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Automation Threat and Income Smoothing

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Automation Threat and Income Smoothing

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A thesis submitted in partial fulfillment of the requirements

for the degree of

Master of Philosophy

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DECLARATION

I hereby declare that this thesis represents my own work which has been done after registration for the degree of MPhil at Hong Kong Baptist University, and has not been previously included in a thesis or dissertation submitted to this or any other institution for a degree, diploma or other qualifications.

I have read the University's current research ethics guidelines, and accept responsibility for the conduct of the procedures in accordance with the University's Research Ethics Committee (REC). I have attempted to identify all the risks related to this research that may arise in conducting this research, and acknowledged my obligations and the rights of the participants.

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ABSTRACT

This study investigates whether the substitutability of labor with automated capital (SLAC) affects corporate income smoothing behavior. I posit that SLAC reduces firms' systematic and operational risks and weakens workers' bargaining power, thereby moderating managers' incentives to use income smoothing to lower perceived firm risk and increase managers' bargaining power. Using data from U.S. firms, I document a negative correlation between SLAC and income smoothing. Using an instrumental variable that helps isolate the source of variation in SLAC stemming only from the development of automation technology, I draw a causal relation between SLAC and income smoothing. Additional analyses suggest that the relation between SLAC and income smoothing is less likely to be driven by the possibility that firms with high SLAC are in the process of automating their production. Further analyses show that the effect of SLAC on income smoothing is more pronounced when the potential benefits of automation are higher. This study contributes to the literature by identifying an important novel determinant of income smoothing and by leading the way in examining the effects of automation technology on firms' accounting policies.

Keywords: substitutability of labor with automated capital; income smoothing; firm risk; bargaining power

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I. Introduction

Over the past few decades, there has been a rapid development of artificial intelligence (AI) and robotics, resulting in the potential replacement of numerous workers, particularly those engaged in routine and programmable tasks. In light of this, extensive research has been conducted to examine the impact of automation on various factors such as wages (Acemoglu et al., 2001; Dinlersoz and Greenwood, 2016), unemployment (Acemoglu and Restrepo 2020; Autor and Salomons, 2018; Lee and Kim, 2023), productivity (Graetz and Michaels, 2018), firm value (Zhang, 2019), capital structure (Liu, 2020) and cash holding (Bates et al., 2023). These changes resulting from the adoption of automation significantly influence the risk profile of firms and subsequently alter the role of accounting information in providing risk-related information to various stakeholders. Specially, this study aims to investigate the effect of the substitutability of labor with automated capital (SLAC) on income smoothness.

Income smoothness is chosen as the primary focus of this study due to its multifaceted nature. Firstly, it serves as an effective tool for firm managers to communicate risk information to external stakeholders. SLAC provides firms with the option to strategically replace labor with automation during economic downturns, potentially reducing systematic and operational risks (Zhang, 2019). Consequently, when firms face lower risk due to SLAC, managers may have less incentive to use smoothed earnings as a means to mitigate perceived high risk by external stakeholders. Secondly, income smoothness plays a crucial role in balancing the bargaining power between the firm and its employees, as highlighted in prior literature (e.g., Hamm et al., 2018). The introduction of SLAC poses the potential threat of employee layoffs, which can alter the relative bargaining power between managers and employees. Consequently, this shift in bargaining power may impact the incentive for managers to engage in earnings smoothness practices as a way to mitigate potential labor costs. By investigating the relationship between SLAC and income smoothness, this study aims to contribute to a deeper understanding of the implications of automation on firms' reporting behavior.

Notably, SLAC represents the extent to which a firm can replace labor with automation capital, rather than solely examining actual automation, as firms with the option to automate may not necessarily proceed with automation in their production processes (Zhang, 2019).[1] I argue that SLAC negatively affects income smoothing through two channels: *bargaining power* and *risk perception*. The first channel is bargaining power. Both too low and too high earnings lead to an increase in labor costs when firms are faced with strong worker power; the former increases labor costs through increased unemployment risk, and the latter increases labor costs by boosting employees' incentive to seek a larger portion of profits and thus transferring more wealth from shareholders to employees. Consequently, firms with strong worker power are motivated to engage in income smoothing activities (Hamm et al., 2018). I argue that SLAC decreases workers' power by providing firms the opportunity for labor–automation substitution. This enables firms to counteract the threat of worker strikes and other forms of collective action. In this vein, weak worker power associated with SLAC reduces managers' incentive to use income smoothing to curb labor costs. Therefore, the bargaining power channel implies that there is a negative association between SLAC and income smoothing.

[1] Note that this study distinguishes between SLAC (the option to automate) and actual automation by a firm, and focuses on the former. See Section 2.1 for details. In addition, I use the terms SLAC, the option to automate, automatability, and automation threat interchangeably.

Regarding the risk perception channel, markets regard earnings volatility as risky and, hence, demand a risk premium. Consequently, managers tend to exploit income smoothing as a strategy to lower the market perception of firm risk (Graham et al., 2005). As such, firms' income smoothing incentives resulting from risk concerns may decrease if firm risk is perceived to be relatively low (i.e., the need to manage the perception of firm risk is limited) (Ferracuti et al., 2023; Kim et al., 2021). The literature shows that investors may perceive high-SLAC firms to be less risky in terms of systematic risk and operational risk for two reasons. First, SLAC affords firms the option to optimally replace labor with automation, which hedges their value against unfavorable macroeconomic shocks (Zhang, 2019). Second, compared with low-SLAC firms, high-SLAC firms tend to have a larger proportion of low- and medium-skilled workers, allowing their lower labor-induced operating leverage, larger operating flexibility, and thus lower operating risk (Bates et al. 2023). Thus, the risk perception channel implies that SLAC has a negative effect on income smoothing. Based on the combined reasoning, I argue that SLAC negatively affects income smoothing.

Nonetheless, there may exist countervailing factors against the above-mentioned arguments. One such factor is the possibility that workers who are particularly vulnerable to being replaced by automation are more inclined to join labor unions. This increased union power could potentially counterbalance the bargaining advantage that managers derive from SLAC. In addition, high-SLAC firms, which have a larger proportion of low- and medium-skilled workers, may face increased risks in certain situations. For instance, these firms could be more susceptible to policy uncertainty associated with labor regulations, including overtime rules and work-safety requirements. Such specific risks may outweigh the risk reduction benefits brought about by SLAC. Consequently, these countervailing factors have the potential to undermine the arguments put forth in support of my hypothesis.

To test my hypothesis, I follow Bates et al. (2023) and measure SLAC using the weighted average probability of computerization across all occupations that constitute an industry in a certain year. I measure income smoothing with a common factor, which is aggregated based on three commonly used measures: (1) the ratio of the standard deviation of operating earnings to the standard deviation of cash flows from operations; (2) the Spearman correlation between the change in total accruals and the change in cash flows from operations; (3) the Spearman correlation between the change in discretionary accruals and the change in the pre-managed income. Using U.S. firm data from 1999 to 2018, I show that SLAC is negatively correlated with income smoothing. An increase of one standard deviation in SLAC results in a decrease equivalent to 28.515% of the median value of the measure of income smoothing. This finding supports the idea that SLAC negatively affects income smoothing. To address the potential endogeneity of SLAC, I construct an instrumental variable (IV) using the average robot density of five European countries that surpass the U.S. in terms of robotics technology.[2] Doing so allows me to isolate variations in automation threat arising from technological development. The IV estimates demonstrate a causal relationship between SLAC and income smoothing. To alleviate the concern that the negative relationship is driven by changes in firm fundamentals resulting from firms' ongoing automating behavior, I restrict the sample to firms and industries that are less likely to be

[2] They are Denmark, Finland, France, Italy, and Sweden. Acemoglu and Restrepo (2022) document that these countries lead the U.S. in robotics technology mainly due to their demographic factors (i.e., an aging population).

automating. The empirical results show that the negative correlation between SLAC and income smoothing still holds, mitigating the concern that my results may be driven by changes in firm fundamentals.

I examine the channels through which SLAC decreases income smoothing. First, I posit that SLAC decreases income smoothing by reducing firms' operational and systematic risks. Consistent with this prediction, I find that natural disasters that convincingly disrupt production have a less detrimental effect on the financial performance of high-SLAC firms compared to low-SLAC firms, suggesting that high-SLAC firms are better positioned to withstand production disruptions compared to low-SLAC firms. Second, to test the channel of bargaining power. I use labor strikes to proxy for workers' bargaining power in a four-digit NAICS industry. I find that both the likelihood and number of labor strikes are smaller within high-SLAC industries than within low-SLAC ones. These findings suggest that workers' bargaining power in high-SLAC firms is weaker than that in low-SLAC firms, supporting the bargaining power channel. In sum, the results of the channel tests indicate that SLAC affects corporate income smoothing through the risk perception and bargaining power channels.

Finally, I focus on the cross-sectional variations in the effect of SLAC on income smoothing. Although SLAC affords a firm the option to replace labor with automation, firms' decision to automate production involves weighing benefits (improved productivity and reduced labor costs) against costs associated with labor market frictions, purchases of relevant equipment, and interruptions in production, etc. As such, it is reasonable that, before exercising the option to automate, the magnitude of the automation threat increases in the net benefit of potential automation. It translates to the prediction that the effect of SLAC on income smoothing decreases (increases) if automation costs are relatively high (low) and if automation benefits are relatively low (high). Consistent with this prediction, I find that the relationship between SLAC and income smoothing is more pronounced when workers can enjoy higher unemployment insurance benefits, when computer price is lower, when firms are more labor-intensive, and when firms are headquartered in states with relatively high minimum wages. In summary, the results of cross-sectional analyses indicate that the effect of SLAC on income smoothing is more pronounced when the potential benefits (costs) of automation are higher (lower).

