Automation Cost Flexibility and Firm Value

Barıs Ince [*], Cansu Iskenderoglu[†]

December 9, 2024

Abstract

This paper documents that industrial robots enhance firms' ability to reduce operating costs, especially during periods of declining sales. Building on this, we propose a firm-level measure of automation cost flexibility (ACF), which quantifies a firm's capacity to reduce operating costs through automation. Using this measure, we find that firms with greater ACF exhibit higher firm values. To establish a causal effect of ACF on firm value, we employ: (i) a difference-in-differences specification with a matching algorithm, and (ii) exploit the 2011 Thailand hard drive crisis as an exogenous shock. The paper further reveals that the positive impact of ACF is more pronounced for firms in highly competitive industries, those facing significant competitive threats, industries with high strategic interactions, and smaller firms. This suggests that cost flexibility encompasses a strategic dimension.

JEL classification: G30; G32; O33.

Keywords: Automation; Industrial robots; Automation cost flexibility; Firm value.

[*]Michael Smurfit Graduate Business School, University College Dublin, e-mail: baris.ince.fin@gmail.com.

[†]Faculty of Business, Özyeğin University, Cekmekoy, Istanbul, Turkey 34794, e-mail: cansu.iskenderoglu@ozyegin.edu.tr.

1. Introduction

In today's fast-changing business environment, a firm's ability to adapt to varying market conditions is essential for enhancing its value. Industrial robots and automation have transformed production across numerous industries, influencing firms' production methods, labor dynamics, and capital costs. These technological advancements directly impact a firm's capacity to respond to rapidly changing market conditions. Addressing the importance of automation in achieving cost efficiency, this study introduces a novel measure of automation cost flexibility and examines its role in firm valuation.

We first investigate the benefits of industrial robots on operating costs through regressions of operating costs on industrial robots. Building on this, we introduce a firm-level time-varying measure of automation cost flexibility that captures a firm's ability to lower operating costs through automation. We then analyze the impact of automation cost flexibility on firm value and explore how this effect varies across firms.

Keynes (1930) was among the first economists to explore the potential impacts of technological advancements on labor, output, productivity, and economic growth. In recent years, advancements in automation and robotics have significantly transformed various industries and reshaped business operations, capturing economists' attention to study the broader effects of technological innovation. Zeira (1998); Acemoglu and Autor (2011); Autor (2015); Acemoglu and Restrepo (2018, 2020) document the impact of automation on employment, labor share, wages, productivity, and growth.[1]

While the macroeconomic effects of technological innovations are well-documented, relatively little research addresses their implications for firm-level financial outcomes. Recent

[1] Graetz and Michaels (2018), Humlum (2019), Acemoglu, Lelarge, and Restrepo (2020), and Koch, Manuylov, and Smolka (2021) find evidence of decreasing labor shares among firms adopting robots or computer numerically controlled (CNC) machinery in different countries. Acemoglu et al. (2020) documents that while firm-level robot adoption correlates with declining labor and production worker shares, it also corresponds with increased value added and productivity; overall employment grows faster in firms adopting robots. Additionally, Acemoglu and Restrepo (2022) provide evidence of automation's heterogeneous impact on workers of different skill levels, showing that employment and wages declined for low-education workers in roles that automation could perform, whereas high-education workers, unaffected by displacement, experienced real wage gains. Hubmer and Restrepo (2024) finds that large firms, which automate more tasks, reduce the aggregate labor share, while median-sized firms continue to rely on labor-intensive technologies.

corporate finance studies primarily examine automation's (i.e., labor-saving innovations) effects on capital structure, liquidity policies, and the costs of debt and equity (Cheng, Lyandres, Zhou, and Zhou (2023), Qiu, Wan, and Wang (2024), Bates, Du, and Wang (2024), Conlon, Cotter, and Ince (2024)).[2]

Many studies use proxies for automation (e.g., patents, the potential to replace labor with automated capital) or assign industry-level information to firms. Since firm-level automation data is unavailable in the United States, Bates et al. (2024) and Qiu et al. (2024) use occupational computerization probability and automation patents as proxies.[3] Bates et al. (2024) find that workforce automation potential enhances operating flexibility, allowing firms to reduce precautionary cash holdings, while Qiu et al. (2024) document that labor-saving innovations decrease wage rigidity, enabling firms to hold more financial leverage. Using industry-level data on industrial robots, Conlon et al. (2024) show that robots lower firms' operating leverage and cost of equity.

However, no prior study directly quantifies a firm's cost benefits from automation or examines its impact on firm value. This paper addresses this gap by introducing a firm-level measure of automation cost flexibility and analyzing its effect on firm valuation. Specifically, this study (i) documents that industrial robots reduce firms' operating costs and increase cost flexibility, (ii) introduces a novel measure of automation cost flexibility through regressions of operating costs on industrial robots, (iii) assesses the impact of automation cost flexibility on firm value, (iv) validates this measure and provides causal interpretation by examining its effects on operational outcomes (e.g., employment, cost flexibility) and firm valuation, (v) uses the Thailand hard drive crisis as an exogenous shock to test for causal impacts on automation costs, and (vi) highlights the importance of cross-sectional attributes in the relationship

[2]In asset pricing, Zhang (2019) uses the share of routine-task labor as a proxy for automation potential and finds that firms with a higher share of routine tasks invest more in machinery during unfavorable market conditions, allowing them to reduce operating costs and limit declines in market value compared to peers, leading to lower expected stock returns. Lin, Palazzo, and Yang (2020) shows that firms with older capital, being less flexible in technology upgrades, face higher risks from technological shocks, yielding significantly higher returns than firms with newer capital. Knesl (2023) measures automation potential by the proportion of employees in routine-intensive occupations, documenting that firms with a greater share of displaceable labor are less exposed to technology shocks and earn a premium of 4% per year.

[3]Cheng et al. (2023) uses firm-level panel data on industrial robot deployment in China, finding that robot adoption increases leverage and reduces the cost of debt.

between automation and firm value.

First, this paper documents the operating cost benefits of industrial robots (automation). To do so, we build on the empirical models of Anderson, Banker, and Janakiraman (2003) and Chen, Harford, and Kamara (2019). Anderson et al. (2003) introduce a model estimating the response of SGA expenses to contemporaneous changes in sales revenue.[4] Using the approach from Anderson et al. (2003), Chen et al. (2019) examine how operating costs respond to changes in sales revenue during periods of increasing and decreasing sales, finding that costs are less responsive during sales declines, supporting the notion that operating costs exhibit stickiness (inflexibility).

Following this framework, we introduce panel regressions of the logarithmic changes in operating costs on logarithmic changes in industrial robots, including an interaction term between changes in robots and a dummy variable for sales-decreasing periods, with sales controlled. The results show a coefficient of -0.017 on changes in robots, and a combined effect of -0.167 when the interaction term is included. This implies that in a sales-increasing period, operating costs decrease by 0.017% for each 1% increase in industrial robots, while in a sales-decreasing period, a 1% increase in robots corresponds to a 0.167% decrease in operating costs. These findings demonstrate the operating cost flexibility provided by industrial robots (automation).

Industrial robots reduce reliance on labor, a variable cost, and enable consistent, scalable operations without the need for overtime, benefits, or layoffs during periods of low demand. This efficiency allows firms to adjust production and operational costs more flexibly, especially valuable when revenue is constrained.

Moreover, as industrial robots replace traditional machinery, they enhance a firm's ability to scale production up or down in response to fluctuating demand. Unlike traditional machinery, which requires significant upfront investment and incurs fixed costs regardless of output, robots offer greater flexibility by lowering labor costs, minimizing waste, and optimiz-

[4] Banker and Johnston (1993), Noreen and Soderstrom (1994), Noreen and Soderstrom (1997), and Balakrishnan, Petersen, and Soderstrom (2004) document asymmetric cost behavior in industries such as airlines and hospitals. Anderson et al. (2003) extend this literature by introducing an empirical model applicable across various firms and industries.

ing production processes even in low-sales periods. Additionally, robots generally have lower maintenance costs and longer lifespans compared to traditional machinery, which helps firms reduce fixed costs and avoid expensive repairs or upgrades.[5]

Building on the asymmetric behavior of cost structures in response to changes in sales revenue, Chen et al. (2019) introduce a firm-level measure of operating cost flexibility. This measure is derived from regressions of the logarithmic changes in operating costs on the logarithmic changes in sales and an interaction term between changes in sales and a sales-decreasing period dummy. In this model, the sum of the coefficients represents a firm's ability to reduce operating costs during sales declines, where a higher value indicates greater flexibility.[6]

Motivated by Chen et al. (2019) and the cost flexibility benefits of industrial robots, we introduce a time-varying, firm-level measure of automation cost flexibility. This measure is based on firm-specific time-series regressions of logarithmic changes in operating costs on logarithmic changes in industrial robots and an interaction term with a sales-decreasing dummy variable, controlling for sales. In this framework, automation cost flexibility is the negative sum of the coefficients on the robotics terms, representing a firm's ability to reduce operating costs through automation. A higher value indicates greater cost flexibility achieved via automation, particularly valuable during periods of declining sales. In other words, this measure captures how effectively a firm leverages automation to enhance cost flexibility.[7]

We examine the characteristics of firms with varying levels of automation cost flexibility (ACF). Our analysis reveals that firms with higher ACF typically exhibit greater overall

[5]Robots offer substantial financial benefits by optimizing a firm's cost structure. Robotics enable operational flexibility, allowing firms to quickly adjust production in response to market demand changes (Zeira, 1998; Autor, 2015; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2020).

[6]In a corporate finance context, Ince (2024) extends the model of Anderson et al. (2003) by incorporating federal-level regulatory restrictions and an interaction term with a sales-decreasing dummy. Ince (2024) introduces a measure of regulatory inflexibility, where the sum of coefficients in firm-level regressions of SGA expenses on regulatory restrictions reflects declining levels of regulatory cost flexibility.

[7]A question arises when assigning industry-level robotics data to firm-level analysis and estimating automation cost flexibility (ACF) using firm-specific regressions of cost structures on industry-level robotics. While a firm's robot adoption increases the industry's total robotics stock, this does not necessarily imply proportional changes in other firms' robotics. However, one firm's robot adoption can still influence the cost structures of other firms in the industry. Section 3.3 discusses potential channels through which one firm's adoption of robots may impact the cost structures of non-adopting firms.

operating cost flexibility, larger asset bases, lower cash holdings, higher financial leverage, and reduced capital expenditures. These findings align with those of Cheng et al. (2023) and Bates et al. (2024), supporting the idea that industrial robots (automation) enhance operating flexibility, allowing firms to maintain lower cash reserves while assuming more financial leverage.

Notably, while many firms exhibit positive ACF—indicating operational benefits from automation—some firms display negative ACF. This suggests that not all firms benefit equally from automation; in some cases, adopting robots does not yield expected efficiencies and may even introduce operational challenges. Negative ACF can occur when a firm's existing operational structures do not align well with automation requirements, leading to inefficiencies and added complexity. For example, firms with rigid organizational frameworks or those in industries with volatile demand may struggle to integrate automation in ways that enhance cost efficiency. Additionally, firms with limited capital reserves may find it challenging to achieve economies of scale through automation, resulting in higher per-unit costs and diminished flexibility.

We introduce a validation test to assess whether our automation cost flexibility (ACF) measure effectively captures a firm's cost benefits from industrial robots. Specifically, we analyze changes in firms' employee counts and total operating cost flexibility (OCF; Chen et al. (2019)) when they experience a significant increase in ACF, comparing these changes to "matched" firms that do not experience such increases. Since industrial robots directly impact labor needs, a substantial rise in ACF is expected to correlate with reductions in employee numbers. In other words, if ACF accurately reflects a firm's cost benefits from automation, we would expect to see a decrease in its workforce. Additionally, we hypothesize that increased automation cost flexibility will contribute to a firm's overall OCF, reflecting its ability to reduce costs during sales downturns, a pattern not anticipated in the comparison group.

To test this, we match firms with a substantial ACF increase to firms with similar characteristics (e.g., capital expenditures, fixed assets, employee count) but without a comparable ACF increase. This approach allows us to examine changes in employment and OCF between otherwise comparable firms, with the significant ACF increase as the distinguishing factor for “treated” firms. Our findings show that, on average, employment in “treated” firms declines significantly post-event, while employment in “matched” firms increases over the same period. Additionally, OCF rises sharply in “treated” firms post-event, while it remains stable in “matched” firms. These results suggest that automation cost flexibility reduces workforce size and enhances overall operating cost flexibility, supporting the validity of our ACF measure.

We examine the impact of firm-level automation cost flexibility on firm value, measured by Tobin’s Q. Our findings indicate that firms with greater automation cost flexibility tend to have higher values, suggesting that cost flexibility from automation enhances firm value. These results remain robust even when controlling for operating cost flexibility (Chen et al. (2019)) and changes in industrial robots, highlighting that the impact of automation cost flexibility on firm value is distinct from both the sensitivity of operating costs to sales fluctuations (operating cost flexibility) and from mere increases in robotic adoption. This implies that investors value a firm’s ability to reduce operating costs specifically through automation, rather than a firm’s overall cost flexibility or its level of robotics adoption.

One potential concern is that the positive impact of automation cost flexibility on value might be driven primarily by large firms, given their greater resources for automation investment. To address this, we conduct additional analyses, excluding the largest firms (top 10 percent and 20 percent by asset size). The results remain positive and statistically significant, suggesting that this relationship is not solely attributable to the largest firms. Similarly, one might argue that the smallest firms, with potentially limited resources, could exhibit different patterns of automation cost flexibility. To test this, we exclude firms in the bottom 10 percent and 20 percent by asset size. Our findings remain robust, confirming that the positive impact of automation cost flexibility on firm value is not limited to the smallest firms alone.

To further validate the firm-level measure of automation cost flexibility (ACF) and establish a causal effect of ACF on firm value, we implement a difference-in-differences analysis on a sample of ”treated” firms and their matched counterparts. In the matching process, each treated firm (with a significant increase in ACF) is paired with a firm that does not experience a similar increase in ACF but shares key characteristics, such as size, capital expenditure, age, leverage, cash holdings, R&D intensity, profitability, sales growth, fixed assets, and number of employees, using the minimum Mahalanobis distance method. Our results show that treated firms experience a 13.4% increase in Tobin's Q over the same period relative to their matched counterparts. This finding not only supports the validity of the ACF measure but also provides causal evidence of the positive impact of ACF on firm value.

To further investigate the causal relationship between automation cost flexibility and firm value, we follow Bates et al. (2024) and leverage the 2011 Thailand hard drive crisis as an exogenous shock. Thailand is a key global hub for manufacturing electronic components essential for automation systems. Severe flooding in 2011 led to a global shortage of hard drives and a spike in prices, thereby raising automation costs for firms and industries dependent on these components. We use the 2011 Thailand flooding as an exogenous shock, as it did not directly affect U.S. firms' value but indirectly impacted those reliant on electronic components by increasing automation costs (e.g., maintaining or adapting operations). This strengthens the exogeneity argument, as any observed changes in firm value are likely due to firms' automation cost flexibility rather than other endogenous factors. Our findings indicate that the previously positive relationship between automation cost flexibility and firm value turns significantly negative during the crisis, providing causal evidence that automation cost flexibility directly influences firm value.

