquirers and targets further emphasizes the role of cash reserves and financial market accessibility. Additionally, studies such as Phillips & Zhdanov (2013) and Bena & Li (2014) observe that within the same industry, larger firms are more likely to allocate their capital to acquire smaller, patent-successful firms, whereas smaller firms are inclined to invest heavily in R&D to become attractive acquisition targets later on. The marginal effect of R&D for targets, which is positive across columns (4), (8), and (12) with values of 2.61%, 1.05%, and 0.65% respectively, supports the notion that firms heavily investing in R&D are more likely to be acquired or divest major assets. In the control samples B and C, the marginal effect of R&D for acquiror remains insignificant (-0.43% and -0.01%), while in the random sample A, it is significantly positive (2.26%), suggesting that R&D activity is clustered[21] by industry, see (Andrade et al., 2001; Harford, 2005), and firm size, (Phillips & Zhdanov, 2013; Bena & Li, 2014). This finding explains why the marginal effect is significant in the random sample A but not in sample B & C where we controlling for industry (SIC) and asset size.

For other controlling variables such as ROA, sales growth, M/B and 1-year stock return, the signs are also in line with the literature in the field. Firms with positive ROA, high sales growth, high M/B ratios, and high 1-year returns are more likely to act as acquirers, while firms with declining ROA, low or negative sales growth, low M/B ratios, and low stock returns tend to be targets.

In summary, the findings presented in Table 2 validate my hypothesis that exposure to automation serves as a significant driving factor in the incidence of M&A transactions. This effect remains consistent even after accounting for other key factors influencing M&A activity, such as industry, size, and the market-to-book ratio (M/B). Moreover, the coefficients for the control variables: Size, R&D, ROA, sales growth, and stock return, are consistent with existing literature,

[21] Because in all three samples A, B, and C, for each deals, the other five firms without M&A in the last three years are selected from the same year, therefore removing the M&A clustering by time, see **Invalid source specified.**

further reinforcing the robustness of the observed impact of automation exposure on M&A occurrences.

	Panel A Sample A: Random Pool				Panel B Sample B: Control SIC & Size				Panel C Sample C: Control SIC, Size & M/B			
	Acq (1)	Tar (2)	Acq (3)	Tar (4)	Acq (5)	Tar (6)	Acq (7)	Tar (8)	Acq (9)	Tar (10)	Acq (11)	Tar (12)
Auto	7.31***	5.39***	7.03***	3.69***	6.13***	4.34***	14.61***	5.45***	5.76***	4.00***	13.76***	4.62***
	(33.56)	(27.58)	(8.89)	(5.41)	(27.55)	(21.80)	(15.34)	(8.10)	(25.85)	(20.14)	(14.48)	(6.92)
NonAuto			-7.85***	-3.41***			-13.76***	-4.47***			-13.27***	-3.66***
			(-8.70)	(-4.58)			(-12.73)	(-6.05)			(-12.26)	(-5.08)
Chem			1.73***	1.28***			3.96***	2.45***			3.92***	2.30***
			(4.71)	(3.78)			(9.00)	(6.89)			(8.86)	(6.38)
Ln(AT)			12.57***	7.39***								
			(63.31)	(44.83)								
RD/AT			2.26***	2.61***			-0.43	1.05***			-0.01	0.65***
			(9.06)	(10.98)			(-1.03)	(3.92)			(0.18)	(2.60)
Gr Sale			1.12***	-4.58***			0.97	-4.74***			1.20**	-4.82***
			(2.67)	(-12.66)			(1.56)	(-12.84)			(2.35)	(-13.12)
ROA			4.38***	-1.41***			4.51***	-1.78***			4.98***	-2.22***
			(14.80)	(-4.40)			(14.74)	(-6.26)			(17.51)	(-8.34)
Lev			-2.40***	0.36			-1.30***	0.88***			-1.47***	0.76***
			(-10.13)	(0.92)			(-4.82)	(3.96)			(-5.52)	(3.28)
CH/AT			-1.07***	-4.39***			-3.00***	-5.28***			-2.50***	-5.35***
			(-5.61)	(-15.74)			(-11.73)	(-18.29)			(-10.41)	(-18.56)
MtB			-0.40**	-2.18***			1.03***	-1.69***				
			(-2.51)	(-8.02)			(3.35)	(-5.72)				
1yr Ret			1.17***	-0.70***			0.86***	-0.63***			1.15***	-0.72***
			(5.73)	(-3.10)			(3.73)	(-2.86)			(5.15)	(-3.16)
Indus fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-square	3.5%	3.5%	12.1%	12.1%	1.5%	1.5%	3.4%	3.4%	1.3%	1.3%	3.0%	3.0%
N-obs	79,575	79,575	71,508	71,508	80,768	80,768	74,048	74,048	80,772	80,772	74,291	74,291

