Automation Exposure and Investment Efficiency

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*Corresponding author. We appreciate helpful comments from Junhong Yang, Chao Yin, and the seminar participants from Durham University. The financial support from Durham University Business School, Hunan University, and Central South University is gratefully acknowledged. All errors are our own.

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Abstract

This paper investigates the effect of automation exposure on firms' investment efficiency. Using a sample of U.S. public firms spanning the period 1980–2020, we document a negative effect of automation exposure on both investment-cash flow sensitivity and investment-price sensitivity. Our main finding remains robust after accounting for a range of potential endogeneity concerns. The negative effect on investment-cash flow sensitivity is more pronounced among firms with financial constraints, while the negative effect on investment-price sensitivity is stronger for firms with higher stock price informativeness and more managerial incentives to learn from the market. Overall, our study highlights to the important role of automation technologies in shaping corporate activities.

JEL Classifications: G11, G14, G31, M52

Keywords: Automation, Investment-cash flow sensitivity, Investment-price sensitivity, Financial Constraints, Price informativeness

1. Introduction

Within the realm of economics, automation is commonly conceptualized as a labor-saving technological advancement that executes processes or procedures with minimal human intervention. Over the last two decades, there has been a remarkable advancement in artificial intelligence which that streamlines production processes, subsequently diminishing the necessity for human labor in particular tasks.[1] Moreover, the impact of automation has extended to diverse industries, rendering even non-routine soft skills redundant due to advancements in computing power utilized for artificial intelligence, machine learning, and data analytics. As automation continues its ascendancy, existing literature has explored the influence of automation exposure on various aspects of firms' operations, including employment (Zator, 2019; Acemoglu and Restrepo, 2020), workforce composition (Acemoglu and Autor, 2011; Autor and Dorn, 2013), wages (Arnoud, 2018; Acemoglu and Restrepo, 2019; Leduc and Liu, 2019; Acemoglu and Restrepo, 2020), productivity (Graetz and Michaels, 2017), and financial leverage (Qiu et al., 2020). In this paper, we examine if automation exposure affects corporate investment decisions through the lenses of investment-cash flow sensitivity and investment-price sensitivity.

The importance of investment-cash flow and investment-price sensitivity lies in their ability to provide insights into a firm's investment efficiency. These two sensitivities offer valuable perspectives on how firms allocate their capital resources in response to various

[1] The International Federation of Robotics (IFR) reports that there are about 2.7 million industrial robots operational worldwide in 2020, while there are 255 pieces of industrial robots for per 10000 workers in the U.S, both reaching a record level. which reaches a record level. In the U.S., there are 255 pieces of industrial robots for per 10000 workers.

economic shocks. Specifically, investment-cash flow sensitivity measures the reliance of a firm's investment on its internal cash flow, indicating the extent to which a firm uses its own generated funds to finance new projects rather than relying on external financing sources. Investment-price sensitivity measures the responsiveness of a firm's investment to stock prices, reflecting how managers learn information from market valuation and make their investment decisions accordingly.

We posit that automation exposure is negatively associated with investment-cash flow sensitivity. Previous studies suggest that employment protection mechanisms, such as labor unions and employment protection laws, exert a discernible impact on firms' financial constraints (e.g., Matsa, 2010; Chen et al., 2012; Alimov, 2015). Chen et al. (2011a) highlights how labor unions foster wage rigidity and stringent layoff practices, subsequently heightening firms' adjustment costs and operational leverage. Employment protection laws also amplify the cost of workforce reduction, contributing to increased operational leverage (e.g., Simintzi et al., 2015; Beuselinck et al., 2021). Serfling (2016) and Bai et al. (2020) extend these findings by demonstrating the crowding-out effect of operational leverage on financial leverage, effectively compressing debt capacity. In addition, workers' claims take precedence over debt creditors during firm bankruptcy, which further increases firms' external financial costs (Campello et al., 2018; Blaylock et al., 2015).

Automation technologies help mitigate the financial constraints stemming from employment protection. Through automation's potential for workforce replacement, bargaining power shifts from labor unions and workers to management, which in turn reduces wage rigidities (Arnoud, 2018; Leduc and Liu, 2019). Automation also reduces labor adjustment costs since comparing to laying off workers, firms do not need to make redundancy pay when retiring automated machines. As financial constraints decrease, firms rely less on internal cash flow to respond to their investment opportunities, thus resulting in lower investment-cash flow sensitivity.

Furthermore, we expect that automation technologies have a negative impact on investment-price sensitivity. Acknowledging the reality of diverse skill levels among workers (Ghalya et al., 2017), it is difficult for outsiders to evaluate a firm's human capital. The worker heterogeneity creates uncertainty in predicting firms' future output and performance, contributing to an information asymmetry between firms and external investors who lack insights in worker differentiation.

The adoption of automation technologies can mitigate the information asymmetry due to work heterogeneity. First, automation reduces uncertainty in workers' productivity, enhancing the quality of information available to investors. Additionally, automation facilitates information comparability among peer firms, enabling better accuracy of predicting firm future performance. The improved information transparency may diminish the advantages held by informed traders, potentially dissuading their participation and encouraging noise traders (e.g., Shi et al., 2016; Jayaraman and Wu, 2019). As informed trades are crowded out by noisy trades, stock price informativeness will decrease, leading to a decline in investment-price sensitivity (Chen et al., 2007; Edmans et al., 2017).

To explore the impact of automation exposure on investment efficiency, we use a sample of U.S. public firms between 1980 and 2020. Employing the methodology of Qiu et al. (2020) and Mann and Püttmann (2021), we quantify firm-level automation exposure using patent text analyses. Our baseline regression analyses confirm a negative relation between automation and both investment-cash flow sensitivity and investment-price sensitivity. A one standard deviation increase in automation exposure corresponds to a 16.67% decrease in investment-cash flow sensitivity and a 14.96% decrease in investment-price sensitivity for an average firm in our sample.

To address the potential endogeneity issues in our empirical tests, we first employ a two-stage least squares (2SLS) regression with the robotics adoption in European countries as an instrument variable (IV). Second, we adopt propensity score matching (PSM) and entropy balancing (EB) matching approaches to identify firm-year observations with high and low automation exposures, which are indistinguishable on observed firm characteristics. Third, we add additional control variables into our baseline regression to control for leverage, cash holding, collateral, return on assets, non-automation technologies, and chemical and pharmaceutical technologies. Fourth, we estimate our baseline regression with various combinations of high-dimensional fixed effects. Our main findings remain robust in these identification tests.

To examine the underlying mechanisms of automation's influence on investment efficiency, we explore the financial constraints and price informativeness channels. First, we show that the observed negative impact of automation exposure on investment-cash flow sensitivity is more pronounced for firms with higher financial constraints, while the effect of automation exposure on investment-price sensitivity does not exhibit cross-sectional variations with respect to financial constraints. Second, we find that the negative relation between automation exposure on investment-price flow sensitivity is stronger for firms with a higher level of stock price informativeness and with more managerial incentive to learn from the market, while the empirical relation between automation exposure and investment-cash flow sensitivity does not vary with respect to stock price informativeness and managerial learning incentive.

Our study makes two contributions to the literature. First, we provide novel evidence regarding the impact of automation exposure on corporate investment. While previous literature has explored how automation influences various aspects of firm operations such as employment, worker structure, wages, productivity, and leverage (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Graetz and Michaels, 2017; Arnoud, 2018; Zator, 2019; Acemoglu and Restrepo, 2020; Qiu et al., 2020), few studies have delved into the research of corporate investment. Our findings highlight the role of automation technologies in affecting investment efficiency.

Second, our study augments the literature on how firms' investment reacts to the changes in internal cash flow and stock prices. Prior studies have explored a range of factors influencing investment-cash flow sensitivity, including financial constraints, information asymmetry, and labor unions (Fazzari et al., 1987; Ascioglu et al., 2008; Chen and Chen, 2013; Chowdhury et al., 2016). Our findings highlight that automation can mitigate the financial constraints exerted by employment protection mechanisms. Consequently, as firms experience reduced financial constraints, investment-cash flow sensitivity decreases. Earlier studies have also examined numerous factors affecting investment-price sensitivity, including stock price informativeness (Chen et al., 2007), control-ownership dynamics (Jiang et al., 2011), cross-listing (Foucault and Fresard, 2012), and mandatory disclosure (Jayaraman and Wu, 2019), among others. In alignment with this strand of literature, our paper highlights that automation reduces investment-price sensitivity by crowding out informed trades.

The remainder of our paper is organized as follows. Section 2 discusses the related literature and hypothesis development. Section 3 introduces the data, variable definitions, and empirical test design. Section 4 reports the results of empirical tests. Section 5 concludes.

2. Related literature and hypotheses

2.1. Related literature

2.1.1. Automation

The far-reaching impact of automation technologies extends across various dimensions of firms' operations. First, the adoption of automation technologies triggers a two-fold impact on labor employment. On one hand, firms with automation technologies tend to have less labor-intensive job openings, leading to a decrease in labor employment—a phenomenon referred to as the replace effect. On the other hand, automation technologies enhance firms' overall productivity by optimizing the allocation of various factor inputs, thereby increasing the demand for higher-skilled labor positions—known as the productivity effect. The net influence of automation on labor employment hinges on the interplay between these two effects. Empirical evidence suggests that the replace effect tends to dominate the productivity effect. Acemoglu and Restrepo (2020) find that introducing one robot per thousand workers results in a reduction of the local employment ratio by 0.39%. Graetz and Michaels (2017) unveil that automation adoption fosters an annual productivity growth of approximately 0.36%, albeit at the cost of decreasing low-skilled employment in labor structures. Zator (2019) also shows that automation adoption not only curtails employment but also augments productivity.

Second, the adoption of automation technologies exerts downward pressure on workers' wages. Arnoud (2018) illustrates how the automation threat redistributes bargaining power from workers to management, encouraging workers to accept lower wages during compensation negotiations. Acemoglu and Restrepo (2020) also find that the introduction of one robot per thousand workers leads to a wage reduction of 0.42%.

Third, the shifting bargaining power from labor unions and workers to firm management, a consequence of the threat of replacing labor with automation (Leduc and Liu, 2019; Arnoud, 2018), has a positive effect on firms' financial leverage. On one hand, the ability of firms to threaten labor replacement with automation weakens workers' capacity to negotiate higher wages, leading to wage compression. On the other hand, existing labor protections—such as labor unions, minimum wage regulations, and employment protection laws—hinder firms' flexibility in adjusting wages and initiating layoffs (Atanassov and Kim 2009; Chen et al., 2011a; Kuzmina 2013; Simintzi et al., 2015; Serfling 2016). With the balance of bargaining power tilting towards firms, wage rigidity decreases, which enables firms to enhance their financial leverage. Qiu et al. (2020) provide empirical evidence that a one-standard-deviation increase in automation exposure corresponds to a 1.3% increase in firms' financial leverage.

2.1.2. Investment-cash flow sensitivity

Due to the information asymmetry between managers and investors, investors demand a premium to compensate for the associated agency risks, resulting in higher costs for external financing compared to internal financing. Myers and Majluf (1984) introduce the peckingorder theory, indicating that firms prioritize internal cash over external financing. As a result, there exists a positive correlation between firms' investment and cash flow (Campbell et al., 2012; Mulier et al., 2016).