This study makes several notable contributions to the existing literature. Firstly, it enriches the literature on corporate income smoothing by identifying a novel determinant of income smoothing. While previous studies have predominantly explored the determinants of income smoothing through the lens of capital market incentives or managerial compensation motivations (Graham et al., 2005), there is a dearth of research investigating how technological advancements impact firms' income smoothing behavior. This is particularly surprising considering the transformative influence that advanced technologies, such as AI and robots, exert on business operations. By examining the impact of automation threat on income smoothing from the perspective of the employment relationship, this study bridges the gap in the literature and sheds light on an understudied aspect of income smoothing dynamics.

A closely related paper is Ng et al. (2019), which finds that firms have an incentive to exploit income smoothing to mitigate employees' concerns about unemployment risk and thus decrease labor costs. I complement Ng et al. (2019) by documenting that such incentives may be blunted for high-SLAC firms in which workers' bargaining power is limited. Another related paper is Hamm et al. (2018), which finds that labor union strength increases firms' income smoothing behavior. Using a different setting, i.e., the development of automation technology, this study provides consistent evidence suggesting that workers' bargaining power increases employers' income smoothing. This setting is very powerful because automation technology, which makes numerous tasks replaceable, has a more fundamental effect on firm-labor relations. For example, Acemoglu et al. (2001) argue that skilled-biased technical change plays an important role in deunionization in the U.S. and U.K. Similarly, Dinlersoz and Greenwood (2016) suggest that the observed trends in union membership in the U.S. can be attributed to technological advancements. In addition, this study provides direct empirical evidence that automation technology (i.e., SLAC) indeed affects workers' bargaining power. Therefore, the focus of this study is a more fundamental determinant of income smoothing.

Second, this study contributes to the automation literature. Given the widespread concern that automation may lead to large-scale unemployment, many studies examine how automation affects wages, unemployment, and unionization (Acemoglu et al., 2001; Dinlersoz and Greenwood, 2016; Graetz and Michaels, 2018; Leduc and Liu, 2023, Lee and Kim, 2023). Several studies investigate the effects of real automation or the option to automate on firms' financial policies, such as financial leverage (Cheng et al., 2022; Liu, 2020) and cash holdings (Bates et al., 2023; Liu, 2020). This study extends the literature on the consequences of automation by investigating how automation affects firms' accounting choices. To the best of my knowledge, this study is the first to link automation and accounting choices. This link is important because the effect of automation on business operations indicates its implications for firms' accounting policies. Therefore, this study is the first to demonstrate how technological development (i.e. automation) affects firms' accounting choices.

The remainder of this article is organized as follows. Section II presents the related literature. Section III states the research hypothesis. Section IV describes the data and research methodology. Section V presents the empirical results. Section VI concludes the paper.

II. Literature Review

2.1 Related Literature on Automation Threat

The development of robotics and AI has led to concerns about "technological unemployment," i.e., automation-related technology could wipe out numerous low- and medium-skill jobs and lead to joblessness (Autor, 2015). In light of this, much of the literature has investigated how actual automation affects wages and unemployment but provides mixed evidence (Acemoglu et al., 2001; Acemoglu and Restrepo, 2020, 2022; Autor and Salomons, 2018; Graetz and Michaels, 2018). One possible explanation for this mixed evidence is the slow adoption of automation technology (Arnoud, 2018). Zhang (2019) posits that numerous firms do not automate their production even though they have the option to do so. In other words, such firms may choose to retain the option rather than exercise it, depending on whether the option to automate is in the money (i.e., firms optimally exercise the option). Therefore, some studies examine the effect of automation threat rather than actual automation (i.e., the effect of automatability even in the absence of actual automation).

One stream of the literature examines the effect of automation threat on worker power. Leduc and Liu (2023) find that automation threat increases managers' bargaining power relative to workers' bargaining power. The authors posit that if labor takes a strong stance in wage negotiations, managers endowed with the option to automate may choose to exercise it (i.e., replace labor with automation), which would negatively affect incumbent workers in the long run. Aware of the outside option owned by managers, labor may *ex ante* take a relatively weak position in negotiations to avoid long-run harm caused by automation. In this sense, automation threat decreases workers' power. Similarly, Arnoud (2018) suggests that automation threat increases managers' relative bargaining power, thereby reducing workers' average wages. Consistently, Qiu et al. (2020) document that exposure to automation technology increases firms' financial leverage, suggesting that automation threat decreases workers' bargaining power and labor costs and, thus, allows firms to increase their financial leverage. In summary, existing studies suggest that automation threat positively affects managers' bargaining power relative to workers' bargaining power.

In addition, the literature also suggests that automation threat affects firm risk perception. Bates et al. (2023) demonstrate that high-SLAC firms maintain lower amounts of precautionary cash. The authors argue that the option to automate provides operational flexibility to firms, which reduces firms' operational risk. Zhang (2019) posits that firms' options can be used to protect firm value from unfavorable economic shocks; therefore, the option to automate decreases firms' systematic risk. Supporting the view of Zhang (2019), Kopytov et al. (2018) empirically demonstrate that there are many technological advancements that favor skilled employees during an economic downturn.

In summary, the literature suggests that the option to automate affects firms' financial policies or firm value by affecting workers' bargaining power or firm risk perception.

2.2 Related Literature on Income Smoothing

The literature examines how firm risk affects corporate income smoothing behavior. Graham et al. (2005) document that 97% of the surveyed managers favor smooth earnings over bumpy earnings. Such a preference may result from the market's aversion to risk and the fact that managers perceive smooth earnings to be less risky. As such, firms are motivated to smooth income to reduce investors' perception of firm risk. For example, Graham et al. (2005) show that managers may manage risk perception via income smoothing even at the cost of firms' economic value. Ferracuti et al. (2023) find that the likelihood of firms engaging in income smoothing behavior decreases if they are less exposed to risk from forex fluctuations. Kim et al. (2021) suggest that firms' real income smoothing reduces the risk perception of equity investors and creditors.

One stream of the literature investigates how firms' accounting policies are affected by workers' power, which is often proxied by labor union strength. Labor is an important stakeholder group of a firm. Workers not only contribute substantially to firm value but also try to seek a larger portion of firm profits. The two roles of employees correspond to managers' two competing incentives: the incentive to reduce employees' risk perception, and the incentive to increase bargaining power during negotiations with workers to shelter resources from rent seeking by labor. Indeed, firms have an incentive to reduce employees' perception of firm risk to attract and retain talent and decrease labor costs (Chang et al., 2022; Hamm et al., 2018; Liu et al., 2021; Ng et al., 2019). Consistent with the risk-reducing incentive, Chang et al. (2022) document that firms facing strong labor unions are more likely than others to manage their earnings upward via real activities. The authors find that managers have an incentive to present better future firm prospects to decrease employees' concerns about unemployment and, thus, curb labor costs. Liu et al. (2021) use the same logic to explain why an increase in labor unemployment insurance leads to more accounting conservatism. More relevantly, Ng et al. (2019) suggest that firms exploit income smoothing to moderate employees' concerns about unemployment. Correspondingly, they find that unemployment insurance benefits reduce corporate income smoothing. Ng et al. (2019) also point out that the reduced incentive of income smoothing caused by unemployment insurance is based on the premise that firms' income smoothing behavior may be costly. Income smoothing may entail compliance costs (Ng et al., 2019), sacrifice corporate economic value (Khurana et al., 2018), and lead to more volatile earnings (Baik et al., 2020).

In contrast, managers are motivated to enhance their bargaining power relative to employees' bargaining power and to shelter resources from labor's demand for profit sharing. Regarding labor unions as rent seekers, Watts and Zimmerman (1986) posit that managers may strategically reduce firm earnings. By doing so, they can improve their bargaining position during negotiations with organized labor and avoid wealth transfer from shareholders to workers. This view is empirically supported by several studies. Bova (2013) demonstrates that firms facing labor unions are more likely to miss analyst forecasts through downward earnings management. Basu et al. (2022) find that firms hesitate to offer non-Generally Accepted Accounting Principles (non-GAAP) earnings after employees unionize, as non-GAAP earnings metrics are typically higher than GAAP earnings. Hilary

(2006) and Chung et al. (2016) suggest that unionized firms try to be opaque to outsiders to strengthen their bargaining position during negotiations with labor unions.[3]

More relevantly, Hamm et al. (2018) argue that managers balance these two competing incentives when making income smoothing decisions. Specifically, managers manage earnings downward to avoid rent seeking by labor unions when earnings are too high and manage earnings upward to cater to employees' risk aversion when earnings are too low. Hamm et al. (2018) document that firms facing strong labor unions engage in more income smoothing behavior than do other firms.

In summary, the literature suggests that firms' income smoothing behavior is affected by their incentives to reduce perceived firm risk and improve their bargaining power during negotiations with workers. The novelty of this study is that it reveals another related determinant of income smoothing.

III. Hypothesis Development

In this study, I argue that SLAC negatively affects corporate income smoothing through the following two channels.

Bargaining Power Channel. Graham et al. (2005) indicate that firms proactively engage in income smoothing behavior to shape stakeholders' perceptions and, thus, achieve better terms during negotiations with them. Corroborating this notion, Hamm et al. (2018) document that managers engage in income smoothing to deal with powerful workers, who comprise an important

[3] Nevertheless, several studies provide evidence inconsistent with the view that managers manipulate accounting policies or financial reporting to increase their bargaining power. For example, Liberty and Zimmerman (1986) document that earnings were not lower than expected during labor talks. Osma et al. (2015) argue that the negotiation between managers and organized labor is not a one-shot but rather a repeated game; as a result, firms' accounting policies are cooperation-oriented. As such, firms may choose to use accounting discretion to signal true performance to labor unions. Doing so helps avoid labor unions' unreasonable profit sharing demand arising from information asymmetry. In line with the cooperation view, Khurana and Zhong (2023) suggest that strong worker power induces manager-employee alliances.

stakeholder of a firm. Specifically, managers have an incentive to shelter resources from employees' profit sharing demand. Thus, they tend to manage earnings downward to avoid wealth transfer from shareholders to employees during periods of good firm performance. Nonetheless, too volatile or negative earnings may be perceived as unemployment risk, which would lead to *ex ante* higher labor costs; to control such costs, managers are more likely to manage earnings upward during periods of poor firm performance. Taken together, firms with strong worker power are more likely to smooth earnings than are other firms (Hamm et al., 2018).