Table 2: show the result of the baseline equation (1) testing hypothesis 1 – impact of automation on M&A decision:

$$mlogit(Y_{t+\tau}) = \alpha + \beta_{1,t+\tau}Auto_t + \sum\theta_{t+\tau,k}C_{\{t+\tau,k\}} + fixed(indus)$$

Y variable take three values: zero for no M&A, one for acquiror and two for target. **Key independent variable** is **Auto** which is the aggregate of automation over the last 5 years. To make the results interpretable, I report the marginal probability rather than the coefficient. Marginal probability is the difference in probability output when allowing a variable to vary by one standard deviation while keeping others at their mean level. Z-statistics are reported in brackets. List of controlling variables include: NonAuto (measure patents that is not related to automation) and Chem (measure patents related to Pharmaceutical and Chemical). The rest of controlling variables follow Bena & Li (2014): Ln(Size), Sale Growth, ROA, Leverage, Cash Holding ratio, Market to Book, and Stock return. All result are controlled for industry fixed effect.

There are three samples used (following Bena & Li (2014)): **Sample A** – randomly pooling other 5 firms that has no M&A activities during the last 3years. **Sample B** – controlling for Size: for each M&A deals I select (i) other 5 firms within same year and same industry (SIC 4-digits) that has no M&A in the last three years, (ii) have similar asset size. If there is not enough sample at 4 digits SIC, I move up to 3 digits SIC. **Sample C** – controlling for Size and MtB: for each M&A deals I select (i) other 5 firms within the same year, same industry (SIC 4-digits), (ii) have close propensity score (on Size and MtB factors). If 4-digits SIC does not have enough sample size, then I move up 1 digit.

Columns (1) - (4) use Sample A, columns (5) to (8) use Sample B, and column (9) to (12) use Sample C. Odd columns report marginal effect and z-statistics for Acquiror and even columns report for Target. For each sample, the first two columns report the simple multinomial logistics result with a single independent variable Auto only. The rest two columns in each sample report the full models.

Significant marginal effect are reported in parentheses with (***), (**), (*) respectively for 1%, 5%, and 10

4.4.2 Hypothesis 2: Automation-Acquisition

Building on the findings from the first hypothesis that firms with high automation exposure are more likely to engage in M&A activities, the second hypothesis investigates the mechanism by which product similarity influences automation-acquisition decisions. Automation-acquisition refers to acquisitions driven by automation purposes.

Table 3 presents the results from equations (2) and (3). Equation (2) examines the linear impacts of local similarity (ProdSim variable) and its interaction with the automation variable (Auto×ProdSim). Equation (3) explores the two-stages effect of product similarity by employing a quadratic form for local similarity (ProdSim^2) and its interaction with automation ($\text{Auto}\times\text{ProdSim}^2$). For each sample, the analysis displays the results from equation (2) in the first two columns, followed by the results from equation (3) in the two subsequent columns. Across all samples, the marginal effects of automation on M&A decisions remain positive and significant in both equations. This consistency aligns with the baseline findings from equation (1), where firms with higher automation exposure consistently show a higher likelihood of being the acquirer compared to being the target, with the ratio being approximately two to three times higher.

For local similarity (ProdSim), the results confirm our predictions regarding the two-stages effect of product similarity. Across all samples, the coefficient for the quadratic interaction ($\text{Auto}\times\text{ProdSim}^2$) for acquirers is positive and significant (In columns 3, 7, 11, the marginal values (coefficients) are 1.3% (0.77), 3.7% (1.37), and 3.2% (1.15) respectively). Meanwhile, the marginal effect of ProdSim^2 is insignificant for Sample A (marginal -0.2%) and negatively significant for Samples B and C (marginal (coefficient) at -4.1% (-8.22) and -3.2% (-6.16)). Remind the quadratic form of ProdSim is: $(\delta_2\times\text{Auto} + \gamma_2)\times\text{ProdSim2} + (\delta_1\times\text{Auto} + \gamma_1)\times\text{ProdSim}. + \ldots$ The negative coefficient for ProdSim^2 (γ_2) suggests the existence of a threshold level of automation ($Auto^* = -\gamma_2/\delta_2$) such that when Auto ≥ $Auto^*$, the quadratic form of ProdSim becomes upward. When quadratic ProdSim is upward, there exists a $ProdSim^*$ such that when ProdSim ≥ $ProdSim^*$, the function is increasing (i.e., increasing the likelihood of being an acquirer). Mathematically, the threshold value $ProdSim^*$ (Auto), as a function of Auto, can be expressed as:

$$ProdSim^*(Auto) = -\frac{1}{2}\frac{(\gamma_1 + \delta_1 Auto)}{(\gamma_2 + \delta_2 Auto)} \tag{5}$$