As financial constraints intensify, firms experience higher external financing costs, resulting in a heightened reliance on internal funds and subsequently increasing investment-cash flow sensitivity. Fazzari et al. (1987) find that cash flow exerts a more pronounced influence on investment for financially constrained firms. Drawing from data on unlisted SMEs across six European countries, Mulier et al. (2016) also find that the most financially constrained firms exhibit the highest investment-cash flow sensitivity. Ağca and Mozumdar (2017) further confirm the importance of cash flow as a significant determinant of investment. They also show that investment-cash flow sensitivity is more pronounced for firms with more financial constraints.

2.1.3. Investment-price sensitivity

Market participants engage in stock trading on the secondary market, thereby causing stock prices to amalgamate information from various sources including corporate managers, informed traders, and noisy traders. The Efficient Market Hypothesis suggests that financial markets are highly efficient in processing and reflecting all available information into asset prices. However, Bond et al. (2012) challenge this notion, asserting that price efficiency might not truly align with managerial efficiency. They argue that genuine efficiency is measured by the extent to which stock prices disclose necessary information for managers to enact actions that maximize firm value. For example, high price efficiency does not guarantee useful managerial insights if stock prices incorporate minimal information from informed traders. In such cases, managers may garner insufficient new information to guide their investment decisions. Consequently, Bond et al. (2012) distinguish between forecasting price efficiency (FPE) and revelatory price efficiency (RPE). FPE reflects the overall volume of information contained within stock prices, while RPE quantifies the quantity of novel information that managers do not know.

Bond et al. (2012) illustrate two channels through which stock prices may affect firm investment. The first one is the learning channel. While managers possess more information about their firms than investors, they only possess a fraction of the necessary information required to make well-informed investment decisions. Informed traders, who hold private information that is unknown to managers but can help managers make better investment decisions, engage in stock trading and integrate their private information into prices, thereby enhancing RPE. Therefore, managers can learn the private information from stock prices to guide their investment decisions. The second one is the incentives channel. Even if managers do not actively derive information from stock prices, their incentives to take real actions still depend on those prices. This is because managers' compensation is intricately linked to their firms' stock prices. When stock prices do not reflect fundamental value but are instead influenced by random fluctuations, managers possess limited incentives to maximize firm value through investment.

Previous studies suggest that informed trading is positively related to stock price informativeness, and in turn strengthens investment-price sensitivity. Using price non-synchronicity and the probability of informed trading (PIN) as proxies for stock price informativeness, Chen et al. (2007) document a positive relation between stock price informativeness and investment-price sensitivity. Similarly, Bai et al. (2016) find that investment-price sensitivity is higher when stock prices contain more private information from informed traders. Jayaraman and Wu (2019) argue that managers glean insights about firms' future growth opportunities from the information embedded within stock prices, which increases firms’ investment efficiency. Edmans et al. (2017) add another facet by highlighting the source of information. They demonstrate that an increase in outsiders' information, even without a corresponding increase in total information, improves investment-price sensitivity.

2.2. Hypotheses

2.2.1. Financial constraints hypothesis

Previous studies show that employment protection driven by labor unions and employment protection laws increase firms’ external financing costs, even resulting in financial constraints (Matsa, 2010; Chen et al., 2011a; Chen et al., 2012; Alimov, 2015). Chen et al. (2011b) argue that stronger labor unions lead to lower operating cash flow and return on assets, thereby increasing credit risk and bond yield spreads. Their empirical findings indicate a significantly positive relation between the strength of labor unions and bond yield spreads. Campello et al. (2018) also provide evidence that the presence of labor unions leads to lower bond prices. Employment protection enables workers to share more firm value, especially during bankruptcy liquidation processes. In bankruptcy liquidation proceedings, workers' claims hold priority over those of unsecured and secured creditors under Chapter 7 rules. Therefore, investors demand higher premium for firms with better employment protection (Blaylock et al., 2015; Campello et al., 2018). Alimov (2015) finds that enhanced employment protection laws are associated with larger loan spreads, more rigid non-price loan contract clauses, and more dispersed loan ownership structures.

In addition, workers' wages and benefits are recorded as costs on balance sheets, contributing to increased operating leverage. Bai et al. (2020) and Serfling (2016) indicate that operating leverage stemming from worker compensations reduces financial leverage and squeezes debt capacity. Previous studies also suggest that firms in labor intensive industries often adopt conservative financial policies due to concerns about financial constraints. Beuselinck et al. (2021) illustrate that employment protection increases the adjustment costs of hiring and firing workers and in turn firms reserve more cash to improve liquidity management.

The adoption of automation technologies reduces firms' dependence on labor inputs in their operations. First, the adoption of automated technology curtails labor unions' negotiating power by replacing workers (Qiu et al., 2020). This shift in bargaining power from labor unions and workers to firm management reduces wage rigidity and enhances operational flexibility (Arnoud, 2018; Leduc and Liu, 2019). Second, the adoption of automation machinery reduces the adjustment costs associated with worker layoffs. The costs of automated machinery are accounted for on the balance sheet as depreciation and amortization items. Even when these machines are eventually scrapped, firms do not incur redundancy payments as they would with worker layoffs. Therefore, automation technologies minimize investment adjustment costs by lowering operational expenses.

Based on the aforementioned studies, automation technologies can alleviate financial constraints by mitigating the impact of worker-related pressures on firms, and in turn encourage creditors to offer more funding to firms with automation exposures. With better access to external financing, firms have a lower reliance on internal cash flow and respond to investment opportunities with less financial constraint, which weakens investment-cash flow sensitivity. Therefore, we propose the following two hypotheses regarding the impact of automation exposure on investment-cash flow sensitivity:

HYPOTHESIS 1. Automation exposure has a negative effect on investment-cash flow sensitivity.

HYPOTHESIS 2. The negative effect of automation exposure on investment-cash flow sensitivity is stronger among firms with more financial constraints.

2.2.2. Informed trading hypothesis

Human capital encompasses the skills, knowledge, and expertise that individuals bring to their roles within organizations. Workers, being a heterogeneous productive factor, exhibit variations primarily attributed to differences in skill levels and expertise (Ghalya et al., 2017). Belo et al. (2017) show that workers with diverse skills assume distinct roles in firms' production processes, yielding varied contributions to firms' value and output. However, this heterogeneity among workers remains opaque to outside investors, posing a challenge in accurately forecasting a firm's output and performance.

The adoption of automation technologies can alleviate information asymmetry between firms and investors by reducing worker heterogeneity. In contrast to workers, automation technologies greatly reduce the uncertainty in production processes driven by heterogeneous labor skills and human capital. Graetz and Michaels (2018) demonstrate that the adoption of automation technologies results in a decreased proportion of low-skill workers while simultaneously enhancing firms' productivity. The enhancement in production efficiency through automation serves to bolster the quality of information available to outside investors. Furthermore, automation improves the comparability of information derived from peer firms. In industries with less automation exposure, production efficiency is frequently determined by worker heterogeneity, encompassing factors like human capital, which is not easily observed by investors. This lack of observability makes it difficult for investors to accurately evaluate a focal firm's performance based on information from peer firms. However, for firms in the industries with more automation exposure, investors can enhance their firm valuation by analyzing peer firms' production data linked to automation technologies. Therefore, automation helps enhance information transparency by attenuating the challenges associated with predicting production efficiency and performance.

Worker heterogeneity elevates the advantage of informed traders who possess the capacity and specialized skills to collect and analyze information grounded in their specialized skills. Since automation exposure mitigates asymmetric information between firms and investors, it serves to level the informational disparities between noise and informed traders. Enhanced information transparency due to automation exposure may crowd out informed traders and foster the trading of noise traders. Drawing on research on price-based feedback to managerial actions (Bond et al., 2012; Jayaraman and Wu, 2019), by impounding information that is known to managers into stock prices, automation technologies could potentially crowd out information of informed traders that is unknown to managers. It becomes more challenging for managers to learn from stock prices and to make investment decisions based on the private information held by informed traders.

Consequently, we posit the following hypotheses:

HYPOTHESIS 3. Automation exposure has a negative effect on investment-price sensitivity.

HYPOTHESIS 4. The negative effect of automation exposure on investment-price sensitivity is stronger among firms with a higher level of stock price informativeness.

3. Data description and research design

3.1. Sample selection

We obtain financial data of U.S. public firms from COMPUSTAT for the period between 1976 and 2020. Patent classification and assignment data from 1976 to 2014 are available directly from Mann and Püttmann (2021).[2] To cover most recent years, we employ the method illustrated in Mann and Püttmann (2021) and extend the patent dataset to encompass the years 2015 through 2020. Specifically, we obtain the full text of utility patents granted by the United States Patent and Trademark Office (USPTO) between 2015 and 2020 from Google.[3] Given that our measure of automation exposure is based on patent information from the preceding five years, the effective sample period for our regression analyses spans from 1980 to 2020. In addition, we collect institutional ownership data from the Thompson Reuters 13f Holdings and stock order data from the Trade and Quote database (TAQ).

Next, we exclude firms in the financial and utilities industries (Standard Industrial Classification (SIC) codes 6000–6999 and 4900–4999) and firm–year observations with missing

[2] We would like to thank Katja Mann and Lukas Püttmann for sharing the data on https://github.com/lpuettmann/automation-patents.

[3] google.com/googlebooks/uspto-patents.html. Please refer to Mann and Püttmann (2021) for the detailed discussions of their patent data.

or negative total assets or total sales. After applying these sample selection criteria, our effective sample comprises 121,298 firm–year observations with 9,213 unique firms. To mitigate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

3.2. Automation measure

According to Mann and Püttmann (2021), an automation patent is defined as "a device that carries out a process independently of human intervention". This broad definition encompasses various manifestations, including physical machines, machine combinations, algorithms, and computer programs. Utilizing a naive Bayes algorithm coupled with machine learning methodologies, Mann and Püttmann (2021) analyze the description content of nearly 5 million U.S. utility patents spanning from 1976 to 2014. Through their analysis, they categorize these patents into automation and non-automation classifications. Additionally, Mann and Püttmann (2021) use the patents' technology class to assign them to industries in which they are likely to be used, drawing on Silverman's (2002) concordance. We follow Mann and Püttmann's (2021) approach and extend their patent data from 2014 to 2020.

Utilizing the counts of automation and non-automation patents within each industry, we adopt the formula introduced by Qiu et al. (2020) to gauge a firm's exposure to automation technologies. For each four-digit SIC industry j in year t, we calculate the cumulative number of automation patents granted over the preceding five years and denote the cumulative sum as the *Number of Automation Patents*$_{j,t}$. Then we adopt the historical segment data from COMPUSTAT to quantify firm i's proportion of segment sales within industry j during year t

($Weight_{i,j,t}$). Firm i's automation exposure ($AUTO_{i,t}$) is calculated as the natural logarithm of the sum of $Weight_{i,j,t}$×$Number\ of\ Automation\ Patents_{j,t}$ across all four-digit SIC industries encompassed within the firms' operational scope:

$$AUTO_{\mathrm{i,t}} = log(\textstyle\sum_{j=1}^{n} Weight_{i,j,t} \times Number\ of\ Automation\ Patents_{j,t}) \qquad (1)$$

where n is the number of four-digit SIC industries in which firm i operates.