I argue that SLAC decreases workers' relative bargaining power during negotiations with managers. Workers' bargaining power is largely derived from the threat to withhold labor services. However, high-SLAC firms are less exposed to this threat because they have a powerful tool at their disposal, namely the option to replace workers with automation, and could optimally exercise this option if it becomes more valuable. Thus, workers' power decreases in high-SLAC firms. This implies that high-SLAC firms attach less importance to worker power when making accounting decisions. Therefore, high-SLAC firms with reduced worker power have less of an incentive to engage in income smoothing activities. The reduced workers' bargaining power suggests that SLAC decreases corporate income smoothing.

Risk Perception Channel. Markets regard earnings volatility as risky and, hence, demand a risk premium. Consequently, managers have a tendency to reduce the market's perception of firm risk by engaging in income smoothing activities. As such, firms' income smoothing incentives resulting from risk concerns may reduce if stakeholders' perceived firm risk is relatively low.

High-SLAC firms have relatively low perceived systematic and operational risks. Zhang (2019) finds that the option to replace labor with automation capital protects firms' value from unfavorable macroeconomic shocks (firms optimally choose to automate when their productivity is low). Thus, the systematic risk of firms with such an option is perceived by investors to be relatively low, as empirically documented by Zhang (2019). Additionally, workplace automation is typically designed to replace low- and medium-skilled workers who perform routine and codifiable tasks, whereas high-skill workers are relatively immune to automation. In this sense, high-SLAC firms tend to have a greater proportion of low- and medium-skilled workers. Because low- and medium-skilled labor is associated with low labor adjustment costs, high operating flexibility, and hence low firm risk (Ghaly et al., 2017), the operational risk of high-SLAC firms (with low- and medium-skilled workers) is expected to be relatively low.[4] Consistent with the view of high-SLAC firms being less risky than low-SLAC firms, Bates et al. (2023) document that high-SLAC firms maintain lower amounts of precautionary cash. Therefore, due to the relatively low perceived systematic and operational risks, high-SLAC firms are expected to have less of an incentive to use income smoothing to lower investors' perception of firm risk.

Based on the above analysis, I propose the following hypothesis:

Hypothesis 1: High-SLAC firms engage in less income smoothing behavior than low-SLAC firms.

Despite the above-mentioned arguments, there may be other factors working against my hypothesis. First, in the bargaining power channel, SLAC increases

[4] Because it costs more to hire, train, retain, and lay off high-skilled labor, labor adjustment costs increase with labor skill. Thus, skilled labor increases labor-induced operating leverage and firm risk (Ghaly et al., 2017).

managers' bargaining power relative to workers' bargaining power and results in less income smoothing. However, it is possible that workers vulnerable to automation are more likely than less-vulnerable workers to join a labor union, and the resulting increased union power offsets managers' bargaining advantage derived from SLAC. If so, the negative association between SLAC and income smoothing may not be observable. Second, in the risk perception channel, high-SLAC firms are perceived to be less risky. However, high-SLAC firms characterized by a higher proportion of low- and medium-skilled workers may be exposed to more risk in some circumstances. For example, as I mentioned earlier, high-SLAC firms are characterized by a larger proportion of low-skilled workers, who are often the focus of government policies. Therefore, high-SLAC firms may be more exposed to regulation uncertainty, such as overtime rules and work-safety requirements. If such risk dominates the risk reduced by SLAC, my hypothesis may not hold.

IV. Data and Methodology

4.1 Measure of SLAC

Only a few studies focus on firms' exposure to automation. Zhang (2019) constructs an exquisite firm-specific measure of automation exposure, which focuses on the information of the firms surveyed by the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics (BLS). He uses the percentage of wages paid for routine firm tasks as a proxy for a firm's automation potential. The limitation of this measure is that it involves only the surveyed firms.

Graetz and Michaels (2018) construct an industry-specific replaceability index, which measures the extent to which an industry can be replaced by automation. They use data from the International Federation of Robotics (IFR) on robot applications and the 1980 U.S. Census on working hours spent by workers in various occupation–industry combinations, and consider an occupation as replaceable if the title of the occupation matches any of the IFR application categories. The authors measure the replaceability index as the proportion of hours spent by workers on replaceable tasks for an industry. The limitation of the replaceability index is that this indicator is time-invariant and applies only to IFR industries.

Leduc and Liu (2023) use an industry-specific measure constructed by the McKinsey Global Institute (Manyika et al., 2017) as a proxy for the automation potential of a two-digit Standard Industrial Classification (SIC) industry. Manyika et al. (2017) evaluate the automatability of a task based on its physical characteristics and use the weighted average of the automatability of tasks in an industry to measure the industry's automation exposure. Similarly, Bates et al. (2023) construct a measure of the automation exposure of a four-digit North American Industry Classification System (NAICS) industry using data from the OES program. Specifically, Bates et al. (2023) use data on the probability of the computerization of an occupation developed by Frey and Osborne (2017) and measure SLAC as the weighted average probability of computerization across all occupations that constitute an industry in a certain year. Unlike Manyika et al. (2017), who evaluate the automatability of a task based on its physical characteristics, Bates et al. (2023) focus on the automatability of an occupation based on the probability of the occupation becoming computerized. Overall, Bates et al. (2023) provide a time-varying and exquisite measure that can better identify the automation exposure of more industries at a granular level. Therefore, I follow Bates et al. (2023) and construct the variable of interest.

Specifically, I construct SLAC using two datasets. I first obtain data on the probability of an occupation being replaced with automation from Frey and Osborne (2017). The authors examine the characteristics of tasks involved in an occupation and accordingly estimate the probability of an occupation becoming computerized according to technological capabilities such as machine learning and robotics technologies. A higher probability indicates a higher likelihood of the occupation being replaced with automation.

In addition to the probability of an occupation being replaced, data on the occupation composition of an industry are needed to calculate an industry-level SLAC. Thus, I obtain the occupational employment and wage estimates for each industry-year from the OES program maintained by the BLS. The data are available on a yearly basis from 1999 onwards.[5] However, one problem arises when I combine the two datasets. The occupation used to estimate the probability of being replaced is based on the 2010 Standard Occupational Classification (SOC) system, whereas the OES data use the 2000 SOC system for 1999-2009, the 2010 SOC system for 2010-2018 and the 2018 SOC system from 2019 onwards. To address this issue, I use the crosswalk tables provided by the BLS to unify the SOC codes of different systems. However, I find that linking the 2018 SOC system to the 2010 SOC system leads to considerable changes in the measure of SLAC that do not truly reflect the change in automatability for many industries. This is because the OES program broke out and merged many occupation(s) when transferring from the 2010 SOC system to the 2018 SOC system. To avoid the effect of this change in the measure of SLAC arising from occupation reclassification, I restrict the sample period to 1999 to 2018. Additionally, this study uses the three-digit SIC industry

[5] The data are available at https://www.bls.gov/oes/data.htm.

code from 1999–2001 and the four-digit NAICS code from 2002 onwards, following the industry code used by the OES program.

Following Bates et al. (2023), I combine the two datasets and construct the measure of SLAC for each industry-year as follows:

$$SLAC_{k,t} = \sum_{j} Prob_j \times \frac{Emp_{k,j,t} \times Wage_{k,j,t}}{\sum_j Emp_{k,j,t} \times Wage_{k,j,t}} \quad (1)$$

where $Prob_j$ is the probability of occupation j being computerized, and $Emp_{k,j,t}$ and $Wage_{k,j,t}$ are the number of employees and the average annual wages of workers assigned to occupation j in industry k for year t, respectively. $SLAC_{k,t}$ is the wage-weighted average probability of occupations in industry k being replaced with automation in year t. Higher values of SLAC implies greater automation threat. Moreover, the industrial trend of SLAC indicates the evolution of the distribution of employment across occupations.

I validate the measure of SLAC by comparing it with the replaceability index of Graetz and Michaels (2018). The replaceability index is a time-invariant industry-level index calculated based on data that capture the proportion of time spent on replaceable tasks in an industry. This index exhibits a strong positive correlation with the adoption of robots. I calculate Pearson's correlation coefficient between the replaceability index and the average industry-level SLAC over the sample period of 1999-2018. The correlation coefficient is 0.425 and significant, lending credence to the measure of SLAC.

Table 1 lists the top 10 four-digit NAICS industries with the lowest SLAC values and the top 10 industries with the highest SLAC values. As can be seen, industries related to child day care, hospital services, and educational services have low SLAC valuess and, thus, employees in such industries are less vulnerable to automation. In contrast, industries related to restaurants, transportation, gasoline stations, and securities have high SLAC values, indicating that employees in such industries are more subject to automation threat.

[Insert Table 1 Here]

Figure 1 presents the time trends of SLAC in four selected industries from 2002–2018. These four industries are selected because they have the highest or lowest SLAC values and 17 years of data. The industries with the highest SLAC values are Special Food Services (NAICS code: 7223) and Investigation and Security Services (NAICS code: 5616), while the industries with the lowest SLAC values are Outpatient Care Centers (NAICS code: 6214) and Child Day Care Services (NAICS code: 6244). As expected, Figure 1 shows a relatively stable trend for low-SLAC industries (Outpatient Care Centers and Child Day Care Services). Note that high-SLAC industries (Special Food Services and Investigation and Security Services) also show a stable trend, suggesting that high-SLAC firms do not necessarily automate their production, which is consistent with the findings of Zhang (2019).