To simplify the analysis, Table 3 – Panel B reports the estimated $Auto^*$ and $ProdSim^*(Auto)$ from coefficients γ1, γ2, δ1, and δ2. The $ProdSim^*(Auto)$ column shows Auto values ranging from 4 to 10. Columns (2) to (4) display the $ProdSim^*$ values corresponding to these Auto values for samples A, B, and C. Note that Auto values are positive and ProdSim values range from 0 to 1. In Sample B, when $Auto_1$ is 5, $ProdSim^*$ calculates to -0.40. When $Auto_2$ increases to 9, $ProdSim^*$ reaches 0.52. Figure 1 illustrates these results on an xy-axis where the x-axis represents ProdSim values (ProdSim, not threshold $ProdSim^*$) and the y-axis shows the probability outcomes. At an $Auto_1$ value of 5, which is below the threshold $Auto^*$ of 6.01, the curve trends downward from the maximum turning point of $ProdSim^*$ = -0.40. Since ProdSim takes value from range 0 to 1, this indicating a decreasing probability of pursuing automation-acquisition as ProdSim increases. This suggests that when automation is not sufficiently extensive, the costs of automation-acquisition may outweigh the benefits. Conversely, when $Auto_2$ is 9, surpassing $Auto^*$ of 6.01, the curve trends upward with the turning point $ProdSim^*$ at 0.52. This indicates that as ProdSim exceeds this threshold ($ProdSim^*$ = 0.52), the likelihood of pursuing automation-acquisition increases, especially when there is minimal opportunity for product differentiation.

In the scenario where automation is sufficiently high and product similarity increases past the $ProdSim^*$ threshold, firms are more likely to adopt automation-acquisition strategies as lower cost and competitive pricing become viable strategies. This is particularly relevant when the firm's products are very similar to those of rivals, and there is limited scope for differentiation. This indicates that a firm's decision to pursue automation-acquisition strategies is highly dependent on the current level of automation and the extent of product similarity with rivals. If the automation level is not adequately high, firms may decide against such costly strategies (as illustrated by the red line in Figure 1). Conversely, when automation levels are sufficiently high, firms are more inclined to engage in automation-acquisition strategies, especially when there is little opportunity for product differentiation.

For equation (3) involving targets, the marginal effects associated with the interaction terms are insignificant, supporting the focus on acquirers as the primary subject of interest. For equation (2), the results across the three samples are consistent with Hoberg & Phillips (2010), which found a negative association for local similarity (ProdSim) and a positive effect for broad similarity (BroadSim). Other controlling variables such as ROA, sales growth, and 1-year stock return maintain their expected signs and significance, aligning with the baseline results reported in Table 2. This consistency across variables underscores the robustness of the observed impacts of automation exposure on M&A transaction incidents.