3.3. Empirical model

To examine the impact of automation on firms' investment efficiency, we estimate the following regression equation:

$$INV_{i,t} = \beta_0 + \beta_1 AUTO_{i,t-1} + \beta_2 CF_{i,t-1} + \beta_3 AUTO_{i,t-1} \times CF_{i,t-1} + \beta_4 Q_{i,t-1} + \beta_5 AUTO_{i,t-1} \times Q_{i,t-1} + \beta_6 SIZE_{i,t-1} + \tau_t + \alpha_i + \varepsilon_{i,t} \qquad (2)$$

where i represents firm; t represents fiscal year; $INV_{i,t}$ represents firm i's investment in year t, measured as capital expenditures scaled by lagged total assets; $AUTO_{i,t}$ indicates firm i's automation exposure; $CF_{i,t}$ represents as firm i's cash flow, measured as earnings before extraordinary items plus depreciation and amortization plus R&D expenses, scaled by total assets; $Q_{i,t}$ is Tobin's Q, measured as the market value of assets minus deferred taxes, scaled by the book value of total assets; and $SIZE_{i,t}$ is the natural logarithm of the book value of total assets. Following previous studies on investment efficiency, we control for the time fixed effect (τ_t) to account for individual firm-specific trends and financial market dynamics which can change over time, and include the firm fixed effects (α_i) to account for time-invariant unobservable factors.

Our variables of interest are two interaction terms: $AUTO_{i,t-1} \times CF_{i,t-1}$ and $AUTO_{i,t-1} \times$

$Q_{i,t-1}$. In regression equation (2), β_3 captures firms' investment efficiency based on the information of internal cash flow (the investment-cash flow sensitivity), while β_5 reveals firms' investment efficiency according to the information of external stock prices (the investment-price sensitivity). Based on the financial constraints hypothesis, we expect β_3 to be significantly negative. Likewise, in line with the informed trading hypothesis, we expect β_5 to be significantly negative.

4. Empirical results

4.1. Descriptive statistics

Table 1 presents descriptive statistics for the main variables used in our empirical analysis. The mean, median, and standard deviation of *AUTO* are 4.7530, 4.9090, and 2.0720, respectively, which are consistent with those reported in Qiu et al. (2020). Based on the mean value of *AUTO*, we can infer that, on average, firms have been granted 116 automation patents in the last five years (Exp(4.7530) = 116). Moreover, the average value of INV is 0.0723, and the average value of Q is 1.8020, which aligns with Bhandari and Javakhadze (2017). The average *SIZE* is 4.8090, consistent with Qiu et al. (2020), while the average *CF* is 0.0522, consistent with Chen et al. (2007). In summary, the descriptive statistics of these variables are in line with previous research.

[Insert Table 1 here]

4.2 Baseline regression analysis

Table 2 presents the empirical results regarding the influence of automation on firms' investment efficiency. We examine four different models with various combinations of fixed effects. Model 1 does not control any fixed effect. Model 2 controls for the year and state fixed effects. Model 3 includes controls for the year and industry fixed effects. Model 4 incorporates the year and firm fixed effects.

Regarding investment efficiency based on the information of internal cash flow, the coefficients of *CF* are all and statistically significant at the 1% level in all four models, indicating a positive relation between corporate investment and cash flow. This finding is consistent with those documented in the literature (e.g., Jiang et al., 2011; Bhandari and Javakhadze, 2017). More importantly, the coefficients of *AUTO×CF* are all negative and statistically significant at the 1% level in all four models. For example, in model 4, we observe that a one standard deviation increase in *AUTO* is associated with a 0.0145 (=2.0720×-0.0070) decrease in investment-cash flow sensitivity. Since the coefficient of *CF* is 0.0869 in model 4, we can infer that a one standard deviation increase in automation exposure corresponds to a 16.69% (=-0.0145/0.0869) decrease in investment-cash flow sensitivity on average. Our results lend support to *H1* that automation exposure is negatively related to investment-cash flow sensitivity.

Turning our focus to investment efficiency based on external stock price information, we observe that the coefficients of *Q* are positive and statistically significant at the 1% level in all four models. This finding aligns with prior research, which highlighting how managers often rely on their firms' stock prices to gain insights into investment opportunities, resulting in a positive investment-price sensitivity (e.g., Chen et al., 2007; Edmans et al., 2017; Billett et al., 2020). We also observe that the coefficients of *AUTO×Q* are all negative and statistically significant at the 1% level, suggesting that firms with higher automation exposure exhibit weaker investment-price sensitivity. To illustrate the economic significance of automation exposure on investment-price sensitivity, we use model 4 as an example. Here, a one standard deviation increase in *AUTO* corresponds to a decrease of 0.0021 (=2.0720×-0.0010) in investment-price sensitivity. Considering the coefficient of Q (0.0128) in model 4, this implies that automation reduces investment-price sensitivity by an average of 16.41% (=-0.0021/0.0128). These findings provide support for *H3* that automation exposure is negatively associated with investment-price sensitivity.

[Insert Table 2 here]

4.3 Identification tests

Our baseline analyses show that automation exposure is negatively related to both investment-cash flow sensitivity and investment-price sensitivity. In this section, we undertake a comprehensive set of identification tests to address the potential endogeneity concerns on our finding.

First, we employ an instrumental variable (IV) method to mitigate potential issues stemming from simultaneity or omitted variables, thereby enhancing the causal interpretation of the relation between automation exposure and investment efficiency. Second, we implement propensity score matching (PSM) and entropy balancing (EB) matching to address any underlying selection bias that might affect our results. The two matching techniques allow us to create matched groups, ensuring a more balanced and meaningful comparison. Third, we extend our baseline regression by adding additional control variables that could potentially confound our main finding. Lastly, we apply high-dimensional fixed effects to address concerns related to unobservable heterogeneity.

4.3.1. Instrument variable method

The adoption and integration of automation technology often entail a significant cost, which may lead to an increase in investment expenditures. This possibility raises concerns about the potential interdependence between automation exposure and investment decisions. To mitigate the simultaneity issue as well as the impact of omitted variables in our empirical analysis, we employ a 2SLS regression. The IV for automation exposure in our 2SLS regression is $wAUTO\_EURO5$, the segment-sales-weighted sum of average adjusted penetration of robots across five European countries, including Denmark, Finland, France, Italy, and Sweden. Previous studies, such as Acemoglu and Restrepo (2020) and Qiu et al. (2020), use the penetration of robots in European countries as an instrument for U.S. firms' automation exposure.

Specifically, we utilize the methodology introduced by Acemoglu and Restrepo (2020) to calculate $wAUTO\_EURO5$. We collect industry-level adjusted data on robot penetration for the five European countries. The data on industry-specific robot stock and adoption for European countries are from the International Federation of Robotics (IFR). The data on industry output growth rates and employment figures are from EUKLEMS, which provides industry-level data on productivity and growth across European counties. For each industry j, we first calculate the average of adjusted penetration of robots across the five European countries between year t-5 and year t-1:

$$AUTO\_EURO5_{j,(t-5,t-1)} = \frac{1}{5}\sum_{k\in EURO5}\left[\frac{M^k_{j,t-1}-M^k_{j,t-5}}{L^k_{j,1995}} - g^k_{j,(t-5,t-1)}\frac{M^k_{j,t-5}}{L^k_{j,1995}}\right] \tag{3a}$$

where *Euro5* refers to a set of five European countries, $M_{j,t-1}^{k}$ and $M_{j,t-5}^{k}$ refer to the robot stock quantity within industry *j* in country *k* during the year *t-1* and *t-5* respectively, $L_{j,1995}^{k}$ represents the baseline level of employment within industry *j* in country *k* as of 1995, $g_{j,(t-5,t-1)}^{k}$ is the output growth rate of industry *j* in country *k* between year *t-5* and year *t-1*.

Next, we proceed to calculate firm-level adjusted robot penetration data for five European countries. To achieve this, we align the industry-level adjusted robot penetration data for European countries with the corresponding four-digit SIC industry codes used in the U.S.. Then our approach closely resembles the one outlined in Section 3.2. We utilize historical segment data obtained from COMPUSTAT to derive a weighted factor, denoted as $w_{i,j,t-1}$, representing the percentage of firm *i*'s segment sales within a specific four-digit SIC industry j in year t-1. Our IV, $wAUTO\_EURO5_{i,t-1}$, is calculated as the sum of the product of $AUTO\_EURO5_{j,(t-5,t-1)}$ and $w_{i,j,t-1}$ across all four-digit SIC industries relevant to the firms' operations, using the following formula:

$$wAUTO\_EURO5_{i,t-1} = \sum_{j=1}^{n} w_{i,j,t} AUTO\_EURO5_{j,(t-5,t-1)} \tag{3b}$$

where *n* is the number of four-digit SIC industries in which firm *i* operates.

It is crucial to note that *wAUTO_EURO5* effectively fulfils the criteria for an IV. The rationale behind this assertion is two-fold. First, European countries exhibit a notable advancement in automation technologies, and it is reasonable to expect that knowledge diffusion might traverse geographical boundaries, subsequently influencing automation trends in the United States (Acemoglu and Restrepo, 2022). Acemoglu and Restrepo (2022) emphasize that the variation in automation technology advancement between the U.S. and European countries is predominantly attributed to demographic disparities, rather than being the result of time-varying economic conditions or industry-specific shocks. Therefore, the penetration of robots in European countries satisfies the IV's relevance condition. Second, our IV satisfies the exogeneity condition that the penetration of robots in European countries only affects U.S. firms' investment decisions through U.S. firms' automation exposure. This assumption is grounded in the understanding that U.S. firms' investment choices are primarily shaped by factors inherent to the domestic automation environment, rather than being directly influenced by the advancements in European industry automation technologies.

We adopt the following 2SLS specifications:

$$AUTO_{i,t-1} = \beta_0 + \beta_1 wAUTO\_EURO5_{i,t-2} + \beta_2 CF_{i,t-1} + \beta_3 Q_{i,t-1} + \beta_4 SIZE_{i,t-1} + \varepsilon_{i,t-1} \quad \text{(4a)}$$

$$INV_{i,t} = \beta_0 + \beta_1 \widehat{AUTO}_{i,t-1} + \beta_2 CF_{i,t-1} + \beta_3 \widehat{AUTO}_{i,t-1} CF_{i,t-1} + \beta_4 Q_{i,t-1} + \beta_5 \widehat{AUTO}_{i,t-1} Q_{i,t-1} + \beta_6 SIZE_{i,t-1} + \tau_t + \theta_i + \varepsilon_{i,t} \quad \text{(4b)}$$

where $\widehat{AUTO}_{i,t-1}$ is the predicted $AUTO_{i,t-1}$ estimated by Equation (4a). Table 3 presents the results of our 2SLS regressions. Column (1) shows that in the first-stage regression, the coefficients of *wAUTO_EURO5* are positive and statistically significant at the 1% level, indicating that our IV is relevant. Meanwhile, the F-statistics is the first-stage is 99.64 which is greater than 10, indicating that wAUTO_EURO5 is not a weak instrument variable. Columns (2)–(5) report the results of the second-stage regressions. We observe that the coefficients of $AUTO \times Q$ and $AUTO \times CF$ are negative and statistically significant, consistent with the baseline regression results reported in Table (2).

[Insert Table 3 here]

4.3.2. PSM and EB matching

Next, we address the endogenous issue arising from selection bias. If firms' adoption of automation technologies is not random but rather contingent on firm-level characteristics, we may have a biased estimation of the impact of automation exposure on investment efficiency. To mitigate this potential selection bias concern, we employ PSM and EB matching to construct treatment and control groups in which firms exhibit comparable firm-level characteristics.

Following the PSM approach outlined by Rosenbaum and Rubin (1983), we divide our sample into the treatment group comprising firms with high automation exposure and the control group comprising firms with low automation exposure. Specifically, the high automation group encompasses firm–year observations ranked within the top 40% of annual automation exposure, while the low automation group includes those ranked within the bottom 40% of annual automation exposure.[4] Subsequently, we employ a probit regression to estimate the likelihood of a firm being assigned to the high automation group. We include *CF*, *Q*, *SIZE*, *LEV*, *ROA*, *CASH*, and *PPE* in the probit regression to estimate propensity scores. Details of these variables are provided in Appendix A. Column (1) of Panel A of Table 4 reports the results for the probit regression. We observe that the *PPE* is positively related to the likelihood that a firm is assigned to the high automation group, while *ROA* and *CASH* demonstrate a negative relation with this likelihood.