To strengthen the causal relationship and ensure the parallel trend assumption, we examine the dynamic impact of the Thailand crisis. Firm valuation shows no significant difference before the shock, and a negative impact is observed on firm valuation in the year of the shock, corresponding with the spike in hard drive prices. This effect diminishes as hard drive prices gradually return to pre-crisis levels. Roberts and Whited (2013) discuss using a difference-in-differences analysis on pre-event years as a falsification test to ensure internal validity. In this context, the methodology involves making a false assumption that the flooding takes place before its actual occurrence in 2011 and assigning a value of one to the flooding dummy variable based on this false assumption. The interaction terms between this dummy variable and the automation cost flexibility are highly insignificant. Similarly, when assigning a value of one to the flooding dummy variable for the years following the flooding, the estimated coefficients on the interaction terms are insignificant.

We also investigate the cross-sectional heterogeneities in the impact of automation cost flexibility on firm values. In particular, we explore how industry competition, product market threats, strategic interactions within industries, and firm size impact the effect of automation cost flexibility on firm value. First, the positive effect of automation cost flexibility is more pronounced on firms in highly competitive industries, that face more competitive threats in their product markets, and in industries with greater market leadership turnover rates, indicating strategic rivalry within an industry. These results are consistent with the idea that automaton cost flexibility creates a strategic advantage to the firms that face competitive pressure in product markets. Second, the effect of automation cost flexibility on firm values is greater for smaller firms and firms with smaller market shares, suggesting that automation creates cost flexibility to firms that are more likely to be financially constrained.

The rest of the paper is organized as follows. The next subsection reviews the literature and discusses the contribution of this paper to the existing literature. Section 2 describes the data and variables. Section 3 examines the relationship between automation and firms' operating costs, introduces a firm-specific automation cost flexibility measure, and provides descriptive statistics along with a validation test. Section 4 explores the impact of automation cost flexibility on firm value. Section 5 presents cross-sectional heterogeneity in the impact of automation cost flexibility. Section 6 concludes the paper.

1.1. Literature review

This paper is related to finance and accounting literature documenting asymmetric (sticky) cost behavior with respect to sales revenue and corporate-level characteristics. Early studies by Banker and Johnston (1993), Noreen and Soderstrom (1994), Noreen and Soderstrom (1997), and Balakrishnan et al. (2004) provide evidence for industry-specific asymmetric cost behaviors. Anderson et al. (2003) introduce an empirical model relating changes in SG&A expenses to sales revenue, applicable at the firm level. They find that SG&A expenses increase significantly during sales-increasing periods, but decrease less during sales-decreasing periods. This provides evidence for the asymmetric (sticky) cost behavior. Anderson et al. (2003) further introduce interaction terms between: i) a dummy variable indicating a sales revenue decrease, sales growth, and asset intensity (asset to sales revenue) and ii) a dummy variable indicating a sales revenue decrease, sales growth, employee intensity (employee to sales revenue) as independent variables. They find significant and negative coefficients on both interaction terms, suggesting that costs are stickier for firms with greater asset and employee intensity. Employing a similar empirical model to Anderson et al. (2003) in a corporate governance framework, Chen, Lu, and Sougiannis (2012) find greater cost asymmetry among firms whose managers have higher incentives to build empires.

In a corporate finance context, Chen et al. (2019) estimate the sensitivity of operating costs (Cost of Goods Sold (COGS) plus Selling, General, and Administrative (SG&A) expenses) to the changes in sales revenues during sales-increasing and sales-decreasing periods. They estimate firm-specific time-series regressions of logarithmic changes in operating costs on logarithmic changes in sales revenue and introduce a firm-level measure of operating cost flexibility, quantifying a firm's ability to decrease its costs in a sales-decreasing period. They find a positive association between operating cost flexibility and a firm's financial leverage, suggesting that operating flexibility enables firms to use greater financial leverage. More recently, Ince (2024) employs a variant of Anderson et al. (2003), introducing logarithmic changes in regulatory restrictions and an interaction term between changes in regulations and a sales-decreasing period dummy variable. Ince (2024) offers a firm-level measure of regulatory cost inflexibility (the sum of the coefficients on the regulations-related variables), representing a firm's ability to cut regulatory-driven costs in a sales-decreasing period.

While the literature identifies various factors constraining cost structures and contributing to cost stickiness, including asset intensity, employee intensity, corporate governance related, and regulations, this paper is one of the first to identify a factor that decreases firms' cost stickiness and enhances operating flexibility. We show that industrial robots (automation), a form of tangible assets, improve firms' ability to cut operating costs both in sales-increasing and sales-decreasing periods, thereby enhancing operating cost flexibility. Building on this finding, we propose a firm-level measure of automation cost flexibility, quantifying a firm's capability to reduce operating costs as a result of automation.

This paper also relates to the growing literature on automation and its impact on firm-level outcomes. In corporate finance literature, existing studies often use proxies for automation to investigate their effects on financial variables such as wage rigidity, operating leverage, cash holdings, financial leverage, cost of debt, and cost of equity. Cheng et al. (2023) find that robot adoption increases leverage and reduces the cost of debt in China by providing a hedge against labor cost fluctuations. Exploiting automation-related patents as a proxy for labor-saving innovations, Qiu et al. (2024) document that such innovations reduce wage rigidity and allow firms to increase financial leverage. While doing so, they exploit industry-level robots data from EURO5 countries (Denmark, Finland, France, Italy, and Sweden) as an instrumental variable for US firms.

Bates et al. (2024) use the occupational probability of computerization as a measure of automation, matching industry-level automation information to firms. They find that automation brings operating flexibility, allowing firms to hold less precautionary cash.[8] To provide a causal interpretation, they exploit the 2011 Thailand flooding as an exogenous shock to hard drive supply and automation costs. Conlon et al. (2024) assign industry-level industrial robotics data to firms, documenting that robots reduce a firm's labor and non-labor (production) operating leverage and exposure to systematic risks. Hence, robots decrease a firm's cost of equity. Similarly, Yanguang (2024) matches industry-level robotics information to firms and investigates the impact of robots on corporate financial policies. As industrial robots decrease operating leverage, they lead to higher financial leverage and lower cash holdings.

Given the lack of firm-level robotics and automation data in the United States, most studies either introduce proxies for automation and/or match industry-level robotics information to firms. These proxies include the number of automation-based patents, routine and non-routine tasks, and the share of displaceable labor. In this paper, we match industry-level robotics data to firms and estimate sensitivity of each firm's cost structure to the changes in industry-level robots. This methodology generates a direct measure of robotics sensitivity at the firm level in the United States, which we term "automation cost flexibility".

Additionally, most studies in the finance literature focus on the impact of automation

[8]While doing so, Bates et al. (2024) do not provide a direct test on the impact of automation on operating flexibility.

on corporate financial policies (e.g., financial leverage and cash holdings) and cost of capital (e.g.., equity and debt).[9] While doing so, they primarily motivate their findings through labor benefits of automation. More specifically, as automation substitutes for labor, it decreases wage rigidity and operating leverage. Put differently, the existing corporate finance literature focuses on the "displacement effect" of automation. However, as documented by macroeconomics literature, industrial robots and automation can also increase the demand for labor and employment through "productivity" and "reinstatement" effects.[10] In other words, while automation might decrease labor demand, reduce the number of employees, and lower wage rigidity for some firms, it might have different effects for other firms. Our methodology allows to capture the diverse cost flexibility implications of industrial robots. Then, adding to the literature, we investigate the impact of firm-level automation cost flexibility on a firm's value and further explore the cross-sectional variation in the impact of automation cost flexibility.

2. Data and variables

2.1. *Industrial robots*

Our study focuses on the impact of automation cost flexibility on firms' values. To do so, we introduce a firm-level measure of automation cost flexibility by estimating firm-level sensitivity of logarithmic changes in costs to changes in industrial robots. Section 3 provides detailed information on the construction of the automation cost flexibility measure.

[9] In a recent study, Babina, Fedyk, He, and Hodson (2024) investigate the impact of artificial intelligence on a firm's growth by exploiting employee resume data and introducing a proxy for firm-level AI investments. They find that AI drives firm growth by: i) reducing product innovation costs and ii) lowering operating costs.

[10] Acemoglu and Restrepo (2020) propose displacement, productivity, and reinstatement effects as three channels through which automation affects tasks, labor, and productivity. According to the "displacement effect", as industrial robots replace workers in tasks that human workers previously performed, they decrease employment and labor share. The "productivity effect" refers to the channel that as automation enhances productivity by lowering the costs of tasks, performing tasks faster and accurately, contributing to the speed and efficiency, automation leads to an increased demand for labor in non-automated tasks over the long run. According to the "reinstatement effect", automation not only impact the demand for labor existing jobs, it can also create new tasks (i.e., programming, designing, and maintaining high-tech equipment, such as software and application development) and create demand for new jobs that did not exist before.

To investigate the importance of automation cost flexibility on firm valuation, first, we need to quantify automation usage. There, we rely on operational industrial robotics stock measure provided by the International Federation of Robotics (IFR). The IFR defines an industrial robot (based on the definition of the ISO) as "an automatically controlled, reprogrammable, and multipurpose [machine]" (IFR, 2014). That is, industrial robots are fully autonomous machines that do not need a human operator and can be programmed to perform several manual tasks, such as welding, painting, assembly, handling materials, and packaging.

The IFR provides two sets of industrial robots data at the industry level (ISIC, International Standard Industrial Classification codes) starting from 2004: i) robotics installation, ii) operational robotics stock. While robotics installation refers to newly installed industrial robotics by an industry in a given year, operational robotics stock is the number of total robots in an industry that are ready to perform tasks. Put differently, while robotics installation is a flow variable, operational robotics is a stock variable. There is consistent data for 4 broad industries: i) manufacturing, ii) mining and quarrying, iii) construction, and iv) education, research, and development. Within manufacturing industry, there is detailed data for a set of 13 industries, roughly at the three-digit level. Figure 1 plots the number of aggregate and manufacturing industry-based robotics adoption from 2004 to 2021. Panel A (B) reports the number of newly installed robotics (currently deployed robots).

[Fig. 1 about here.]

The blue lines plot the number of aggregate robotics installation and operational stock in the United States in a given year, whereas the red lines plot the number of robots adopted by the manufacturing industry. Panel A shows that while the rate of robotics installation fluctuates over time, the overall trend is increasing. However, the graph hints a decreasing trend throughout the period following the 2007-2008 Global Financial Crisis. Additionally, there is an observable decrease in robotics installation around the COVID-19 pandemic era. Panel A suggests that manufacturing is the industry installing the greatest portion of aggregate robotics installations. Panel B documents the operational robotics stock of all industries and manufacturing industry. The panel hints that number of newly installed robots is greater than number of robots getting obsolete in all years so that operational robotics stock reflects a monotonic increasing trend. Consistent with Panel A, manufacturing is the industry employing and operating the greatest portion of industrial robots. Figure 1 clearly suggests that the role (portion) of industrial robots has been increasing significantly throughout the years and this is expected to bring important firm-, industry-, and aggregate-level outcomes.

To provide a better understanding of industry-level robotics adoption and cross-industry differences, Table 1 reports four main industries and the subindustries within the manufacturing industry, their ISIC codes and parents codes, and the time-series averages of selected moments (mean, standard deviation, minimum, and maximum) of industry-level industrial robotics stock.[11] The first row of Table 1 reports the robotics information at the aggregate level, the parent of all industries. The time-series average of industrial robotics stock is 214,619 with a minimum of 123,663 (in year 2004) and a maximum of 340,785 (in year 2021).

[Table 1 about here.]

Manufacturing, mining and quarrying, construction, education, and research, and development industries have ISIC codes of D, C, F, and P, respectively and they all have the parent code of 0.[12] Consistent with Figure 1, manufacturing industry is employing the greatest portion of industrial robots. The manufacturing industry is divided into subindustries including food and beverages; textiles; wood and furniture; paper and printing; plastics and chemical products; other chemical productions; rubber and plastic products; metals; automotive; other vehicles; all other manufacturing branches, where all these industries have the parent code of D. Further, plastics and chemical products, metals, and automotive industries are subdivided into industries with finer level data. Automotive, metals, and plastic and chemical products

[11]The IFR provides industry-level robotics adoption information at the industry level using International Standard Industrial Classification (ISIC). Since firm-level ISIC code information is not available at Compustat, we match ISIC codes with SIC-2 level industry classification (Standard Industry Classification) codes. For this purpose, we use the matching methodology developed by a working group including Eurostat, Instituto Nacional de Estadística y Geografía (INEGI), Statistics Canada, the United Nations Statistics Division (UNSD), and the United States Economic Classification Policy Committee (ECPC). For a detailed explanation, see https://mdgs.un.org/unsd/classifications/.

[12]While the main four industries constitute a significant portion of all robots installed and deployed at the aggregate level, nearly 10 percent of the total robotics are operated by “undefined” industries.

are the industries with the greatest robotics stock with time-series averages of 80,947, 14,745, and 13,802, respectively. Within automotive (metals) industry, motor vehicles (electrical and electronics) is the one employing industrial robots the most. Finally, while mining and quarrying, construction, and education, research, and development industries' robotics adoption has increased over time, they employ significantly fewer robots compared to the manufacturing industry.

2.2. *Tobin's Q and other variables*

We use Tobin's Q, the ratio of market value of assets to book value of assets, to measure a firm's value. We compute Tobin's Q following the definition of Kaplan and Zingales (1997) and bound it above at 10 by dividing the market value of assets by the sum of 0.1 multiplied by the market value of assets and 0.9 multiplied by the book value of assets, to reduce the effect of potential measurement error in the book value of assets (Ozbas and Scharfstein, 2010). The market value of assets is equal to the book value of assets (AT) plus the market value of common equity (CSHO x PRCC F) less the book value of common equity (CEQ) and balance sheet deferred taxes (TXDB).

We control for independent variables that might impact firm value, such as firm size, firm age, leverage, cash holdings, R&D intensity, profitability, capital expenditure, sales growth, fixed asset to total assets, and number of employees (Buchanan, Cao, and Chen, 2018). Specifically, we define firm size as the natural logarithm of the book value of assets and firm age as the natural logarithm of one plus the number of years since the firm is first listed in Compustat. Capital expenditure is total capital expenditures scaled by the book value of total assets. Market leverage is defined as total book debt divided by total book debt plus the market value of equity. We measure cash holdings as cash divided by total assets. We measure R&D intensity as research and development expense to total book asset ratio, we set research and development expense to zero when it is missing. We define profitability as the ratio of net income to book value of equity. Sales growth is current sales divided by previous year's sales minus one. We measure fixed assets to book asset as the ratio of property, plant, and equipment to book value of total assets. We take the natural logarithm of number of employees.

All continuous variables are winsorized at the 0.5% level to eliminate the impact of extreme outliers.

3. A new measure: automation cost flexibility

3.1. Operating flexibility

To quantify operating leverage and analyze its impact on profitability and default risk, Chen et al. (2019) estimate the response of cost structures to the changes in sales revenue. Specifically, they find that, on average, firms adjust their COGS by 0.86% and their SG&A expenses by 0.41% in response to a 1% decrease in sales revenue. This implies that SG&A expenses are highly fixed and sticky compared to COGS. Hence, they use SG&A expenses scaled by total assets to quantify operating leverage.