	Sample A: Random Pool				Sample B: Control SIC, Size				Sample C: Control SIC, Size, M/B			
	Acq (1)	Tar (2)	Acq (3)	Tar (4)	Acq (5)	Tar (6)	Acq (7)	Tar (8)	Acq (9)	Tar (10)	Acq (11)	Tar (12)
Auto	8.3***	3.4***	8.6***	3.4***	16.2***	6.9***	17.1***	6.9***	15.3***	6.0***	16.0***	6.0***
	(17.0)	(9.8)	(17.0)	(9.4)	(14.9)	(8.7)	(15.2)	(8.6)	(14.1)	(7.7)	(14.2)	(7.5)
PS	-1.6***	-3.0***	-1.6***	-4.3***	0.2	-1.8**	3.2**	-2.5*	0.0	-2.0**	2.3	-3.1**
	(-6.4)	(-11.7)	(-3.9)	(-7.4)	(0.0)	(-2.2)	(2.0)	(-1.8)	(-0.2)	(-2.4)	(1.3)	(-2.4)
PS^2			-0.2	1.8***			-4.1**	0.9			-3.2*	1.5
			(-0.4)	(3.7)			(-2.4)	(0.4)			(-1.9)	(1.0)
Auto×PS	-0.2	-0.3	-1.4***	-0.8	-1.8**	-1.3*	-4.8***	-1.6	-1.8**	-1.2	-4.4***	-1.3
	(-0.8)	(-1.6)	(-3.5)	(-1.6)	(-2.3)	(-1.7)	(-3.6)	(-1.6)	(-2.2)	(-1.6)	(-3.3)	(-1.3)
Auto×PS^2			1.3***	0.3			3.7***	0.5			3.2**	0.1
			(3.6)	(0.6)			(2.9)	(0.7)			(2.4)	(0.3)
BS	1.8***	1.9***	1.8***	2.1***	1.7*	1.4*	0.4	1.7*	2.1**	1.6*	1.1	2.0**
	(5.4)	(6.1)	(5.1)	(4.7)	(1.9)	(1.7)	(0.5)	(1.8)	(2.3)	(1.9)	(1.2)	(2.2)
Auto×BS	-1.3***	0.0	-0.5	0.5	-0.7	0.1	0.7	0.4	-1.2	0.0	0.1	0.3
	(-4.3)	(0.0)	(-1.5)	(1.3)	(-0.7)	(0.1)	(0.6)	(0.5)	(-1.1)	(0.0)	(0.1)	(0.3)
NonAuto	-8.1***	-3.0***	-8.0***	-2.9***	-13.8***	-5.4***	-13.7***	-5.4***	-13.1***	-4.6***	-13.0***	-4.6***
	(-16.1)	(-7.9)	(-16.0)	(-7.7)	(-11.6)	(-6.3)	(-11.6)	(-6.3)	(-11.0)	(-5.5)	(-11.0)	(-5.4)
Chem	1.3***	1.1***	1.2***	1.0***	3.4***	2.4***	3.3***	2.4***	3.4***	2.3***	3.3***	2.3***
	(6.2)	(6.2)	(5.7)	(5.7)	(7.1)	(6.2)	(6.9)	(6.1)	(7.0)	(5.8)	(6.8)	(5.7)
Ln(AT)	13.5***	8.2***	13.5***	8.3***								
	(176.7)	(127.8)	(175.2)	(125.9)								
RD/AT	2.6***	3.0***	2.6***	3.0***	-0.4	1.3***	-0.4	1.3***	0.0	0.7***	0.0	0.7***
	(24.7)	(36.0)	(24.5)	(35.9)	(-0.8)	(4.4)	(-0.9)	(4.3)	(0.3)	(2.8)	(0.2)	(2.8)
Gr Sale	1.1***	-4.4***	1.1***	-4.3***	0.9	-4.4***	0.8	-4.4***	1.1*	-4.5***	1.1*	-4.5***
	(8.0)	(-38.2)	(8.1)	(-38.0)	(1.2)	(-11.3)	(1.1)	(-11.2)	(1.9)	(-11.7)	(1.8)	(-11.6)
ROA	4.6***	-1.8***	4.6***	-1.8***	4.5***	-1.9***	4.5***	-1.9***	5.0***	-2.4***	5.0***	-2.4***
	(43.3)	(-26.4)	(43.3)	(-26.8)	(13.8)	(-6.2)	(13.7)	(-6.1)	(16.3)	(-8.5)	(16.3)	(-8.5)
Lev	-2.6***	0.5***	-2.6***	0.5***	-1.3***	1.3***	-1.3***	1.3***	-1.5***	1.2***	-1.5***	1.2***
	(-25.2)	(6.7)	(-25.3)	(6.8)	(-4.0)	(5.6)	(-4.0)	(5.6)	(-4.8)	(4.9)	(-4.8)	(5.0)
CH/AT	-1.3***	-4.4***	-1.3***	-4.4***	-3.3***	-5.1***	-3.3***	-5.1***	-2.8***	-5.2***	-2.8***	-5.2***
	(-12.4)	(-45.1)	(-12.2)	(-44.4)	(-11.7)	(-16.7)	(-11.7)	(-16.7)	(-10.5)	(-17.2)	(-10.5)	(-17.1)
MtB	-0.4***	-2.5***	-0.4***	-2.5***	0.9***	-2.1***	0.9***	-2.1***				
	(-3.5)	(-27.2)	(-3.6)	(-27.4)	(2.7)	(-6.5)	(2.6)	(-6.5)				
1yr Ret	1.5***	-1.0***	1.5***	-1.0***	1.1***	-1.0***	1.1***	-1.0***	1.4***	-1.1***	1.4***	-1.1***
	(18.8)	(-13.2)	(18.8)	(-13.3)	(4.3)	(-4.0)	(4.3)	(-4.0)	(5.6)	(-4.5)	(5.6)	(-4.6)
Indus fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-square	3.5%	3.5%	12.1%	12.1%	1.5%	1.5%	3.4%	3.4%	1.3%	1.3%	3.0%	3.0%
N-obs	79,575	79,575	71,508	71,508	80,768	80,768	74,048	74,048	80,772	80,772	74,291	74,291