Based on the propensity scores derived from the probit regression, we implement a one-

[4] Our PSM and EB estimation results are robust to the following cutoffs: annual top and bottom 50%, annual top and bottom 1/3, and annual top and bottom 25%.

to-one nearest neighbor matching without replacement. We ensure that the absolute value of the difference between the propensity scores of a firm in the high automation (treatment) group and its matched counterpart in the low automation (control) group does not exceed 1%. This matching process yields a set of 10,533 paired firm–year observations in both the treatment and control groups.

To assess the efficiency of our PSM procedure, we first re-estimate the probit regression using the propensity score matched sample and present the results in column (2) of Panel A of Table 4. The coefficients of covariates are all statistically insignificant at the 10% level, suggesting that firms in the treatment and control groups are indistinguishable in terms of the covariates after the matching. In addition, the magnitude of these coefficients is notably reduced compared to those in column (1) of Panel A, indicating that the statistical insignificance is not just a result of reduced sample size. The pseudo R^2 drops from 0.5466 in column (1) to 0.0082 in column (2), also indicating a decrease in the joint power of covariates to explain the likelihood of a firm being assigned to the high automation group. Next, we examine the pre-match and post-match mean differences in firm characteristics between the treatment and control groups. Panel B of Table 4 demonstrates that the univariate differences in all the covariates between the treatment and control groups are statistically significant in the pre-match sample, while these univariate differences are no longer statistically significant in the post-match sample. Taken together, the results from these two efficiency tests highlight that the difference in investment efficiency between the treatment and control groups is primarily attributed to automation exposure rather than observed firm characteristics.

In the last step of our PSM procedure, we re-evaluate the empirical relation between automation exposure and investment efficiency using the propensity score matched sample. The results presented in Panel C of Table 4 reinforce that firms with higher automation exposure have lower investment-cash flow sensitivity and investment-price sensitivity.

[Insert Table 4 here]

Our PSM procedure discard "unmatched" data points, with 85,851 in the pre-match sample but only 21,066 in the post-match sample. Consequently, we examine the robustness of our findings using EB matching, a method that redistributes the weights assigned to observations in control groups to achieve rigorous covariate balance. EB matching imposes constraints to align moments of covariate distributions, including the first, second, and even higher moments, thus ensuring a close resemblance between treatment and control groups. Moreover, EB doesn't rely on specific research designs for achieving covariate balance, addressing concerns about the influence of model specifications (DeFond et al., 2016).

In our EB matching procedure, we impose three balance conditions: the mean, variance, and skewness of the matching variables (comprising all covariates used in our PSM procedure) must be equivalent between the treatment and control groups. Defining the treatment and control groups based on firm–year observations with annual top 40% and bottom 40% of *AUTO*, we demonstrate in Panel A of Table 5 that the application of EB matching results in identical mean, variance, and skewness for firm characteristics across the treatment and control groups.

Utilizing these matching weights, we re-estimate our baseline regression in the EB matched sample. This process effectively eliminates measured confounding between the treatment and control groups, aligning with Hainmueller's (2012) argument that the enhanced balance achieved through EB can lead to reduced approximation bias and diminished model dependence, especially in finite samples.[5] As shown in Panel B of Table 5, the results of the EB-based regression validate our main finding by confirming that The coefficients of *AUTO*×*Q* and *AUTO*×*CF* remain negative and significantly significant at the 1% level across all four columns.

[Insert Table 5 here]

4.3.3. Additional controls

Endogeneity due to omitted variables may potentially compromise the robustness of our main finding. Certain firm characteristics exert concurrent influence over the decisions of both corporate investment and automation adoption, thereby amplifying the observed empirical relation between automation exposure and investment efficiency. In this section, we extend our baseline regression by including a set of firm characteristics as additional control variables.

Qiu et al. (2020) demonstrate a rising trend of both automation and non-automation technologies over time. To differentiate effects of automation exposure and non-automation technologies on investment efficiency, we directly control for firm-level non-automation technology exposure (*NONAUTO*). In line with Qiu et al. (2020), the definition of *NONAUTO* mirrors that of *AUTO*. Specifically, in year *t*, we compute the sum of non-automation patents

[5] The maximum assigned weight does not exceed 13.5, and only about 0.2% of firm–year observations in the control group exhibit weights greater than 3. This extreme weight scenario poses minimal concern within our analysis. However, to address any lingering concern, we confirm that our findings remain nearly unchanged after excluding observations with substantial weights (above 1 or 3) and subsequently rerunning the EB matching procedure.

(excluding chemical and pharmaceutical patents) available in the last five years within four-digit SIC industry *j*, denoted as *Number of Non-Automation Patents*$_{j,t}$. Then we calculate *NONAUTO* as the logarithm of the sum of product of *Number of Non-Automation Patents*$_{j,t}$ and firm *i*'s proportion of segment sales within industry *j* during year *t* (*Weight*$_{i,j,t}$) across all four-digit SIC industries relevant to firm *i*'s business scope:

$$NONAUTO_{i,t} = log(\sum_{j=1}^{n} Weight_{i,j,t} \times Number\ of\ Non - Automation\ Patents_{j,t}) \quad (5a)$$

To further account for the patents affiliated with chemical and pharmaceutical industries, we include a control variable (*CHEMI&PHARMA*) to encompass firms' technologies within these specific sectors. *CHEMI&PHARMA* serves as a proxy for a firm's exposure to chemical and pharmaceutical technologies. The definition of *CHEMI&PHARMA* parallels that of *AUTO* and *NONAUTO*, as outlined in the following formula:

$$CHEMI\&PHARMA_{\ i,t} = log(\sum_{j=1}^{n} Weight_{i,j,t} \times Number\ of\ CHEMI\ \&\ PHARMA\ Patents_{j,t}) \quad (5b)$$

Next, we introduce four firm characteristics as additional control variables. First, Qiu et al. (2020) document a positive correlation between automation exposure and firm leverage, while Aivazian et al. (2005) find a negative relation between leverage and investment expenditure. As such, we control for firm leverage (LEV) which is interconnected with both automation exposure and corporate investment. Second, Asker et al. (2015) show that firms' cash holdings are related to their investment decisions. Additionally, firms with substantial cash reserves are in a better position to afford the adoption of automation technologies. Thus, we include corporate cash holdings as an additional control variable (*CASH*). Third, a firm's tangible long-term assets can be used as collateral for external financing. Gan (2007) underscores a positive impact of collateral on corporate investment. Firms with higher levels of tangible long-term assets might also have greater financial resources to invest in automation technologies. Consequently, we control for collateral measured by property, plant, and equipment (PPE). At last, we include firm profitability (ROA) as an additional control variable, since firms with superior profitability are better positioned to capture future investment opportunities and afford the costs of automation systems.

In column (1) of Table 6, we add *NONAUTO* and *CHEMI&PHARMA* as additional control variables in our baseline Equation (2). In column (2) of Table 6, we add LEV, ROA, CASH, and PPE as control variables. In column (3), we include all six additional control variables. In column (4), we add four interaction terms *NONAUTO×CF*, *NONAUTO×Q*, *CHEMI&PHARMA×CF*, and *CHEMI&PHARMA×Q*. The coefficients of *AUTO×Q* and *AUTO×CF* remain negative and statistically significant, echoing the findings of our baseline regression. This persistence underscores the robustness of our main finding, even upon the introduction of additional control variables.

[Insert Table 6 here]

4.3.4. High-dimensional fixed effects

In this section, we further address the potential influence of unobservable heterogeneity on our main findings. Despite the implementation of two matching methods to mitigate selection bias concerns and the inclusion of supplementary control variables, the underlying relation between automation exposure and investment efficiency could still be impacted by latent heterogeneity. To effectively control for unobservable factors, we employ the high-dimensional fixed effects approach outlined by Gormley and Matsa (2014).[6]

Table 7 presents the empirical results of our baseline regression with the integration of three combinations of high-dimensional fixed effects. In column (1), we re-estimate our baseline regression with the firm and interacted state–year fixed effects. In column (2), we repeat the process while accounting for the firm and interacted industry–year fixed effects. In column (3), we extend our analysis to include the firm, interacted state–year, and interacted industry–year fixed effects. These fixed effects serve to control for latent and time-invariant firm characteristics, unobserved factors unique to both geographic regions and varying time periods, and unobserved factors associated with specific industries and different time periods. In column (4), we include all four individual fixed effects in our baseline regression, mitigating the effects of unobserved factors that are time-invariant and firm-specific (firm), temporal and time-varying (year), time-invariant and state-specific, and time-invariant and industry-specific (industry). The coefficients of $AUTO \times Q$ and $AUTO \times CF$ are negative and statistically significant across all columns, suggesting that our main finding persists even after the integration of high-dimensional fixed effects.

[Insert Table 7 here]

4.4. Cross-sectional analyses

In this section, we examine two mechanisms through which automation exposure may affect investment efficiency. Drawing from the financial constraints hypothesis, we expect that

[6] Gormley and Matsa (2014) show that fixed effects approach yields more consistent estimates in the presence of unobserved group heterogeneity than the other widely used empirical methods.

the observed negative relation between automation exposure and investment-cash flow sensitivity is more pronounced form firms with financial constraints. Based on the price informativeness hypothesis, we conjecture that the adverse effect of automation exposure on investment-price sensitivity arises through crowding out informed trades.

4.4.1. Financial constraints and investment-cash flow sensitivity

Our investigation begins by examining the potential of automation to mitigate firms' financial constraints and its subsequent impact on investment-cash flow sensitivity. According to the financial constraints hypothesis, the adoption of automation alleviates the restrictions imposed by employment protection factors such as labor unions and employment protection laws, thereby easing firms' financial constraints. This relief from financial constraints can, in turn, enable firms to reduce their dependence on internal cash flows when making investment decisions (Fazzari et al., 1987; Mulier et al., 2016). If the financial constraints hypothesis holds true, we expect that the negative impact of automation on investment-cash flow sensitivity is more pronounced among financially constrained firms.

We employ two proxies to gauge firms' financial constraints. The first proxy is the KZ index proposed by Kaplan and Zingales (1997), which measures financial constraints using the following formula:

$$KZ_{i,t} = -1.002CF_{i,t} + 3.139TLTD_{i,t} - 39.369TDIV_{i,t} - 1.315CASH_{i,t} + 0.283Q_{i,t} \quad \text{(6a)}$$

where $CF_{i,t}$ represents firm i's cash flow in year t, $TLTD_{i,t}$ denotes the ratio of long-term debt to total assets, $TDIV_{i,t}$ is the ratio of total dividends to total assets, $CASH_{i,t}$ represents the ratio of cash holdings to total assets, and $Q_{i,t}$ denotes Tobin's Q. A higher $KZ_{i,t}$ value indicates a greater level of financial constraints, implying that a firm faces difficulties in accessing external financing sources and is more reliant on its own internal funds.

The second proxy is the SA index developed by Hadlock and Pierce (2010), which quantifies financial constraints through the following equation:

$$SA_{i,t} = -0.737SIZE_{i,t} + 0.043SIZE_{i,t}^2 - 0.04AGE_{i,t} \quad (6b)$$

where $SIZE_{i,t}$ represents the natural logarithm of firm i's total assets in year t and $AGE_{i,t}$ indicates firm i's age measured in years as of year t. The SA index combines the effects of firm size and age to capture different dimensions of financial constraints. A higher $SA_{i,t}$ value indicates a greater level of financial constraints.