Further, Chen et al. (2019) introduce a firm-level measure of operating cost flexibility through firm-specific time-series regressions of logarithmic changes in operating costs on logarithmic changes in sales revenue:

$$\log[\frac{COSTS_{i,t}}{COSTS_{i,t-1}}] = \beta_{0,i,t} + \beta_{1,i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_{2,i,t} * Decrease - Dummy_{i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \epsilon_{i,t} \tag{1}$$

where COSTS is the sum of COGS and SG&A expenses and $Decrease - Dummy_{i,t}$ is a dummy variable that takes a value of 1 if the firm i's sales revenue decreases from time period t-1 to t, and 0 otherwise. Operating cost flexibility measure is equal to the sum of the coefficient on the logarithmic changes in sales (β_1) and the coefficient on the interaction term between the changes in sales and the dummy variable that indicates a sales-decreasing period (β_2). The operating cost flexibility measure quantifies the percentage change in operating costs for each 1% decrease in sales revenues where a greater value of flexibility implies greater adjustment flexibility. Put differently, operating cost flexibility measures the degree that a firm can cut its operating costs in a sales-decreasing period.

3.2. *Automation cost flexibility*

We investigate the sensitivity of operating costs to the changes in sales and industrial robots at the firm-level and quantify the response of operating costs to the changes in sales and industrial robots. Building on the empirical models of Anderson et al. (2003) and Chen et al. (2019), we add the logarithmic changes in industry-specific yearly-varying robotics operational stock and an interaction term between a sales-decreasing dummy variable and the changes in robotics to Equation 1:

$$\log[\frac{COSTS_{i,t}}{COSTS_{i,t-1}}] = \beta_0 + \beta_1 * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_2 * Decrease-Dummy_{i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_3 * \log[\frac{ROBOTS_{i,t}}{ROBOTS_{j,t-1}}] + \beta_4 * Decrease-Dummy_{i,t} * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \alpha_j + \alpha_t + \epsilon_{j,t} \tag{2}$$

Here, subscript i, j, and t denote firm, industry (based on two-digit SIC grouping), and year, respectively; α_j and α_t are industry- and year-fixed effects. The dependent variable, $COSTS_{i,t}$, is the sum of COGS and SG&A expenses incurred by firm i at year t, $SALE_{i,t}$ is the sales revenue generated by firm i at year t, and $ROBOTS_{j,t}$ is the total number of operational robotics stock of the industry j that firm i belongs to at year t.

Table 2 reports the results of estimating Equation 2 for the pooled sample. Column 1 reports univariate regression results estimating the sensitivity of changes in total operating costs to the changes in sales volume. The estimated coefficient on the logarithmic changes in the sales (β_1 = 0.209) implies that, if the relation between costs and volume is symmetric, operating costs increase (decrease) on average 0.209% per 1% increase (decrease) in sales. Column 2 adds the interaction term between logarithmic changes in sales and a dummy variable that indicates decreasing sales volume from time period t-1 to t (Decrease-Dummy). As the dummy variable takes a value of 0 when sales revenue increases, the coefficient β_1 estimates the percentage increase in operating costs associated with a 1% increase in sales. On the other hand, as the dummy variable takes a value of 1 when revenue decreases, β_1 + β_2 quantifies the percentage change in operating costs as a response to a 1% decrease in sales. Column 2 reports an estimated value of β_1 of 0.216 indicating that operating costs increase by 0.216% if the sales revenue increase by 1%. The estimated coefficient of -0.015 on the decrease dummy variable provides consistent findings to the sticky costs hypothesis. The summed value of β_1 + β_2 = 0.201 indicates that operating costs decrease on average by 0.201% per 1% decrease in sales revenue. Column 3 adds the changes in operational robotics stock to the regression specification. Put differently, it investigates the sensitivity of operating costs to a 1% change in robotics stock while controlling for the changes in sales revenue and asymmetric cost behavior of operating expenses. The estimated coefficient on the logarithmic changes in robotics stock is -0.074 (β_3 = -0.074) and it is statistically significant at the 1% level. This indicates that operating expenses decrease on average 0.074% per 1% increase in robotics stock. Column 4 adds the interaction term between logarithmic changes in operational robotics stock and Decrease-Dummy. The estimated coefficient of -0.017 on operational robotics stock (β_3 = -0.017) implies that, in a sales-increasing period, operating expenses decrease by 0.017% as a response to 1% increase in industry-level industrial robotics stock. On the other hand, the summed value of β_3 + β_4 = -0.167 indicates that operating expenses decrease by 0.167% per 1% increase in robotics during a sales-decreasing period. These results present that industrial robots decrease operating expenses in both sales-increasing and sales-decreasing periods. [13]

[Table 2 about here.]

As presented in Figure 1 and Table 1, since manufacturing industry employs the greatest portion of industrial robots, we estimate Equation 2 for firm in manufacturing industries (SIC

[13] Adding to their empirical model, Anderson et al. (2003) introduce two interaction terms between: i) dummy variable indicating a sales revenue decrease, sales growth, and asset intensity (asset to sales revenue) and ii) dummy variable indicating a sales revenue decrease, sales growth, employee intensity (employee to sales revenue) as independent variables. They find significant and negative coefficients on both interaction terms suggesting that costs are stickier for firms with greater asset intensity and employee intensity. Similarly, while testing the importance of corporate governance measures on the asymmetric behavior of SG&A expenses, Chen et al. (2012) control for economic variables such as asset intensity and employee intensity, and interaction terms such as Decrease Dummy*Sales Growth*Asset Intensity and Decrease Dummy*Sales Growth*Employee Intensity. Our results are robust to adding asset intensity, employee intensity, and the interaction terms between the sales dummy variable and the mentioned variables. Industrial robots (automation) likely to affect firms' asset intensity and employee intensity. Hence, to capture the total effects of robots on firms' cost structure, the main regression models exclude asset intensity and employee intensity.

codes between 2000-3999). In particular, Table IA.1 reports the OLS estimates of Equation 2 for firms in manufacturing industries and it presents similar results to our main findings as in Table 2.[14]

3.3. *Firm-level automation cost flexibility*

Chen et al. (2019) introduce a firm-level measure of operating cost flexibility through firm-specific time-series regressions of logarithmic changes in operating costs on logarithmic changes in sales revenue and an interaction term between changes in sales and a dummy variable indicating a sales-decreasing period (Equation 1). Operating cost flexibility is equal to the sum of the coefficients on the logarithmic changes in sales (β_1) and on the interaction term between the changes in sales and the dummy variable (β_2). The operating cost flexibility measure quantifies the percentage change in operating costs associated with 1% decrease in sales revenues where a greater sum of the coefficients implies greater operating flexibility. Following their methodology, we introduce firm-specific time-series regressions of logarithmic changes in operating costs on logarithmic changes in sales revenue and logarithmic changes in operational robotics stock, and the interaction terms between the mentioned variables and Decrease-Dummy (dummy variable that indicates decreasing sales volume) using the 5 most recent yearly observations:[15]

$$\log[\frac{COSTS_{i,t}}{COSTS_{i,t-1}}] = \beta_{0,i,t} + \beta_{1,i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_{2,i,t} * Decrease-Dummy_{i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] \\ + \beta_{3,i,t} * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \beta_{4,i,t} * Decrease - Dummy_{i,t} * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \epsilon_{i,t} \quad (3)$$

and estimate firm-specific yearly-varying sales betas ($\beta_{1,i,t}$ and $\beta_{2,i,t}$) and robotics sen-

[14]To examine the sensitivity of COGS and SG&A expenses separately and the sensitivity of employment to the changes in industrial robots, we estimate Equation 2 by employing the log changes in COGS (Panel A of Table IA.2), log changes in SG&A expenses (Panel B of Table IA.2), and log changes in employment (Panel C of Table IA.2) as dependent variables. Consistent with our main findings (Table 2), industrial robots decrease COGS and SG&A expenses both in sales-increasing and sales-decreasing periods. Panel C of Table IA.2 in the Internet Appendix displays that industrial robots also decrease employment in both sales-increasing and sales-decreasing periods.

[15]We obtain similar results when we use 4-year or 6-year window to construct automation flexibility measure.

sitivity betas ($\beta_{3,i,t}$ and $\beta_{4,i,t}$). Based on the estimated betas, we construct a firm-specific time-varying automation cost flexibility (ACF) measure:

$$ACF_{i,t} = -(\beta_{3,i,t} + \beta_{4,i,t}). \tag{4}$$

ACF is defined as the negative of the sensitivity of changes in the operating expenses to the changes in operational robotics stock in Equation 3. Put differently, ACF quantifies the proportion of changes in operating costs attributable to the changes in industrial robots and a firm's ability to cut its operating costs. A higher value of ACF indicates a greater automation cost flexibility.

A natural question arises when assigning industry-level robotics data to firm-level analysis and estimating firm-level automation cost flexibility (ACF) through firm-specific regressions of cost structures on industry-level robot usage. As a firm installs or adopts robots, it increases the industry's overall robotics stock, but this does not necessarily mean that other firms' robotics stock changes at the same rate. However, this situation can still affect the cost structures of other firms in the industry. Consider an industry with two firms: one adopts new robots, while the other does not. The adoption of industrial robots by one firm can potentially impact the cost structure of the non-adopting firm in several ways. Automation often leads to lower production costs and increased efficiency for the adopting firm, allowing it to offer products or services at lower prices or with higher quality. Competing firms may feel pressured to adopt similar technologies to maintain market share and profitability; failing to do so could result in losing customers to the more efficient competitor.

Additionally, non-adopting firms might have to lower their prices in response, which would impact their profit margins unless they can similarly reduce costs through automation or other means. To remain competitive, these firms might also need to invest more in their human workforce, as labor costs are typically more "sticky" than capital costs, making them harder to adjust downward. This is particularly challenging during periods of reduced demand, where a firm may struggle to quickly reduce labor costs, thereby constraining its cost structures and limiting cost flexibility. Finally, the adoption of industrial robots by one firm can create technological spillovers that benefit others in the industry, even those that do not adopt robots. For example, robot technology suppliers may enhance their products or lower prices over time, indirectly impacting all firms within the industry.

3.4. Summary statistics

Table 3 reports the selected moments (mean, standard deviation, 10th percentile, 25th percentile, 75th percentile, and 90th percentile) for three sets of variables: i) automation cost flexibility, ii) operating cost flexibility, and iii) Tobin's Q and the independent variables used to estimate Tobin's Q.

The first three rows document the statistics for the main automation cost flexibility measure (ACF, the negative of (β_3 + β_4)), β_3, and β_4, estimated through Equation 3. Automation cost flexibility is the main variable of interest, indicating increasing (decreasing) operating flexibility (inflexibility) brought by industrial robots (automation). β_3 is the coefficient on the logarithmic changes in the operational robotics stock in Equation 3, and β_4 is the coefficient on the interaction term between the logarithmic changes in robotics and the sales-decreasing dummy variable.

[Table 3 about here.]

The first row presents the summary statistics for ACF. The mean, standard deviation, 10th percentile, 25th percentile, 75th percentile, and 90th percentile values for automation cost flexibility are -0.037, 19.213, -5.792, -0.914, 0.636, and 4.957, respectively. The considerable differences between the moments indicate cross-sectional variation in firms' automation cost flexibility, quantifying their ability to decrease operating costs due to changes in industrial robots. Additionally, β_3 and β_4 display similar distributions to the main measure of automation cost flexibility and reflect significant cross-sectional differences.

Adding to Table 3, Figure 2 plots the 10th, 25th, 75th, and 90th percentiles of automation cost flexibility from 2009 to 2021. By construction, the upper (lower) line plots the movements in the 90th (10th) percentile, while the central lines sketch the 75th and 25th percentiles. Noticeably, automation cost flexibility displays significant cross-sectional differences and time-series volatility.

[Fig. 2 about here.]

The second set of variables includes operating cost flexibility (OCF, equal to the sum of β_1 and β_2, estimated through Equation 3), β_1, and β_2. Operating cost flexibility measures a firm's ability to decrease its costs during a sales decline while controlling for logarithmic changes in robots. It features considerably lower variance and narrower spreads between their cross-sectional moments compared to those of automation cost flexibility. Other variables include Tobin's Q, firm size, capital expenditures scaled by assets, natural logarithm of firm age, market leverage, cash holdings, R&D intensity, profitability, sales growth, fixed assets scaled by assets, and natural logarithm of the number of employees. These variables display distributions similar to those reported in other studies.

3.5. Characteristics of firms with high vs. low automation cost flexibility

Table 3 and Figure 2 suggest that automation cost flexibility displays significant differences in the cross-section and fluctuates over time. Hence, firms with different levels of automation cost flexibility may significantly differ in their characteristics. Accordingly, Table 4 investigates the characteristics of firms with high vs. low automation cost flexibility.

To better understand the characteristics of firms with high vs. low automation cost flexibility, Table 4 sorts firms based on their ACF in each financial year and assigns them into tercile portfolios. The table reports the time-series averages of the mean values of firm-specific characteristics of ACF sorted portfolios including "ACF" (automation cost flexibility, primary variable introduced by this paper), "OCF" operating cost flexibility measure proposed by Chen et al. (2019), "Asset" book value of assets, "Emp" number of employees, "Emp/sale" number of employees divided by sales, "Cash" cash holdings scaled by the book value of assets, "Lev." market leverage, "CapEx/at" capital expenditure divided by the book value of total assets, “Tangibility” the ratio of property, plant, and equipment to book value of total assets, and “Age” a firm’s age.

[Table 4 about here.]

The first column of Table 4 reports the time-series averages of ACF sorted tercile portfolios. By construction, there is a monotonic increase from the lowest to the highest ACF tercile. The ACF difference between the extreme terciles is 18.576 and statistically significant at the 1% level.

The second column documents the time-series averages of operating cost flexibility (OCF) of ACF-sorted portfolios. Following Chen et al. (2019), we estimate OCF through firm-specific time-series regressions of logarithmic changes in operating costs on logarithmic changes in sales and an interaction term between changes in sales and a decreasing sales dummy variable (Equation 3 without the robotics terms). Put differently, OCF quantifies a firm’s total operating cost flexibility, including potential flexibility brought by industrial robots, where a higher value of OCF indicates greater adjustment flexibility. The time-series averages of OCF for the lowest, medium, and highest AF terciles are 0.150, 0.694, and 0.863, respectively, with the difference between the extreme terciles being highly significant. Specifically, while an average high ACF firm can decrease its operating costs by 0.863% per 1% decrease in its sales revenue, a low ACF firm can only decrease its costs by 0.150% for the same decrease in sales. This suggests that firms with high ACF tend to have higher operating flexibility, supporting the idea that firms’ automation cost flexibility enhances their operating cost flexibility. This contributes to validating our automation cost flexibility measure.

The third column investigates the relation between ACF and and a firm’ asset value (in millions $). Firms with high ACF are significantly larger than firms with low ACF. Investment capacity and economies of scale potentially contribute to this trend. Larger firms typically have greater financial resources and investment capacity, allowing them to invest in advanced robotics technologies. This enables them to adopt and integrate flexible automation more extensively throughout their operations. The significant size spread between the firms with extreme ACF is consistent with Acemoglu, Anderson, Beede, Buffington, Childressm, Dinlersoz, Foster, Goldschlag, Haltiwanger, Kroff, Restrepo, and Zolas (2022). They estimate that the largest firms in an industry are 1.7 times more likely to use automation technologies than the median firms. Similarly, Humlum (2019), Acemoglu et al. (2020), and Koch et al. (2021) provide international evidence for larger firms automating more compared to their smaller counterparts. Hubmer and Restrepo (2024) document that larger firms adopt significantly more capital-intensive technologies for automation as their adoption and integration require significant fixed costs.