[Insert Figure 1 Here]

4.2 Measure of Income Smoothing

I follow the literature and use commonly used methods to measure income smoothing (Baik et al., 2020; Leuz et al., 2003). The first measure, *SMTH1*, is the ratio of the standard deviation of operating earnings (scaled by lagged total assets) to the standard deviation of cash flows from operations (scaled by lagged total assets). The rationale for *SMTH1* is that if managers smooth earnings, the earnings should present a more consistent pattern than cash flows from operations. *SMTH1* is multiplied by -1 so that a greater *SMTH1* indicates a higher level of income smoothing. The second measure, *SMTH2*, is the Spearman correlation between the change in total accruals and the change in cash flows from operations (both scaled by lagged total assets). The third measure, SMTH3, is the Spearman correlation between the change in discretionary accruals and the change in the premanaged income, where the discretionary accruals are estimated from the cross-sectional version of the Jones (1991) model and the premanaged income is calculated as the net income minus discretionary accruals. The intuition for *SMTH2* (*SMTH3*) is that firms smooth income by managing accruals (discretional accruals) downward when firm performance is good and upward when firm performance is poor, where firm performance is proxied by operating cash flows (premanaged income, equal to net income minus discretionary accruals); as such, a smaller correlation indicates greater income smoothing. To ensure that a higher value corresponds to a greater degree of income smoothing, both *SMTH2* and *SMTH3* are multiplied by -1. Following Baik et al. (2020), the above-mentioned calculations of the standard deviations and correlations require a minimum of three years of data from the past five years. To further reduce measurement error, I follow Baik et al. (2020) and conduct factor analysis to aggregate the three measures, with the first common factor as the aggregate income smoothing measure (*SMTH*).[6]

4.3 Data Selection and Sources

The original dataset consists of firms listed in Compustat database from 1999 to 2018. I exclude financial services and utility firms. I match the industry-year SLAC to Compustat firms based on the industry classification code used to construct SLAC. I exclude firms with missing values for the variables. This yields

[6] The results of principal component analysis yield only one common factor with an eigenvalue greater than 1. The common factor explains 50.18% of the total variance of the three individual measures of income smoothing.

42,045 observations. All of the continuous variables are winsorized at the 1st and 99st percentiles of their distributions.

The financial data are obtained from the Compustat database.

4.4 Empirical Models

To examine the correlation between SLAC and income smoothing, I estimate the following regression, which is based on the models of Dou et al. (2013), Hamm et al. (2018), and Baik et al. (2020):

$$\begin{aligned} SMTH_{i,t} = {} & \beta_0 + \beta_1 SLAC_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 BM_{i,t} + \beta_5 GROW_{i,t} \\ & + \beta_6 LOSS_{i,t} + \beta_7 SALEVOL_{i,t} + \beta_8 AVGCFO_{i,t} + \beta_9 TANG_{i,t} \\ & + \beta_{10} HHI_{i,t} + \beta_{11} ISSUE_{i,t} + \beta_{12} DIV_{i,t} + Fixed\ Effects + \varepsilon_t \qquad (2) \end{aligned}$$

where $SMTH_{i,t}$ is the individual measure (*SMTH1*, *SMTH2*, or *SMTH3*) and the aggregate measure (*SMTH*) of income smoothing. SLAC is defined in Section 4.1. To control for firm characteristics of the operating environment and other factors that may concurrently affect SLAC and income smoothing, I include the following variables. *SIZE* denotes the natural log of total assets. *LEV* denotes the ratio of debt to total assets. *BM* denotes the natural log of the ratio of the book value to the market value of equity. *GROW* is defined as $(Sales_t - Sales_{t-1})/Sales_{t-1}$. *LOSS* denotes the proportion of years with a negative net income. *SALEVOL* denotes the standard deviation of sales scaled by the lagged total assets. *AVGCFO* denotes the average cash flows from operations scaled by the lagged total assets. *LOSS*, *SALEVOL*, *AVGCFO* are measured over at least three of the past five years (t-4, t). *TANG* denotes the net value of property, plant, and equipment, scaled by the total assets. *HHI* denotes the industry concentration, which is calculated by summing the squared market share of all the firms in an industry, where market share is the proportion of a firm’s sales to the total sales of its four-digit NAICS industry. *ISSUE* is an indicator variable that measures the net financing of a firm in a year. It takes a value of 1 if the firm has a positive net financing, and 0 otherwise, where net financing is calculated by subtracting the total equity and debt repurchases from the total equity and debt issuances. *DIV* is a dummy variable that takes a value of 1 if a firm pays dividends in a year, and 0 otherwise. In addition, I include the three-digit NAICS industry and year fixed effects. Standard errors are clustered at the firm level to control for potential correlations among the residuals. Hypothesis 1 is supported if β_1 is negative.

V. Empirical Results

5.1 Descriptive Statistics

Table 2 presents the descriptive statistics. The mean (median) of SLAC is 0.427 (0.407). This is comparable to that of Bates et al. (2023). Meanwhile, the mean (median) of *SMTH* is -0.018 (0.250), which is comparable to the observations of Baik et al. (2020). The control variables also exhibit a similar distribution as in Baik et al. (2020) and Hamm et al. (2018).

[Insert Table 2 Here]

5.2 Income Smoothing and SLAC

Hypothesis 1 predicts a negative correlation between SLAC and income smoothing. Table 3 presents the results of running Model (2). With *SMTH* being the dependent variable, the coefficients on *SLAC* are -0.469 (t-stat = -3.632) and -0.699 (t-stat = -3.756) in Column (1) and Column (5), which include industry and firm fixed effects, respectively. To present a full picture of the correlation, I substitute SM*TH1*, *SMTH2*, and *SMTH3*, respectively, for *SMTH* and estimate Model (2). Columns (2) - (4) and Columns (6) – (8) show the results. Although the coefficient on SLAC in Column (2) is positive, it is insignificant. Taken together, these results are consistent with the initial results. The results in Table 3 indicate that there is a negative correlation between SLAC and income smoothing. For economic significance, taking column (1) as an example, the coefficient on *SLAC* is -0.469. This indicates that if SLAC increases by one standard deviation, income smoothing decreases by 28.515% of its median value.[7] The coefficients on control variables suggest that larger firms, firms that experience negative net income, firms with more volatile sales, and firms with a larger proportion of tangible asset tend to engage in less income smoothing behavior, whereas firms with a higher level of financial leverage tend to engage in more income smoothing behavior. These results are consistent with those in Baik et al. (2020) and Hamm et al. (2018), suggesting that the coefficients on the control variables are comparable to the results of previous studies (Baik et al., 2020; Hamm et al., 2018).

[Insert Table 3 Here]

5.3 IV Analysis

One potential obstacle to causal inference is the potential endogeneity of SLAC. I construct SLAC using data on the occupation composition of an industry, employment, and wages (see Equation 1), which makes it possible that industry-level endogeneity may confound my inference (i.e., omitted confounding factors). For example, minimum wage policy changes may pose a greater threat to high-SLAC industries, which by definition tend to have more replaceable and low-skilled workers, thereby resulting in more volatile earnings and seemingly less income smoothing for high-SLAC industries.

To address such endogeneity problems, I use the IV approach as in Acemoglu and Restrepo (2020). It is known that European countries lead the U.S. in robotics technology mainly due to their demographic characteristics, and that the frontier

[7] (-0.469 * 0.152) / 0.250 * 100% = -28.515%

robotics technology in European countries subsequently diffuses to the U.S. (Acemoglu and Restrepo, 2020; 2022). This allows me to use the average industry-level robot density in European countries as an IV. This approach helps to isolate the effect of automation threat on income smoothing that is directly caused by technological development.[8] That is because European countries' robot density is less likely to be affected by idiosyncratic factors in the U.S., such as changes in technology and labor-related policies. Specifically, following Acemoglu and Restrepo (2020), the IV (*Log_Stock*) is measured as the natural log of one plus the average robot stock of an industry in five European countries, namely Denmark, Finland, France, Italy, and Sweden. The validity of this IV necessitates the fulfillment of the relevance and exclusion restriction conditions. The relevance condition is satisfied because the robot density in European countries exhibits the feasibility of replacing labor with automation capital, both technologically and economically, to some extent, indicating the considerable potential for industries in the U.S. to replace labor with automation and, hence, a high automation threat. Regarding the exclusion restriction, it is possible that worldwide supply and demand changes, which affect industries in Europe and the U.S., concurrently affect the installation of robots in European countries and the income smoothing of U.S. firms. If so, the exclusion restriction requirement would not be satisfied. However, this does not seem to be a major concern because Acemoglu and Restrepo (2020) document that robot density in European countries is mainly driven by the demographic factor (i.e., aging population), which is less likely to simultaneously

[8] IFR presents information on robot installations on a country-year-industry basis. Note that IFR data report on 19 industries, the classification of which is based on the Industrial Standard Industrial Classification (ISIC) rev.4. I match the ISIC industry code to the NAICS code by referring to the NAICS–ISIC rev.4 concordance provided by the United Nations Statistical Department. The concordance can be downloaded from https://unstats.un.org/unsd/classifications/Family/Detail/27.

affect income smoothing behavior of U.S. firms. In this sense, the IV is relatively invulnerable to the exclusion restriction concern.