Table 3 – Panel A shows the result of equation (2) and equation (3). Equation (2) and (3) as follows:

$$mlogit(Y_{t+\tau}) = \alpha + \beta_{1,t}Auto_t + \gamma ProdSim_t + \delta Auto_t \times ProdSim_t + \phi BroadSim_t + \omega Auto_t \times BroadSim_t + \sum\theta_{t,k}C_{\{t,k\}}$$

$$mlogit(Y_{t+\tau}) = \alpha + \beta_{1,t}Auto_t + \gamma_1 ProdSim_t + \gamma_2 ProdSim_t^2 + \delta_1 Auto_t \times ProdSim_t + \delta_2 Auto_t ProdSim_t^2 + \phi BroadSim_t + \omega Auto_t \times BroadSim_t + \sum\theta_{t,k}C_{\{t,k\}}$$

Y variable take three values: zero for no M&A, one for acquiror and two for target. **Key independent variable** are **Auto** and **ProdSim (PS).** Auto is the aggregate of automation over the last 5 years. ProdSim is the local similarity, formula follow Hoberg & Phillips (2010). BroadSim is broad similarity, formula follow Hoberg & Phillips (2010). Key focus is the interaction between Auto×ProdSim (for equation 2) and Auto×ProdSim^2 (for equation 3).

To make the results interpretable, I report the marginal probability rather than the coefficient. Marginal probability is the difference in probability output when allowing a variable to vary by one standard deviation while keeping others at their mean level. Z-statistics are reported in brackets. List of controlling variables include: NonAuto (measure patents that is not related to automation) and Chem (measure patents related to Pharmaceutical and Chemical). The rest of controlling variables follow Bena & Li (2014): Ln(Size), Sale Growth, ROA, Leverage, Cash Holding ratio, Market to Book, and Stock return. All result are controlled for industry fixed effect.

There are three samples used (following Bena & Li (2014)): **Sample A** – randomly pooling other 5 firms that has no M&A activities during the last 3years. **Sample B** – controlling for Size: for each M&A deals I select (i) other 5 firms within same year and same industry (SIC 4-digits) that has no M&A in the last three years, (ii) have similar asset size. If there is not enough sample at 4 digits SIC, I move up to 3 digits SIC. **Sample C** – controlling for Size and MtB: for each M&A deals I select (i) other 5 firms within the same year, same industry (SIC 4-digits), (ii) have close propensity score (on Size and MtB factors). If 4-digits SIC does not have enough sample size, then I move up 1 digit.
Columns (1) - (4) use Sample A, columns (5) to (8) use Sample B, and column (9) to (12) use Sample C. Odd columns report marginal effect and z-statistics for Acquiror and even columns report for Target. For each sample, the first two columns report the simple multinomial logistics result with a single independent variable Auto only. The rest two columns in each sample report the full models.

Significant marginal effect are reported in parentheses with (***), (**), (*) respectively for 1%, 5%, and 10

	Sample A	Sample B	Sample C
γ1	-2.56	2.80	1.84
γ2	-1.21	-8.22	-6.16
δ1	-0.23	-0.78	-0.70
δ2	0.77	1.37	1.15
Auto*	1.58	6.01	5.35
ProdSim*(Auto)	Sample A	Sample B	Sample C
4	0.94	-0.06	-0.31
5	0.71	-0.40	-2.08
6	0.58	-56.61	1.59
7	0.50	0.99	0.81
8	0.45	0.64	0.62
9	0.41	0.52	0.53
10	0.38	0.46	0.48

Table 3 – Panel B: reports the key coefficient of ProdSim and ProdSim^2 that is not reported in Panel A. Auto* is the threshold value of Auto such that the quadratic form of ProdSim is positive upward. The low table ProdSim*(Auto) reports scenarios analysis for ProdSim* in accordance to different value of Auto.