Columns 4 and 5 report the number of employees and number of employees scaled by sales for ACF sorted portfolios. Column 4 documents the relation between automation cost flexibility and number of employees (EMP). There is a non-monotonic increase in employment from the lowest to the highest portfolio, with a significant difference between the extreme portfolios. When we scale number of employees by sales (Column 5), the difference between the extreme portfolios becomes insignificant. This suggests that the significant spread in the number of employees is highly driven by the size of the firms with low vs. high automation cost flexibility. This verifies the idea that larger firms (firms with greater number of employees) have more capacity to invest in robotics technologies.[16]

Column 6 presents the cash holdings of firms with different levels of ACF. The results suggest that firms with high ACF hold significantly less cash than firms with low ACF. This result is consistent with Bates et al. (2024) according to which firms with greater potential to replace labor with automated capital tend to hold less precautionary cash. Column 7 suggests that firms with high ACF hold greater leverage compared to the rest of the sample. This result is consistent with Cheng et al. (2023) which finds that adoption of labor-replacing automation technology in China increases financial leverage.[17] Firms with greater automation cost flexibility have a more variable cost structure, allowing them to adjust their expenses more easily in response to changes in demand or market conditions. This flexibility can provide a buffer against financial risk, potentially allowing the firm to take on more leverage with less risk of

[16]The results are similar when we scale number of employees by a firm's asset value.

[17]Once we estimate panel regressions of market leverage on ACF, we find a positive and significant coefficient on ACF. This suggests that firms with greater automation cost flexibility tend to hold higher levels of leverage.

default. The negative (positive) relationship between automation flexibility and cash holdings (leverage), consistent with the existing literature, further contributes to the validation of our measure.

Column 8 shows that firms with low ACF have significantly higher capital expenditures compared to firms with medium and high ACF. While investment in industrial robots requires greater capital expenditure at the beginning; automation often reduces the need for additional capital investment to achieve the same level of output. With automation, firms can achieve higher productivity with existing resources, thus lowering the requirement for additional capital expenditure. Additionally, automation allows for better utilization of existing resources, including machinery, equipment, and labor. By optimizing resource allocation and reducing waste, firms may be able to defer or avoid capital expenditures for expanding capacity or replacing outdated equipment. Automation systems are typically designed for reliability and require less maintenance compared to manual processes or older equipment. Finally, greater automation cost flexibility enables firms to reconfigure production processes more easily to adapt to changing market conditions or product requirements. This flexibility can reduce the need for specialized equipment or machinery, leading to lower capital expenditures.

Column 9 documents that firms with low ACF carry more tangible assets than firms with medium and high ACF. First, firms investing in automation may prioritize spending on intangible assets such as software, intellectual property, and data analytics capabilities rather than traditional tangible assets like machinery and equipment. Second, by leveraging automation to streamline processes, firms can achieve higher output with fewer physical resources, leading to a lower proportion of tangible assets relative to their total assets. Third, automation technologies often enable firms to achieve higher asset turnover rates. As a result, firms may require fewer tangible assets to support a given level of revenue or production output, leading to a lower tangible asset base.

According to the last column, the average age for the lowest, medium, and the highest ACF terciles are 20.48, 25.58, and 20.98, respectively. While firms with medium AF are the oldest, there is a significant age difference between the lowest and the highest ACF firms, suggesting that older firms might possess greater automation cost flexibility due to their accumulated experience, resources, adaptation strategies, strategic partnerships, cultural evolution, and regulatory considerations.

3.6. *Validation*

To validate our firm-level ACF measure, we investigate the changes in employment and operating cost flexibility (OCF) around the significant increase in a firm's ACF measure ("event time") and compare these outcomes to a set of similar firms that do not experience such a change. The idea is that significant jumps in a firm's ACF measure should indicate that the firm is investing in industrial robots (automation). This should be reflected in the firm's employment structure and total operating cost flexibility. Conversely, we would not expect significant changes in the characteristics of firms whose ACF measure does not reflect substantial changes. Specifically, we define a significant increase in ACF at the firm level when a firm's ACF is below -5 (close to the 10th percentile of the ACF measure, as shown in Table 3) in year t-1, and it is above +5 (close to the 90th percentile of the ACF measure, as shown in Table 3) in year t. [18] According to this framework, the firms experiencing the significant increase are "treated" firms. From the set of non-treated firms, we construct a matching sample of firms that are similar to the "treated" firms except for the significant change in their ACF measure.

In particular, to identify the candidate "control" group, we calculate the annual change in the ACF measure and the standard deviation of annual changes for each firm. Then, we rank firms into five categories based on the standard deviation of annual changes in their ACF measures and assign firms in the lowest rank as the set of candidate control firms. Then, for each "treated" firm, we choose its nearest neighbor from the group of candidate control firms that operate in the same industry (two-digit SIC code) in the same year. We match firms based on all control variables in our main Tobin's Q regression. Specifically, we match firms based on their size (the natural logarithm of total assets), capital expenditure over total assets, age, leverage, cash holding, R&D intensity, profitability, sales growth, fixed assets to total assets,

[18] 142 firms in our sample experience such a significant increase in their ACF measure during the sample period.

and the natural logarithm of the number of employees. We use a matching algorithm that simultaneously minimizes the Mahalanobis distance across all these matching characteristics (Frésard and Valta, 2016; Seltzer, Starks, and Zhu, 2022).

After identifying firms with a significant increase in their ACF ("treated" firms) and control firms, we examine the fluctuations in their average employment (employment/sale) and total operating cost flexibility (OCF) around the "event time". Panel A and B of Figure 3 plot the employment and OCF for the "treated" and "control" group from 2 years before to 2 years after the "event time".

[Fig. 3 about here.]

Panel A of Figure 3 shows that average employment experiences a significant decrease for "treated" firms in the two subsequent years following the significant increase in their ACF while average employment for the control group follows an increasing trend during the same period. Additionally, the figure reveals similar trends right before the "event time" and it shows that the difference in employment between the "treated" and control firms is increasing after the "event time". The significant decrease in the number of employees for firms with the largest increases in their automation flexibility can be explained by the displacement effect. As industrial robots replace workers in tasks that human workers previously performed, they decrease employment and labor share. In other words, as firms invest in industrial robots and automation technologies, their need for human labor reduces.

Panel B of Figure 3 plots the average operating cost flexibility (OCF) measure introduced by (Chen et al., 2019), which is the sum of the time series coefficients (β_1+β_2) estimated using equation 3 without the robotics terms, for "treated" and control firms around the "event time". In this context, OCF is a firm's total operating cost flexibility, accounting for the potential flexibility benefits brought by automation. If automation cost flexibility indeed contributes to total operating cost flexibility, we would expect a considerable jump in a firm's OCF when its automation cost flexibility increases significantly. Panel B provides supporting evidence. The figure shows that while the mean OCF of the "treated" firms increases dramatically around the "event time", the mean OCF of the control firms remains stable throughout the same time period. This indicates that investments in automation (industrial robots) are positively reflected in firms' automation cost flexibility, and hence, in their operating cost flexibility. Panel A and B of Figure 3 further validate our firm-level automation cost flexibility measure.

4. Automation cost flexibility and firm value

Our analysis so far presents the operating cost benefits of industrial robots, and we introduce a measure of automation cost flexibility which reflects the importance of automation in a firm's ability to cut its operating costs. We expect that the cost benefits and flexibility led by automation to create a higher firm value. To explore whether such a relation exists, we estimate the impact of automation cost flexibility on firm value through the following specification:

$$Tobin's\ Q_{\mathrm{it}} = \beta_1 \times ACF_{\mathrm{it}} + \gamma X_{\mathrm{it}} + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \epsilon_{\mathrm{it}} \tag{5}$$

where subscripts i indexes firms, and t indexes time; α_{i} and α_{t} are firm and year fixed effects. The dependent variable is Tobin's Q. The main coefficient of interest is β_1 which captures the impact of automation cost flexibility on the firm value proxied by Tobin's Q. The vector X_{it} is a vector of control variables that may affect the firm value as described in Section 2.[19] We report standard errors that are heteroscedasticity-consistent and clustered at the firm level.

Table 5 presents the coefficient estimates. As described in Section 3, to create firm-level ACF measure, we estimate firm-specific time series regressions over a five-year fixed window. As a result, firm-specific time-varying automation flexibility measure starts in year 2009. In columns 6 and 7, we fix firm-level ACF measure to its 2009 value for years between 2005 to 2009. The estimated coefficients on ACF are significantly positive in all specifications. The coefficient on ACF is 0.001 and it is statistically significant at the 1% level in column 1 which accounts for firm-specific control variables and firm- and year-fixed effects. Using the difference of 18.576 between the mean values of the highest and lowest terciles of ACF (Table

[19]We obtain similar results when we use lagged control variables.

4), an estimated coefficient of 0.001 implies a higher firm value of 1.86% (18.576 x 0.001) for the firms with high ACF compared to the firms with low ACF. Additionally, the coefficient signs for the control variables are consistent with the existing empirical evidence.

[Table 5 about here.]

Next three columns add operating flexibility and automation related variables that could potentially capture the channels through which automation cost flexibility impacts firm value. Column 2 adds operating cost flexibility (OCF) measure introduced by Chen et al. (2019) which is the sum of the time series coefficients ($\beta_1 + \beta_2$) estimated using Equation 3.[20] While the coefficient estimate on OCF is positive albeit insignificant, the coefficient on AF is 0.001 and statistically significant at the 1% level. This suggests that automation cost flexibility contributes to a firm's value which cannot be captured a firm's operating cost flexibility. Column 3 includes logarithmic changes in industry (two-digit SIC)-level industrial robots as an independent variable, while accounting for the full set of control variables in column 1. While the coefficient estimate on ACF continues to be positive and significant, there is a negative albeit insignificant relation between changes in robots and a firm's value. This contributes to the idea that the impact of a firm's ability to cut its operating costs due to industrial robots is distinct than a firm's (or the industry it belongs to) operational robotics stock on its value. To further validate our ACF measure and present the robustness of our results, column 4 adds the measure of substitutability of labor with automated capital (SLAC) introduced by Bates et al. (2024) to our main specification. Column 4 reports positive and significant (positive albeit insignificant) coefficient on ACF (SLAC). Columns 2, 3, and 4 provide evidence that the positive and significant relation between ACF and firm value is not driven by operating cost flexibility, changes in industrial robots, and alternative measure of automation.

To better interpret the economic magnitude of ACF on firm value, in columns 5 and 7, we create a HighFlex dummy variable which takes a value of 1 if a firm's ACF is in the first two terciles of the yearly sample distribution, and 0 otherwise. Then, we reestimate the Equation 5 by replacing ACF measure with HighFlex dummy variable. In column 5, the coefficient on

[20]We obtain similar results when we estimate OCF separately without including industrial robots to Equation 3.

HighFlex dummy variable is 0.034 suggesting that firms with greater automation flexibility have a 3.4% higher firm value and it is statistically significant at the 10% level. We obtain similar findings in columns 6 and 7 when we fix a firm's ACF value in 2009 for the years between 2005-2009. In summary, Table 5 provides evidence that firms with greater automation cost flexibility have higher firm values.[21]

To ensure the results are not solely driven by either large or small firms—those with greater or lower capability to adopt robots and automate processes—we exclude the largest and smallest firms from our sample. The results remain robust even after excluding firms in the top and bottom percentiles by asset value (i.e., the highest 10th and 20th percentiles, and the lowest 10th and 20th percentiles).

4.1. Differences-in-differences validation

Section 3.6 proposes a validation test comparing the changes in number of employees and total operating cost flexibility (OCF) of firms experiencing a major jump (from -5 to +5) in their ACF (treated) to matched firms. As treated firms could significantly differ from non-treated firms, we construct a sample of matched firms that have similar characteristics without a significant increase in their ACF.[22] Section 3.6 documents a significant decrease in number of employees and increase in OCF for the treated firms, whereas there is an increase in employees and no significant change in OCF within the sample of matched firms.

To further validate our firm-level ACF measure and provide additional evidence that it is the automation cost flexibility that impacts a firm's value (Tobin's Q), we estimate a difference-in-differences version of our baseline specification (Equation 5) on a sample comprising only "treated" and matched firms:

$$Tobin's\ Q_{\mathrm{it}} = \beta_1 \times TreatAfter_{\mathrm{it}} + \gamma X_{\mathrm{it}} + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \epsilon_{\mathrm{it}}. \tag{6}$$

[21] Since the manufacturing industry employs the greatest portion of industrial robots, we estimate Equation 5 as in Table 5 for firms in manufacturing industries (SIC codes between 2000-3999). As presented in Table IA.3 of the Internet Appendix, our results are economically larger within the sample of manufacturing firms.

[22] Subsection 3.6 "Validation" explains the matching methodology.

TreatAfter_{it} is a dummy variable equal to one for the "treated" firms (i.e., experiencing a significant increase in their automation cost flexibility) for five years following the significant increase in their ACF measure, and zero for the matched firms. The main coefficient of interest is β_1, which measures how on average "treated" firms' value changes compared to the matched firms.

[Table 6 about here.]

Table 6 reports the regression results of estimating Equation 6. While accounting for the full set of control variables, and firm- and year-fixed effects, the coefficient on β_1 is 0.134 and it is significant at 5% level. This indicates that firms with a significant jump in their ACF generate 13.4% more value compared to their similar counterparts over the same period. As this methodology controls for both observed and unobserved firm-specific and time-varying factors, and ensures that treated firms are matched to similar counterparts, the analysis establishes that the observed increase in Tobin's Q is a causal effect of the significant rise in automation cost flexibility. This evidence points to a direct link between automation cost flexibility and the value creation, as reflected in the firm's market valuation.

4.2. *Thailand hard drive shock*

To provide further evidence addressing potential endogeneity concerns and to establish a causal relationship between automation cost flexibility and firm value, we follow Bates et al. (2024) and use the 2011 Thailand hard drive crisis as an exogeneous shock. Thailand, a major manufacturing hub for electronics, automotive, and computer hardware, is the world's second-largest hard drive producer after China. The severe flooding in 2011- one of Thailand's most severe natural disasters- disrupted the production of hard drives and other essential electronic components used in automation systems, causing a global shortage and a surge in prices for these automation-related products.[23]

[23] To illustrate, hard drive prices nearly doubled in 2011, then gradually declined and returned to pre-flood levels in 2012. Figure 5 of Bates et al. (2024) provides evidence of price fluctuations from 2009 to 2015.

The Thailand crisis primarily created a surge in specific input costs (i.e., hard drives and technological components) rather than triggering a broad-based financial or economic crisis. Firms heavily reliant on these components faced increased costs for maintaining or adapting their operations, particularly through automation. However, unless a firm was especially dependent on hard drives, the impact on its intrinsic value would be indirect—mainly through the cost adjustments it would need to make to maintain productivity or adapt its technology stack. As this crisis did not directly affect U.S. firms' value but rather indirectly through increased automation costs, it serves as an event that is entirely exogenous to U.S. firms and unrelated to firm-specific characteristics. This framing ensures that any observed variation in firm value due to the shock is likely mediated by the firm's automation flexibility, not by other endogenous factors.