Using this IV, I estimate a two-stage least squares model. In the first stage, I regress *SLAC* on *Log_Stock*, with all other factors remaining the same as in Model (2).[9] In the second stage, I run the same regression as the baseline regression but replace the independent variable with the predicted value of *SLAC* from the first-stage regression.

Column (1) in Table 4 presents the results of the first-stage regression. It shows that the coefficient on *Log_Stock* is significant and positive. The F-statistic is 92.850, which suggests that the IV used is not a weak instrument.[10] Column (2) presents the results of the second-stage regression. The coefficient on *SLAC* is significant and negative. Overall, the results of the IV analysis rule out the alternative explanation that the observed correlation results from the potential endogeneity of SLAC, drawing the causal inference that SLAC decreases corporate income smoothing.

[Insert Table 4 Here]

5.4 Automating or Automatability?

One concern here is that the empirical results of the main regression could be driven by a change in firm fundamentals potentially caused by firms' in-process automating behavior. High-SLAC firms may be automating their production because they have the scope to do so. In the process, firm fundamentals such as capital expenditure, capital structure, and profitability may also change.[11] The

[9] I exclude the IFR industry labeled "All other nonmanufacturing branches (90)," because this industry includes miscellaneous subindustries of different characteristics.
[10] The Cragg–Donald Wald F statistic is 574.58, which also indicates that the IV analysis is not subject to weak identification.
[11] For example, Graetz and Michaels (2018) document that the use of robots improves firms' total factor productivity. Liu (2020) find that firms with more robots have a higher financial leverage. Li

change in firm fundamentals may reduce corporate income smoothing behavior, resulting in the observed correlation between SLAC and income smoothing. If so, it is the change in firm fundamentals associated with SLAC, rather than SLAC *per se*, that affects income smoothing. Although the IV analysis helps to address this concern, I conduct two tests to further address it. Specifically, I check whether the focal correlation still holds among firms that are less likely to be automating.

First, automating firms probably increase their capital expenditure on technology adoption and equipment (Bates et al., 2023). This suggests that firms with decreased capital–labor ratio are less likely to be automating. Thus, I focus on firms with a negative average growth rate of the capital–labor ratio in the preceding three years. A still negative association between SLAC and income smoothing in the subsample analysis would suggest that the empirical results of the baseline regression are not driven by changes in firm fundamentals derived from firms' automating behavior. Column (1) in Table 5 presents the results. The coefficient on *SLAC* (coefficient = -0.423, t-stat = -2.708) continues to be significant and negative. As such, these results indicate that my baseline regression results cannot be attributed entirely to the possibility that high-SLAC firms are automating and their firm fundamentals thus changed. For comparison, Column (2) presents the regression results using the sample with a non-decreasing capital–labor ratio.

The second test focuses on automation-related patents as an industry-level proxy for the extent to which firms are automating (Mann and Püttmann, 2023). The authors use automation-related patents based on the text of the patent documents and link automation-related patents to the industries of their use. Industries with fewer automation patents are considered to be less actively engaged

et al. (2023) show that industries that use more robots have a low elasticity of operating costs to sales during an economic upturn.

in automating. Hence, I restrict the sample to firms that belong to industry-years with the number of automation patents that are below the median. Again, a negative correlation for the subsample is expected. Column (3) in Table 5 shows that the coefficient on *SLAC* (coefficient = -0.633, t-stat = -3.046) is significant and negative. This indicates that the focal correlation remains for a subsample of firms that are less likely to be automating. Column (4) also presents the regression results using firm-years with the number of automation patents that are above the median.

Taken together, these findings suggest that the focal correlation is not driven by changes in firm fundamentals arising from firms' in-process automating behavior.

[Insert Table 5 Here]

5.5 Channel Tests

Next, I test the proposed channels through which SLAC affects corporate income smoothing. The baseline regression results show that income smoothing decreases with *SLAC*. I posit that the negative relationship is driven through two channels: risk perception and bargaining power.

First, I test the risk perception channel. I hypothesize that high-SLAC firms, characterized by their flexibility in adopting automation and lower labor adjustment costs, are likely to exhibit reduced operational and systemic risks. This suggests that high-SLAC firms are better positioned to withstand production disruptions compared to low-SLAC firms. As such, I expect high-SLAC firms to suffer less from the events that disrupt production. To examine this prediction, I exploit quasi-experimental shocks to firm production, namely natural disasters (i.e., flooding, hurricane, severe storm, and tornado), and examine whether natural disasters have a less detrimental effect on the financial performance of high-SLAC firms compared to low-SLAC firms. I conduct a difference-in-difference (DID) analysis to examine this issue. The treatment group consists of impacted firms with SLAC values above the median, whereas the control group comprises impacted firms with SLAC values below the median, where impacted firms refer to firms headquartered in the counties that suffer natural disasters in a year. The DID analysis is conducted over a two-year window, including the year preceding the natural disaster and the disaster year (POST). [12] Firms' financial performance is proxied by ROA, calculated as income before extraordinary items divided by the total assets. I obtain the county-year data on natural disasters during the period from 2002 to 2018 from the Spatial Hazard Events and Losses Database for the United States and obtain the information of the county where firms are headquartered in a certain year from the website of University of Notre Dame.[13] To ensure that firms' production process is indeed disrupted to some extent by natural disasters, I focus only on the natural disasters that cause property losses exceeding 100 million US dollars.

Panel A in Table 6 presents the results. Column (1) shows that the coefficient on *TREAT * POST* is positive and significant at the 5% level. When control variables are included, the coefficient is still positive and significant at the 5% level, as shown in Column (2). These results suggest that high-SLAC firms perform better than low-SLAC firms during natural disasters, consistent with the conjecture that high-SLAC firms can better withstand production disruptions. Taken together, these results suggest that high-SLAC firms are less risky than low-SLAC firms, supporting the risk perception channel.

[12] Since most natural disasters involved happened in the first half of the fiscal year, impacted firms are expected to take timely measures to deal with production disruptions in the current year. As such, I focus on the disasaster year (t) rather than the next year (t+1).

[13] https://sraf.nd.edu/sec-edgar-data/10-x-header-data/.

Second, I test the bargaining power channel. I posit that SLAC affects income smoothing through reducing workers' bargaining power. To test this channel, I use labor strikes to proxy for workers' bargaining power of a four-digit NAICS industry. The rationality of the proxy is that workers' bargaining power is largely derived from the threat to withhold labor services, i.e., strikes. Specifically, I measure workers' bargaining power using two variables, *STRIKE_DUM* and *STRIKE_N*. *STRIKE_DUM* is a dummy variable that takes the value of one if there is at least one strike within a four-digit NAICS industry in a given year, and zero otherwise. *STRIKE_N* is the number of labor strikes within a four-digit NAICS industry in a given year. A larger number of strikes indicates higher workers' bargaining power. I obtain data on labor strikes during the period from 2002 to 2018 from BLS.

Since both the dependent variables (*STRIKE_DUM and STRIKE_N*) and the independent variable (*SLAC*) are industry-specific, I run the regression at the industry level. Following prior literature (e.g., Myers and Saretto, 2016), I control firm size (*SIZE*), leverage (*LEV*) and its change (*LEV_CH*), profitability (*ROA*) and its change (*ROA_CH*), cash holding level (*CASH*) and its change (*CASH_CH*) in the regression model. All these variables are aggregated at the four-digit NAICS industry level. I also control industry-specific unionization rate (*MEM*) and unemployment rate (*UNEMPLOYMENT*), the data of which are from the Union Membership and Coverage Database and BLS, respectively. As in the baseline regression, three-digit NAICS industry fixed effect and year fixed effect are controlled.

Column (1) in Panel B, Table 6 presents the results of estimating a logit model. The coefficient on SLAC is negative and significant at the 5% level, suggesting that labor strikes are less likely to occur within high-SLAC industries than within low-

SLAC ones. In Column (2) where the dependent variable is the number of strikes, the coefficient on SLAC is negative and significant at the 5% level, suggesting that the number of labor strikes of high-SLAC industries is smaller than that of low-SLAC ones. Taken together, these results suggest that workers' bargaining power in high-SLAC firms is weaker than that in low-SLAC firms, supporting the argument that automation threat reduces workers' bargaining power.

[Insert Table 6 Here]

5.6 Cross-sectional Analysis

To lend further credence to the empirical results, I conduct multiple cross-sectional analyses. Although automation is aimed at improving productivity and reducing labor costs, its adoption is relatively slow because automation entails costs arising from the purchase of relevant equipment, labor market frictions, and production interruptions (for example, Zhang, 2019). The potential benefits (costs) of automation increase (decrease) the attractiveness of automation and the threat of replacement of labor with automation, thereby increasing (decreasing) the effect of SLAC on income smoothing. As such, I expect factors that increase the benefits (costs) of automation to strengthen (attenuate) the negative relationship between SLAC and income smoothing.

First, I test whether the focal relationship is affected by the unemployment insurance benefits provided by all states in the U.S. The unemployment insurance program offers temporary financial assistance to eligible individuals who experience unemployment. Thus, unemployment insurance benefits help reduce workers' willingness to protest when they are faced with layoffs and consequently decrease firms' cost of replacing workers with automation. Hence, I expect the unemployment insurance benefits associated with low automation costs to enhance the focal relationship. To calculate the annual unemployment insurance benefits (*UI*), following Agrawal and Matsa (2013), I multiply the maximum weekly benefit amount by the maximum benefit duration in weeks. Then, I link a firm to the information on the applicable UI benefits via the state in which the firm is headquartered. Column (1) in Table 7 presents the results. The coefficient on *SLAC* * *UI* (coefficient = -0.405, t-stat = -4.524) is significant and negative, indicating that the relatively low cost of automation-associated unemployment benefits amplifies the effect of SLAC. The coefficient on *SLAC* is 3.077, comparable to the coefficients on *SLAC* in Table 3 when the coefficients on *SLAC* * *UI* and *SLAC* are joint considered.[14]

Next, I investigate whether the cost of switching to automation affects the focal relationship. Automation requires the input of a large number of computers and peripherals, the price of which matters for firms' automation decisions. Therefore, following Leduc and Liu (2023), I use adjusted computer price as a proxy for the cost of automation, with a higher computer price indicating higher automation costs. I calculate computer price as an annual chain price index of private investment in computers and peripherals, deflated by the chained personal consumption expenditure price index.[15] I expect computer price to dampen the focal relationship. Column (2) in Table 7 shows the results. The coefficient on *SLAC* * *COMPUTERPRICE* (coefficient = 0.214, t-stat = 4.989) is significant and positive. This indicates that high automation costs associated with a high price of computer-related equipment attenuate the influence of SLAC.