We assign firm–year observations to either the high or low financial constraints sub-sample based on whether their KZ index exceeds or falls below the annual industry median, and similarly for the SA index. Subsequently, we re-estimate the baseline regression, Equation (2), within these sub-samples. Panel A of Table 8 presents the results of our cross-sectional analysis with respect to financial constraints. Specifically, columns (1) and (2) report the results based on the KZ index, while columns (3) and (4) present the results based on the SA index.

We observe that the coefficients of $AUTO \times CF$ remain negative and statistically significant in both the high and low financial constraints sub-samples. More importantly, the absolute value of the coefficients of $AUTO \times CF$ is higher in the high financial constraints sub-samples compared to the low financial constraints sub-samples. Employing seemingly unrelated regressions, we validate that the coefficients of $AUTO \times CF$ significantly differ between these two sub-samples, lending support to the financial constraints hypothesis. Additionally, we find that the coefficients of $AUTO \times Q$ are negative and statistically significant in both high and low financial constraints sub-samples. However, our SUR analysis indicates that the coefficients of $AUTO \times Q$ do not exhibit statistically significant differences between these two sub-samples. Taken together, our findings support *H2* and indicate that automation exposure plays a pivotal role in easing financial constraints for firms, subsequently leading to reduced investment-cash flow sensitivity. However, the financial constraints mechanism falls short of explaining the empirical association between automation exposure and investment-price sensitivity.

[Insert Table 8 here]

4.4.2. Informed trading and investment-price sensitivity

Next, we examine whether the informed trading mechanism contributes to the negative impact of automation on investment-price sensitivity. As per the informed trading hypothesis, the integration of automation technologies enhances firms' transparency, leading to a reduction in information asymmetry. This, in turn, weakens the advantage of informed traders and fosters more noisy trades (Shi et al., 2016). The reduction in informed trades diminishes price informativeness, impeding managers from extracting sufficient information from stock prices to guide their investment decisions (Chen et al., 2007; Edmans et al., 2017). To examine the informed trading hypothesis, we explore the cross-sectional variation of the relation between automation and investment-price sensitivity with respect to two dimensions: informed trading reflected as stock price informativeness and managerial incentives to learn from the market.

First, if the informed trading hypothesis holds true, we expect that the negative impact of automation on investment-price sensitivity is more pronounced among firms with a higher level of informed trading. Following Roll (1988), Chen et al. (2007), Kang and Nam (2015), and Jayaraman and Wu (2019), we adopt the probability of informed trading (PIN) and price nonsynchronicity as our two measures of the amount of private information in stock prices.

A higher value of *PIN* indicates a greater prevalence of informed trades within a stock. This measure is rooted in the market microstructure theory put forth by Glosten and Milgrom (1985). Easley et al. (1996) formulate a model to gauge *PIN* based on the disbalance between buy and sell orders. Suppose that both informed traders and uninformed traders trade in a competitive and risk-neutral market. Trading takes place over discrete trading days (t=1,...,T) with continuous trading occurring on each trading day. The probability of new information arriving on a given day is α, with probability of δ the news is bad and with probability of 1–δ the news is good. The trading orders conform to Poisson distributions. Informed traders trade only when there is new information, with an arrival rate of μ. On the other hand, uninformed traders trade irrespective of whether new information is unveiled or not, with the arrival rate of ε_b for buy orders and ε_s for sell orders. *PIN* is defined as:

$$PIN = \frac{\alpha\mu}{\alpha\mu+\varepsilon_s+\varepsilon_b} \qquad (7a)$$

where the denominator is the total arrival rate for all trading orders and the numerator is the arrival rate for informed trading orders.

The five parameters in Equation (7a) are estimated by a maximizing likelihood method with the following likelihood function on a given trading day:

$$L(\alpha, \mu, \delta, \varepsilon_s, \varepsilon_b | B, S) = (1-\alpha)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-(\varepsilon_s+\mu)}\frac{(\varepsilon_s+\mu)^S}{S!}$$
$$+\alpha(1-\delta)e^{-\varepsilon_b+\mu}\frac{(\varepsilon_b+\mu)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} \qquad (7b)$$

where B stands for the daily buying orders and S represents the daily selling orders. Using trading data from the TAQ database and assuming independence across trading days, we maximize the following likelihood function within a year:

$$\Gamma = \prod_{t=1}^{T} L(\alpha, \mu, \delta, \varepsilon_s, \varepsilon_b | B_t, S_t) \qquad (7c)$$

where T is the number of trading days in a year. To alleviate computational challenges when estimating the likelihood function, we follow Easley et al. (2010) and we take the logarithm of the likelihood function (7c).

Our second measure of informed trading is price nonsynchronicity, which is calculated based on the correlation between a firm's stock return and the market's return. Roll (1988) posits that price nonsynchronicity is closely tied to the presence of private information. When a firm's stock return exhibits a strong correlation with overall market returns, the firm's stock price is less likely to reflect firm-specific information that can be valuable for managerial investment decisions. Therefore, when a stock's return displays lower correlation with market returns, it indicates a higher degree of informed trading and greater stock price informativeness. This perspective is supported by Durnev et al. (2003), who affirm that price nonsynchronicity tends to capture more private information rather than mere market noise. Following Morck et al. (2000), we calculate price nonsynchronicity using the following market model:

$$r_{i,w} = \alpha_i + \beta_i r_{m,w} + \varepsilon_{i,w} \qquad (8)$$

where $r_{i,w}$ is firm i's stock return in week w, $r_{m,w}$ is market return in week w. We then quantify price nonsynchronicity as one minus the R^2 value derived from the regression Equation (8), denoted as *NONSYN*.

We divide our sample into high or low informed trading sub-samples based on these two proxies. Firm–year observations in the high (low) informed trading sub-samples are those with *PIN* or *NONSYN* above (below) its annual industry median. We then re-estimate our baseline regression in these sub-samples and tabulate the results in Panel B of Table 8. We observe that the coefficients of *AUTO×Q* remain negative and statistically significant across both high and low informed trading sub-samples. More importantly, the absolute value of the coefficients of *AUTO×Q* for the high informed trading sub-samples is larger than that of the corresponding low informed trading sub-samples. Employing SUR, we confirm that the differences in the coefficients of *AUTO×Q* between the high and low informed trading sub-samples are statistically significant. Moreover, the SUR analysis indicates that the coefficients of *AUTO×CF* do not display any significant variation between the high and low informed trades sub-samples.

Second, if the informed trading hypothesis holds true, we also expect that the negative impact of automation on investment-price sensitivity is more pronounced among firms in which managers have a higher incentive to learn from the market. We adopt the correlation in sales between a focal firm and its product market peers ($R_{product}$) and sales volatility (*Sales_Volatility*) as our two measures of managerial learning incentive.

Our first proxy for managerial learning incentive is based on product correlation. The stock prices or investment decisions of peer firms can provide insights into a focal firm's fundamental information. When there is a substantial correlation in product-related factors between a focal firm and its product market peers, the capacity for the focal firm's managers and investors to gain insights from their peers' activities increases. Consequently, this dynamic reduces managers' incentive to learn from their firm's stock prices. This notion is supported by the findings of Foucault and Fresard (2011), who reveal that an increase in the correlation of product demand among a focal firm and its peer firms results in a reduction in the firm's investment-price sensitivity. Bustamante and Fresard (2021) also find that managers make investment decisions by acquiring fundamental information about their firms through observing investment decisions of their product market peers.

We expect that the managers of firms with lower levels of product correlation with their peers have a higher incentive to learn from the market and that the impact of automation exposure on investment-price sensitivity is more pronounced among these firms. Following the approach of Foucault and Fresard (2014), we gauge the firms' product correlation by measuring the correlation in sales between a focal firm and its product market peers, denoted as $R_{product}$. The correlation is estimated as follows:

$$Sales_{i,q} = a_1 + b_1 Sales_{i's\ peers,q} + \varepsilon_{i,q} \qquad (9)$$

where $Sales_{i,q}$ is firm i's sales in quarter q, and $Sales_{i's\ peers,q}$ is firm i's peers' average sales in quarter q. We use 12 quarters as the rolling window to estimate Equation (9) within the same two-digit SIC industry. Then, the coefficient b_1 is our proxy $R_{product}$, which measures the correlation of sales between firm i and its product market peers. A higher value of $R_{product}$ is associated with less managers' incentive to learn from the market.

Our second proxy for managerial learning incentive is based on product market uncertainty. Product market uncertainty can significantly affect a manager's ability to gather information from peer firms and, to some extent, reflects the overall uncertainty within a firm's information environment. As argued by Allen (1992), product market uncertainty plays an important role in influencing a manager's motivation to learn from stock prices. When product market uncertainty is high, managers tend to exhibit a stronger incentive to seek information from stock prices. If automation exposure reduces investment-price sensitivity through crowding out informed trading, then we conjecture that the impact of automation exposure on investment-price sensitivity is more pronounced among firms with higher levels of product market uncertainty. From the perspective of information demand, managers of such firms have a stronger incentive to learn from the market.

We adopt a firm's sales volatility to measure product market uncertainty, denoted as *Sales_Volatility*. We define *Sales_Volatility* as the 3-year moving variances of the annual growth rate of sales. A higher *Sales_Volatility* value indicates greater product market uncertainty.

We divide our sample into two sub-samples in which firms have high and low managerial learning incentive. Firm–year observations in the high (low) managerial learning incentive sub-samples are those with $R_{product}$ below (above) its annual industry median and those with *Sales_Volatility* above (below) annual industry median. We then re-estimate our baseline regression in these sub-samples and tabulate the results in Panel C of Table 8. We observe that the coefficients of *AUTO×Q* remain negative and statistically significant across both sub-samples. The absolute value of the coefficients of *AUTO×Q* for the high managerial learning incentive sub-samples is larger than that of *AUTO×Q* for the corresponding low managerial learning incentive sub-samples. Based on SUR, we confirm that the differences in the coefficients of *AUTO×Q* between the high and low managerial learning incentive sub-samples are statistically significant. Moreover, the SUR analysis indicates that the coefficients of *AUTO×CF* do not exhibit any significant differences between the high and low managerial learning incentive sub-samples.

Based on both information supply and information demand sides, our results in Panels B and C of Table 8 suggest that automation exposure crowds out informed traders and reduces stock price informativeness, consequently leading to a lower investment-price sensitivity. Taken all three panels of Table 8 together, when considering the influence of automation exposure on firms' investment efficiency, the impact of automation on investment-cash flow sensitivity emerges primarily from the financial constraints channel. On the other hand, the impact of automation on investment-price sensitivity is attributed to the informed trading channel.

4.5. Supplementary tests

4.5.1. Financial crisis periods

Our sample covers two financial crisis periods: the bust of dotcom bubble spanning 2000 to 2003 and global financial crisis spanning 2007 to 2009. During the financial crisis periods, firms' investment decisions may be influenced by constrained capital availability. However, the adopted automation technologies likely continue to exert an effect on firm operations. To isolate the impact of automation exposure from crisis-induced investment dynamics, we exclude firm–year observations from the financial crisis periods and present our baseline regression results in Table 9.