The causal pathway is as follows: the Thailand crisis led to increased automation costs worldwide, thereby influencing firm value through these higher costs. To test this prediction, we estimate the following regression model exploiting the Thailand flooding as an exogenous shock:

$$Tobin's\ Q_{\mathrm{it}} = \beta_1 \times ACF_{\mathrm{it}} + \beta_2 \times Flooding_{\mathrm{t}} + \beta_3 \times (Flooding_{\mathrm{t}} \times ACF_{\mathrm{it}}) + \gamma X_{\mathrm{it}} + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \epsilon_{\mathrm{it}} \quad (7)$$

Subscripts i, and t represent firms, and time, respectively. The vector X_{it} includes the control variables used in the main regression specifications. α_i and α_t are firm and year fixed effects, respectively. Flooding is an indicator variable that is equal to one for the year 2011 representing the period of significant increase in automation as a result of Thailand hard drive crisis. We adjust the standard errors for clustering at the firm level. The main parameter of interest in Equation 7 is β_3, the coefficient of the interaction term, ($Flooding_t$ x ACF_{it}).

Table 7 presents the regression results. In columns 3 and 4, firm-level ACF is fixed to its 2009 value for the years between 2005 to 2009. Column 1 provides the benchmark specification, with a coefficient of -0.003 on the interaction term ($Flooding_t$ x ACF_{it}), significant at the 10% level. Column 3 yields similar results, with the coefficient of interest β_3 being is significant at the 5% level. This indicates that the positive relationship between ACF and firm value is mitigated during the crisis period.

[Table 7 about here.]

Columns 1 and 3 yield negative and significant coefficients on the interaction terms, providing further takeaways on the impact of automation cost flexibility (ACF) on firm value. The regression specifications indicate a negative sum of the coefficients, $\beta_1 + \beta_3$, implying that the usual positive relationship between ACF and firm value reverses during the crisis period. Since the Thailand hard drive crisis did not directly affect U.S. firms' value, this negative relationship provides evidence that automation cost flexibility causally impacts firm value through its role in responding to automation cost shocks.

Not all companies are equally affected by increased automation costs due to the component shortage. The second part of our analyses focuses on firms in high-computerization industries, where industrial robots heavily rely on computers for automation. Following Bates et al. (2024), we calculate the ratio of investments in computers and peripheral equipment to total investments in equipment and machinery using the 1997 Bureau of Economic Analysis (BEA) capital flow table.[24] We define industries with ratios above the median (estimated by Osborne and Frey (2013); Frey and Osborne (2017)) as high computerization industries. Accordingly, Column 2 modifies the Flooding dummy to be 1 for firms in these industries in 2011, and 0 otherwise. Column 4 fixes measure for the years between 2005 and 2009 to its 2009 value.

Moving from column 1 to 2, the estimated coefficient on the interaction term (Flooding_t x ACF_{it}) becomes more negative, increasing in magnitude from -0.003 to -0.010 and becoming statistically significant at the 5% level. Column 4, which fixes the ACF measure to 2009 values, yields similar results.[25] These findings indicate that firms with high dependence on

[24]The BEA capital flow data is obtained at https://apps.bea.gov/industry/xls/flow1997.xls.

[25]As the manufacturing industry employs the greatest portion of industrial robots, we estimate Equation 7 for the firms in manufacturing industries (SIC codes between 2000-3999). The results are presented in Table IA.4 in the Internet Appendix. In columns 2 and 4, we follow Bates et al. (2024) to identify industries that are expected to be affected more significantly within the manufacturing industry. Specifically, in columns 2 and 4, Flooding is equal to one for firms operating in industries that rely more on computers systems based on the probability of computerization, estimated by Osborne

computers and peripheral equipment experienced a more pronounced negative impact of ACF on firm value.

Table 7 demonstrates that the Thailand hard drive crisis reversed the typical positive impact of automation flexibility on firm value. During this crisis, firms with high automation cost flexibility experienced a negative impact on value, suggesting that while ACF generally enhances firm value, exogenous shocks that raise automation costs can temporarily counteract these benefits. By utilizing the Thailand hard drive crisis as an exogenous shock to automation costs, our results mitigate potential endogeneity concerns and support a causal interpretation: it is the automation cost flexibility that affects firm value.

4.3. Testing for pretreatment trends

To further address potential endogeneity concerns and test the parallel trend assumption, we analyze the dynamic effects of the Thailand shock by replacing the Flooding dummy variable with three time-specific dummy variables: Before$^{\text{-1 to -3}}$, set to one for 1 to 3 years prior to the Thailand shock (2008, 2009, and 2010); Current^{0}, set to one for the Thailand flooding year, 2011; and After$^{\text{1 to 2}}$, set to one for the 1 to 2 years following the shock (2012 and 2013). The coefficients on the interaction term (Before$^{\text{-1 to -3}}$ x ACF) enable us to assess any pre-existing trends before the Thailand crisis.

The results in Table 8 indicate no pre-existing trends in firm value before the Thailand hard drive crisis, as the estimated coefficients on Before$^{\text{-1 to -3}}$ x ACF are statistically insignificant across all specifications. However, the coefficient estimates on Current^{0} x ACF in columns 1 and 3 are both -0.003 and statistically significant at the 5% level, while the estimates on After$^{\text{1 to 2}}$ x ACF are insignificant. This pattern suggests that the significant negative impact occurs only during the shock year, when hard drive prices spiked, while no significant effect is observed in the following years as prices began to decline. Furthermore, these results demonstrate that our continuous firm-level, time-varying ACF measure, derived directly from industrial robot stock, is highly sensitive to changes in automation costs.

and Frey (2013); Frey and Osborne (2017) based on occupational characteristics and technological developments, in year 2011 and zero otherwise. As the table reports, the estimated coefficients are economically larger within the manufacturing industries.

[Table 8 about here.]

As in Table 7, Columns 2 and 4 explore the dynamic impact of the Thailand shock specifically for industries with a higher reliance on computers and peripheral equipment for automation. We construct $\text{Before}^{\text{-1 to -3}}$, Current^{0}, and $\text{After}^{\text{1 to 2}}$ dummies and assign value of one based on years as defined above but only for firms in industries with a higher probability of computerization (based on the median value), estimated by Osborne and Frey (2013); Frey and Osborne (2017), zero otherwise. The coefficients on $\text{Before}^{\text{-1 to -3}}$ x ACF in columns 2 and 4 remain insignificant, while the coefficients on Current^{0} x ACF are -0.108 and -0.118, respectively, both statistically significant at the 5% level. These findings suggest that firms in more computerization-dependent industries experience a stronger negative impact from rising hard drive prices.

The results in Table 8 show no significant differences before the Thailand shock, confirming that the parallel trends assumption holds. Additionally, we conduct placebo tests by shifting the shock year to alternative years before and after 2011, consistently obtaining insignificant results (not tabulated for brevity). These placebo tests support a causal interpretation of the relationship between automation cost flexibility and firm value.[26]

These results reinforce the exogeneity of the Thailand shock in the difference-in-differences framework. The absence of significant pretreatment effects (no pre-existing trends) suggests that firm value trends were similar for firms with varying levels of automation flexibility before the crisis. This supports the parallel trends assumption, indicating that any changes observed during the crisis year can be attributed to the shock rather than underlying differences between the groups. Further, the analyses strengthen the causal interpretation, showing that it is the automation cost flexibility that drives changes in firm value, rather than other endogenous factors. The placebo tests further bolster this interpretation, as shifting the shock year yields insignificant results, underscoring that the observed effects are uniquely tied to the Thailand crisis and not to random temporal variations.

[26]Table IA.5 in the Internet Appendix presents similar results for firms in manufacturing industries (SIC codes 2000-3999), further confirming that the parallel trends assumption holds for these firms as well.

5. Cross-sectional tests

In this section, we explore the cross-sectional heterogeneity of the sample to shed further light on the effect of automation cost flexibility on firm value. To investigate the cross-sectional variation, we divide our sample into subsamples based on industry or firm-level characteristics. We then estimate Equation 5 for these subsamples and compare the coefficient estimates on ACF between them.

Our first set of tests focuses on how product market competition and strategic interactions between firms impact the effect of automation cost flexibility on firm value. Firms facing constant competitive risks and threats in product markets can use financial or operating flexibility to react more aggressively to these threats. For instance, deep-pocketed firms can adopt aggressive competitive strategies to the detriment of rival firms (Bolton and Scharfstein, 1990). Consistent with this idea, existing research shows that firms facing higher predation risk or competitive threats hold more cash and liquid assets and pay lower dividends to create flexibility. The strategic value of cash is greater in more competitive markets (Haushalter, Klasa, and Maxwell, 2007; Fresard, 2010; Hoberg, Phillips, and Prabhala, 2014). Since automation provides operating cost flexibility, we expect the impact to be greater on firms in more competitive markets or those facing greater product market threats, as the strategic value of cost flexibility will be higher for these firms.

First, we examine whether the impact of automation cost flexibility on firm value varies with product market competition. We measure product market competition at the two-digit SIC code level using the Herfindahl-Hirschman Index (HHI), a widely used measure for product market competition (Giroud and Mueller, 2010; Valta, 2012). The HHI is defined as the sum of squared market shares, computed using firms' sales. Higher HHI levels indicate higher industry concentration and, therefore, weaker product market competition. Since automation lowers operating costs, automation cost flexibility should provide a strategic advantage, especially for firms in more competitive industries. To test this prediction, we split our sample into two based on the annual median level of industry concentration in a given year.

The results in column 1 of Table 9 show that automation cost flexibility leads to higher firm values for firms in more competitive industries (the coefficient estimate on AF is 0.002 and statistically significant at the 1% level), whereas there is no impact on firms in more concentrated industries (the coefficient estimate on ACF is 0.000 and insignificant). The difference between these two coefficient estimates is also statistically significant (p-value = 0.025), supporting the hypothesis that the positive impact of automation cost flexibility on firm value is more pronounced for firms in more competitive industries, as these firms benefit more from a decrease in operating costs.

[Table 9 about here.]

Knesl (2023) presents that firms with high share of displaceable labor have strong negative exposure to technology shocks and examines whether the impact of technology shocks on financial performance differ between highly competitive and less competitive industries. He presents evidence that industry competition increases the negative impact of technology shocks on firms' financial performance as automation becomes a costly necessity for firms and erodes potential rents. Note that these results are not inconsistent with our findings of the more pronounced positive impact of automation flexibility on firm value in more competitive industries. Knesl (2023) specifically focuses on the transition of firms from labor-based to capital-based production as a result of exogenous technology shocks and does not consider staggered technology adoption whereas we do not analyze the impact of technological shocks and we focus on how cost flexibility created by industrial robots impacts firm value.

We next investigate whether the impact of automation cost flexibility on firm value is more pronounced for firms that face more competitive threats. To test this idea, we use the product market fluidity measure developed by Hoberg et al. (2014), which captures competitive threats and product market interactions. Hoberg et al. (2014) show that firms facing greater product market fluidity are less likely to pay dividends or repurchase shares and hold higher cash balances. We expect the positive impact of automation cost flexibility to be more pronounced on firms with greater product market fluidity, as a decrease in operating costs can provide more flexibility to firms in less stable markets.

In column 2 of Table 9, we divide the sample into terciles each year and assign firms in the lowest tercile and higher terciles to “low fluidity” and “high fluidity”, respectively. As shown, automation cost flexibility creates higher firm values for firms facing greater product market fluidity; the coefficient estimate on ACF is 0.001 and statistically significant at the 5% level for these firms, while the coefficient estimate on ACF is zero and insignificant for firms with low product market fluidity. The difference between these two coefficient estimates is also statistically significant (p-value = 0.034).

To further test how competition and strategic interactions in product markets affect the impact of automation cost flexibility on firm value, in column 3, we use the market leadership turnover rate introduced by Dou, Ji, and Wu (2022). We expect the positive impact of automation cost flexibility to be more pronounced in industries with higher market leadership turnover rates, as cost flexibility could create greater benefits for firms in industries with greater competition for market leadership. We define a “high” market leadership turnover indicator variable that equals one if any of the four largest firms ranked by sales in the two-digit SIC industry in year t+1 are not among the four largest firms in year t; otherwise, it takes a value of zero (categorized as “low” market leadership turnover). Consistent with our prediction, automation cost flexibility creates a positive impact on firms that operate in industries with high market leadership turnover. Specifically, the coefficient on ACF is 0.003 and statistically significant at the 5% level for firms in industries with high market leadership turnover, whereas it is zero for firms in industries with low market leadership turnover (i.e., in industries with highly persistent market leadership). The difference between the coefficient estimates is also statistically significant at the 1% level.

We also examine variation in how automation cost flexibility affects firm value based on firm size. As small firms are more likely to be financially constrained, we expect the decrease in operating costs led by automation to create a more pronounced impact on smaller firms. To test this prediction, we divide the sample firms into quartiles based on firm size (total firm assets) each year and firms in the highest quartile are categorized as “big”, and those in the lower quartiles are “small”.

As presented in column 4, automation cost flexibility creates a positive impact on firm value for smaller firms. Specifically, the coefficient estimate on ACF is 0.002 and statistically significant at the 1% level, while it is zero and insignificant for bigger firms. The difference between the coefficient estimates is also statistically significant at the 10% level. Overall, the positive impact of automation flexibility appears mostly in smaller firms that are more likely to be financially constrained, as these firms benefit more from a decrease in operating costs.

Finally, in column 5, we divide the sample firms into subsamples based on firm's market share each year and compare the firms in the highest quartile with the firms in the lower quartiles. Market share is defined as the ratio of a firm's sales to total industry sales at the two-digit SIC level. We expect that cost flexibility led by automation will create greater benefits for firms with lower market share in the industry, as a decrease in operating costs might provide a greater competitive advantage for these firms. Consistent with our prediction, automation cost flexibility creates a positive impact on firms with lower market shares in the industry. The coefficient on ACF is 0.002 and statistically significant at the 1% level for firms with low market shares, while it is zero and insignificant for firms with high market shares. The difference between the coefficient estimates is also statistically significant (p-value = 0.021).[27]

Overall, the results in this section show that the positive impact of automation cost flexibility appears mostly in firms that operate in more competitive industries, face greater threats in their product markets, are in industries with greater strategic competition, and are more likely to be financially constrained. These findings are consistent with the idea that cost flexibility provides a strategic value.

6. Conclusion

This paper provides evidence for operating cost benefits of industrial robots. Specifically, we find that industrial robots decrease a firm's operating costs both in a sales-increasing and sales-decreasing period. Motivated by an operating flexibility channel, we introduce a firm-level measure of automation cost flexibility reflecting the importance of automation in a firm's

[27] In Table IA.6 in the Internet Appendix, we estimate the results in Table 8 for firms in manufacturing industries (SIC codes between 2000-3999). We obtain similar findings for manufacturing industries.

ability to decrease its operating costs.

We investigate the firm-level characteristics of firms with differing levels of automation cost flexibility. Specifically, firms with higher automation cost flexibility tend to have greater operating cost flexibility, larger asset base, less cash holdings, and lower capital expenditures. Furthermore, we match firms with a substantial increase in their automation cost flexibility (treated) to firms with similar characteristics but without a comparable increase in automation cost flexibility (matched). Firms with a major jump in their automation cost flexibility experience a decrease in their number of employees and an increase in their total operating cost flexibility, whereas we do not observe a similar pattern across matched firms.