[14] -0.405 * 9.338 + 3.077 = -0.705, where -0.405 is the coefficient on *SLAC* * *UI* and 9.338 is the mean value of *UI*.
[15] The two price indices are obtained from the Bureau of Economic Analysis.

In addition to the potential costs of automation, the potential benefits of automation also affect the relationship between SLAC and automation. I first investigate how labor intensity affects the focal relationship. Because automation is designed to replace workers and decrease labor costs, labor-intensive firms tend to benefit more from automation. Given the high value of the option to automate, I expect the focal relationship to be enhanced in labor-intensive firms. Following the literature (e.g., Hilary, 2006), I measure the labor intensity of a firm as the number of employees of a firm, divided by its total assets. Although labor intensity is related to SLAC in terms of variable construction, in this test, it differs from the SLAC measure in that labor intensity is at the firm level. The industry-specific measure of SLAC disregards intra-industry variation in firms' exposure to automation technology. However, although firms in the same industry share the same measure of SLAC, they are faced with a different cost–benefit tradeoff if they have different levels of labor intensity. Therefore, this test explores the intra-industry variation in the effect of SLAC. Column (3) in Table 7 reports the regression results. The coefficient on *SLAC * LABORINTENSITY* (coefficient = -7.792, t-stat = -2.438) is significant and negative. This suggests that the potentially greater benefits of automation associated with a high degree of labor intensity enhance the negative effect of SLAC on income smoothing.

Finally, I examine how variations in minimum wages across different U.S. states affect the focal relationship. A high minimum wage corresponds to higher overall labor costs (e.g., Hau et al., 2020). Hence, firms operating in states with high minimum wages tend to be exposed to higher labor costs and, hence, may benefit more from automation. Therefore, I propose that the greater benefits associated with a high minimum wage strengthen the focal relationship. I use the state-level minimum wage dataset developed by Vaghul and Zipperer (2016).

Column (4) in Table 7 reports the regression results. The coefficient on *SLAC * MINIMUMWAGE* (coefficient = -0.200, t-stat = -10.010) is significant and negative, which is consistent with my expectation. These results suggest that the negative effect of SLAC on income smoothing is more pronounced for firms in states with high minimum wages than in states with low minimum wages.

[Insert Table 7 Here]

VI. Conclusions

Advances in AI and robotics are changing the methods of industrial production, allowing a wide range of tasks to be replaced with automation. Although many studies investigate how automation affects employment, wage inequality, productivity, and financial policies, few studies focus on how automation affects firms' accounting choices. This study fills this gap in the literature by investigating how SLAC affects firms' income smoothing behavior. I posit that there are two channels, namely risk perception and bargaining power, through which SLAC negatively affects income smoothing. Regarding the risk perception channel, high-SLAC firms have the option to optimally replace labor with automation, which protects their value from negative macroeconomic shocks. Additionally, high-SLAC firms tend to have a greater proportion of low- and medium-skilled workers, resulting in a lower labor-induced operating leverage and operational risk. Given the potential costs of automation, the relatively low perception of firm risk afforded by SLAC reduces managers' incentive to use income smoothing to lower firm risk. Regarding the bargaining power channel, firms with strong worker power tend to engage in income smoothing behavior to shelter resources from labor's demand for profit sharing and avoid high labor costs arising from the unemployment risk. This study argues that SLAC increases managers' bargaining position relative to workers' bargaining position, thereby reducing labor-induced income smoothing behavior. Both the risk perception and bargaining power channels indicate that SLAC decreases corporate income smoothing.

Based on data from U.S. firms, I find that SLAC is negatively correlated with income smoothing. The results of the IV analysis suggest that the negative relationship is driven by the causal effect of SLAC on income smoothing. The results of additional tests suggest that the negative relationship is less likely to be attributed to changes in firm fundamentals that result from the possibility of firms being automating. Additionally, I demonstrate that both the risk perception and bargaining power channels are valid. The results of cross-sectional analyses reveal that the effect of SLAC is greater when the potential benefits (costs) of automation are higher (lower).

This study contributes several new insights to the literature. First, it identifies an important and novel determinant of income smoothing by demonstrating that the automation threat negatively affects corporate income smoothing. This study also complements the literature on how employee-related factors affect firms' income smoothing behavior. It shows that the effect of labor-related factors on income smoothing, as demonstrated by the literature, may vary with firms' opportunity to automate their production. Second, this study links automation and accounting choices. The fundamental effect of automation on business operations indicates its implications for firms' accounting policies. This study is the first to demonstrate how technology development (i.e. automation) affects firms' accounting choices.

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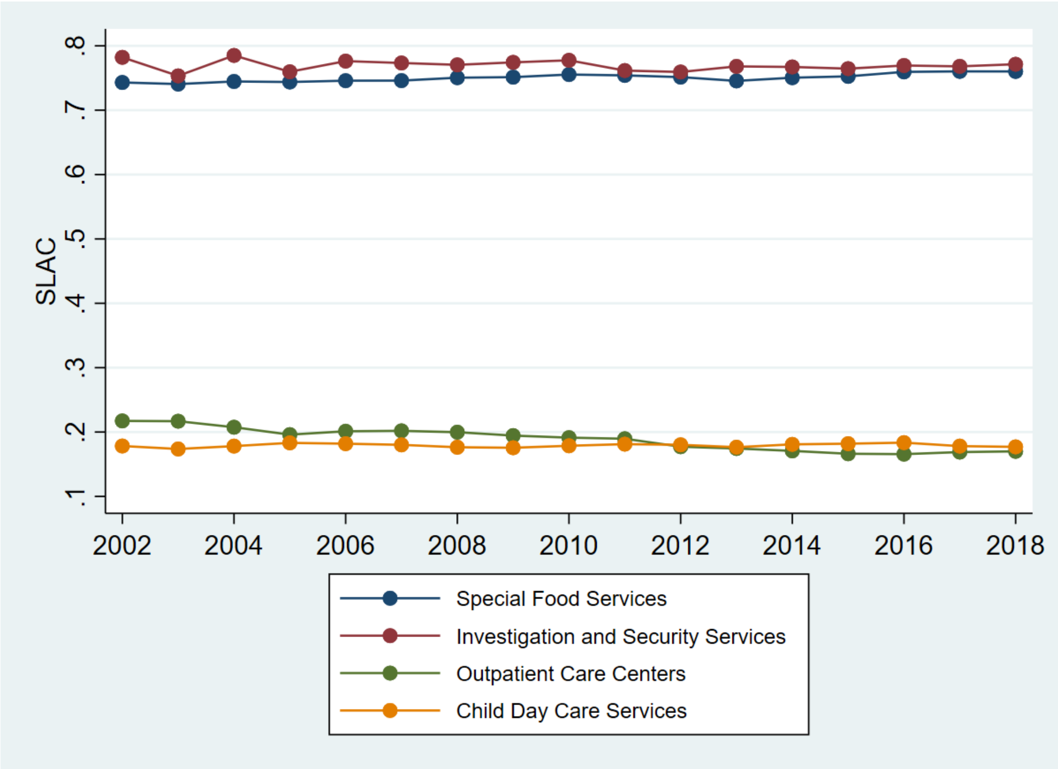
Appendix A Variable Definitions

Variable	Definition
Measure for SLAC	
SLAC	The wage-weighted average probability of occupations in a 4-digit NAICS industry being replaced with automation in a year, following Bates et al. (2023): $$SLAC_{k,t} = \sum_j Prob_j \times \frac{Emp_{k,j,t} \times Wage_{k,j,t}}{\sum_j Emp_{k,j,t} \times Wage_{k,j,t}}$$ where $Prob_j$ is the probability of occupation j being computerized; $Emp_{k,j,t}$ and $Wage_{k,j,t}$ are the number of employees and the average annual wages of workers assigned to occupation j in industry k for year t, respectively.
Measure of Income Smooth	
SMTH1	The ratio of the standard deviation of operating earnings (scaled by lagged total assets) to the standard deviation of cash flows from operations (scaled by lagged total assets).
SMTH2	The Spearman correlation between the change in total accruals and the change in cash flows from operations (both scaled by lagged total assets).
SMTH3	The Spearman correlation between the change in discretionary accruals and the change in the premanaged income, where the discretionary accruals are estimated from the cross-sectional version of the Jones (1991) model and the premanaged income is calculated as the net income minus discretionary accruals.
SMTH	The first common factor identified by factor analysis based on the three measures of income smoothing, SMTH1, SMTH2, and SMTH3.
Other variables	
Log_Stock	The natural log of 1 plus the average robot stock of an industry in five European countries, namely Denmark, Finland, France, Italy, and Sweden.
SIZE	The natural log of total assets at the end of a year.
LEV	The ratio of debt to total assets.
BM	The natural log of the ratio of the book value to the market value of equity.
GROW	The annual change in revenues defined as ($Sales_t$ – $Sales_{t-1}$)/$Sales_{t-1}$.
LOSS	The proportion of years with a negative net income over at least three of the last five years (t-4,t).
SALEVOL	The standard deviation of sales scaled by the lagged total assets over at least three of the last five years (t-4,t).
AVGCFO	The average cash flows from operations scaled by the lagged total assets over at least three of the last five years (t-4, t).

TANG	The net value of property, plant, and equipment, scaled by total assets.
HHI	The industry concentration, which is calculated by summing the squared market share of all the firms in an industry, where market share is the proportion of a firm's sales to the total sales of its four-digit NAICS industry.
ISSUE	An indicator variable that measures the net financing of a firm in a year. It takes a value of 1 if the firm has a positive net financing, and 0 otherwise, where net financing is calculated by subtracting the total equity and debt repurchases from the total equity and debt issuances.
DIV	A dummy variable that takes a value of 1 if a firm pays dividends in a year, and 0 otherwise.
ROA	The income before extraordinary items divided by the total assets.
STRIKE_DUM	A dummy variable that takes the value of one if there is at least one strike within a four-digit NAICS industry in a given year, and zero otherwise.
STRIKE_N	The number of labor strikes within a four-digit NAICS industry in a given year.
LEV_CH	The change in LEV ($LEV_t – LEV_{t-1}$).
ROA_CH	The change in ROA ($ROA_t – ROA_{t-1}$).
CASH	The cash holding level of a firm, calculated as the amount of cash and short-term investment divided by the total assets.
CASH_CH	The change in CASH ($CASH_t – CASH_{t-1}$).
MEM	The proportion of union members in a four-digit NAICS industry.
UNEMPLOYMENT	The unemployment rate of a four-digit NAICS industry, multiplied by 100.
UI	The product of maximum weekly benefit amount and the maximum benefit duration in weeks.
COMPUTERPRICE	The annual chain price index of private investment in computers and peripherals, deflated by the chained personal consumption expenditure price index.
LABORINTENSITY	The ratio of number of employees of a firm to its total assets.
MINIUMWAGE	The state-level minimum wage from Vaghul and Zipperer (2016).

Figure 1 The Evolution of SLAC for Selected Industries



This figure portrays the time trends of SLAC measures for selected industries, including Special Food Services (NAICS code: 7223), Investigation and Security Services (NAICS code: 5616), Outpatient Care Centers (NAICS code: 6214) and Child Day Care Services (NAICS code: 6244).

TABLE 1 Industries with the Lowest and Highest SLAC

Industries with Lowest SLAC	SLAC	Rank
Child Day Care Services	0.179	1
Outpatient Care Centers	0.189	2
Specialty (except Psychiatric and Substance Abuse) Hospitals	0.193	3
Other Schools and Instruction	0.197	4
Elementary and Secondary Schools	0.199	5
General Medical and Surgical Hospitals	0.203	6
Junior Colleges	0.206	7
Psychiatric and Substance Abuse Hospitals	0.208	8
Software Publishers	0.212	9
Offices of Physicians	0.215	10
Industries with Highest SLAC	**SLAC**	**Rank**
Restaurants and Other Eating Places	0.829	1
Full-Service Restaurants	0.821	2
Limited-Service Eating Places	0.809	3
School and Employee Bus Transportation	0.806	4
Taxi and Limousine Service	0.777	5
Gasoline Stations	0.774	6
Drinking Places (Alcoholic Beverages)	0.771	7
Investigation and Security Services	0.770	8
Offices of Real Estate Agents and Brokers	0.754	9
Special Food Services	0.750	10

This table displays the top ten 4-digit NAICS industries with the lowest SLAC and the top ten industries with the highest SLAC. The industries are sorted by average industry-level SLAC during the period of 2002-2018.

TABLE 2 Summary Statistics of the Main Variables

Variables	Obs	Mean	SD	P25	P50	P75	Min	Max
SMTH	42,045	-0.018	0.932	-0.538	0.250	0.706	-3.113	1.097
SMTH1	42,045	-1.135	0.760	-1.389	-0.978	-0.648	-4.710	-0.134
SMTH2	42,045	0.444	0.567	0.112	0.668	0.907	-0.982	0.999
SMTH3	42,045	0.744	0.401	0.699	0.924	0.985	-0.842	1.000
SLAC	42,045	0.427	0.152	0.317	0.407	0.548	0.169	0.832
Log_Stock	27,985	8.077	1.697	7.483	8.321	9.464	2.833	10.725
SIZE	42,045	5.437	2.224	3.798	5.376	6.980	0.525	10.677
LEV	42,045	0.440	0.222	0.257	0.431	0.602	0.047	0.954
BM	42,045	-0.850	0.933	-1.379	-0.790	-0.239	-3.715	1.362
GROW	42,045	0.155	0.582	-0.050	0.068	0.213	-0.908	4.057
LOSS	42,045	0.392	0.374	0.000	0.200	0.800	0.000	1.000
SALEVOL	42,045	0.353	0.475	0.105	0.203	0.396	0.014	3.267
AVGCFO	42,045	0.004	0.293	-0.005	0.079	0.137	-1.568	0.390
TANG	42,045	0.215	0.218	0.058	0.133	0.295	0.002	0.901
HHI	42,045	-0.182	0.113	-0.233	-0.151	-0.092	-0.801	-0.055
ISSUE	42,045	0.771	0.420	1.000	1.000	1.000	0.000	1.000
DIV	42,045	0.257	0.437	0.000	0.000	1.000	0.000	1.000
STRIKE_DUM	402	0.097	0.296	0.000	0.000	0.000	0.000	1.000
STRIKE_N	934	0.054	0.284	0.000	0.000	0.000	0.000	3.000
LEV_CH	934	0.005	0.031	-0.013	0.004	0.022	-0.160	0.299
ROA	934	-0.015	0.088	-0.054	0.006	0.043	-0.404	0.175
ROA_CH	934	-0.001	0.046	-0.024	-0.002	0.021	-0.202	0.200
CASH	934	0.176	0.103	0.102	0.151	0.233	0.006	0.591
CASH_CH	934	-0.002	0.026	-0.018	-0.001	0.013	-0.103	0.139
MEM	934	0.085	0.066	0.032	0.074	0.117	0.000	0.283
UNEMPLOYMENT	934	5.881	2.468	4.000	5.300	7.000	1.600	17.800
UI	31,480	9.338	0.346	9.158	9.354	9.465	8.333	10.389
COMPUTERPRICE	42,045	1.941	1.133	1.000	1.409	2.756	0.890	4.646
LABORINTENSITY	41,356	0.006	0.009	0.002	0.004	0.007	0.000	0.067
MINIUMWAGE	41,949	6.794	1.422	5.150	6.750	7.500	5.150	11.100

This table reports the summary statistics for the variables used in this research. All variables are defined in Appendix A.

TABLE 3 The Relation between SLAC and Income Smoothing

DV = SMTH	(1) SMTH	(2) SMTH1	(3) SMTH2	(4) SMTH3	(5) SMTH	(6) SMTH1	(7) SMTH2	(8) SMTH3
SLAC	-0.469***	0.057	-0.063	-0.369***	-0.699***	-0.324**	-0.289**	-0.254***
	(-3.632)	(0.541)	(-0.824)	(-6.372)	(-3.756)	(-2.137)	(-2.406)	(-3.144)
SIZE	-0.012**	-0.012***	-0.013***	0.003	0.013	-0.034***	0.012	0.010
	(-2.534)	(-2.763)	(-4.314)	(1.384)	(0.832)	(-2.629)	(1.324)	(1.462)
LEV	0.299***	0.238***	0.182***	0.045***	0.066	0.063	-0.003	0.046**
	(7.653)	(7.702)	(7.656)	(2.606)	(1.297)	(1.514)	(-0.090)	(2.025)
BM	0.069***	0.029***	0.038***	0.020***	0.015	0.003	0.006	0.006
	(7.757)	(4.015)	(7.455)	(4.930)	(1.586)	(0.315)	(1.092)	(1.475)
GROW	-0.006	0.011	-0.005	-0.005	-0.005	0.022***	-0.004	-0.008**
	(-0.631)	(1.420)	(-0.836)	(-1.138)	(-0.659)	(3.372)	(-0.736)	(-2.092)
LOSS	-0.696***	-0.263***	-0.371***	-0.217***	-0.588***	-0.301***	-0.277***	-0.191***
	(-22.350)	(-10.354)	(-19.669)	(-16.078)	(-14.019)	(-8.578)	(-10.865)	(-10.837)
SALEVOL	-0.239***	-0.187***	-0.047***	-0.109***	-0.258***	-0.238***	-0.054***	-0.103***
	(-11.415)	(-9.766)	(-3.949)	(-10.798)	(-9.947)	(-10.547)	(-3.750)	(-8.156)
AVGCFO	0.437***	0.016	0.320***	0.132***	0.326***	-0.049	0.244***	0.122***
	(10.860)	(0.544)	(13.244)	(6.707)	(5.443)	(-1.177)	(6.813)	(4.058)
TANG	-0.150***	-0.185***	-0.076**	-0.017	-0.000	-0.093	-0.024	0.034
	(-2.679)	(-3.865)	(-2.225)	(-0.687)	(-0.001)	(-1.188)	(-0.431)	(0.822)
HHI	-0.094	-0.219***	-0.213***	0.146***	-0.135	-0.191*	-0.106	0.030
	(-1.071)	(-3.232)	(-4.094)	(3.784)	(-0.989)	(-1.768)	(-1.288)	(0.546)
ISSUE	-0.013	-0.026**	-0.007	0.002	-0.000	0.002	-0.007	0.005
	(-0.965)	(-2.240)	(-0.934)	(0.340)	(-0.003)	(0.235)	(-0.935)	(0.988)
DIV	0.079***	0.001	0.044***	0.031***	-0.001	-0.039*	0.011	0.001
	(4.080)	(0.075)	(3.677)	(4.101)	(-0.057)	(-1.737)	(0.687)	(0.067)
Constant	0.537***	-0.990***	0.627***	1.028***	0.491***	-0.643***	0.624***	0.892***
	(8.138)	(-18.092)	(15.997)	(35.381)	(3.866)	(-6.137)	(8.236)	(16.467)
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	42,045	42,045	42,025	42,045	42,045	42,045	42,045	42,045
Adj. R-squared	0.201	0.075	0.189	0.149	0.517	0.363	0.496	0.488

This table reports the regression results of income smoothing (SMTH) on SLAC. All variables are defined in Appendix A. The dependent variables in Column (1) and (5) are the aggregate measure of income smoothing. Column (1) – (4) include industry fixed effect while Column (5) – (8) include firm fixed effect. The standard errors are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. All tests are two-tailed.