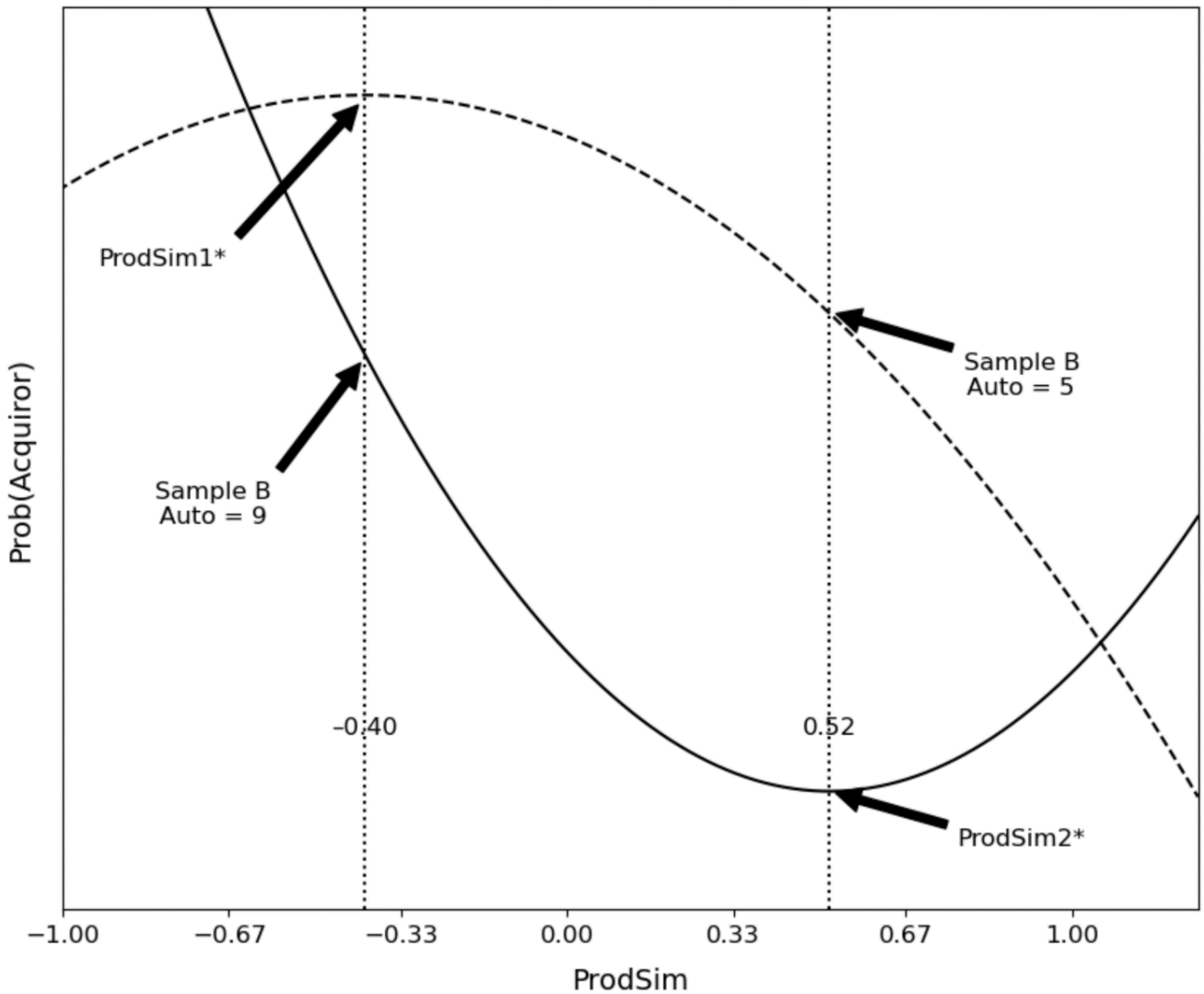

Figure 1: graph the case of sample B in Table 3 – Panel B with different value of Auto and ProdSim*(Auto). In sample B, the threshold Auto* is 6.01. Firms with automation exposure below/above 6.01 should have quadratic curve downward/upward.

ProdSim1* is the case when Auto = 5.0 (Auto < Auto*=6.01), the quadratic curve is downward (dash-line). ProdSim1* curve illustrates the case when automation is insufficient, higher product similarity reduces the likelihood of acquiring. The curve trends downward from the maximum turning point of ProdSim* = -0.40. Since ProdSim takes value from range 0 to 1, this indicating a decreasing probability of pursuing automation-acquisition as ProdSim increases.

ProdSim2* is the case when Auto = 9.0 (Auto > Auto*=6.01), the quadratic curve is upward (solid line). ProdSim2* indicates that as ProdSim exceeds this threshold (ProdSim* = 0.52), the likelihood of pursuing automation-acquisition increases, when there is minimal opportunity for product differentiation.

4.4.3 Hypothesis 3: Post-merge and alleviation of financial constraints

Table 4 – Panel A reports the proportion of deal driven by automation (called Auto-acquisition). The proportion of Auto-acquisition are smallest in the first 5 years, around 12.6% then remain stable around 20% or more from 1985 until 2014.

Table 4 – Panel B reports the result of equation (4). Dependent variables are the difference between the average of leading five years to the average of lagging five years. I use the change measurement rather than level measurements because automation implementation takes time for integration. In addition, change measurement allow us to see the impact over longer periods and avoid temporary variations in each year. I use various measurement for profitability including: Operating profit, ROA, EBITDA/AT, and Cash flow. I also use ΔWW, the change in WW-index of average leading five years and average lagging five years. D_{AA} is dummy variable indicate if a firm has any Auto-acquisition during the last 3 years. Odd/even columns report result without/with dummy Auto-acquisition and the interaction.

Following theory suggested by Knesl (2023), all firms have the incentive to adopt new automation technology to gain competitive edge over their rivals. As more firms adopting automation, the competitive edge fades and the automation become the necessity cost if firms want to remain competitive in the market. This lower the profit margin for all firms.

From column (1) to column (8), using four different profitability measures, the coefficient of ΔAuto are consistent negative, as suggested in Knesl (2023). In even columns (2, 4, 6, 8), we observe a negative sign for both dummy D_{AA} and the interaction terms Auto×D_{AA}. However, only the coefficient of D_{AA} (γ) is significant while coefficient of the interaction term δ is insignificant. I would interpret the result as we have the evidence for the negative impact of firms pursuing automation-acquisition. The result implies that such negative impact is independent on firm's automation exposure. (add one more sentence here is you think there is something cool to write here). In the contrast, for ΔWW, we observe a positive and significant impact of both dummy variable D_{AA} and the interaction term Auto×D_{AA}. The result is in line with our prediction that auto-acquirer is more likely to have an increased in financial constraints in subsequent periods. The positive significant of γ suggest that such negative impact is sensitive to automation exposure.

4.5 Conclusion

This essay, I explore an important branch of technology, automation, on M&A. Empirical study shows that firm's with high automation exposure are more likely to involve in M&A transactions. The analysis reveals that the relationship between product similarity (ProdSim) and automation acquisition decisions exhibits a two-stage effect. At lower levels of automation (Auto), an increase in product similarity decreases the likelihood of pursuing automation-acquisition strategies, suggesting that the costs of automation might outweigh the benefits when automation is not sufficiently advanced. However, when automation levels are high, the effect of product similarity becomes positive, indicating that firms are more likely to engage in automation-acquisition as product similarity increases past a critical threshold ($ProdSim^*$). This threshold behavior highlights that high automation capabilities coupled with significant product similarity can drive firms to adopt automation-acquisition strategies, especially when there is limited scope for differentiation.. And lastly, I confirm the prediction of Knels (2023) that automation technology will lower profit and increase financial constraints for all firms. Firms that actively involving in auto-acquisition suffer from "winner curse" that have more reduction in operating profit and higher financial constraints in subsequent periods.

year	Auto-acquisition	Total M&A deals	Percentage (%)
1980-1984	31	247	12.6
1985-1989	52	256	20.3
1990-1994	75	280	26.8
1995-1999	577	3008	19.2
2000-2004	474	2245	21.1
2005-2009	368	1740	21.1
2010-2014	329	1475	22.3

Table 4 – Panel A – Distribution of M&A deal that relates (driven by) automation. To classified if a deal is automation driven, I use two methods. In the first method, following (Phan, 2024), I calculate the probability contribution for each factor k, called PC(k), using the baseline equation (1). For each PC(i), the value shows how much probability each factor X(i) contribute to the total probability outcome. The advantage of probability contributions method is to express total probability outcomes into the linear sum of probabilities contribution, P = ΣPC(k) (where P: total probability outcomes). If PC(auto) is the second or the highest probability contribution then I assign that M&A deals to automation related. I choose the second highest value to control for size effect because large firm tend to acquire small for patents rather investing in RD. The second method is to calcualte the outcome probability with and without automation factors. If the probability outcome without automation is less than 50% (I choose 50% because it is a common threshold in logistics regression analysis), and the probability with automation is larger than 50%, then I consider that automation is a critical factor in merge/acquisition. Such merge/acquisition will be classified as Auto-acquisition. A deal falls into one of the two methods are classified as Auto-acquisition.

Column 1 is groupby for every 5 years. Column 2 are Auto-acquisition deals. Column 3 are all deals in the sample. And column 4 is the percentage of Auto-acquisition deal in the sample.

	Δ(Profit)		Δ(EBITDA/AT)		Δ(ROA)		Δ(Cash Flow)		Δ(WW)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔAuto	-0.05***	-0.04***	-0.05***	-0.04***	-0.07***	-0.07***	-0.07***	-0.07***	5.96***	5.75***
	(-3.03)	(-2.72)	(-3.03)	(-2.72)	(-4.26)	(-3.96)	(-4.13)	(-3.83)	(15.53)	(14.71)
ΔAuto* Auto-acquisition		-0.06		-0.06		-0.06		-0.04		4.03**
		(-0.89)		(-0.89)		(-0.80)		(-0.54)		(2.43)
Auto-acquisition		-0.48***		-0.48***		-0.44***		-0.87***		2.46
		(-3.78)		(-3.78)		(-3.38)		(-6.05)		(0.82)
MtB	0.07***	0.08***	0.07***	0.08***	0.17***	0.17***	0.50***	0.50***	-6.28***	-6.30***
	(3.35)	(3.47)	(3.35)	(3.47)	(7.54)	(7.64)	(20.03)	(20.21)	(-11.92)	(-11.96)
Ln(Sale)	-2.88***	-2.87***	-2.88***	-2.87***	-3.25***	-3.24***	-2.77***	-2.75***	58.82***	58.74***
	(-50.97)	(-50.78)	(-50.97)	(-50.78)	(-55.12)	(-54.95)	(-43.07)	(-42.81)	(43.50)	(43.42)
Leverage	0.07***	0.07***	0.07***	0.07***	0.06***	0.06***	0.07***	0.07***	-0.51***	-0.51***
	(31.24)	(31.04)	(31.24)	(31.04)	(28.00)	(27.82)	(31.16)	(30.87)	(-10.16)	(-10.10)
Ln(Age)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.01***	0.01***	-0.79***	-0.79***
	(7.77)	(7.71)	(7.77)	(7.71)	(10.29)	(10.23)	(5.11)	(5.01)	(-14.97)	(-14.98)
Fixed-firm	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed-year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-square	36.8%	36.8%	36.8%	36.8%	37.3%	37.3%	26.0%	26.0%	37.4%	37.4%
N-obs	56,928	56,928	56,928	56,928	56,981	56,981	55,061	55,061	56,928	56,928