We then find that firms with greater automation cost flexibility exhibit higher firm value (Tobin's Q). To provide further causal link between automation cost flexibility and firm value, we exploit the 2011 flooding in Thailand (Bates et al., 2024) as an exogenous shock for automation costs. We find that the positive impact of automation cost flexibility on firm value is mitigated during the Thailand crisis, providing evidence of a causal component to our main result.

This paper also examines the cross-sectional heterogeneities in the impact of automation cost flexibility on firm values. The positive impact of automation flexibility on firm value is more pronounced on firms that operate in more competitive industries, that face greater threats in product markets, in industries with greater strategic competition, and smaller firms. The magnified impact on these firms suggest that automation cost flexibility creates strategic advantage to firms that face constant competitive threats in product markets and firms that are more likely to be financially constrained.

References

Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Childressm, E., Dinlersoz, E., Foster, L., Goldschlag, N., Haltiwanger, J., Kroff, Z., Restrepo, P., Zolas, N., 2022. Automation and the workforce: A firm-level view from the 2019 annual business survey. University Chicago Press .

Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies: Implications for employment and earnings. In: *Handbook of labor economics*, Elsevier, vol. 4, pp. 1043–1171.

Acemoglu, D., Lelarge, C., Restrepo, P., 2020. Competing with robots: firm-level evidence from france. AEA Papers and Proceeding 110, 383–388.

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. American economic review 108, 1488–1542.

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: Evidence from us labor markets. Journal of political economy 128, 2188–2244.

Acemoglu, D., Restrepo, P., 2022. Tasks, automation, and the rise in u.s. wage inequality. Econometrica 90, 1973–2016.

Anderson, M. C., Banker, R. D., Janakiraman, S. N., 2003. Are selling, general, and administrative costs "sticky"? Journal of accounting research 41, 47–63.

Autor, D. H., 2015. Why are there still so many jobs? the history and future of workplace automation. Journal of economic perspectives 29, 3–30.

Babina, T., Fedyk, A., He, A., Hodson, J., 2024. Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics 151, 103745.

Balakrishnan, R., Petersen, M. J., Soderstrom, N. S., 2004. Does capacity utilization affect the "stickiness" of cost? Journal of Accounting, Auditing & Finance 19, 283–300.

Banker, R. D., Johnston, H. H., 1993. An empirical study of cost drivers in the us airline industry. Accounting Review pp. 576–601.

Bates, T. W., Du, F., Wang, J. J., 2024. Workplace automation and corporate liquidity policy. Management Science forthcoming.

Bolton, P., Scharfstein, D. S., 1990. A theory of predation based on agency problems in financial contracting. The American economic review pp. 93–106.

Buchanan, B., Cao, C. X., Chen, C., 2018. Corporate social responsibility, firm value, and influential institutional ownership. Journal of Corporate Finance 52, 73–95.

Chen, Clara, X., Lu, H., Sougiannis, T., 2012. The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. Contemporary Accounting Research 29, 252–282.

Chen, Z., Harford, J., Kamara, A., 2019. Operating leverage, profitability, and capital structure. Journal of financial and quantitative analysis 54, 369–392.

Cheng, X., Lyandres, E., Zhou, K., Zhou, T., 2023. Labor-replacing automation and finance. Management Science forthcoming.

Conlon, T., Cotter, J., Ince, B., 2024. More robots less cost of equity. Working paper .

Dou, W. W., Ji, Y., Wu, W., 2022. The oligopoly lucas tree. The Review of Financial Studies 35, 3867–3921.

Fresard, L., 2010. Financial strength and product market behavior: The real effects of corporate cash holdings. The Journal of finance 65, 1097–1122.

Frésard, L., Valta, P., 2016. How does corporate investment respond to increased entry threat? The Review of Corporate Finance Studies 5, 1–35.

Frey, C. B., Osborne, M. A., 2017. The future of employment: How susceptible are jobs to computerisation? Technological forecasting and social change 114, 254–280.

Giroud, X., Mueller, H. M., 2010. Does corporate governance matter in competitive industries? Journal of financial economics 95, 312–331.

Graetz, G., Michaels, G., 2018. Robots at work. Review of Economics and Statistics 100, 753–768.

Haushalter, D., Klasa, S., Maxwell, W. F., 2007. The influence of product market dynamics on a firm's cash holdings and hedging behavior. Journal of financial Economics 84, 797–825.

Hoberg, G., Phillips, G., Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. The Journal of Finance 69, 293–324.

Hubmer, J., Restrepo, P., 2024. Not a typical firm: capital-labor substitution and firms' labor shares. Working paper .

Humlum, A., 2019. Robot adoption and labor market dynamics. Discussion paper, MIMEO, Princeton University .

Ince, B., 2024. How do regulatory costs affect mergers and acquisitions decisions and outcomes? Journal of Banking & Finance p. 107156.

Kaplan, S. N., Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? The quarterly journal of economics 112, 169–215.

Keynes, J. M., 1930. Economic possibilities for our grandchildren. In: *Essays in persuasion*, Springer, pp. 321–332.

Knesl, J., 2023. Automation and the displacement of labor by capital: Asset pricing theory and empirical evidence. Journal of financial economics 147, 271–296.

Koch, M., Manuylov, I., Smolka, M., 2021. Robots and firms. Economic Journal 131, 2553–2584.

Lin, X., Palazzo, B., Yang, F., 2020. The risks of old capital age: asset pricing implications of technology adoption. Journal of Monetary Economics 115, 145–161.

Noreen, E., Soderstrom, N., 1994. Are overhead costs strictly proportional to activity?: Evidence from hospital departments. Journal of accounting and economics 17, 255–278.

Noreen, E., Soderstrom, N., 1997. The accuracy of proportional cost models: evidence from hospital service departments. Review of accounting Studies 2, 89–114.

Osborne, M. A., Frey, C. B., 2013. The future of employment. University of Oxford 17.

Ozbas, O., Scharfstein, D. S., 2010. Evidence on the dark side of internal capital markets. The Review of Financial Studies 23, 581–599.

Qiu, J., Wan, C., Wang, Y., 2024. Labor-saving innovations and capital structure. Journal of Corporate Finance 84, 102510.

Roberts, M., Whited, T., 2013. Endogeneity in empirical corporate finance. Handbook of the Economics of Finance 2, 493–572.

Seltzer, L. H., Starks, L., Zhu, Q., 2022. Climate regulatory risk and corporate bonds. Tech. rep., National Bureau of Economic Research.

Valta, P., 2012. Competition and the cost of debt. Journal of financial economics 105, 661–682.

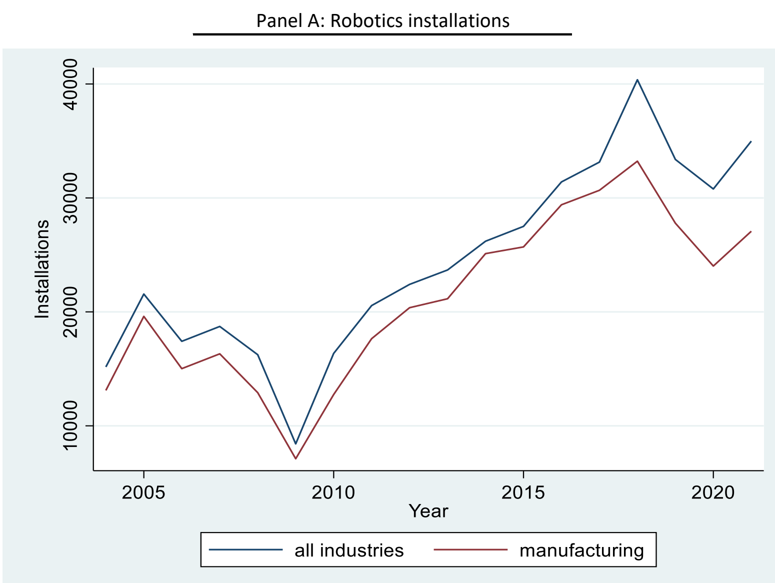
Yanguang, L., 2024. Robots, labor market frictions, and corporate financial policy. Working paper .

Zeira, J., 1998. Workers, machines, and economic growth. The Quarterly Journal of Economics 113, 1091–1117.

Zhang, M. B., 2019. Labor-technology substitution: Implications for asset pricing. The Journal of Finance 74, 1793–1839.

Fig. 1. Robotics growth

International Federation of Robotics (IFR) quantifies aggregate and industry-level yearly robotics installation and operational robotics stock (number of robots currently deployed). The IFR reports the country-level aggregate and industry-level robotics usage data starting from 2004. This figure plots the number of aggregate and manufacturing industry based robotics installation (Panel A) and operational stock (Panel B) from 2004 to 2021. The blue (red) lines plot the number of robotics usage at the aggregate (manufacturing industry) level.



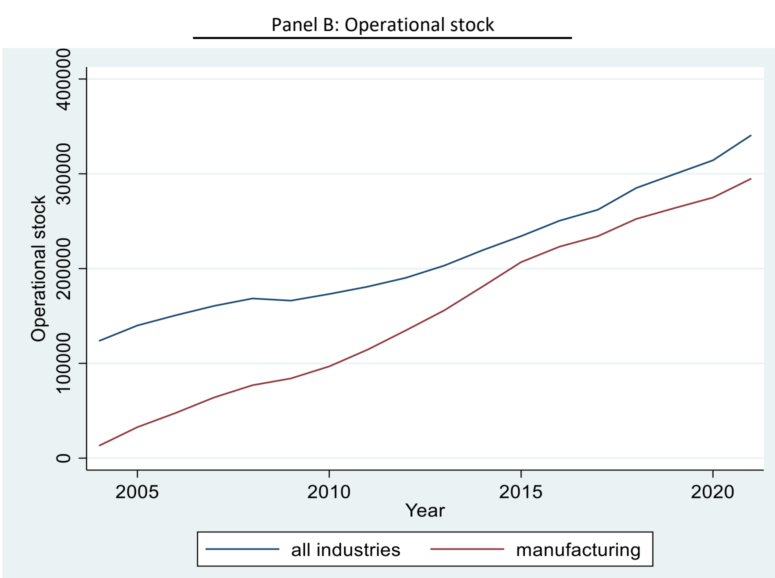


Fig. 2. Automation cost flexibility over time

This figure plots the selected cross-sectional moments (10th percentile, 25th percentile, 75th percentile, and 90th percentile) of automation cost flexibility (estimated through Equations 3 and 4) from 2009 to 2021. By construction, the upper (lower) line plots the movements in the 90th (10th) percentile, whereas the central lines sketch the 75th and 25th percentiles.

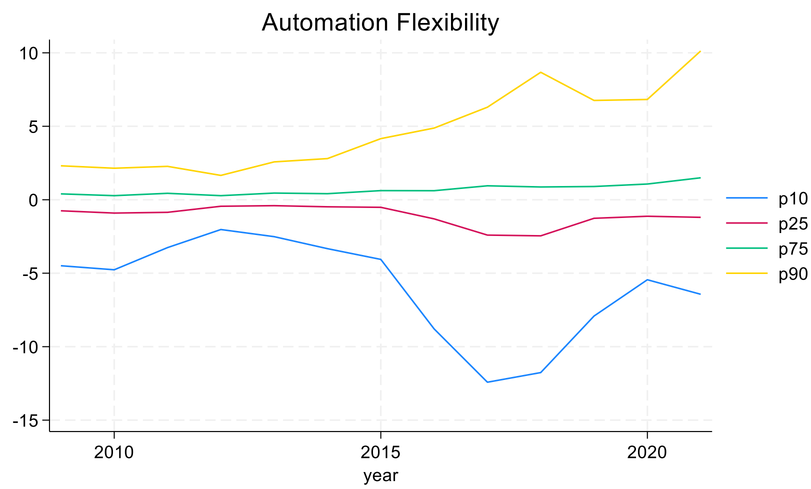


Fig. 3. Firm-level outcomes around the significant increase in ACF for ”treated” and matched firms

This figure presents average employment and operating cost flexibility (OCF) for ”treated” and control firms in years relative to the significant increase in a firm’s ACF measure for ”treated” firms. We define the firms that experience significant increase in their ACF measure in a given year as the “treated” firms. We define significant increase in ACF at the firm-level when a firm’s ACF is below -5 (close to 10th percentile of ACF measure, Table 3) in year t-1, and it is above +5 (close to 90th percentile of ACF measure, Table 3) in year t. To identify the set of candidate control firms, we rank firms into five categories based on the standard deviation of annual changes in their ACF measures and assign firms in the lowest rank as the set of candidate control firms. Then for each treated firm we choose its nearest neighbor from the group of candidate control firms that operate in the same industry (two-digit SIC code) in the same year. Firms are matched based on minimum Mahalanobis distance across their size (the natural logarithm of total assets), capital expenditure over total asset, age, leverage, cash holding, R&D intensity, profitability, sales growth, fixed asset to total asset, and natural logarithm of number of employees. In Panel A, employment is defined as the number of employees scaled by sales. In Panel B, operating cost flexibility (OCF) is the sum the time series coefficients (β_1+β_2) estimated using equation 3 without the robotics terms as introduced by Chen et al. (2019).

Table 1. Industry-based operational robotics stock

International Federation of Robotics (IFR) quantifies aggregate and industry-level yearly robotics installation and operational robotics stock. While the IFR reports the country-level aggregate industrial robotics installation and operational stock from 1993 onwards, it provides industry-level robotics usage data from 2004. In manufacturing, there is consistent data for a detailed set of 13 industries (roughly at the three-digit level). Outside of manufacturing, there is consistent data in 3 broad industries (roughly at the two-digit level). This table reports the industry names with available robotics information, their main and parent International Standard Industrial Classification (ISIC) codes, and the selected moments of industry-level operational robotics stock including the time-series average (mean), standard deviation (SD), minimum (Min.), and maximum (Max.). The data period is from 2004 to 2021.

Industry	ISIC code	Parent code	Mean	SD	Min.	Max.
All industries	0		214,619	64,562	123,663	340,785
-Manufacturing	D	0	152,894	91,040	13,110	294,917
—Food and beverages	10-12	D	7,997	5,512	628	19,512
—Textiles (including apparel)	13-15	D	98	114	0	355
—Wood and furniture	16	D	118	140	0	417
—Paper and printing	17-18	D	202	202	0	565
—Plastics and chemical products	19-22	D	13,802	7,830	1,146	26,374
—–Other chemical products	20-21	19-22	84	90	0	254
—–Rubber and plastic products (non-auto)	22	19-22	9,756	5,097	916	16,700
—Metals	24-28	D	14,745	8,519	1,378	29,297
—–Basic metals	24	24-28	4,071	4,884	0	14,748
—–Metal products (non-automotive)	25	24-28	8,647	2,909	1,378	12,122
—–Electrical and electronics	26-27	24-28	27,228	17,826	1,307	5,2237
—–Industrial machinery	28	24-28	2,022	1,927	0	5,484
—Automotive	29	D	80,947	43,596	8,651	141,855
—–Motor vehicles	291	29	42,838	20,763	4,701	66,486
—–Automotive parts	293	29	38,070	23,236	3,950	75,253
—–Automotive unspecified	299	29	38	52	0	116
—Other vehicles	30	D	435	449	0	1,341
—All other manufacturing branches	91	D	6,894	7,094	0	21,469
-Mining and quarrying	C	0	20	22	0	57
-Construction	F	0	128	126	0	410
-Education, research, and development	P	0	599	624	0	1,854

Table 2. The sensitivity of operating costs to changes in sales and industrial robots

This table reports the coefficient estimates of the following regression specifications:

$$\log[\frac{COSTS_{i,t}}{COSTS_{i,t-1}}] = \beta_0 + \beta_1 * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_2 * Decrease - Dummy_{i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}]$$
$$+ \beta_3 * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \beta_4 * Decrease - Dummy_{i,t} * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \alpha_j + \alpha_t + \epsilon_{j,t}$$

Subscripts i, j, and t denote firm, industry, and year, respectively. $COSTS_{i,t}$ refers to operating costs (sum of COGS and SG&A expenses) incurred by firm i at year t, $SALE_{i,t}$ corresponds to the sales revenue generated by firm i at year t, and $ROBOTS_{j,t}$ refers to the total operational robotics stock of the industry j that firm i belongs to at year t. $Decrease-Dummy_{i,t}$ is a dummy variable that takes a value of 1 if firm i's sales revenue decreases from time period t-1 to t, and 0 otherwise. Industry definitions are based on two-digit SIC grouping. Standard errors that are heteroscedasticity-consistent and clustered at the industry level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from 2005 to 2021.