TABLE 4 The IV Estimation Results

VARIABLES	(1) SLAC	(2) SMTH
SLAC		-5.653***
		(-3.350)
Log_Stock	0.015***	
	(9.636)	
SIZE	0.000	-0.022***
	(0.107)	(-3.857)
LEV	-0.008***	0.279***
	(-5.885)	(5.715)
BM	-0.002***	0.067***
	(-7.008)	(5.752)
GROW	-0.000	-0.000
	(-0.108)	(-0.046)
LOSS	-0.000	-0.129***
	(-0.069)	(-16.917)
SALEVOL	0.003***	-0.237***
	(3.675)	(-7.728)
AVGCFO	-0.002	0.479***
	(-1.367)	(10.264)
TANG	0.002	-0.081
	(1.347)	(-1.178)
HHI	0.019***	-0.059
	(3.068)	(-0.352)
ISSUE	0.000	-0.003
	(0.475)	(-0.179)
DIV	0.001	0.122***
	(1.085)	(5.099)
N	27,985	27,985
Adjusted R-squared	0.931	0.179
F-stats	92.850	
P-value	0.000	
Year FE	Yes	Yes
Industry FE	Yes	Yes

This table reports the regression results of the IV analysis. The IV (Log_Stock) is constructed as the average robot density of five European countries. All variables are defined in Appendix A. Columns (1) and (2) report the regression results of the first-stage regression and the second-stage regression, respectively. The standard errors are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. All tests are two-tailed.

TABLE 5 Results that Rule out the Alternative Explanation

DV = SMTH	(1)	(2)	(3)	(4)
	average growth rate of capital-labor ratio		**number of automation patents**	
	negative	positive	below the median	above the median
SLAC	-0.423***	-0.497***	-0.633***	-0.299
	(-2.708)	(-3.278)	(-3.046)	(-1.199)
SIZE	-0.019***	-0.006	-0.003	-0.020***
	(-3.398)	(-1.102)	(-0.323)	(-2.611)
LEV	0.290***	0.282***	0.292***	0.330***
	(6.120)	(6.035)	(4.574)	(5.224)
BM	0.073***	0.062***	0.065***	0.094***
	(6.717)	(5.775)	(4.642)	(6.367)
GROW	0.006	-0.022	-0.009	-0.013
	(0.482)	(-1.503)	(-0.650)	(-0.653)
LOSS	-0.720***	-0.648***	-0.692***	-0.846***
	(-19.725)	(-17.273)	(-13.492)	(-16.892)
SALEVOL	-0.214***	-0.265***	-0.197***	-0.284***
	(-8.240)	(-10.433)	(-6.038)	(-7.749)
AVGCFO	0.481***	0.408***	0.494***	0.214***
	(9.539)	(8.295)	(7.739)	(2.864)
TANG	-0.089	-0.205***	-0.031	-0.040
	(-1.283)	(-3.175)	(-0.333)	(-0.454)
HHI	-0.065	-0.128	-0.031	-0.280*
	(-0.612)	(-1.283)	(-0.183)	(-1.882)
ISSUE	-0.038**	0.005	-0.047**	0.004
	(-2.202)	(0.295)	(-2.130)	(0.204)
DIV	0.067***	0.082***	0.092***	0.116***
	(2.879)	(3.752)	(2.710)	(3.895)
Constant	0.560***	0.521***	0.567***	0.445***
	(7.105)	(6.788)	(5.692)	(3.455)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	20,333	20,857	14,399	15,730
Adj. R-squared	0.207	0.193	0.225	0.186

This table reports the regression results of income smoothing (SMTH) on SLAC in different subsamples. All variables are defined in Appendix A. Columns (1) and (2) report the regression results using the subsample based on whether firms experience a negative average capital-labor ratio during the last three years, and Columns (3) and (4) report the results using the subsample based on whether an industry has above-median automation patents. The standard errors are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. The sample period is 1999-2018 in Columns (1) and (2) and 2002-2014 in Columns (3) and (4).

TABLE 6 Channel Tests

Panel A The test of risk perception channel

VARIABLES	(1) ROA	(2) ROA
*TREAT * POST*	0.079**	0.061**
	(2.566)	(2.249)
POST	0.008	0.024
	(0.353)	(0.875)
SIZE		0.167**
		(2.307)
LEV		-0.260
		(-1.212)
BM		0.014
		(0.516)
TANG		-0.085
		(-0.491)
Constant	-0.033***	-0.896**
	(-5.126)	(-2.304)
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	728	728
Adjusted R-squared	0.514	0.559

This table reports the regression results of DID analysis. All variables are defined in Appendix A. The standard errors are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. All tests are two-tailed.

Panel B The test of the bargaining power channel

VARIABLES	(1) STRIKE_DUM	(2) STRIKE_N
SLAC	-6.144**	-0.556**
	(-1.997)	(-2.330)
SIZE	0.128	0.023
	(0.494)	(1.298)
LEV	1.956	-0.032
	(0.433)	(-0.150)
LEV_CH	8.496	0.392
	(0.999)	(1.623)
ROA	6.589*	0.046
	(1.693*)	(0.446)
ROA_CH	-5.820	-0.086
	(-1.533)	(-0.582)
CASH	-2.037	-0.285
	(-0.434)	(-1.266)
CASH_CH	4.542	0.305
	(0.602)	(1.059)
MEM	8.114	0.189
	(1.286)	(0.654)
UNEMPLOYMENT	-0.105	-0.005
	(-0.440)	(-0.803)
Constant	-1.701	0.314*
	(-0.420)	(1.817)
Year FE	Yes	Yes
Industry FE	Yes	Yes
N	402	934
Adjusted R-squared	0.300	0.217

This table reports the regression results of strike related variables (STRIKE_DUM and STRIKE_N) on SLAC. The regression is estimated at the four-digit NAICS industry level. As such, control variables (i.e., *SIZE, LEV, LEV_CH, ROA, ROA_CH, CASH, CASH_CH*) are aggregated at the four-digit NAICS industry level. All variables are defined in Appendix A. The standard errors are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. In Column (1) and Column (2), z-statistics and t-statistics are presented in parentheses, respectively. All tests are two-tailed.

TABLE 7 Cross-Sectional Analysis

DV = SMTH	(1) UI Benefits	(2) Computer Price	(3) Labor Intensity	(4) Minimum Wage
SLAC	3.077***	-0.844***	-0.434***	0.910***
	(3.666)	(-5.674)	(-6.082)	(5.871)
*SLAC * UI*	-0.405***			
	(-4.524)			
UI	0.169***			
	(4.496)			
*SLAC * COMPUTERPRICE*		0.214***		
		(4.989)		
*SLAC * LABORINTENSITY*			-7.792**	
			(-2.438)	
LABORINTENSITY			7.758***	
			(4.547)	
*SLAC * MINIMUMWAGE*				-0.200***
				(-10.010)
MINIMUMWAGE				0.065***
				(6.728)
SIZE	-0.015***	-0.012**	-0.008***	-0.012***
	(-5.349)	(-2.460)	(-3.317)	(-5.030)
LEV	0.298***	0.289***	0.277***	0.289***
	(12.135)	(7.388)	(12.898)	(13.676)
BM	0.070***	0.066***	0.067***	0.067***
	(11.764)	(7.467)	(13.335)	(13.456)
GROW	0.005	-0.007	-0.006	-0.008
	(0.536)	(-0.742)	(-0.850)	(-1.087)
LOSS	-0.639***	-0.691***	-0.695***	-0.690***
	(-35.660)	(-22.223)	(-42.921)	(-42.897)
SALEVOL	-0.266***	-0.234***	-0.245***	-0.235***
	(-22.960)	(-11.171)	(-25.961)	(-25.145)
AVGCFO	0.484***	0.437***	0.434***	0.436***
	(22.296)	(10.834)	(22.637)	(22.963)
TANG	-0.156***	-0.147***	-0.167***	-0.153***
	(-4.556)	(-2.635)	(-5.507)	(-5.132)
HHI	-0.135***	-0.085	-0.112**	-0.077*
	(-2.713)	(-0.968)	(-2.513)	(-1.751)
ISSUE	-0.007	-0.012	-0.012	-0.012
	(-0.585)	(-0.912)	(-1.143)	(-1.223)
DIV	0.071***	0.083***	0.072***	0.081***
	(5.640)	(4.273)	(6.198)	(7.067)
Constant	-0.949***	0.509***	0.488***	0.076
	(-2.687)	(7.719)	(13.260)	(0.992)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	31,480	42,045	41,356	41,949
Adj. R-squared	0.196	0.202	0.203	0.203

This table reports the regression results of income smoothing (SMTH) on SLAC and the interaction between SLAC and various factors related to automation costs or benefits. All variables are defined in Appendix A. The standard errors are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses. All tests are two-tailed.

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