Table 4 – Panel B: reports the effect of Auto-acquisition deal on post-acquisition. The equation:

$$\Delta Y_{i,t+\tau} = \alpha + \beta_1 \Delta Auto_{i,t} + \gamma D_{AA} + \delta D_{AA} \Delta Autoo_{i,t} + \sum_{k \in N} \lambda_k^{\tau} C_{k+\tau} + firm_i + year_t$$

Dependent variables are the difference between the average of leading five years to the average of lagging five years. Independent variable (ΔAuto) is the difference between automation exposure over the last five years. I use various measures for profitability inlcuding: Operating profit, ROA, EBITDA/AT, and Cash flow. I also use ΔWW, the change in WW-index of average leading five years and average lagging five years. Following theory suggested by Knesl (2023), automation technology will lead to lower profit for all firms, the coefficient β is expected to be negative. D_{AA} is dummy variable indicate if a firm has any Auto-acquisition during the last 3 years.

Odd/even columns report result without/with dummy Auto-acquisition and the interaction. All result include firm and year fixed effect. t-statistics are reported in brackets. Coefficient significant at 1%, 5%, and 10% are marked with ***, *, and *

5 Chapter 5: General Conclusions

This thesis includes three topics on corporate finance: (1) Automation Exposure and Financial Constraints, (2) Corporate Cash Shortfall and External Financing: International Evidence, and (3) Automation Exposure and M&A.

In chapter 2 "Automation Exposure and Financial Constraints", I examine how automation technology's advancement interacts with a firm's financial strength. I hypothesize that firms with more exposure to new automation technology will face more severe financial constraints. The empirical results are consistent with this hypothesis. Further analysis reveals the following insights and provides plausible explanations for the pattern. First, I find that higher exposure to automation technology thrusts firms into an 'arms race' in investment and R&D spending, which in turn suggests a heightened need for financing and exacerbates financial constraints. Second, firms with higher automation exposure experience lower asset tangibility, resulting in less collateral value for borrowing. In addition, I find consistent evidence that high automation exposure firms generate less net cash flow internally in later years.

In chapter 3 "Corporate Cash Shortfall and External Financing: International Evidence", I conduct empirical research if funding horizon theory can explain the behavior of raising external financing in non-U.S. countries as it is in the U.S. And further, I test if the nature of cash need will determine if firm issuing equity or debt or both. The result shows the evidence of funding horizon theory in non-U.S. markets which include Asia Pacific, European and Japan; however, the effect is relatively small to the finding in the U.S. Further analysis reveals that an abnormal high distribution of firms issuing security encounters no cash shortage which leads to the conjecture other factors such as growth opportunity, market timing and corporate governance may drive such issuance behavior. I find that growth factors are at least as strong as cash depletion factor. If the external capital is raised for capital expenditure, debt is preferred in three regions; however, fund is raised for general purpose, the choice of equity and debt varies by regions and countries. I also find the effect of market timing, both equity timing and debt timing. Remarkably, European firms are the most sensitive to change in interest rate that for one standard deviation change in interest rate leads to more than 50% reduction the likelihood of issuing debt.

In chapter 4 “Automation Exposure and M&A”, following from the findings in chapter 02 that firms with high automation exposure are drawn into an arm race, the fastest way to acquire new automation technologies is to buy it rather than investing in R&D. For this, I conduct an empirical study to find if firms with high automation exposure are more likely to involve in M&A transactions. I find persistent evidence that firms with high automation exposure are actively involving in M&A transactions. The effect is robust even after controlling for industry, size, and B/M effect. Next, I find that firms with high automation exposure tend to acquire firms that offer most similar products. And lastly, (working) evidence shows that firms actively in M&A does not gain more than firm’s without M&A.

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