Dependent variable:	Logarithmic changes in costs			
	(1)	(2)	(3)	(4)
$\hat{\beta}_1$	0.209**	0.216***	0.215***	0.207**
	(0.08)	(0.07)	(0.07)	(0.07)
$\hat{\beta}_2$		-0.015	-0.014	-0.018
		(0.02)	(0.02)	(0.02)
$\hat{\beta}_3$			-0.074***	-0.017
			(0.02)	(0.03)
$\hat{\beta}_4$				-0.150***
				(0.03)
$\hat{\beta}_0$	0.161***	0.157***	0.199***	0.197***
	(0.02)	(0.02)	(0.03)	(0.03)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	20,905	20,905	20,905	20,905
R^2	0.163	0.163	0.164	0.167

Table 3. Summary statistics

This table reports the mean, standard deviation (SD), 10th percentile, 25th percentile, 75th percentile, and 90th percentile for three sets of variables. The first set is automation cost flexibility related variables: the primary automation cost flexibility measure (ACF, estimated through Equations 3 and 4), β_3 (the coefficient on the logarithmic changes in robots in Equation 3), and β_4 (the coefficient on the interaction term between the logarithmic changes in robots and the dummy variable indicating sales-decreasing period). The second set of variables includes operating cost flexibility (OCF, equal to the sum of β_1 and β_2 estimated through Equation 3), β_1, and β_2. The rest of the variables are Tobin's Q and the independent variables that are used as controls to estimate Tobin's Q: size (natural logaritm of total assets), capital expenditures scaled by assets (Capex/at), natural logarithm of firm age (Age), market leverage, cash scaled by assets (cash holdings), R&D expenses divided by the book value of total assets (R&D intensity) , return on equity (Profitability), one-year-growth in sales (Sales growth), the book value of property, plant, equipment, and inventory scaled by the book value of total assets (Fixed asset/total asset), and the natural logarithm of number of employees (LnEmployees).

Variables Automation cost flexibility	Mean	SD	p10	p25	p75	p90
ACF	-0.037	19.213	-5.792	-0.914	0.636	4.957
$\hat{\beta}_3$	-0.705	268.430	-3.795	-0.455	0.665	4.905
$\hat{\beta}_4$	0.341	282.063	-3.470	-0.211	0.236	3.287
Operating cost flexibility						
OCF	0.399	10.127	-1.859	-0.059	1.182	2.570
$\hat{\beta}_1$	0.817	148.649	-1.439	-0.035	1.149	2.330
$\hat{\beta}_2$	1.045	122.610	-3.042	-0.213	0.281	2.960
Other variables						
Tobin's Q	1.886	1.516	0.766	0.997	2.179	3.607
Size	6.089	2.905	2.422	4.251	8.050	9.737
Capex/at	0.060	0.084	0.001	0.010	0.075	0.152
Age	2.883	0.666	1.946	2.303	3.367	3.871
Leverage	0.254	0.256	0.000	0.033	0.391	0.657
Cash holdings	0.173	0.221	0.006	0.028	0.214	0.490
R&D intensity	0.093	0.321	0.000	0.000	0.030	0.273
Profitability	-0.086	3.037	-0.901	-0.216	0.171	0.469
Sales growth	0.489	3.875	-0.430	-0.132	0.218	0.654
Fixed asset/total asset	0.800	0.862	0.039	0.204	1.098	1.598
LnEmployees	6.494	2.628	2.944	4.564	8.455	9.923

Table 4. Firm characteristics sorted on automation cost flexibility

This table sorts firms based on their automation cost flexibility (ACF, estimated through Equations 3 and 4) in every year and assigns them into tercile portfolios. High (low) portfolio is the portfolio of firms with the highest (lowest) ACF. This table reports the time-series average of the mean values of firm-specific characteristics of ACF sorted portfolios including "OCF" operating cost flexibility measure proposed by Chen et al. (2019), "Asset" book value of assets, "Emp" number of employees, "Emp/sale" number of employees divided by sales, "Cash" cash holdings scaled by the book value of assets, "Lev." market leverage, "CapEx/at" capital expenditure divided by the book value of total assets, "Tangibility" the ratio of property, plant, and equipment to book value of total assets, and "Age" a firm's age. The last row (High-Low) report the differences in time-series averages of firm-specific characteristics between firms in extreme (high vs. low) portfolios of automation cost flexibility. *, **, and *** denote significance of the differences at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	ACF	OCF	ASSET	EMP	EMP/SALE
Low	-9.320	0.150	7012	6.249	0.020
Mid	-0.037	0.694	9499	12.716	0.013
High	9.256	0.863	8259	7.879	0.018
High - Low	18.576***	0.713***	1247***	1.630***	-0.003

	(6)	(7)	(8)	(9)	(10)
	CASH	LEV	CAPEX/AT	TANGIBILITY	AGE
Low	0.182	0.259	0.072	0.915	20.484
Mid	0.165	0.238	0.046	0.596	25.587
High	0.172	0.265	0.063	0.889	20.986
High - Low	-0.010**	0.006	-0.009***	-0.026*	0.502**

Table 5. Automation cost flexibility and firm value

This table presents the impact of automation cost flexibility (ACF) on firm value by estimating the following equation:

$$Tobin's\ Q_{\rm it} = \beta_1 \times ACF_{\rm it} + \gamma X_{\rm it} + \alpha_{\rm i} + \alpha_{\rm t} + \epsilon_{\rm it}$$

Subscripts i, and t denote firm, and year, respectively. $\alpha_{\rm i}$ and $\alpha_{\rm t}$ are firm and year fixed effects, respectively. X is a matrix of control variables as described in Section 2. The construction of firm-level ACF measure is provided in Section 3. Operating cost flexibility (OCF) measure is the sum of the time series coefficients (β_1 + β_2) in Equation 3 as introduced by Chen et al. (2019). SLAC is substitutability of labor with automated capital as introduced by Bates et al. (2024). We set SLAC to zero when it is missing for our sample of firms. In columns 5 and 7, HighFlex is a dummy variable which is equal to one if a firm's ACF measure is in the first or second terciles of the yearly sample distribution, and zero otherwise. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ACF	0.001***	0.001***	0.001***	0.001***		0.001***	
	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	
HighFlex					0.034*		0.040**
					(0.02)		(0.02)
OCF		0.000					
		(0.00)					
Ln(change in robots)			-0.019				
			(0.10)				
SLAC				0.006			
				(0.08)			
CapEx/book asset	0.673***	0.673***	0.673***	0.673***	0.677***	0.626***	0.630***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Size	-0.524***	-0.524***	-0.524***	-0.524***	-0.524***	-0.508***	-0.508***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Age	-0.113	-0.114	-0.114	-0.114	(0.11)	(0.12)	(0.12)
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.10)	(0.10)
Leverage	-0.955***	-0.955***	-0.955***	-0.955***	-0.954***	-0.920***	-0.920***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
Cash holdings	0.337***	0.337***	0.337***	0.337***	0.339***	0.423***	0.426***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)
R&D intensity	0.542***	0.542***	0.542***	0.542***	0.544***	0.562***	0.564***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Profitability	0.000	0.001	0.001	0.001	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sales growth	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed asset/total asset	0.040	0.040	0.040	0.040	0.040	0.050	0.050
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LnEmployees	0.186***	0.186***	0.186***	0.186***	0.186***	0.185***	0.184***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,851	12,851	12,851	12,851	12,851	14,124	14,124
R^2	0.865	0.865	0.865	0.865	0.865	0.856	0.856

Table 6. Automation cost flexibility and firm value: Difference-in-differences regression for firm value after significant increase in a firm's ACF measure

This table presents the estimates from the following difference-in-differences regression:

$$Tobin's\ Q_{\mathrm{it}} = \beta_1 \times TreatAfter_{\mathrm{it}} + \gamma X_{\mathrm{it}} + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \epsilon_{\mathrm{it}}$$

Subscripts i, and t denote firm, and year, respectively. α_{i} and α_{t} are firm and year fixed effects, respectively. X is a matrix of control variables as described in Section 2. The sample comprises "treated" and matched firms. TreatAfter is a dummy variable equal to one for treated firms for the five years following the significant increase in their ACF measure. We define the firms that experience significant increase in their ACF measure in a given year as the "treated" firms. We define significant increase in ACF at the firm-level when a firm's ACF is below -5 (close to 10th percentile of ACF measure, Table 3) in year t-1, and it is above +5 (close to 90th percentile of ACF measure, Table 3) in year t. To identify the set of candidate control firms, we rank firms into five categories based on the standard deviation of annual changes in their ACF measures and assign firms in the lowest rank as the set of candidate control firms. Then for each treated firm we choose its nearest neighbor from the group of candidate control firms that operate in the same industry (two-digit SIC code) in the same year. Firms are matched based on minimum Mahalanobis distance across their size (the natural logarithm of total assets), capital expenditure over total asset, age, leverage, cash holding, R&D intensity, profitability, sales growth, fixed asset to total asset, and natural logarithm of number of employees. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q
	(1)
TreatAfter	0.134**
	(0.06)
CapEx/book asset	0.851**
	(0.38)
Size	-0.437***
	(0.07)
Age	-0.075
	(0.14)
Leverage	-0.692***
	(0.16)
Cash holdings	0.956***
	(0.23)
R&D intensity	0.419***
	(0.12)
Profitability	-0.008
	(0.01)
Sales growth	0.002
	(0.00)
Fixed asset/total asset	-0.005
	(0.07)
LnEmployees	0.104**
	(0.04)
Firm F.E.	Yes
Year F.E.	Yes

Table 7. The impact of the 2011 Thailand hard drive crisis

This table presents the impact of the 2011 Thailand hard drive crisis. The construction of firm-level ACF measure is provided in Section 3. Flooding is defined using two different alternatives. Specifically, Flooding is a dummy variable which is equal to one in year 2011, and zero otherwise (columns 1 and 3). Alternatively, following Bates et al. (2024), Flooding is equal to one for firms in industries with higher probability of computerization (based on median value), estimated by Osborne and Frey (2013); Frey and Osborne (2017) based on occupational characteristics and technological developments, in year 2011 and zero otherwise (columns 2 and 4). In columns 3 and 4, firm-level ACF measure is fixed to 2009 value for years between 2005 to 2009. The detailed definitions of control variables are provided in Section 2. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q			
	(1)	(2)	(3)	(4)
ACF	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Flooding	0.020	-0.080	-0.061	-0.135**
	(0.04)	(0.06)	(0.06)	(0.06)
Flooding x ACF	-0.003*	-0.010**	-0.003**	-0.011**
	(0.00)	(0.05)	(0.00)	(0.05)
CapEx/book asset	0.672***	0.673***	0.625***	0.627***
	(0.17)	(0.17)	(0.17)	(0.17)
Size	-0.524***	-0.525***	-0.508***	-0.508***
	(0.05)	(0.05)	(0.05)	(0.05)
Age	-0.114	-0.112	-0.12	-0.119
	(0.12)	(0.12)	(0.10)	(0.10)
Leverage	-0.956***	-0.955***	-0.921***	-0.919***
	(0.08)	(0.08)	(0.07)	(0.07)
Cash holdings	0.336***	0.337***	0.422***	0.423***
	(0.12)	(0.12)	(0.11)	(0.11)
R&D intensity	0.542***	0.542***	0.562***	0.562***
	(0.08)	(0.08)	(0.08)	(0.08)
Profitability	0.001	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Sales growth	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Fixed asset/total asset	0.040	0.040	0.050	0.050
	(0.04)	(0.04)	(0.04)	(0.04)
LnEmployees	0.186***	0.186***	0.185***	0.185***
	(0.03)	(0.03)	(0.02)	(0.02)
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	12,851	12,851	14,124	14,124
R^2	0.865	0.865	0.856	0.856

Table 8. The 2011 Thailand hard drive crisis: Dynamics

This table presents the dynamic effect of the 2011 Thailand hard drive crisis. The construction of firm-level ACF measure is provided in Section 3. Before$^{-1 \text{ to } -3}$ is a dummy variable equal to one if it is 1 to 3 years before the Thailand shock (years 2010, 2009, and 2008), Current^{0} is a dummy variable equal to one for the year 2011 indicating the Thailand flooding, and After$^{1 \text{ to } 2}$ is equal to one if it is 1 or 2 years after the Thailand shock (years 2012, and 2013). In columns 2 and 4, following Bates et al. (2024), Before$^{-1 \text{ to } -3}$, Current^{0}, and After$^{1 \text{ to } 2}$ dummy variables are equal to one for the same years for firms in industries with higher probability of computerization (based on median value), estimated by Osborne and Frey (2013); Frey and Osborne (2017) based on occupational characteristics and technological developments, and zero otherwise. In columns 3 and 4, firm-level ACF measure is fixed to 2009 value for years between 2005 to 2009. The detailed definitions of control variables are provided in Section 2. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q			
	(1)	(2)	(3)	(4)
ACF	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Before$^{-1 \text{ to } -3}$	-0.032***	-0.004	0.011*	-0.001
	(0.09)	(0.10)	(0.06)	(0.08)
Current^{0}	-0.030***	-0.009	-0.006	-0.014**
	(0.08)	(0.07)	(0.06)	(0.07)
After$^{1 \text{ to } 2}$	-0.019***	-0.003	0.005	-0.004
	(0.06)	(0.05)	(0.07)	(0.05)
Before$^{-1 \text{ to } -3}$ x ACF	-0.003	0.005	-0.002	0.016
	(0.00)	(0.01)	(0.00)	(0.02)
Current^{0} x ACF	-0.003**	-0.010**	-0.003**	-0.011**
	(0.00)	(0.05)	(0.00)	(0.05)
After$^{1 \text{ to } 2}$ x ACF	-0.001	0.001	-0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	12,851	12,851	14,124	14,124
R^2	0.866	0.865	0.856	0.856

Table 9. The cross-sectional variation in the impact of automation cost flexibility on firm value