In column (1), we remove firm–year observations during the period of 2000–2003. In column (2), we exclude firm–year observations during the period of 2007–2009. In column (3), we collectively exclude the samples from the two crisis periods. All three columns of Table 9 show that the coefficients of *AUTO×CF* and *AUTO×Q* remain negative and statistically significant, indicating that our main finding remains robust after removing data from the periods marked by financial turmoil. In column (4), we only retain the sample years between 2000 and 2003 and between 2007 and 2009. During the two crisis periods, the coefficient of $AUTO\times CF$ is statistically insignificant, while the coefficient of $AUTO\times Q$ remains negative and statistically significant but with a smaller size.

[Insert Table 9 here]

4.5.2. Alternative measures of automation exposure

In this section, we replace the measure of automation exposure ($AUTO$) in our baseline regression by two alternative proxies. Following Qiu et al. (2024), we utilize the number of a firm's automation patents based on two ways of adjusting the patent truncation bias to measure the firm's automation exposure. First, we calculate the adjusted automation patents of a firm in the given year, denoted as Adj_AUTO.

$$Adj\_AUTO_{i,t} = \frac{Number \quad of \quad Automation \quad Patents_{i,t}}{\sum_{i=1}^{N} Number \quad of \quad Automation \quad Patents_{j,t}}$$

where *Number of Automation Patents*$_{i,t}$ represents the number of firm i's automation patents in year t and N represents the total number of firms in year t. Then, we transform Adj_AUTO using the inverse hyperbolic sine function to alleviate the skewness of its distribution, denoted as $AUTO\_Alt1$.

$$AUTO\_Alt1_{i,t} = arcsinh(Adj\_AUTO_{i,t}) = log(Adj\_AUTO_{i,t} + \sqrt{{Adj\_AUTO_{i,t}}^2 + 1})$$

Second, since patent numbers and citations vary across technology classes and over time, Qiu et al. (2024) propose another alternative proxy for automation exposure. The technology-class adjusted automation is defined as the total number of automation patents filed by firm i in year t scaled by the total number of automation patents in each technology class filed by all the firms in year *t*. The technology class classification is based on the Cooperative Patent Classification (CPC).[7] Similar to *AUTO_Alt1*, we also transform the technology-class adjusted automation patents by using the inverse hyperbolic sine function, denoted as *AUTO_Alt2*.

Table 10 reports the empirical results of our baseline regression using these two alternative measures of automation exposure. Columns (1) and (2) show that the coefficients of the four interaction terms, *AUTO_Alt1×Q*, *AUTO_Alt1×CF*, *AUTO_Alt2×Q*, and *AUTO_Alt1×CF*, are all negative and statistically significant at the 1% level. These results suggest that our main findings hold even when we use alternative measures of automation exposure.

[Insert Table 10 here]

5. Conclusions

This paper focuses on examining the impact of automation exposure on corporate investment efficiency. Building on the methodologies of Mann and Püttmann (2018) and Qiu et al. (2020), our study employs a firm-level automation exposure measure derived from textual analysis of U.S. utility patents. We find that automation exposure has a negative effect on both investment-cash flow sensitivity and investment-price sensitivity. The negative effect remains consistent in our identification tests to address potential endogeneity concerns: an IV instrumental method, PSM and EB matching, adding additional controls, and high-

[7] The CPC classification data for granted patents is from: https://patentsview.org/download/data-download-tables

dimensional fixed effects. Furthermore, we reveal two channels through which automation affects investment behavior. First, automation mitigates investment-cash flow sensitivity by alleviating financial constraints. Second, automation weakens investment-price sensitivity by crowding out informed trades and reducing stock price informativeness. Our research contributes to the automation literature by extending the scope of the impacts of automation technologies to corporate investment efficiency. As technological advancements continue to shape economies, exploring the effects of automation exposure on corporate activities remains a compelling and relevant avenue of future research.

Appendix A

Table A1. Variable definitions

This table describes variable definitions and corresponding data sources. M&P refers to Mann and Püttmann (2021), 13f refer to the Thompson Reuters Institutional Managers Holdings database, and TAQ refers to the Trade and Quote database. Compustat data items are reported in the paratheses.

Variables	Definitions	Sources
Dependent variable		
INV	Capital expenditures (*CAPX*) scaled by lagged total assets (*AT*).	Compustat
Independent variables		
AUTO	The natural logarithm of the segment-sales-weighted sum of one plus the number of automation patents available in the past five years across all four-digit SIC industries in which a firm operates (Qiu et al., 2020; Mann and Püttmann, 2021).	M&P and Google
Q	The ratio of the market value of assets (*DLTT*+*DLC*+*PRCC_F*×*CSHPRI*) minus deferred taxes (*TXDB*) over the book value of assets (*AT*).	Compustat
Control variables		
CF	Earnings before extraordinary items (*IB*) plus depreciation and amortization (*DP*) plus R&D expenses (*XRD*), scaled by total assets (*AT*).	Compustat
SIZE	The natural logarithm of the book value of assets (*AT*).	Compustat
wAUTO_EURO5	The average of the adjusted penetration of robots across five European countries: Denmark, Finland, France, Italy, and Sweden. (Qiu et al., 2020; Mann and Püttmann, 2021).	
NONAUTO	The natural logarithm of the segment-sales-weighted sum of one plus the number of non-automation patents available in the past five years across all four-digit SIC industries in which a firm operates (Qiu et al., 2020; Mann and Püttmann, 2021).	
CHEM&PHARM	The natural logarithm of the segment-sales-weighted sum of one plus the number of chemical and pharmaceutical patents available in the past five years across all four-digit SIC industries in which a firm operates (Qiu et al., 2020).	

LEV	The book value of debt (*DLTT* + *DLC*) divided by total assets (*AT*).	Compustat
ROA	Income before depreciation (*OIBDP*) divided by total assets (*AT*).	Compustat
CASH	Cash (*CHE*) scaled by total assets (*AT*)	Compustat
PPE	Property, plant, and equipment (*PPEGT*) scaled by total assets (AT).	Compustat
PIN	An indicator variable that equals to one if the probability of informed trading in a firm's stocks is above the annual industrial median, and zero otherwise.	*TAQ*
KZ	Kaplan-Zingales index: KZ=-1.002CF +3.139$TLTD$-39.369$TDIV$-1.315$CASH$+0.283Q	Compustat
SA	Size and Age index: SA= -0.737$SIZE$+0.043$SIZE^2$-0.04AGE	Compustat

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Table1. Descriptive statistics

This table presents the descriptive statistics of all variables used in our empirical analysis. Our sample covers the period from 1980 to 2020, comprising 121,298 firm–year observations with 9,213 firms. The number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile are reported left to right, in sequence for each variable. The left-to-right sequence for each variable includes the number of observations (Obs.), mean, standard deviation (S.D.), 25th percentile (P25), median, and 75th percentile (P75). All continuous variables are winsorized at the 1st and 99th percentiles. For detailed definitions of all variables, please refer to Appendix A.

Variables	Obs.	Mean	S.D.	P25	Median	P75
AUTO	121,298	4.7530	2.0720	3.4610	4.9090	6.1500
INV	121,298	0.0723	0.0961	0.0186	0.0418	0.0863
CF	121,298	0.0522	0.2080	0.0239	0.0911	0.1520
Q	121,298	1.8020	2.2090	0.7500	1.1230	1.9210
SIZE	121,298	4.8090	2.2290	3.1240	4.6660	6.3320
wAUTO_EURO5	40,300	-0.3550	1.7610	-1.3630	-0.3500	0.6480
NONAUTO	121,298	5.2130	1.8290	4.1230	5.6970	6.4570
CHEMI&PHARMA	121,298	3.3510	2.1310	1.5940	3.4330	4.6100
LEV	121,298	0.2610	0.3580	0.0395	0.1980	0.3650
ROA	121,298	0.0446	0.2450	0.0183	0.1070	0.1700
CASH	121,298	0.1170	0.1580	0.0167	0.0529	0.1520
PPE	121,298	0.5460	0.4240	0.2290	0.4460	0.7630
KZ	121,298	0.5310	0.4990	0.0000	1.0000	1.0000
SA	121,298	0.4690	0.4990	0.0000	0.0000	1.0000
PIN	75,300	0.5000	0.5000	0.0000	0.0000	1.0000
NONSYN	121,298	0.8696	0.1500	0.8050	0.9280	0.9840

Table 2. Automation exposure and investment efficiency

This table presents the regression results of Equation (2) with different specifications of fixed effects. The sample covers 121,298 firm–year observations with non-missing values for the regression variables during 1980–2020. Model 1 does not control any fixed effect. Model 2 controls for the year and state fixed effects. Model 3 controls for the year and industry fixed effects. Model 4 controls for the year and firm fixed effects. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	INV_t (1)	INV_t (2)	INV_t (3)	INV_t (4)
$AUTO_{t-1}$	-0.0020***	0.0014***	0.0016***	0.0010**
	(-6.55)	(4.00)	(3.89)	(2.05)
CF_{t-1}	0.1270***	0.1068***	0.1085***	0.0869***
	(19.27)	(15.94)	(18.23)	(14.73)
$AUTO\times CF_{t-1}$	-0.0121***	-0.0108***	-0.0103***	-0.0070***
	(-11.47)	(-10.06)	(-10.61)	(-7.06)
Q_{t-1}	0.0106***	0.0122***	0.0133***	0.0128***
	(13.59)	(15.72)	(17.23)	(15.97)
$AUTO\times Q_{t-1}$	-0.0010***	-0.0011***	-0.0011***	-0.0010***
	(-7.95)	(-8.65)	(-8.81)	(-7.20)
$SIZE_{t-1}$	-0.0014***	0.0010***	-0.0008***	-0.0130***
	(-4.57)	(3.37)	(-2.69)	(-19.23)
CONSTANT	0.0751***	0.1621***	0.0835***	0.1474***
	(34.63)	(7.20)	(10.95)	(42.93)
Year fixed effects	No	Yes	Yes	Yes
State fixed effects	No	Yes	No	No
Industry fixed effects	No	No	Yes	No
Firm fixed effects	No	No	No	Yes
Observations	121,298	121,298	121,298	121,298
Adjusted R^2	0.0413	0.1180	0.2644	0.1165

Table 3. Instrument variable

This table presents the results of 2SLS regressions, specified in Equations (4a) and (4b). Column (1) reports the results of the first-stage regression, in which the penetration of robots in European countries, *wAUTO_EURO5*, defined in Equation 3(b), is the IV. Columns (2)–(5) report the results of the second-stage regressions, in which $\widehat{AUTO}_{i,t-1}$ is the predicted value of $AUTO_{t-1}$ from the first-stage regression. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

First stage			Second stage			
	$AUTO_{t-1}$		INV_t	INV_t	INV_t	INV_t
	(1)		(2)	(3)	(4)	(5)
$wAUTO\_EURO5_{t-2}$	0.0214***	$\widehat{AUTO}_{i,t-1}$	-0.0111***	-0.1559***	-0.0677***	-0.0381**
	(6.15)		(-7.20)	(-6.85)	(-3.14)	(-2.28)
CF_{t-1}	-0.0070	CF_{t-1}	0.2415***	0.2419***	0.2488***	0.1774***
	(-0.32)		(7.64)	(7.48)	(7.49)	(5.29)
Q_{t-1}	-0.0063***	$\widehat{AUTO}_{i,t-1} \times CF_{t-1}$	-0.0350***	-0.0353***	-0.0360***	-0.0238***
	(-3.11)		(-6.71)	(-6.63)	(-6.60)	(-4.24)
$SIZE_{t-1}$	0.0260***	Q_{t-1}	0.0203***	0.0163***	0.0123***	0.0135***
	(5.00)		(5.71)	(4.39)	(2.76)	(3.43)
CONSTANT	4.2458***	$\widehat{AUTO}_{i,t-1} \times Q_{t-1}$	-0.0029***	-0.0022***	-0.0013*	-0.0014**
	(49.48)		(-4.84)	(-3.60)	(-1.83)	(-2.03)
		$SIZE_{t-1}$	0.0024***	0.0056***	0.0023***	-0.0069***
			(4.56)	(7.27)	(3.00)	(-6.26)
		CONSTANT	0.1008***	0.8069***	0.3546***	0.2716***
			(11.13)	(7.69)	(3.84)	(3.77)
Year fixed effects	YES		NO	YES	YES	YES
State fixed effects	NO		NO	YES	NO	NO
Industry fixed effects	NO		NO	NO	YES	NO
Firm fixed effects	YES		NO	NO	NO	YES
Observations	40,326		40,326	40,326	40,326	40,326
Adjusted R^2	0.3709		0.0404	0.1619	0.3278	0.0994
F-statistics	99.64					

Table 4. Propensity score matching (PSM)

Panel A. First-stage regression of PSM

Panel A presents the results of the probit regression estimating propensity scores. The sample covers firm–year observations with the value of *AUTO* above 60th annual percentile and below 40th annual percentile. We use a one-to-one nearest neighbor matching without replace and with a caliper width of 1%. Column (1) reports the results of the probit regression in the pre-match sample, and column (2) reports the results of the probit regression in the post-match sample. For detailed definitions of all variables, please refer to Appendix A. The z-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	Pre-match (1)	Post-match (2)
CF_{t-1}	0.1009	-0.0038
	(1.22)	(-0.04)
Q_{t-1}	-0.0050	0.0052
	(-0.88)	(0.74)
$SIZE_{t-1}$	0.0126	-0.0033
	(1.11)	(-0.24)
LEV_{t-1}	-0.0034	0.0076
	(-0.09)	(0.16)
ROA_{t-1}	-0.1687*	0.0463
	(-1.95)	(0.46)
$CASH_{t-1}$	-0.1542*	-0.0109
	(-1.76)	(-0.10)
PPE_{t-1}	0.3042***	-0.0272
	(5.82)	(-0.48)
CONSTANT	-2.2329***	0.6209
	(-6.19)	(1.17)
Pseudo R^2	0.5466	0.0082
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	85,851	21,066

Panel B. Pre-match and post-match differences in covariates

Panel B presents the differences in the covariates between the treatment and control groups. Columns (1)–(2) and (4)–(5) report the means of the covariates. Columns (3) and 6 report the differences in the means between the treatment and control groups. For detailed definitions of all variables, please refer to Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Pre-match (Obs.=42,926 in each group)			Post-match (Obs.=10,533 in each group)		
	Low *AUTO*	High *AUTO*	Differences T-stat.	Low *AUTO*	High *AUTO*	Differences T-stat.
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CF_{t-1}	0.0523	0.0574	-0.0051***	0.0277	0.0274	0.0003
			(-3.7760)			(0.1051)
Q_{t-1}	1.7798	1.8127	-0.0329**	1.8974	1.9323	-0.0349
			(-2.3231)			(-1.0357)
$SIZE_{t-1}$	4.8795	4.6032	0.2763***	4.4523	4.4465	0.0058
			(19.6270)			(0.1844)
LEV_{t-1}	0.2588	0.2483	0.0105***	0.2737	0.2768	-0.0031
			(4.5482)			(-0.5414)
ROA_{t-1}	0.0602	0.0379	0.0223***	0.0157	0.0163	-0.0006
			(14.5445)			(-0.1781)
$CASH_{t-1}$	0.1145	0.1197	-0.0052***	0.1226	0.1230	-0.0004
			(-5.2785)			(-0.1707)
PPE_{t-1}	0.5020	0.5382	-0.0362***	0.5119	0.5077	0.0042
			(-14.0199)			(0.7627)

Panel C. PSM estimations

Panel C presents the regression results of Equation (2) estimated in the propensity score matched sample. The model specifications are the same as those reported in Table 2. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	INV_t	INV_t	INV_t	INV_t
Variables	(1)	(2)	(3)	(4)
$AUTO_{t-1}$	-0.0027***	0.0001	0.0008	0.0016*
	(-4.62)	(0.12)	(1.45)	(1.88)
CF_{t-1}	0.0907***	0.0705***	0.0827***	0.0615***
	(7.96)	(6.10)	(6.97)	(4.65)
$AUTO \times CF_{t-1}$	-0.0076***	-0.0061***	-0.0082***	-0.0047**
	(-3.88)	(-3.07)	(-4.02)	(-2.17)
Q_{t-1}	0.0084***	0.0094***	0.0097***	0.0107***
	(6.40)	(7.29)	(7.36)	(6.93)
$AUTO \times Q_{t-1}$	-0.0006***	-0.0007***	-0.0007***	-0.0008***
	(-2.68)	(-3.06)	(-2.90)	(-3.25)
$SIZE_{t-1}$	-0.0007*	0.0014***	-0.0003	-0.0124***
	(-1.68)	(3.11)	(-0.56)	(-9.39)
CONSTANT	0.0703***	0.1764***	0.0783***	0.1353***
	(20.07)	(5.58)	(4.52)	(17.95)
Year fixed effects	No	Yes	Yes	Yes
State fixed effects	No	Yes	No	No
Industry fixed effects	No	No	Yes	No
Firm fixed effects	No	No	No	Yes
Observations	21,066	21,066	21,066	21,066
Adjusted R^2	0.0404	0.1032	0.1839	0.0990

Table 5. Entropy balancing (EB) matching

Panel A. Matching efficiency of EB matching

Panel A presents mean, variance, and skewness of the covariates between the treatment and control groups, before and after EB matching.

Pre-matching without weighting:						
	Low *AUTO* (Obs.=47,830)			High *AUTO* (Obs.=49,915)		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Variables	(1)	(2)	(3)	(4)	(6)	(6)
CF_{t-1}	0.0574	0.0478	-2.1780	0.0523	0.0409	-2.3150
Q_{t-1}	1.8130	4.8600	4.7320	1.7800	4.9000	4.5480
$SIZE_{t-1}$	4.6030	5.0840	0.4704	4.8790	4.6020	0.2128
LEV_{t-1}	0.2483	0.1369	6.2360	0.2588	0.1234	6.1830
ROA_{t-1}	0.0379	0.0602	-2.4240	0.0602	0.0549	-2.6150
$CASH_{t-1}$	0.1197	0.0225	2.1800	0.1145	0.0249	2.3430
PPE_{t-1}	0.5382	0.1748	1.7890	0.5021	0.1506	1.2520
Post-matching with weighting:						
	Low *AUTO* (Obs.=47,830)			High *AUTO* (Obs.=49,915)		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Variables	(1)	(2)	(3)	(4)	(6)	(6)
CF_{t-1}	0.0574	0.0478	-2.1780	0.0574	0.0478	-2.1780
Q_{t-1}	1.8130	4.8600	4.7320	1.8130	4.8600	4.7320
$SIZE_{t-1}$	4.6030	5.0840	0.4704	4.6030	5.0840	0.4704
LEV_{t-1}	0.2483	0.1369	6.2360	0.2483	0.1369	6.2360
ROA_{t-1}	0.0379	0.0602	-2.4240	0.0379	0.0602	-2.4240
$CASH_{t-1}$	0.1197	0.0225	2.1800	0.1197	0.0225	2.1800
PPE_{t-1}	0.5382	0.1748	1.7890	0.5382	0.1748	1.7890

Panel B. EB matching estimations

Panel B presents the regression results of Equation (2) estimated in the EB matched sample. The model specifications are the same as those reported in Table 2. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	INV_t (1)	INV_t (2)	INV_t (3)	INV_t (4)
$AUTO_{t-1}$	-0.0025***	0.0005	0.0010**	0.0008
	(-8.14)	(1.53)	(2.30)	(1.52)
CF_{t-1}	0.0938***	0.0795***	0.0871***	0.0730***
	(13.80)	(11.64)	(13.46)	(11.55)
$AUTO \times CF_{t-1}$	-0.0085***	-0.0077***	-0.0077***	-0.0052***
	(-7.93)	(-7.16)	(-7.50)	(-5.04)
Q_{t-1}	0.0103***	0.0119***	0.0129***	0.0124***
	(12.10)	(14.04)	(15.25)	(14.58)
$AUTO \times Q_{t-1}$	-0.0009***	-0.0010***	-0.0011***	-0.0009***
	(-6.52)	(-7.44)	(-7.65)	(-6.52)
$SIZE_{t-1}$	-0.0007**	0.0015***	-0.0002	-0.0132***
	(-2.11)	(4.56)	(-0.49)	(-17.89)
CONSTANT	0.0711***	0.0453***	0.0489***	0.1095***
	(31.65)	(17.74)	(17.42)	(24.05)
Year fixed effects	No	Yes	Yes	Yes
State fixed effects	No	Yes	No	No
Industry fixed effects	No	No	Yes	No
Firm fixed effects	No	No	No	Yes
Observations	97,745	97,745	97,744	97,328
Adjusted R^2	0.0423	0.1098	0.2439	0.4508

Table 6. Additional controls

This table presents the regression results of Equation (2) with additional control variables. The sample covers firm–year observations with non-missing values for the regression variables during 1980–2020. In column (1), we add *NONAUTO* and *CHEMI&PHARMA*. In column (2), we add *LEV*, *ROA*, *CASH* and *PPE*. In column (3), we add all six additional control variables. In column (4), we add four interaction terms $NONAUTO_{t-1}\times CF_{t-1}$, $NONAUTO_{t-1}\times Q_{t-1}$, $CHEMI\&PHARMA_{t-1}\times CF_{t-1}$, and $CHEMI\&PHARMA_{t-1}\times Q_{t-1}$. We control for the year and firm fixed effects in all columns. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	INV_t (1)	INV_t (2)	INV_t (3)	INV_t (4)
$AUTO_{t-1}$	0.0007	0.0011**	0.0009	0.0056***
	(0.93)	(2.28)	(1.32)	(6.82)
CF_{t-1}	0.0867***	0.0582***	0.0580***	0.0349***
	(14.70)	(9.65)	(9.61)	(5.73)
$AUTO\times CF_{t-1}$	-0.0070***	-0.0074***	-0.0073***	-0.0246***
	(-7.03)	(-7.62)	(-7.59)	(-11.56)
Q_{t-1}	0.0128***	0.0127***	0.0127***	0.0099***
	(15.94)	(16.18)	(16.14)	(12.92)
$AUTO\times Q_{t-1}$	-0.0010***	-0.0008***	-0.0008***	-0.0026***
	(-7.17)	(-6.36)	(-6.33)	(-9.53)
$SIZE_{t-1}$	-0.0130***	-0.0154***	-0.0155***	-0.0148***
	(-19.23)	(-19.78)	(-19.79)	(-19.10)
$NONAUTO_{t-1}$	-0.0001		-0.0004	-0.0082***
	(-0.06)		(-0.46)	(-7.78)
$CHEMI\&PHARMA_{t-1}$	0.0008		0.0010	0.0040***
	(1.15)		(1.47)	(5.50)
LEV_{t-1}		-0.0210***	-0.0210***	-0.0203***
		(-11.73)	(-11.72)	(-11.39)
ROA_{t-1}		0.0301***	0.0301***	0.0267***
		(9.91)	(9.90)	(8.77)
$CASH_{t-1}$		0.0058**	0.0057**	0.0066**
		(2.01)	(1.99)	(2.32)
PPE_{t-1}		-0.0152***	-0.0152***	-0.0139***
		(-6.40)	(-6.44)	(-5.87)
$NONAUTO_{t-1}\times CF_{t-1}$				0.0254***
				(9.49)
$NONAUTO_{t-1}\times Q_{t-1}$				0.0032***
				(9.46)
$CHEMI\&PHARMA_{t-1}\times CF_{t-1}$				-0.0053***
				(-4.38)
$CHEMI\&PHARMA_{t-1}\times Q_{t-1}$				-0.0013***
				(-8.64)
CONSTANT	0.1454***	0.1660***	0.1651***	0.1707***
	(28.27)	(38.08)	(28.37)	(29.07)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	121,298	121,298	121,298	121,298
Adjusted R^2	0.1166	0.1264	0.1264	0.1325

Table 7. High-dimensional fixed effects

This table presents the regression results of Equation (2) with various combinations of fixed effects. The sample covers firm–year observations with non-missing values for the regression variables during 1980–2020. In column (1), we control for the firm and interacted state×year fixed effects. In column (2), we control for the firm and interacted industry×year fixed effects. In column (3), we control for the firm, interacted state×year, and interacted industry×year fixed effects. In column (4), we control for the firm, year, state, and industry fixed effects. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	INV_t (1)	INV_t (2)	INV_t (3)	INV_t (4)
$AUTO_{t-1}$	0.0123***	0.0110***	0.0109***	0.0128***
	(36.69)	(30.89)	(30.38)	(38.44)
CF_{t-1}	-0.0009***	-0.0008***	-0.0008***	-0.0010***
	(-15.07)	(-12.27)	(-11.96)	(-16.06)
$AUTO \times CF_{t-1}$	0.0010***	0.0015***	0.0014***	0.0010***
	(3.13)	(4.12)	(3.86)	(3.19)
Q_{t-1}	0.0822***	0.0702***	0.0680***	0.0869***
	(22.97)	(18.63)	(17.91)	(24.29)
$AUTO \times Q_{t-1}$	-0.0065***	-0.0053***	-0.0050***	-0.0070***
	(-10.20)	(-7.90)	(-7.41)	(-10.96)
$SIZE_{t-1}$	-0.0131***	-0.0140***	-0.0138***	-0.0130***
	(-38.22)	(-37.71)	(-36.63)	(-38.51)
$CONSTANT$	0.1137***	0.1175***	0.1169***	0.1129***
	(50.80)	(47.29)	(46.45)	(50.88)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes
State fixed effects	No	No	No	Yes
Industry fixed effects	No	No	No	Yes
State×Year fixed effects	Yes	No	Yes	No
Industry×Year fixed effects	No	Yes	Yes	No
Observations	121,007	119,130	119,001	121,125
Adjusted R^2	0.4593	0.4768	0.4794	0.4488

Table 8. Cross-sectional analyses

Panel A. Financial constraints

Panel A presents the results of cross-sectional analyses based on financial constraints. We classify firms–year observations into high and low sub-samples based on the annual industry median of the KZ index and SA index. All columns include the year and firm fixed effects. We adopt seemingly unrelated regressions to examine whether the coefficients of *AUTO ×Q* and *AUTO ×CF* exhibit statistically significant difference between the high and low sub-samples. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	High *KZ*	Low *KZ*	High *SA*	Low *SA*
	INV_t	INV_t	INV_t	INV_t
Variables	(1)	(2)	(3)	(4)
$AUTO_{t-1}$	0.0001	0.0023***	0.0013*	0.0013**
	(0.19)	(3.95)	(1.72)	(2.26)
CF_{t-1}	0.1000***	0.0656***	0.0699***	0.1115***
	(13.21)	(7.52)	(10.59)	(9.71)
$AUTO \times CF_{t-1}$	-0.0082***	-0.0052***	-0.0057***	-0.0083***
	(-6.36)	(-3.63)	(-5.20)	(-4.33)
Q_{t-1}	0.0116***	0.0156***	0.0113***	0.0148***
	(12.13)	(11.78)	(11.80)	(11.17)
$AUTO \times Q_{t-1}$	-0.0009***	-0.0012***	-0.0009***	-0.0009***
	(-5.72)	(-5.33)	(-6.03)	(-3.99)
$SIZE_{t-1}$	-0.0161***	-0.0109***	-0.0188***	-0.0143***
	(-17.88)	(-11.45)	(-17.75)	(-16.54)
CONSTANT	0.1742***	0.1216***	0.1615***	0.1616***
	(36.11)	(26.28)	(31.22)	(30.59)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	64,391	56,795	56,835	64,463
Adjusted R^2	0.1170	0.1158	0.0903	0.1630
Prob>chi2(*AUTO*×*CF*)	0.0651*		0.0743*	
Prob>chi2(*AUTO*×*Q*)	0.4313		0.2883	

Panel B. Informed trading

Panel B presents the results of cross-sectional analyses based on stock price informativeness. We classify firms–year observations into high and low sub-samples based on the annual industry median of *PIN* and *NONSYN*. All columns include the year and firm fixed effects. We adopt seemingly unrelated regressions to examine whether the coefficients of *AUTO*×*Q* and *AUTO*×*CF* exhibit statistically significant difference between the high and low sub-samples. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	High *PIN*	Low *PIN*	High *NONSYN*	Low *NONSYN*
	INV_t	INV_t	INV_t	INV_t
Variables	(1)	(2)	(3)	(4)
$AUTO_{t-1}$	0.0021**	0.0007	0.0013**	0.0009
	(2.52)	(0.92)	(2.09)	(1.33)
CF_{t-1}	0.0439***	0.0650***	0.0736***	0.0992***
	(5.36)	(6.43)	(10.81)	(8.56)
$AUTO \times CF_{t-1}$	-0.0021	-0.0049***	-0.0052***	-0.0084***
	(-1.57)	(-2.85)	(-4.77)	(-4.19)
Q_{t-1}	0.0116***	0.0090***	0.0134***	0.0124***
	(8.15)	(7.38)	(11.56)	(10.25)
$AUTO \times Q_{t-1}$	-0.0009***	-0.0004*	-0.0011***	-0.0007***
	(-3.99)	(-1.81)	(-5.95)	(-3.43)
$SIZE_{t-1}$	-0.0158***	-0.0133***	-0.0128***	-0.0141***
	(-14.20)	(-13.77)	(-14.86)	(-15.57)
CONSTANT	0.1130***	0.1322***	0.1311***	0.1692***
	(12.88)	(16.76)	(30.35)	(32.08)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	37,620	37,672	61,183	52,914
Adjusted R^2	0.0984	0.1454	0.0926	0.1571
Prob>chi2(*AUTO*×*CF*)	0.1013		0.1081	
Prob>chi2(*AUTO*×*Q*)	0.0636*		0.0947*	

Panel C. Managerial learning incentive

Panel C presents the results of cross-sectional analyses based on managerial learning incentives. We classify firms–year observations into high and low sub-samples based on the annual industry median of $R_{product}$ and *Sales_Volatility*. All columns include the year and firm fixed effects. We adopt seemingly unrelated regressions to examine whether the coefficients of *AUTO*×*Q* and *AUTO*×*CF* exhibit statistically significant difference between the high and low sub-samples. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	High $R_{product}$	Low $R_{product}$	High *Sales_Volatility*	Low *Sales_Volatility*
	INV_t	INV_t	INV_t	INV_t
Variables	(4)	(3)	(5)	(6)
$AUTO_{t-1}$	0.0008	0.0007	0.0014**	0.0004
	(1.25)	(1.11)	(2.20)	(0.66)
CF_{t-1}	0.1044***	0.0734***	0.0747***	0.1394***
	(12.05)	(9.54)	(11.06)	(11.76)
$AUTO{\times}CF_{t-1}$	-0.0074***	-0.0063***	-0.0069***	-0.0109***
	(-5.16)	(-4.85)	(-6.10)	(-5.58)
Q_{t-1}	0.0119***	0.0126***	0.0125***	0.0107***
	(11.79)	(11.68)	(12.52)	(8.83)
$AUTO{\times}Q_{t-1}$	-0.0007***	-0.0011***	-0.0011***	-0.0005**
	(-3.82)	(-6.22)	(-6.73)	(-2.33)
$SIZE_{t-1}$	-0.0142***	-0.0129***	-0.0127***	-0.0109***
	(-15.95)	(-14.72)	(-13.24)	(-12.42)
CONSTANT	0.1591***	0.1392***	0.1330***	0.1395***
	(31.43)	(32.27)	(29.56)	(27.23)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	59,379	59,382	61,905	54,196
Adjusted R^2	0.1409	0.0924	0.0856	0.1514
Prob>chi2(AUTO×CF)	0.6737		0.1238	
Prob>chi2(AUTO×Q)	0.0343**		0.0010***	

Table 9. Financial crisis periods

This table presents the regression results of Equation (2) after dropping financial crisis periods. In column (1), we drop the sample years between 2000 and 2003. In column (2), we drop the sample years between 2007 and 2009. In column (3), we drop the sample years between 2000 and 2003 and between 2007 and 2009. In column (4), we only retain the sample years between 2000 and 2003 and between 2007 and 2009. For detailed definitions of all variables, please refer to Appendix A. All columns include the year and firm fixed effects. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	INV_t (1)	INV_t (2)	INV_t (3)	INV_t (4)
$AUTO_{t-1}$	0.0013**	0.0011**	0.0014***	0.0004
	(2.52)	(2.12)	(2.67)	(0.28)
CF_{t-1}	0.1028***	0.0907***	0.1087***	0.0204**
	(15.37)	(14.45)	(15.08)	(2.30)
$AUTO \times CF_{t-1}$	-0.0088***	-0.0075***	-0.0095***	0.0007
	(-7.80)	(-7.07)	(-7.75)	(0.50)
Q_{t-1}	0.0142***	0.0133***	0.0149***	0.0074***
	(14.92)	(15.89)	(14.86)	(6.98)
$AUTO \times Q_{t-1}$	-0.0012***	-0.0010***	-0.0012***	-0.0003*
	(-7.33)	(-7.16)	(-7.27)	(-1.67)
$SIZE_{t-1}$	-0.0131***	-0.0133***	-0.0134***	-0.0178***
	(-17.71)	(-19.57)	(-18.03)	(-10.81)
CONSTANT	0.1449***	0.1473***	0.1442***	0.1485***
	(39.34)	(42.70)	(38.95)	(13.54)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	106,637	112,899	98,238	23,060
Adjusted R^2	0.1160	0.1171	0.1161	0.1179

Table 10 Alternative measure of automation exposure

This table presents the regression results of Equation (2) with alternative measures of automation exposure. In columns (1) and (2), *AUTO_Alt1* and *AUTO_Alt2* are the proxies for automation exposure, respectively. All columns include the year and firm fixed effects. For detailed definitions of all variables, please refer to Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	INV_t (1)	INV_t (2)
$AUTO\_Alt1_{t-1}$	1.2257*	
	(1.86)	
$AUTO\_Alt2_{t-1}$		0.1549
		(0.35)
CF_{t-1}	0.1230***	0.1249***
	(23.57)	(23.34)
$Proxy \times CF_{t-1}$	-6.6301***	-7.5384***
	(-3.16)	(-3.39)
Q_{t-1}	0.0114***	0.0115***
	(23.55)	(23.33)
$Proxy \times Q_{t-1}$	-1.2569***	-0.9750***
	(-4.96)	(-5.07)
$SIZE_{t-1}$	-0.0171***	-0.0169***
	(-20.79)	(-20.70)
CONSTANT	0.1783***	0.1773***
	(43.47)	(43.36)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Observations	83,076	83,076
Adjusted R^2	0.1616	0.1626