This table reports estimates of ACF from a series estimation of Equation 5, and presents how industry competition, product market fluidity, market leadership turnover, firm size, and firm's market share are related to the impact of automation cost flexibility on firm value. The construction of firm-level ACF measure is provided in Section 3. In column 1, sample firms are split into two subsamples based on the annual median value of industry concentration in a given year. Industry concentration is measured by HHI (Herfindahl- Hirschman index), which is computed as the sum of squared market shares of all firms in a given two-digit SIC industry. Market shares are computed based on firms' sales. In column 2, firms that are in the lowest tercile of the yearly sample distribution based on fluidity measure are compared to those in higher terciles. Product market fluidity measure is from Hoberg et al. (2014). In column 3, firms are divided based on market leadership turnover indicator. Market leadership turnover rate is defined as high if any of the largest four firms ranked by sales in the two-digit SIC industry in year t+1 is none of the four largest firms in year t. In columns 4 and 5, firms that are in the highest quartile of the yearly sample distribution based on size and market share are compared to those in the lower quartiles, respectively. Firm size is defined as total assets. Firm's market share is defined as the ratio of firm's sales to total industry sales at the two-digit SIC level. The detailed definitions of control variables are provided in Section 2. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. The p-values for the difference between coefficient estimates are calculated using seemingly unrelated regressions. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q				
	Competition	Fluidity	Market turnover	Size	Market share
	(1)	(2)	(3)	(4)	(5)
Subsample 1	Competitive	High	High	Small	Low
ACF	0.002***	0.001**	0.003**	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	7,374	4,123	4,925	7,236	6,956
R^2	0.870	0.793	0.887	0.864	0.862
Subsample 2	Non-competitive	Low	Low	Big	High
ACF	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	5,477	3,085	7,926	5,615	5,895
R^2	0.844	0.860	0.890	0.874	0.854
p-value of difference	0.025	0.034	0.004	0.054	0.021
Controls	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes

Internet Appendix

Automation Cost Flexibility and Firm Value

Table IA.1. The sensitivity of operating costs to changes in sales and industrial robots: Manufacturing firms

This table reports the coefficient estimates of the following regression specifications as in Table 2 for firms in manufacturing industries (SIC codes between 2000-3999):

$$\log[\frac{COSTS_{i,t}}{COSTS_{i,t-1}}] = \beta_0 + \beta_1 * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_2 * Decrease - Dummy_{i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}]$$
$$+ \beta_3 * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \beta_4 * Decrease - Dummy_{i,t} * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \epsilon_{j,t}$$

Subscripts i, j, and t denote firm, industry, and year, respectively. $COSTS_{i,t}$ refers to operating costs (sum of COGS and SG&A expenses) incurred by firm i at year t, $SALE_{i,t}$ corresponds to the sales revenue generated by firm i at year t, and $ROBOTS_{j,t}$ refers to the total operational robotics stock of the industry j that firm i belongs to at year t. $Decrease - Dummy_{i,t}$ is a dummy variable that takes a value of 1 if firm i's sales revenue decreases from time period t-1 to t, and 0 otherwise. Industry definitions are based on two-digit SIC grouping. Standard errors that are heteroscedasticity-consistent and clustered at the industry level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from 2005 to 2021.

Dependent variable:	Logarithmic changes in costs			
	(1)	(2)	(3)	(4)
$\hat{\beta}_1$	0.128**	0.146***	0.146***	0.138***
	(0.04)	(0.04)	(0.04)	(0.04)
$\hat{\beta}_2$		-0.043**	-0.042**	-0.048***
		(0.01)	(0.01)	(0.01)
$\hat{\beta}_3$			-0.061*	-0.004
			(0.03)	(0.03)
$\hat{\beta}_4$				-0.162***
				(0.02)
$\hat{\beta}_0$	0.146***	0.137***	0.182***	0.182***
	(0.02)	(0.02)	(0.02)	(0.02)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	12,327	12,327	12,327	12,327
R^2	0.147	0.149	0.150	0.159

Table IA.2. The sensitivity of COGS, SG&A expenses and Employment to changes in industrial robots

This table presents the sensitivity of COGS, SG&A expenses and employment to the changes in industrial robots by estimating the following regression specifications as in Table 2:

$$\log[\frac{y_{i,t}}{y_{i,t-1}}] = \beta_0 + \beta_1 * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_2 * Decrease - Dummy_{i,t} * \log[\frac{SALE_{i,t}}{SALE_{i,t-1}}] + \beta_3 * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \beta_4 * Decrease - Dummy_{i,t} * \log[\frac{ROBOTS_{j,t}}{ROBOTS_{j,t-1}}] + \epsilon_{j,t}$$

The dependent variable y in the equation is COGS, SG&A expenses and employment of firm i in Panels A, B, and C, respectively. $SALE_{j(i),t}$ corresponds to the sales revenue generated by firm i at year t, and $ROBOTS_{j,t}$ refers to the total operational robotics stock of the industry j that firm i belongs to at year t. $Decrease - Dummy_{i,t}$ is a dummy variable that takes a value of 1 if firm i's sales revenue decreases from time period t-1 to t, and 0 otherwise. Industry definitions are based on two-digit SIC grouping. Standard errors that are heteroscedasticity-consistent and clustered at the industry level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from 2005 to 2021.

Dependent variable:												
	Panel A: Log changes in COGS				Panel B: Log changes in SG&A				Panel C: Log changes in employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{\beta}_1$	0.294**	0.299**	0.299**	0.289*	0.188***	0.207***	0.207***	0.196***	0.132***	0.136***	0.135***	0.130***
	(0.13)	(0.14)	(0.14)	(0.14)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
$\hat{\beta}_2$		-0.012	-0.012	-0.017		-0.043**	-0.042**	-0.045**		-0.008	-0.007	-0.009
		(0.03)	(0.03)	(0.03)		(0.02)	(0.02)	(0.02)		(0.02)	(0.02)	(0.02)
$\hat{\beta}_3$			-0.046*	0.015			-0.067***	-0.022			-0.033***	-0.016
			(0.03)	(0.02)			(0.02)	(0.02)			(0.01)	(0.01)
$\hat{\beta}_4$				-0.164***				-0.147***				-0.049***
				(0.04)				(0.05)				(0.01)
$\hat{\beta}_0$	0.147***	0.144***	0.170***	0.167***	0.149***	0.139***	0.178***	0.180***	0.080***	0.078***	0.112***	0.110***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.01)	(0.02)	(0.01)	(0.01)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,675	20,675	20,675	20,675	17,423	17,423	17,423	17,423	20,391	20,391	20,391	20,391
R^2	0.103	0.103	0.103	0.105	0.137	0.138	0.139	0.144	0.093	0.093	0.095	0.097

Table IA.3. Automation cost flexibility and firm value: Manufacturing firms

This table presents the impact of automation cost flexibility (ACF) on firm value by estimating the following equation as in Table 5 for firms in manufacturing industries (SIC codes between 2000-3999):

$$Tobin's\ Q_{\mathrm{it}} = \beta_1 \times ACF_{\mathrm{it}} + \gamma X_{\mathrm{it}} + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \epsilon_{\mathrm{it}}$$

Subscripts i, and t denote firm, and year, respectively. α_{i} and α_{t} are firm and year fixed effects, respectively. X is a matrix of control variables as described in Section 2. The construction of firm-level ACF measure is provided in Section 3. Operating cost flexibility (OCF) measure is the sum of the time series coefficients (β_1 + β_2) in Equation 3 as introduced by Chen et al. (2019). SLAC is substitutability of labor with automated capital as introduced by Bates et al. (2024). In columns 5 and 7, HighFlex is a dummy variable which is equal to one if a firm's ACF measure is in the first or second terciles of the yearly sample distribution, and zero otherwise. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ACF	0.002***	0.003***	0.002***	0.002***		0.003***	
	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	
HighFlex					0.050*		0.052**
					(0.03)		(0.03)
OCF		0.001					
		(0.00)					
Ln(change in robots)			-0.307***				
			(0.11)				
SLAC				0.070			
				(0.10)			
CapEx/book asset	1.084***	1.087***	1.074***	1.090***	1.108***	0.779**	0.789**
	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.34)	(0.34)
Size	-0.424***	-0.424***	-0.425***	-0.424***	-0.425***	-0.399***	-0.401***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Age	-0.119	-0.120	-0.121	-0.128	-0.112	-0.053	-0.050
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.12)	(0.12)
Leverage	-1.449***	-1.449***	-1.453***	-1.449***	-1.451***	-1.368***	-1.369***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)
Cash holdings	0.137	0.137	0.134	0.138	0.140	0.200	0.200
	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)
R&D intensity	0.637***	0.638***	0.636***	0.639***	0.639***	0.645***	0.647***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Profitability	0.000	0.000	-0.001	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sales growth	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed asset/total asset	0.004	0.004	0.006	0.002	0.000	0.040	0.040
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
LnEmployees	0.151***	0.151***	0.152***	0.150***	0.151***	0.148***	0.148***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,575	7,575	7,575	7,575	7,575	8,273	8,273
R^2	0.863	0.863	0.863	0.863	0.862	0.859	0.859

Table IA.4. The impact of the 2011 Thailand hard drive crisis: Manufacturing firms

This table presents the impact of the 2011 Thailand hard drive crisis as in Table 6 for manufacturing firms. The construction of firm-level ACF measure is provided in Section 3. Flooding is defined using two different alternatives. Specifically, Flooding is a dummy variable which is equal to one in year 2011, and zero otherwise (columns 1 and 3). Alternatively, following Bates et al. (2024), Flooding is equal to one for firms in the top tercile of industries based on the probability of computerization, estimated by Frey and Osborne (2013, 2017) based on occupational characteristics and technological developments, in year 2011 and zero otherwise (columns 2 and 4). In columns 3 and 4, firm-level ACF measure is fixed to 2009 value for years between 2005 to 2009. The detailed definitions of control variables are provided in Section 2. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q			
	(1)	(2)	(3)	(4)
ACF	0.003***	0.002***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
Flooding	-0.006	-0.121	-0.089	-0.127
	(0.04)	(0.14)	(0.06)	(0.11)
Flooding x ACF	-0.006***	-0.269***	-0.006***	-0.330***
	(0.00)	(0.08)	(0.00)	(0.06)
CapEx/book asset	1.080***	1.093***	0.778**	0.789**
	(0.38)	(0.38)	(0.34)	(0.34)
Size	-0.424***	-0.424***	-0.400***	-0.400***
	(0.05)	(0.05)	(0.05)	(0.05)
Age	-0.117	-0.117	-0.052	-0.052
	(0.16)	(0.16)	(0.12)	(0.12)
Leverage	-1.451***	-1.449***	-1.369***	-1.368***
	(0.12)	(0.12)	(0.11)	(0.11)
Cash holdings	0.138	0.136	0.202	0.200
	(0.13)	(0.13)	(0.13)	(0.13)
R&D intensity	0.637***	0.637***	0.645***	0.645***
	(0.08)	(0.08)	(0.08)	(0.08)
Profitability	0.000	0.000	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Sales growth	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Fixed asset/total asset	0.000	0.000	0.040	0.040
	(0.07)	(0.07)	(0.06)	(0.06)
LnEmployees	0.152***	0.152***	0.148***	0.148***
	(0.04)	(0.04)	(0.03)	(0.03)
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	7,575	7,575	8,273	8,273
R^2	0.863	0.863	0.859	0.859

Table IA.5. Dynamic impact of the 2011 Thailand hard drive crisis: Manufacturing firms

This table presents the dynamic effect of the 2011 Thailand hard drive crisis as in Table 7 for manufacturing firms. The construction of firm-level ACF measure is provided in Section 3. $\text{Before}^{\text{-1 to -3}}$ is a dummy variable equal to one if it is 1 to 3 years before the Thailand shock (years 2010, 2009, and 2008), Current^{0} is a dummy variable equal to one for the year 2011 indicating the Thailand flooding, and $\text{After}^{\text{1 to 2}}$ is equal to one if it is 1 or 2 years after the Thailand shock (years 2012, and 2013). In columns 2 and 4, following Bates et al. (2024), $\text{Before}^{\text{-1 to -3}}$, Current^{0}, and $\text{After}^{\text{1 to 2}}$ dummy variables are equal to one for the same years for firms in the top tercile of industries based on the probability of computerization, estimated by Frey and Osborne (2013, 2017) based on occupational characteristics and technological developments, and zero otherwise. In columns 3 and 4, firm-level ACF measure is fixed to 2009 value for years between 2005 to 2009. The detailed definitions of control variables are provided in Section 2. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q			
	(1)	(2)	(3)	(4)
ACF	0.003***	0.003***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
$\text{Before}^{\text{-1 to -3}}$	-0.358***	-0.004	-0.063	-0.151
	(0.10)	(0.31)	(0.06)	(0.19)
Current^{0}	-0.363***	-0.142	-0.089	-0.177
	(0.09)	(0.16)	(0.06)	(0.11)
$\text{After}^{\text{1 to 2}}$	-0.159**	-0.02	0.124	-0.016
	(0.08)	(0.07)	(0.08)	(0.07)
$\text{Before}^{\text{-1 to -3}}$ x ACF	-0.001	0.308	-0.002	0.029
	(0.00)	(0.33)	(0.00)	(0.20)
Current^{0} x ACF	-0.006***	-0.233***	-0.006***	-0.332***
	(0.00)	(0.07)	(0.00)	(0.04)
$\text{After}^{\text{1 to 2}}$ x ACF	-0.001	-0.005***	-0.001	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	7,575	7,575	8,273	8,273
R^2	0.863	0.863	0.859	0.859

Table IA.6. The cross-sectional variation in the impact of automation cost flexibility on firm value: Manufacturing firms

This table reports estimates of ACF from a series estimation of Equation 5, and presents how industry competition, product market fluidity, market leadership turnover, firm size, and firm's market share are related to the impact of automation flexibility on firm value as in Table 8 for manufacturing firms. The construction of firm-level ACF measure is provided in Section 3. In column 1, sample firms are split into two subsamples based on the annual median value of industry concentration in a given year. Industry concentration is measured by HHI (Herfindahl- Hirschman index), which is computed as the sum of squared market shares of all firms in a given two-digit SIC industry. Market shares are computed based on firms' sales. In column 2, firms that are in the lowest tercile of the yearly sample distribution based on fluidity measure are compared to those in higher terciles. Product market fluidity measure is from Hoberg et al. (2014). In column 3, firms are divided based on market leadership turnover indicator. Market leadership turnover rate is defined as high if any of the largest four firms ranked by sales in the two-digit SIC industry in year t+1 is none of the four largest firms in year t. In columns 4 and 5, firms that are in the highest quartile of the yearly sample distribution based on size and market share are compared to those in the lower quartiles, respectively. Firm size is defined as total assets. Firm's market share is defined as the ratio of firm's sales to total industry sales at the two-digit SIC level. The detailed definitions of control variables are provided in Section 2. All continuous variables are winsorized at the 0.5% level. Standard errors that are heteroscedasticity-consistent and clustered at the firm level are reported in parentheses beneath coefficient estimates. The p-values for the difference between coefficient estimates are calculated using seemingly unrelated regressions. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent variable:	Tobin's Q				
	Competition	Fluidity	Market turnover	Size	Market share
	(1)	(2)	(3)	(4)	(5)
Subsample 1	Competitive	High	High	Small	Low
ACF	0.003***	0.003***	0.005***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	3,881	2,790	3,050	3,760	4,485
R^2	0.840	0.758	0.878	0.855	0.850
Subsample 2	Non-competitive	Low	Low	Big	High
ACF	0.001	-0.001*	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	3,694	2,369	4,525	3,815	3,090
R^2	0.894	0.875	0.897	0.882	0.884
p-value of difference	0.046	0.001	0.002	0.021	0.023
Other controls	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes