Workplace Automation and Corporate Financial Policies†

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Abstract

We show that a firm's ability to automate its workforce enhances operating flexibility, allowing for less conservative financial policies. Using an occupational measure of labor's susceptibility to automation, we find that firms with a more substitutable workforce hold less cash, use more financial leverage, and pay higher dividends. We derive causal evidence exploiting the 2011–2012 Thailand hard drive crisis as a shock to the cost of automation. Following adverse shocks to cash flow from state tax increases, firms with an automatable workforce increase investment in equipment and software, reduce labor share in production, and experience a decline in operating leverage.

JEL codes: G32, G35, J23, O33

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1. Introduction

The application of workplace automation has progressed dramatically over the past two decades. The use of automated capital has manifested most notably in the replacement of human workers performing routine tasks with robots and other computer-controlled equipment.[1] With improvements in computing power applied to software technologies, a broad array of non-routine tasks for workers in fields as diverse as radiology, customer service, and real estate agency have become increasingly redundant. Given the mounting potential for the use of automated capital and the implications for labor demand, a growing literature has focused on the impact of automation on wages and employment.[2] In this paper, we study the impact of automation on first-order corporate decisions. Specifically, we examine the extent to which a firm's potential to automate its workforce enhances operating flexibility and allows for more aggressive financial policies.

Labor is a critical input in the production of goods and services, but employing workers exposes a firm to labor market frictions. The costs of screening, training, and firing make labor a quasi-fixed factor (e.g., Oi 1962). Kahn (1997) also shows that firms are reluctant to cut wages, even during periods of financial distress. By making its workforce and wage bill less flexible, labor market frictions increase a firm's sensitivity of operating cash flow to economic shocks, effectively elevating operating leverage.[3] To allay the adverse effects of operating leverage, and to hedge against large unexpected shocks to cash flow that might otherwise result in underinvestment, firms

[1] Using data compiled by the International Federation of Robotics (IFR), we estimate that more than 422,000 industrial and service robots were brought into service worldwide in 2018, increasing the stock of robots in production and services by almost 15% from the previous year.

[2] For example, Autor and Dorn (2013), Brynjolfsson and McAfee (2014), Goos, Manning, and Salomons (2014), Frey and Osborne (2017), Acemoglu and Restrepo (2018, 2020), Autor and Salomons (2018), Graetz and Michaels (2018), and Webb (2020).

[3] Donangelo, Gourio, Kehrig, and Palacios (2019) provide direct evidence on the existence of labor-induced operating leverage using firm-level Census data on labor compensation. They find that labor costs are less elastic to sales than non-labor costs. More generally, research in the asset pricing literature suggests that operating leverage resulting from labor heterogeneity, mobility, wage rigidity, and adjustment costs are first-order determinants of asset prices. Examples include Belo, Lin, and Bazdresch (2014), Donangelo (2014), Belo, Li, Lin, and Zhao (2017), Kuehn, Simutin, and Wang (2017), Donangelo et al. (2019), and Favilukis, Lin, and Zhao (2020). Although the literature uses various proxies for operating leverage, they share the common notion of capturing the sensitivity of operating profits to economic shocks. In our analysis, we follow the standard approach in the literature (e.g., Mandelker and Rhee 1984) and estimate operating leverage as the elasticity of operating cash flow with respect to sales.

often adopt conservative financial policies in cash holdings, financial leverage, and dividends (e.g., Bates, Kahle, and Stulz 2009; Bonaimé, Hankins, and Harford 2014; Simintzi, Vig, and Volpin 2015; Serfling 2016).

While conservative financial policies are a natural response to labor-induced operating leverage, workplace automation provides a viable alternative. Automation enhances operating flexibility by shifting the production function away from labor-intensive methods.[4] Indeed, the relevance of labor's contribution to operating leverage is closely tied to the substitutability between capital and labor. Donangelo et al. (2019) contend that labor-induced operating leverage requires that labor and capital are complements in production. In the framework of Acemoglu and Restrepo (2018, 2020), automation lowers the cost of production and labor share by displacing workers from tasks that can be automated. Similarly, Zhang (2019) shows that the replacement of routine-task labor with automated capital yields significant cost savings and reduces operating leverage. Thus, when firms differ in their labor's susceptibility to replacement with automated capital, we expect that an automatable workforce endows firms with an option to lessen labor-induced operating leverage and allow them to rely less on conservative financial policies.

We begin by constructing a novel measure of the proportion of an industry's existing employees in a given year that are susceptible to replacement by automation, a construct we characterize as the substitutability of labor with automated capital (*SLAC*). This measure is developed using Frey and Osborne's (2013, 2017) analysis of the occupational probability of computerization, which quantifies the potential for specific occupations to be automated based on technological advances in a variety of fields such as artificial intelligence and mobile robotics. In contrast with prior measures of the potential to automate, *SLAC* uniquely accounts for the potential

[4] While labor substitution reduces labor costs, automation itself entails costs including the upfront costs in financing automated capital, and expenses such as energy, maintenance, and labor to run the equipment. Hence, we do not expect firms to automate all aspects of production immediately when an automated technology becomes accessible. Rather, we hypothesize that firms account for such a tradeoff and automate when the option turns in the money. We elaborate on this point in Section 2 and provide supporting evidence in Section 4.2.2 that automation reduces firm-level operating leverage.

to replace labor across a broad set of both routine and non-routine tasks. To validate the measure, we empirically confirm that *SLAC* is negatively correlated with future employment changes and positively correlated with subsequent installation of industrial robots.

Our initial analysis evaluates the relation between the substitutability of labor with automated capital and a first-order corporate policy, precautionary cash holdings. Using a sample of industrial firms from 1999 through 2018, our baseline regressions suggest that a one-standard-deviation increase in *SLAC* is associated with a 5.16 percentage point reduction in cash holdings, defined as cash and short-term investments scaled by total assets. This effect is economically meaningful, as it implies a 25.5% decrease relative to the sample mean. Our results are robust to a suite of fixed effects, and to alternative measures of cash. We refine our analysis by estimating a segment sales-weighted *SLAC* that accounts for the industry composition of multi-segment firms. As expected, segment-weighted *SLAC* has greater explanatory power for financial policies, suggesting that the potential to automate is closely tied to firm production.[5]

To reinforce the causal interpretation of the relation between *SLAC* and financial policies, we exploit the 2011–2012 Thailand hard drive crisis as an exogenous shock to the cost of adopting automated capital. In 2011, flooding in Thailand, the world's second-largest producer of hard disk drives, severely disrupted global hard drive manufacturing capability, leading to a shortage of drives and a spike in unit prices. Since hard drive prices are an important determinant of the cost of automation, this natural disaster in Thailand was a negative shock to the potential to replace labor with automated capital that is orthogonal to potential omitted variables. Therefore, we expect that the effect of *SLAC* on cash holdings, and other short-term financial policies, will be weaker during 2011–2012, particularly for firms that rely more on computers and peripheral equipment for automation. Our evidence supports these predictions.

[5] While our baseline analysis utilizes a measure of *SLAC* based on a firm's primary line of business, all our findings in this paper are robust (and even stronger) using the segment sales-weighted firm-specific *SLAC*.

We evaluate the incremental explanatory power of *SLAC* relative to prior measures constructed to estimate the substitutability of only routine-task labor. To this end, we construct an industry-by-year measure of routine-task labor intensity based on Autor and Dorn (2013). Our findings indicate that *SLAC* is a significantly more comprehensive metric of the potential to automate the workforce relative to the measure that captures only the substitutability of routine tasks. Specifically, in regressions explaining cash holdings, *SLAC* entirely subsumes the explanatory power of *RTI*, and a decomposition suggests that the substitutability of non-routine tasks accounts for about one-half of the impact of prospective automation on liquidity policy.

We perform two distinct analyses that collectively support the mechanism that the ability to substitute automated capital for labor provides an option to lower operating leverage. First, we document a stronger relation between *SLAC* and cash holdings for (i) firms with greater labor-induced operating leverage and (ii) a lower expected cost of worker displacement. For example, *SLAC* is more negatively correlated with cash during periods when hiring costs are high, but less negatively correlated for firms with more low-paid employees. In addition, the relation between *SLAC* and cash is more pronounced for firms with limited union coverage and more generous unemployment insurance benefits.

Second, we examine how firms respond to an exogenous shock that enhances the value of the option to replace labor with automated capital. Our empirical strategy exploits staggered increases in state corporate income tax rates, which negatively impact a firm's operating cash flows in a manner orthogonal to characteristics of its workforce and financial policies. Specifically, we evaluate how firms with varying levels of *SLAC* respond to large increases in state corporate tax rates (100+ basis points) over the three fiscal years that follow. Our results indicate that while, on average, a surge in state tax rates reduces corporate investment, firms with high *SLAC* actually expand their capital stock of equipment and software. In addition, consistent with the substitution of labor with automated capital, high-*SLAC* firms see an increase in the capital-labor ratio, a decrease in production workers, and a decline in labor costs. Most importantly, our evidence indicates that a tax hike increases operating leverage for firms with low *SLAC*. In striking contrast, however, high-*SLAC* firms exhibit a significant reduction in operating leverage following state tax increases, evidence that is consistent with firms automating to enhance operating flexibility.

If the ability to replace labor with automated capital enhances a firm's operating flexibility and affords greater financial flexibility, *SLAC* should relate to financial conservatism more broadly. Our evidence is consistent with this proposition. For example, a one-standard-deviation increase in *SLAC* is associated with a 13.0% (14.9%) increase in book (market) leverage relative to the sample mean. The same increase in *SLAC* is associated with a 21.7% higher common dividend payout, and a distinctly larger proportion of dividends relative to share repurchases. Our causal tests exploiting the 2011 Thailand flooding indicate that, as expected, the estimated effects of *SLAC* on leverage and short-term debt decline during the hard drive crisis. Given the transitory effects of the crisis, however, there is no impact of this event on long-term financial policies.

We evaluate the empirical relevance of a variety of alternative mechanisms that could conceivably explain the observed link between *SLAC* and corporate financial policies. One possibility is that firms with high *SLAC* are actually in the process of automating. The up-front costs associated with technology adoption could lead to lower cash reserves and greater financial leverage. To consider this possibility, we examine the relation between *SLAC* and financial policy for firms that are not in the process of automating, such as those experiencing a decline in the capital-labor ratio. The negative relation between *SLAC* and financial conservatism for this subsample is similar to that observed for the full sample. In addition, we document that the marginal value of cash decreases with *SLAC*. This result is consistent with a lower demand for precautionary cash, and inconsistent with a higher demand for cash to invest in automation.

A second alternative mechanism is that the threat of worker displacement from automation weakens the bargaining power of unionized workers, leading to lower labor costs. Contrary to this alternative explanation, we find that the estimated effects of *SLAC* on financial policies are significantly stronger for firms in industries with lower labor union coverage.

Finally, it is possible that our measure of *SLAC* is correlated with one or more labor-related characteristics known to affect corporate financial policies. To assess this alternative, we incorporate controls for labor-related factors into our baseline specifications, including capital intangibility, labor skill, labor mobility, union coverage, the fraction of low-paid employees, and the ability to offshore labor. After controlling for these labor characteristics, we continue to document that *SLAC* is a unique and economically substantial determinant of financial policies.

This paper makes three main contributions to the literature. First, we provide robust evidence that a firm's ability to automate its existing workforce enhances operating flexibility and allows for less conservative financial policies. Our findings thus add to the literature that relates the impact of operating flexibility on corporate financial decisions, including work by Mandelker and Rhee (1984), Reinartz and Schmid (2016), D'Acunto, Ryan, Pflueger, and Weber (2018), and Kahl, Lunn, and Nilsson (2019). Our findings also extend those in Zhang (2019), who finds that the ability to automate routine-task labor reduces operating leverage and expected returns.

A second contribution of our research is the development of a novel, occupation-based measure of the substitutability of labor with automated capital. Our measure of prospective substitution is unique in that it accounts for technological innovation in fields such as artificial intelligence, machine learning, and mobile robotics that have enabled the automation of certain non-routine tasks. Our findings indicate that this is an economically important extension to earlier measures that solely accounted for the potential to automate routine-task labor.

Finally, our research adds to the literature documenting the first-order impact of labor market frictions on financial policies (e.g., Simintzi et al. 2015; Serfling 2016; Ghaly, Dang, and Stathopoulos 2017; Kuzmina 2018; He, Tian, Yang, and Zuo 2020). We present new evidence that the impact of labor frictions varies with firms' (in)ability to substitute automated capital for labor.

The rest of the paper is organized as follows. Section 2 develops hypotheses. Section 3 describes the primary data used in the paper, and the construction of the *SLAC* measure. Section 4 estimates the relation between *SLAC* and financial policies, provides causal evidence, and demonstrates the economic mechanism. Section 5 considers the empirical relevance of alternative explanations for our findings. Section 6 concludes.

2. Conceptual Framework and Hypothesis Development

Why does the potential to automate a workforce matter for corporate financial policy? We contend that labor's susceptibility to replacement with automated capital endows firms with an option to lessen labor-induced operating leverage, enhance operating flexibility, and adopt less conservative financial policies.

Labor market frictions are a critical source of operating leverage. These frictions have been shown to obtain on a variety of dimensions. For example, Chen, Kacperczyk, and Ortiz-Molina (2011) and Favilukis and Lin (2016) study operating leverage arising from sticky wages. Simintzi et al. (2015) and Serfling (2016) focus on increased firing costs that follow from the adoption of labor protection laws. Belo et al. (2017) and Ghaly et al. (2017) examine labor adjustment costs associated with labor force heterogeneity in skills. These labor frictions lead to pre-committed payments to labor, effectively increasing the sensitivity of a firm's operating cash flow to economic shocks.

One way to hedge labor-induced operating leverage is to increase financial flexibility. Firms hold cash to hedge against adverse cash flow shocks that would cause them to forego valuable investment when external financing is prohibitively costly. Similarly, firms use less financial leverage and limit payout policy when operating leverage is high. For example, Ghaly et al. (2017) show that firms with a high share of skilled workers hold more cash. Simintzi et al. (2015) and Serfling (2016) document that labor reforms that increase operating leverage crowd out the use of financial leverage. He et al. (2020) find that firms reduce dividends in response to close-call union elections.

All else equal, hedging operating leverage through conservative financial policies is costly for firms. A direct cost of cash is the cost of carry, typically expressed as the difference between the risk-free rate (or zero) and the cost of capital for the firm's liquid assets. Azar, Kagy, and Schmalz (2016) find that the level of cash holdings is highly sensitive to the cost of carry. Agency costs of managerial discretion constitute an additional cost of cash balances (e.g., Harford 1999; Dittmar and Mahrt-Smith 2007; Harford, Mansi, and Maxwell 2008). An increase in operating leverage also raises the expected cost of financial distress for a given level of debt. Thus, labor leverage crowds out financial leverage and limits the tax benefits of debt. Finally, the model of Baker, Mendel, and Wurgler (2016) implies that the conservation of cash through dividend policy lowers investors' expectations for future cash flows.

In this paper we consider the impact of recent technological advances on a firm's ability to resolve labor-induced operating leverage. If advances in technology allow automated capital to complete the tasks of human labor, the resulting operating flexibility will unwind the impact of labor frictions. For instance, Acemoglu and Restrepo (2018, 2020) show that, by displacing workers, automation lowers labor share and production costs. Zhang (2019) documents that the replacement of routine-task labor with automated capital yields cost savings and reduces operating leverage. This argument accords with Donangelo et al. (2019), who note that the relevance of labor leverage requires complementarity between labor and capital as inputs to production.

Investment in automated capital can be costly for firms. For instance, adopting new technology involves production and organizational restructuring (e.g., Bresnahan, Brynjolfsson, and Hitt 2002). The up-front costs associated with acquiring automated capital might also require the capacity to finance. For this reason, we do not expect firms to automate all aspects of production immediately when a useful technology becomes accessible. Instead, we hypothesize that firms consider these costs and choose to automate when doing so appears valuable—for example, when the opportunity cost declines or when operating leverage intensifies. In this sense, our mechanism complements Zhang (2019), who shows that firms with a higher share of routine-task labor have lower exposure to systematic risk given their option to displace routine-task labor during economic downturns. If the potential to replace labor with automated capital provides operating flexibility, a firm with a higher *SLAC* should, all else equal, be expected to utilize more aggressive financial policies. We therefore test the following hypothesis.

Hypothesis 1. Firms with a higher substitutability of labor with automated capital (SLAC) have lower cash holdings, more financial leverage, and a higher dividend payout.

Our hypothesized mechanism is that the ability to substitute automated capital for labor moderates the impact of operating leverage. Firms weigh the benefits of adopting automated capital against the costs of switching production technologies. In the context of a large adverse shock to cash flow, the option to displace labor to ease the negative consequences of operating leverage becomes more valuable; thus, we expect firms with higher *SLAC* to respond by investing more in automated capital, such as equipment, software, and algorithms. With worker displacement, these same firms should exhibit an increase in the capital-labor ratio, a decline in labor costs, and a decrease in operating leverage. Given a decline in operating leverage and an expansion of collateralizable assets, we also predict that firms with higher *SLAC* will increase financial leverage following a cash flow shock.

Hypothesis 2. In the context of adverse cash flow shocks, firms with higher SLAC increase investment in automated capital, increase the capital-labor ratio, and exhibit a greater reduction (increase) in operating (financial) leverage relative to firms with lower SLAC.

3. Data and Summary Statistics

3.1 Measuring *SLAC*—the substitutability of labor with automated capital

A central theme of neoclassical economics is that firms optimize factor inputs, namely capital and labor, according to their production function (e.g., Hicks 1932). A key parameter of the production function is the elasticity of substitution between capital and labor. Studies have attempted to estimate this elasticity while accounting for the impact of technological change (e.g., Arrow, Chenery, Minhas, and Solow 1961; Lucas 1969; Chirinko 2008). Although we do not aim to estimate such a parameter, our measure of *SLAC* can be viewed as a time-varying and industry-specific proxy for the substitution between automated capital and labor, which, as we show, shapes firms' combination of factor inputs and financial policies.

To quantify the substitutability of labor with automated capital, we develop our key variable, *SLAC*, based on two primary data sources. The first is the occupational probability of computerization estimated in Frey and Osborne (2013, 2017). Drawing on advances in a variety of fields including engineering sciences and mobile robotics, Frey and Osborne characterize occupations by their susceptibility to automation using computer-controlled equipment. Their method develops estimates for the probability of computerization for occupations defined using the 2010 Standard Occupational Classification (SOC) code. A lower probability implies that the occupation is less likely to be computerized. For example, the occupation "Recreational Therapists" has the lowest estimated probability of computerization (0.0028), while "Telemarketers" has the highest probability (0.99), implying almost certain replacement.[6]

Frey and Osborne's occupational probability of computerization quantifies the impact of technological progress in the 21st century on the potential for capital-labor substitution, extending models of the computerization of routine tasks. Seminal work by Autor, Levy, and Murnane (2003) distinguishes between cognitive and manual tasks on the one hand, and routine and non-routine tasks on the other.[7] To quantify computationally-based substitution for routine-task labor, Autor and Dorn (2013) construct an index of *routine-task intensity* based on routine, non-routine manual, and abstract task inputs in each occupation. Recent advances in fields related to machine learning, machine vision, computational statistics, and other subfields of artificial intelligence (AI) have also turned many non-routine manual and cognitive tasks into well-defined problems. Examples of non-routine manual tasks that can be defined using AI include automobile driving and preparing

[6] Indeed, it is hard to imagine a recreational therapist being a robot because the job requires a diverse set of cognitive tasks such as observing, interacting with the patient, and assessing a patient's objectives for therapy.

[7] Autor et al. (2003) argue that computers are more likely to replace routine-task occupations, but not non-routine-task occupations. Examples of non-routine cognitive occupations include law, medicine, science, engineering, design, and management, whereas driving a truck through city traffic, preparing a meal, installing a carpet, and mowing a lawn are all activities that are intensive in non-routine manual tasks.

a meal. Examples of non-routine cognitive tasks include deciphering handwriting on a personal check, radiological medical imaging diagnoses, and legal writing.[8] Frey and Osborne's measure of prospective labor substitution accounts for a variety of non-routine tasks also subject to automation, providing a comprehensive view of the susceptibility of jobs to computerization.

Our second data source is the time-varying industry-level occupational employment and wage estimates from the Occupational Employment Statistics (OES) program maintained by the Bureau of Labor Statistics (BLS). The OES program collects data on wage and salary workers in nonfarm establishments, and produces estimates of occupational employment and wages. We obtain industry-level occupational employment and wage data from the OES program for 1999–2018.[9] The OES data used the 2000 SOC definitions for 1999–2009 and the 2010 SOC definitions after. We link the 2000 SOC codes to the 2010 SOC codes using a crosswalk table provided by the BLS.[10] Industries are defined using three-digit Standard Industrial Classification (SIC) codes until 2001, and four-digit North American Industry Classification System (NAICS) codes from 2002 onward. On average, there are 377 unique three-digit SIC industries from 1999 to 2001, and 312 unique four-digit NAICS industries for 2002 and after.

Using the SOC codes, we map Frey and Osborne's occupational probability of computerization to the OES industry-level occupational employment and wage data.[11] We construct our measure of the substitutability of labor with automated capital (*SLAC*) for each industry in each year as:

$$SLAC_{j,t} = \sum_{o} Prob_o \times \frac{Emp_{j,o,t} \times Wage_{j,o,t}}{\sum_{o} Emp_{j,o,t} \times Wage_{j,o,t}} \tag{1}$$

[8] For instance, lawyers increasingly rely on machine learning systems capable of scanning large numbers of relevant legal cases to assess the probability of winning a particular case (*Financial Times*, 09/28/2019).
[9] Our sample starts in 1999 because the OES occupational estimates are based on the SOC taxonomy from 1999.
[10] The crosswalk table can be obtained at www.bls.gov/soc/soc_2000_to_2010_crosswalk.xls.
[11] The six-digit 2010 SOC system has 840 occupations. The Frey and Osborne estimates cover 702 detailed occupations; the remaining occupations correspond to about 3% of total employment and mostly contain "all other" titles ending with SOC code 99. For these occupations, we average across the observations that share the same first four digits of the SOC code. For example, the occupation "Religious Workers, All Other" (SOC 21-2099) is obtained from the average of "Clergy" (SOC 21-2011) and "Directors, Religious Activities and Education" (SOC 21-2021).

where $Prob_o$ is Frey and Osborne's probability of computerization for occupation (*o*); $Emp_{j,o,t}$ and $Wage_{j,o,t}$ are, respectively, the number of employees and the average annual wages of workers assigned to occupation (*o*) in industry (*j*) at year (*t*). Following Donangelo (2014) and Zhang (2019), we assign weights to the share of employment across occupations in each industry using the annual wages of workers in that occupation to reflect labor's impact on cash flows.[12] As such, $SLAC_{j,t}$ is the weighted average probability of computerization across all occupations that constitute industry (*j*) in year (*t*), and is between zero and one. A lower *SLAC* implies that a smaller fraction of existing workers in a given industry and year can potentially be replaced with automated capital, and changes in *SLAC* over time reflect the evolution in the distribution of employment across occupations for an industry.

Panel A of Table 1 lists the bottom and top industries sorted by average *SLAC* over our sample period 1999–2018. This table illustrates the substantial cross-sectional variation in *SLAC*. Industries with the lowest *SLAC* include child care, health care, educational services, and research and development. Notably, low-*SLAC* industries include those that rely on highly skilled labor, such as research and development, as well as those that utilize lower-skilled labor, such as child care services. This observation suggests that *SLAC* measures a characteristic of an occupation that is distinct from labor skill.[13] Industries with the highest *SLAC* include restaurants, transportation, gas stations, stores, vending machines, and logging. Not surprisingly, production and services in these industries can be feasibly provided by automated capital.[14]

We validate the occupational probability of computerization, and our industry-year *SLAC* measure, through the lens of realized employment changes and the installation of industrial robots.

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[12] Our results in this paper are essentially unchanged when we construct *SLAC* using only employment data.

[13] Using patent data, Webb (2020) shows that while low-skilled workers are most exposed to replacement by industrial robotics, other automation technologies such as software and artificial intelligence are more likely to substitute for medium- and high-skilled workers.

[14] See, for example, Jane Black, "The Machine That Lets You Skip the Salad Bar," *Wall Street Journal*, February 13, 2020, www.wsj.com/articles/the-machine-that-lets-you-skip-the-salad-bar-11581603393? and Aaron Cohen, "Should Restaurants Replace Humans with Technology?" *QSR*, January 2019, www.qsrmagazine.com/outside-insights/should-restaurants-replace-humans-technology.

If automation-based substitution for labor shapes employment outcomes, and the probability of computerization truly reflects the potential to automate occupations, then the probability should predict occupational changes in employment. For example, Frey and Osborne estimate that telemarketers can be easily displaced by automated interaction strategies such as chatbots. Not surprisingly, the total employment of the "telemarketer" occupation declined by 45% from 283,460 workers in 2010 to 156,100 in 2018. To formally test our prediction, we use the OES employment and wage estimates from 2010 to 2018, given that the probability of computerization is estimated for the 2010 SOC occupations.

[Table 1 and Figure 1 about here]

In Panel A of Figure 1, the binned scatter plot on the left highlights a negative relation between the probability of computerization and employment growth by occupation from 2010 to 2018. For comparison, the plot on the right utilizes Autor and Dorn's (2013) routine-task intensity and illustrates the decline of employment in routine intensive occupations documented in Jaimovich and Siu (2020). Panel B of Table 1 reports ordinary least squares (OLS) estimation results. Column (1) shows that a one-standard-deviation increase in the probability of computerization is associated with a 4.4 percentage point decline in employment growth. The same increase in routine-task intensity is associated with a 2.5 percentage point decline in employment growth (Column 2). Column (3) incorporates both measures, and the probability of computerization continues to be significant. Columns (4)−(6) of the panel show similar results using occupational employment growth weighted by wage. Panel C of Table 1 examines the predictive power of our industry-year *SLAC* measure for annual industry-by-occupation employment growth from 2010 to 2018. As a benchmark, we also construct the industry-year measure of routine-task intensity (*RTI*) by replacing $Prob_o$ in equation (1) with routine-task intensity of Autor and Dorn (2013). The estimates reveal a consistent pattern: industries with high *SLAC* experience robustly lower employment growth, with or without a control for *RTI*.

We also validate our *SLAC* measure using data on the use of industrial robots, a common form of automated capital, particularly for occupations involving routine manual tasks. The International Federation of Robotics (IFR) provides a breakdown of annual installations and the operational stock of industrial robots by industry for six major sectors and 27 detailed manufacturing industries. We match industry-year robot installations in the US with our *SLAC* and *RTI* measures using a method described in Appendix A. The binned scatter plots in Panel B of Figure 1 show that both industry-level *SLAC* and *RTI* in 2010 significantly predict total robot installations by industry between 2010 and 2018. Estimates in Panel D of Table 1 show that *RTI* absorbs the explanatory power of *SLAC* in predicting the adoption of industrial robots when both measures are included in the regressions. This result follows from the fact that the IFR data primarily covers manufacturing industries where routine-task labor is most common.

[Figure 2 about here]

As a final observation, we note that industries with high *SLAC* tend to show a downward trend in *SLAC*, consistent with their adoption of automated capital over time. For example, the industry that employs telemarketers, Business Support Services, experiences a marked decline in *SLAC*, as shown in Panel A of Figure 2. Similarly, the automotive industry is the most active customer for industrial robots, accounting for 44.7% of all new robot installations in the US in 2010–2018 based on the IFR data. This investment coincides with a decrease in *SLAC* for the Motor Vehicle Parts Manufacturing industry. By contrast, Panel B of Figure 2 illustrates that *SLAC* for low-*SLAC* industries, such as Child Day Care Services, is relatively unchanged over time.

3.2 Sample construction and summary statistics

To construct our sample, we start with all Compustat firms from 1999 through 2018 excluding utilities (SIC codes 4900–4999) and financial firms (SIC codes 6000–6999). We match industry-year *SLAC* to Compustat firms according to their historical industry code using the three-digit SIC code prior to 2002, and the four-digit NAICS code thereafter.[15]

[Table 2 about here]

The dependent variable in our first set of baseline regressions is *Cash holdings*, which is defined as cash and short-term investments scaled by total assets. Following Bates et al. (2009), we control for the determinants of cash holdings as: size, market-to-book ratio, cash flow, net working capital, R&D expenses, capital expenditures, leverage, industry cash flow volatility, acquisitions, and an indicator variable for dividend payment. All variable definitions are provided in Appendix A. We drop firm-year observations with negative total assets and missing data for the main control variables. To reduce the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles of the distribution. The final sample consists of 96,039 firm-year observations and 13,228 unique firms. Table 2 reports descriptive statistics. The average (median) of *Cash holdings* is 20.2% (10.6%). The summary statistics are comparable to those reported in Bates et al. The mean and standard deviation of *SLAC* are 46.4% and 15.0%, respectively, and the 10^{th} and 90^{th} percentiles of the distribution are 26.6% and 66.2%.

4. Empirical Tests and Findings

This section summarizes our main findings and provides evidence on the economic mechanism. In Section 4.1, we examine the implications of the substitutability of labor with automated capital for cash holdings. In Section 4.2, we outline analyses that collectively support the mechanism that the prospective substitution of labor with automated capital enhances operating flexibility. Section 4.3 considers the impact of the potential to automate on the use of financial leverage and payout policy.

[15] To confirm that the change in industry classification does not alter our results, we restrict the sample to 2002 onward and all results hold.

4.1 *SLAC* and cash holdings

4.1.1 Baseline analysis

Our initial analysis evaluates the relation between *SLAC* and a first-order aspect of corporate financial policy, cash holdings. Figure 3 summarizes this relation. In Panel A, we sort firm-year observations by *SLAC* into four equally-sized groups. Going from firms with the lowest to the highest *SLAC*, we document a decline in *Cash holdings* from 29% to 10%. This difference is robust over time, as illustrated in Panel B of Figure 3.

[Figure 3 and Table 3 about here]

Next, we estimate the relation between *SLAC* and cash policy, conditioned on observable firm characteristics, using the following OLS specification:

$$Y_{i,t} = \beta_0 + \beta_1 SLAC_{i,t} + \gamma' X + B_t + \mu_j + \varepsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is cash holdings, *SLAC* is our measure of the substitutability of labor with automated capital, and *X* is a vector of firm-level control variables following the specification in Bates et al. (2009). We include year fixed effects in all specifications as our focus is on the cross section controlling for economy-wide conditions. We also include two-digit SIC industry fixed effects, industry-specific time trends, or firm fixed effects to strip out unobservable differences across industries or firms.

The results are presented in Table 3. The known determinants of cash enter with expected signs. Variables such as net working capital, capital expenditures, leverage, acquisition activity, size, and dividend payer dummy have a negative impact on cash holdings, while cash flow, market-to-book, and R&D expenditures have positive and significant coefficients. Notably, the coefficient estimates for *SLAC* are negative and significant indicating that cash holdings are declining in *SLAC*. For instance, based on the coefficient estimate of Column (2), a one-standard-deviation increase in *SLAC* is associated with a 5.16 percentage points (=15.0%×0.344) reduction in *Cash* *holdings*, controlling for industry and year fixed effects. This effect is economically significant, accounting for a 25.5% (=5.16/20.2) reduction relative to the sample mean. Our results remain unchanged in Column (3) when we control for industry-specific time trends to isolate from industry-wide shocks and trends.[16] Incorporating firm fixed effects in Column (4), the coefficient suggests a 4.0% reduction in *Cash holdings* relative to the sample mean for a one-standard-deviation increase in *SLAC*. The decline in economic significance is attributable to the high persistence in *SLAC* over time, suggesting that much of the effect is in the cross section. Although our results are robust regardless of the approach to fixed effects, we rely on specifications that include industry and year fixed effects. This approach allows us to focus on the cross-sectional relation between *SLAC* and firm financial policy, controlling for broad industry heterogeneity.

Our results in Table 3 are robust to alternative measures of cash, including: (i) changes in cash holdings, (ii) the natural logarithm of cash and short-term investments (in 1999 dollars), (iii) cash and short-term investments scaled by total assets net of fixed assets, and (iv) cash and short-term investments scaled by total assets net of cash.

While our baseline analysis utilizes a measure of *SLAC* based on a firm's primary line of business, we also estimate a firm-specific *SLAC* that relies on the segment-based industry composition of individual firms. Specifically, using the Compustat Segment data, we identify multi-segment firms reporting multiple business segments with distinct industry codes, and compute a sales-weighted average *SLAC* using their constituent industries.[17] Table IA.1 in the Internet Appendix summarizes OLS regressions similar to those reported in Table 3, but utilizing firm-specific *SLAC* for multi-segment firms. In the top panel we summarize the relation between *SLAC* and cash holdings using only the primary line of business for multi-segment firms. To

[16] Results are similar if we use alternative industry definitions, such as three-digit SIC, Fama-French 48 industries, or the Hoberg-Phillips (2010, 2016) 50 industries.

[17] Our measure of *SLAC* for segments corresponds to the three-digit SIC industry definition before 2002 and the four-digit NAICS definition afterward. Custodio (2014) notes that the accumulation of goodwill in merger and acquisition accounting biases the book value of assets of conglomerates upwards, and that conglomerates have more flexibility in allocating assets across divisions; therefore, we rely on segment sales to compute weighted average *SLAC*.

account for the true nature of production in multi-segment firms, the second panel of the table evaluates the impact of using a firm-specific segment sales-weighted *SLAC*. Consistent with a reduction in measurement error, the segment sales-weighted *SLAC* has a significantly greater effect on cash holdings, relative to the top panel. The final panel of the table reports regressions for our full sample of both single- and multi-segment firms using the segment sales-weighted *SLAC*. Again, the results demonstrate an improvement from our baseline estimates in Table 3, suggesting that firm-specific *SLAC* provides a better approximation for production in multi-segment firms.

Finally, we conduct a placebo test motivated by the observation that *SLAC* measures the substitutability of labor with automated capital made possible by technological advances in recent decades. While we expect *SLAC* to be negatively associated with corporate cash policies generally, the effect should be weaker in earlier decades. We estimate the relation between *SLAC*, fixed to its value in 1999, and cash holdings for subsamples of Compustat firm-years drawn from up to two decades before the start of our sample. The results are reported in Internet Appendix Table IA.2. As expected, the estimated relation between *SLAC* and *Cash holdings* from 1979 to 1998 is roughly 30% of the magnitude documented in Table 3. For observations from 1979 through 1989, the magnitude declines to about 17%. In contrast, the relation between *SLAC* and cash since 1999 is reliably significant.

4.1.2 Causal evidence from the Thailand hard drive crisis

In this section, we address the potential for an endogenous relation between the substitutability of labor with automated capital and corporate policies. One advantage of *SLAC* in this regard is that it is based on an industry-level occupational characterization of the technological capability to automate. Neither the occupational susceptibility of jobs to computerization, nor industry-level occupational employment, is likely endogenous to individual firm characteristics or policies. To alleviate concerns of reverse causality, we replicate our analysis in Table 3, replacing time-varying *SLAC* with its one-year lagged value, and an ex-ante time-invariant *SLAC* computed at the beginning of the sample period, with the results reported in Internet Appendix Table IA.3.

While these results are suggestive, we also utilize an identification strategy that exploits the 2011–2012 Thailand hard drive crisis as an exogenous shock to the cost of workplace automation.

Thailand is the second-largest producer of hard disk drives, with approximately 40% of the world's production. Unusually severe flooding during the 2011 monsoon season caused widespread damage to the hard drive industry as many production facilities, including those of Western Digital and Seagate, were flooded. This event had an international impact, known as the Thailand hard drive crisis. Disruptions to supply chains caused a global shortage of hard disk drives and a spike in prices, the effects of which rippled into the production of PC, chip, server, and memory products. Figure 4 plots the price for hard disk drives from 2009 to 2015 at a unit price of 0.01 cents in USD per megabyte.[18] Prices nearly doubled in the fall of 2011, and gradually returned to the pre-crisis level by the end of 2012.

[Figure 4 about here]

While technological advances have made workplace automation increasingly feasible, adopting automated technology is costly. As discussed in Section 2, firms consider the cost of replacing labor with automated capital when evaluating the net benefit of automation. A higher perceived cost of automation will diminish the value of the potential to automate. Since hard drives are an integral input to utilizing computer memory, data storage, and server rentals, the price for drives closely determines the prospective cost of adopting automated capital. In this context, the Thailand hard drive crisis induced an exogenous change in the cost of workplace automation that is orthogonal to potential omitted variables. If the effect of *SLAC* on corporate financial policy is indeed causal, we expect *SLAC* to have a more muted impact on short-term financial policies in 2011–2012 when the cost of automation increased. In contrast, the impact of *SLAC* on the use of long-term debt and payout policy will be relatively insensitive to this transitory shock given the stickiness of these policies.

[18] The time series of global hard disk prices are based on the lowest-priced disk drives available on the market at each point in time. We thank John McCallum for kindly sharing this data.

To test this prediction, we employ a difference-in-differences framework as follows:

$$Y_{i,t} = \beta_0 + \beta_1 Flooding_t \times SLAC_{i,t} + \beta_2 SLAC_{i,t} + \gamma' X + B_t + \mu_j + \varepsilon_{i,t}, \qquad (3)$$

where $Y_{i,t}$ is cash holdings, *Flooding* is a dummy variable equal to one for the years 2011 and 2012, and *SLAC* is our measure of the substitutability of labor with automated capital. Our specifications, summarized in Table 4, include the same set of firm-level control variables and fixed effects as in Table 3.

[Table 4 about here]

Consistent with our prediction, the impact of *SLAC* on cash holdings is significantly weaker during the Thailand crisis. Estimates in Column (2) of the top panel of Table 4 show that a one-standard-deviation increase in *SLAC* translates to a 26.0% (=15.0%×0.350/0.202) decline in cash holdings relative to the sample mean in the non-crisis period, but only a 21.4% reduction in cash holdings during the crisis.

Firms that manufacture hard drives suffered a considerable loss from the Thailand flooding. Moreover, disruptions to the hard drive supply chain led to component shortages for firms that were customers and suppliers of the industry, such as Advanced Micro Devices, Dell Technologies, and NetApp. Thus, one concern is that the observed variation is driven by fundamental shocks to the hard drive industry and spillovers to economically related firms, rather than changes in the cost of automation. To alleviate this concern, we drop the 360 firms that belong to the hard drive industry (NAICS code 3341, Computer and Peripheral Equipment Manufacturing), as well as firms that are identified as major customers and suppliers of the hard drive industry, and the results, reported in the middle panel of Table 4, are essentially unchanged.[19]

[19] Regulation S-K and the Statement of Financial Accounting Standard (SFAS) No.14 require that firms disclose all customers representing 10% or more of their total sales. Accordingly, we identify customer and supplier relationships using the Compustat Segment Customer database and the mapping between company name and identifier provided by Cohen and Frazzini (2008) and Cen, Maydew, Zhang, and Zuo (2017).

To provide more confidence in our causality tests, we also focus on a subsample of firms that rely heavily on computers for automation, and thus are particularly sensitive to the change in the cost of automation. Using the 1997 Bureau of Economic Analysis (BEA) capital flow table we calculate the ratio of investments in computers and peripheral equipment to total investments in equipment and machinery for each industry and select the firms in the top tercile industries.[20] Results presented in the bottom panel of Table 4 show that the change in the relation between *SLAC* and cash attributable to the Thailand flooding is more pronounced for firms that utilize a higher proportion of computers and peripheral equipment, evidence that is consistent with the hypothesis that *SLAC* affects corporate financial policy through the net benefit of automation.[21]

Our use of a flooding indicator variable captures the extensive margin of the cost to automate. We also consider the intensive margin by examining changes in the price of hard disk drives. We replace the dummy variable *Flooding* in equation (3) with the deviations from a linear trend in the natural logarithm of annual unit price of hard drives from 1999 to 2018. Our findings, reported in Table IA.4, are robust to this alternative specification. Overall, the evidence from the Thailand hard drive crisis supports a causal interpretation of the relation between the potential to automate and corporate cash holdings.

4.1.3 The potential to automate routine and non-routine tasks

Our measure of the substitutability of labor with automated capital (*SLAC*) is an extension of earlier measures derived from routine-task intensity. Specifically, *SLAC* accounts for the potential to automate both routine and non-routine tasks. To evaluate the incremental contribution

[20] The BEA capital flow data "1997 Investments by Using Industries" can be obtained at https://apps.bea.gov/industry/xls/flow1997.xls. To measure investments in computers and peripheral equipment, we use data item (4). To measure the total investment in equipment and machinery, we use the sum of data items (4)–(9), (13)–(15), and (26)–(29).

[21] In untabulated results, we run the identical regression for the remaining subsample of firms that are less reliant on computers for automation. In this regression, we find that the coefficient on the interaction between *SLAC* and *Flooding* is insignificantly different from zero.

of capturing both aspects of labor, we include Autor and Dorn's (2013) industry-by-year measure of routine-task intensity (*RTI*) in our baseline models, and summarize the results in Table 5.

[Table 5 about here]

Column (1) of Table 5 summarizes an OLS regression in which *RTI* is included in lieu of *SLAC*. The coefficient estimate on *RTI* is negative and statistically significant at the 1% level. The estimate implies that a one-standard-deviation increase in *RTI* translates to a 2.69 percentage point decrease in *Cash holdings*.[22] While the relevance of routine-task intensity for employment and asset returns has been documented, the finding that *RTI* is a significant determinant of corporate liquidity management is noteworthy and novel to the literature.

The regression presented in Column (2) of the table includes both *RTI* and *SLAC* as explanatory variables. *SLAC* is a significant factor in determining cash policy, and statistically subsumes *RTI*, consistent with *SLAC* being a comprehensive construction of the potential to automate the workforce. To assess the relative significance of the substitutability of routine and non-routine-task labor, we regress *SLAC* on *RTI*, controlling for industry and year fixed effects to obtain the residual, *Orthogonal SLAC*. This variable, which is orthogonal to *RTI* by construction, captures the substitutability of only non-routine-task labor. The coefficient for *Orthogonal SLAC* in Column (3) indicates that a one-standard-deviation increase in *Orthogonal SLAC* translates to a 2.32 percentage point decrease in *Cash holdings*. The estimated economic magnitude of the effect is comparable to that of *RTI* in Column (1). Put differently, the substitutability of non-routine-task labor accounts for about one-half of *SLAC*'s total effect on corporate liquidity policy.

4.2 Evidence on the mechanism

Our results so far show that a firm's ability to substitute automation for labor is a novel factor that shapes corporate cash policy. Our proposed mechanism is that the potential to automate

[22] Our results are similar using industry routine-task labor share from Zhang (2019), measured as the fraction of wages paid to routine-task labor of an industry in each year.

acts as a latent hedge to operating leverage, allowing firms to utilize more aggressive financial policies. In this section, we provide evidence to support this mechanism. In Section 4.2.1 we evaluate the moderating effects of the benefits and costs of worker displacement. In Section 4.2.2 we provide evidence on the mechanism by evaluating how firms respond in investment and labor share in production in the context of large increases in state corporate tax rates.

4.2.1 The benefits and costs of worker displacement by automation

Workplace automation is achieved by the adoption of automated capital and the displacement of human workers. The displacement effect lowers the cost of production and relaxes the impact of labor costs on operating leverage. In this framework, we expect to find a stronger relation between *SLAC* and cash when firms face greater labor-induced operating leverage, and a weaker relation when firms face a higher cost of worker displacement.

To evaluate the moderating effects of labor leverage, we examine costs from the perspective of labor market conditions and wages. As noted in Kuehn et al. (2017), employers face significant direct and indirect costs associated with searching for and training new employees. These costs vary positively with labor market tightness, which is measured as the ratio of the help-wanted index of Barnichon (2010) to the unemployment rate. Greater labor market tightness implies that competition for labor among firms is high, and the pool of candidates is shallow. During periods of high labor market tightness, we expect labor costs to contribute more to operating leverage, boosting the effect of the potential to automate on financial policies.

To test this prediction, we extend our baseline empirical specification to interact *SLAC* with labor market tightness, and report the results in Column (1) of Table 6.[23] Consistent with our prediction, labor market tightness has a negative impact on the relation between *SLAC* and cash holdings. For example, when labor market tightness increases by one standard deviation from the sample mean, the estimated relation between *SLAC* and *Cash holdings* changes from −0.348 to

[23] Because both labor market tightness and the help-wanted index are aggregate time-series measures, we do not include them independently in the regressions as they are subsumed by the year fixed effects.

−0.374. Since much of the variation in labor market tightness is driven by its numerator, we also interact *SLAC* with the help-wanted index in Column (2) and obtain similar results.

[Table 6 about here]

We next examine the heterogeneous effect of *SLAC* for the cross section of firms delineated by employee wages. Low-paid workers, such as cashiers, fast-food and dry-cleaning employees, are less competitive to hire and are more likely to be temporary workers (e.g., Booth, Francesconi, and Frank 2002; OECD 2002), thus contributing less to firm operating leverage. Accordingly, the value of the option to automate is relatively low for firms with a greater fraction of low-paid employees, suggesting a weaker relation between *SLAC* and cash holdings. We follow Clemens, Kahn, and Meer (2018) and compute *Low-paid employee* as the fraction of workers in an industry with wage rates below the 10th percentile of the entire wage distribution of employment in that year based on the OES data.[24]

In Column (3) of Table 6, we interact *SLAC* with a dummy variable equal to one if the percentage of low-paid employees is above the sample mean in that year, and zero otherwise. As predicted, firms with a greater fraction of low-paid employees exhibit a weaker relation between *SLAC* and cash holdings. The coefficient estimate for the subsample of firms with an above-average share of low-paid employees (−0.176) is statistically different from the coefficient for the subsample with a below-average share of low-paid employees (−0.394).

We also investigate the cross-sectional implications of heterogeneous costs of worker displacement by automation. Automation entails the displacement and layoff of workers. If the effect of *SLAC* on cash holding policy indeed works through the channel of substituting automated capital for labor, we expect to find a stronger effect for firms with a lower cost of displacing workers. We test this prediction by examining industries that differ along two dimensions of worker displacement costs.

[24] Industries ranked high on the fraction of low-paid employees include Restaurants and Other Eating Places, Child Day Care Services, Motion Picture and Video Industries, and Health and Personal Care Stores.

A relevant obstacle to displacing workers is opposition from labor unions (e.g., Dowrick and Spencer 1994; Chen et al. 2011). There are ample historical and contemporary examples of unions resisting automation, and collective bargaining agreements often constrain firms' ability to lay off workers.[25] Accordingly, we expect that firms in industries with broader union coverage face a greater barrier to prospective automation. We obtain industry-year data on labor union membership coverage from the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003) based on the Current Population Survey. *High union coverage* is a dummy variable that takes the value of one if the percentage of employed workers who are covered by a collective bargaining agreement is above the sample mean in that year, and zero otherwise.

Another factor contributing to displacement costs is the generosity of the unemployment insurance (UI) benefits provided by the state. The unemployment insurance system in the US provides temporary income to eligible workers who lose their jobs. Topel (1983) documents that more generous unemployment insurance benefits increase employers' willingness to lay off workers, making automation more feasible. Hence, we expect the effect of *SLAC* to be stronger for firms whose primary business operations are located in states with more generous unemployment insurance benefits. We obtain information on each state's benefit schedule from the Department of Labor's publication *Significant Provisions of State UI Laws*. Following Agrawal and Matsa (2013), we measure the generosity of each state's UI benefits annually using the product of the maximum weekly benefit amount and the maximum benefit duration in weeks.

Columns (4) and (5) in Table 6 summarize the results of interacting *SLAC* with the indicator variables *High union coverage* and *High UI benefits*. As predicted, the estimated effect of *SLAC* is significantly greater for firms in industries with lower labor union coverage and for firms operating in states that provide more generous unemployment insurance benefits. Consistent with the proposed mechanism, the results in Table 6 indicate that *SLAC* has a stronger impact on

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[25] See, for example, Jonathan Vanian, "How Unions Are Pushing Back Against the Rise of Workplace Technology," *Fortune*, April 30, 2019, www.fortune.com/longform/unions-workplace-technology.

financial policies for firms with (i) greater labor-induced operating leverage, and (ii) a lower expected cost of worker displacement.

4.2.2 Automation and operating leverage: Evidence from state corporate tax hikes

To further pin down the mechanism whereby the option to automate moderates the adverse effects of operating leverage, we examine how firms with varying levels of *SLAC* respond to large negative shocks to operating cash flow. Our empirical strategy exploits significant increases in state corporate income taxes, which exacerbate the negative consequences of operating leverage, and increase the value of the option to automate.

Increases in state corporate tax rates are plausibly exogenous to a firm's workforce and policies, and thus provide an excellent setting to study the impact of shocks to operating cash flow. The staggered nature of state tax changes negates the impact of time-varying economy-wide shocks and omitted variable biases caused by unobservable state- or firm-specific characteristics. Using this quasi-natural experiment, studies have evaluated the causal effects of state corporate tax changes on leverage (Heider and Ljungqvist 2015), corporate innovation (Mukherjee, Singh, and Žaldokas 2017; Atanassov and Liu 2020), entrepreneurship (Curtis and Decker 2018), and the reallocation of business activity (Giroud and Rauh 2019). Given that large tax increases are perceived to be long-lasting policies, we follow Giroud and Rauh (2019), and define a large increase in the tax rate as one that is greater than, or equal to, 100 basis points. In the presence of imperfect external capital markets, firms save a portion of after-tax profits as precautionary cash balances. Hence, a large tax increase reduces a firm's operating cash flow for current investment and cash savings for future investment, aggravating the adverse effects of operating leverage.

We test whether a tax hike has a differential impact on corporate automation and operating leverage that is predictably determined by *SLAC*. Under Hypothesis 2, when a firm faces an adverse shock to cash flow, the demand for precautionary cash rises, increasing the value of the option to reduce labor leverage. Firms with a more substitutable workforce are more likely to exercise the option to automate. Consequently, our mechanism suggests that corporate tax hikes for high-*SLAC* firms are met with investment in automated capital, an increase in capital-labor ratio, the displacement of workers, and a decline in labor costs. Automation reduces the impact of labor costs on operating leverage and increases collateralizable assets, with both channels predicting an increase in financial leverage for firms with higher *SLAC*.

We acquire state corporate income tax information for 1999–2012 from Giroud and Rauh (2019) and extend it to 2018 using data from the Tax Foundation and *The Book of the States*.[26] In our sample period there are nine large tax increases: Alabama in 2001 (1.5%), Connecticut in 2012 (1.5%), Illinois in 2011 (2.2%) and in 2018 (1.75%), Maryland in 2008 (1.25%), Michigan in 2008 (3.05%) and in 2012 (1.05%), New Hampshire in 1999 (1%), and Oregon in 2009 (1.3%). Analysis of state tax changes requires the correct identification of the state that taxes a firm's business profits each year. To map tax rates to sample firms we first use the state of major business operations whenever available based on Garcia and Norli (2012)'s most mentioned state in a firm's 10-K reports; otherwise we rely on a firm's historical headquarters state using parsed 10-K data from Bill McDonald, and the headquarters state from Compustat.[27] This procedure leaves us with a sample of 64,340 firm-year observations for 8,776 unique firms.[28] There are 1,020 firm-year observations categorized as treated, accounting for 1.6% of the sample.

To evaluate whether firms invest in automated capital and displace workers, we examine outcomes for capital stock, capital-labor ratio, and the quantity and cost of production workers. A firm's automated capital can be physical equipment (computers, robots, and automatic assembly machines) as well as intangible technology (software, algorithms, and data analytics). We measure a firm's automated capital as equipment and software, a subcomponent of property, plant, and equipment, scaled by total assets. Equipment and software are the sum of machinery and equipment (such as computer equipment, vehicles, warehouse equipment, and automotive

[26] For states with multiple tax brackets, we focus on changes in the top tax bracket while accounting for tax surcharges.
[27] The data by Bill McDonald is available at www.sraf.nd.edu. Our results are robust if we rely on a firm's historical headquarters state for the entire sample period; see Table IA.5 of the Internet Appendix.
[28] Our analysis is limited to the subsample of firms with major business operations located/headquartered in the US.

equipment) and other equipment, typically capitalized software such as computer software, information systems, ERP systems, and general information technology.[29] We use the natural logarithm of the value of equipment and software per thousand employees to measure the capital-labor ratio. Data on production workers and labor expenses are scarce on Compustat so we rely on the NBER-CES Manufacturing Industry Database, which provides detailed information on annual employment, payroll, and other input costs for the manufacturing sector at the six-digit NAICS level.[30] We map the data to our sample of firms using NAICS codes. The variables of interest are the number of production workers and the share of production worker wages relative to total operating expenses (the sum of total payroll, cost of materials, and cost of electricity and fuels).

We estimate the following model:

$$Y_{i,t+s} = \beta_0 + \beta_1 Tax\ Increase_{i,t} \times SLAC_{i,t} + \beta_2 SLAC_{i,t} + \beta_3 Tax\ Increase_{i,t} + \gamma' X + B_t + \mu_j + \sigma_k + \varepsilon_{i,t}, \qquad (4)$$

where i indexes firm, t indexes year, and s is equal to one, two, or three years. The dependent variable $Y_{i,t+s}$ takes the value of a firm's equipment and software, capital-labor ratio, the natural logarithm of the number of production workers, the share of production worker wages out of total operating expenses, operating leverage estimated as the elasticity of net income plus depreciation with respect to sales using data for the past three years, and financial leverage.[31] $Tax\ Increase_{i,t}$ is an indicator variable equal to one if firm i experiences an increase in the corporate income tax rate of 100 basis points or more in its state of major business operations in year t, and zero otherwise. The set of control variables, X, include *Size*, *Cash holdings*, *Cash flow*, and *Tobin's q*, when the dependent variable measures capital and labor inputs in production. When $Y_{i,t+s}$ takes the value of

[29] Other than the accounted equipment and software, automated capital could also include intangible inputs in research and development. To account for the potential intangible components of automated capital, we follow Peters and Taylor (2017) and compute capitalized R&D expenditures scaled by total assets and obtain similar results.
[30] www.nber.org/research/data/nber-ces-manufacturing-industry-database.
[31] We follow Mandelker and Rhee (1984) and estimate firm-level operating leverage as the elasticity of operating cash flow with respect to sales. We exclude depreciation from our calculation given that it is a non-cash expense.

operating and financial leverage, we incorporate a set of explanatory variables commonly used in leverage regressions (*Size*, *Tangibility*, *Cash flow*, *Tobin's q*, *Ind. CF volatility*, *Dividend payer*, *Modified Z-score*). We also control for state-level economic conditions following Heider and Ljungqvist (2015), including the state unemployment rate and the growth rate in the gross state product (GSP). Finally, we incorporate a full set of year (B_t), industry (μ_j), and state fixed effects (σ_k). Since our tests exploit staggered state-level tax changes, we include state fixed effects to account for unobserved time-invariant differences between states.

[Table 7 about here]

Table 7 summarizes the results of our regressions. In Panel A we consider the response of capital and labor inputs in production. On average, an increase in the state corporate tax rate reduces the amount of capital inputs and the capital-labor ratio. This finding coheres with the literature documenting the adverse effects of corporate income taxes on investment and growth.[32] Our results, however, also reveal a novel pattern of cross-sectional heterogeneity in how firms invest following significant tax increases. Consistent with high-*SLAC* firms automating production, these firms expand their capital stock and exhibit an increase in the capital-labor ratio, over each of the three fiscal years after a tax increase.[33] To gauge the economic magnitude of the estimated effect, we compare the response of a firm from the 90th percentile of *SLAC* (0.668) with that of a firm from the 10th percentile of *SLAC* (0.262). In the third fiscal year after a large tax increase, equipment and software increase by 8.1% (=(−0.151+0.267×0.668)/0.338) of its sample mean for the high-*SLAC* firm, but decline by 24.0% of sample mean for the low-*SLAC* firm.

The results in Panel A are also consistent with the displacement of labor by high-*SLAC* firms following tax hikes, suggesting that the accelerated investment in automated capital

[32] For example, Giroud and Rauh (2019) find that increases in state-level corporate tax rates reduce firm employment and capital stock. Mukherjee et al. (2017) find that state tax increases reduce corporate innovation.
[33] In untabulated results, we find that the coefficient estimate of the interaction term (*SLAC×Tax Increase*) becomes insignificant when $Y_{i,t+s}$ takes the value of property, plant, and equipment other than equipment and software. This placebo test suggests that the differential responses in physical capital occur in equipment and software and not in an expansion of property and plant.

coincides with a decline in the relative reliance on labor inputs in production. For example, the 90th percentile *SLAC* firm exhibits a drop of 17.1% (=0.446−0.924×0.668) in the number of production workers, and a reduction of 10.7% in the share of production worker wages to total operating expenses of the sample mean in year *t*+3. These adjustments in production are consistent with the estimated heterogeneous response in capital-labor ratio at the cross-section.

In Panel B of Table 7, we examine the response of operating leverage and financial leverage following state tax increases. While our results in Panel A suggest that labor substitution reduces labor costs, the net effect of automation on operating leverage remains an empirical question. Automation involves a shift toward more capital-intensive production methods, which typically entail expenses allocated to cost of goods sold such as energy, maintenance, and labor to run the equipment. Columns (1)–(3) show that operating leverage generally increases following a tax hike. In contrast, high-*SLAC* firms see a significant reduction in operating leverage relative to other firms. This evidence is consistent with the mechanism that automation in high-*SLAC* firms results in an overall shift from fixed costs to variable costs and a net reduction in operating leverage.[34]

Columns (4)–(6) indicate that firms with higher *SLAC* exhibit a greater increase in financial leverage in the second and third years after rate increases. In addition to tax-based incentives for financial leverage (e.g., Heider and Ljungqvist 2015), this result is consistent with two unique economic channels tied to workplace automation. First, high-*SLAC* firms are more likely to replace labor with automated capital and reduce operating leverage, allowing for greater financial leverage. Second, investment in automated capital increases the share of collateralizable assets.

Table IA.5 of the Internet Appendix summarizes a variety of alternative specifications for robustness. First, we specify a longer duration to the cash flow shocks associated with state tax rate increases. Specifically, we set the variable, *Tax increase*, to be equal to one for the year of,

[34] Our hypothesis and findings are consistent with Ljungqvist, Zhang, and Zuo (2017), who show that firms have an incentive to reduce operating risk after a tax increase. Because the ability to reduce operating leverage differs across firms, Ljungqvist et al. (2017) find an insignificant response in operating leverage for an average firm. Our results complement by showing that firms with an automatable workforce respond to a tax increase by automating their workforce and see a reduction in operating leverage.

and one year after, the rate increase. Second, we identify a firm's state according to its historical headquarters state for the entire sample period based on Bill McDonald's parsed 10K location data and Compustat. Third, instead of using time-varying *SLAC*, we use an ex-ante time-invariant *SLAC* measured in 1999 to eliminate the dynamic response of *SLAC* to tax hikes. Finally, we control for state-specific time trends in addition to state, year, and industry fixed effects. Overall, the results in Table 7 are robust to these alternative specifications.

4.3 *SLAC*, leverage, and dividend policies

We have provided extensive evidence that labor's susceptibility to replacement by automated capital is an economically important determinant of a firm's cash policy. Nonetheless, cash is just one facet of a firm's financial policies affected by operating leverage. If the potential substitution of labor with automated capital enhances operating flexibility, *SLAC* should be negatively correlated with financial conservatism more broadly, as evidenced by a firm's use of financial leverage and its payout policy.

Our primary measures of financial leverage include leverage (debt over the book value of assets), market leverage (debt over the market value of assets), net leverage (net debt over the book value of assets), and the natural logarithm of one plus total debt, short-term debt, and long-term debt, all in 1999 dollars. We follow the literature including Rajan and Zingales (1995), Frank and Goyal (2009), and Serfling (2016) and control for firm-level explanatory variables including size, tangibility, cash flow, Tobin's *q*, industry cash flow volatility, a dividend payer dummy, and the modified Altman's z-score.

[Table 8 about here]

Panel A of Table 8 presents the results estimating the relation between *SLAC* and financial leverage. Across all measures of leverage, the coefficient estimate of *SLAC* is positive and statistically significant at the 1% level. For instance, estimates in Columns (1) and (2) indicate that a one-standard-deviation increase in *SLAC* translates to a 13.0% (=15.0%×0.291/0.337) increase in leverage, and a 14.9% increase in market leverage, relative to the sample mean. Given the negative correlation between *SLAC* and cash holdings, we expect a more substantial impact on net leverage. As shown in Column (3), the same change in *SLAC* implies an increase of 0.093 in net leverage, which is approximately 68.7% of the sample mean. Columns (4)–(6) show that the effect is not due to differences in the denominator of leverage measures.

We next consider how *SLAC* is associated with payout policy. To the extent that *SLAC* moderates the impact of labor-induced operating leverage on dividend policy, we predict that, all else equal, firms with higher *SLAC* will be able to maintain a higher level of dividends. Following Crane, Michenaud, and Weston (2016) and He et al. (2020), we measure a firm's dividend payout using both common dividends and total dividends, either scaled by total assets or in natural logarithm. In addition, greater financial flexibility allows firms to tilt to a greater dividend payout relative to share repurchases as shown in Bonaimé et al. (2014). To test this implication, we calculate the fraction of total payout distributed as common dividends. We control for a broad set of firm characteristics known to affect dividend policy, including firm size, cash flow, leverage, Tobin's *q*, the volatility of industry cash flow, as well as cash holdings and asset tangibility, both of which impact a firm's budget constraint (e.g., Jagannathan, Stephens, and Weisbach 2000).

Panel B of Table 8 summarizes our results. Consistent with our prediction, there is a robust positive relation between *SLAC* and dividend payout. For instance, the coefficient of 0.013 in Column (1) indicates that a one-standard-deviation increase in *SLAC* is associated with a 21.7% increase in common dividends relative to the sample mean. Columns (2)–(4) show that results are similar for total dividends and are not a consequence of variation in the denominator. Results in Column (5) also indicate a significant relation between *SLAC* and a firm's payout policy generally.

We investigate the causal implications of *SLAC* for leverage and payout policy in the context of the 2011–2012 Thailand hard drive crisis. As discussed in Section 4.1.2, the hedging benefit of automation declined with an increase in the cost of automation during the crisis. Hence, if *SLAC* has a causal effect on corporate financial policy, we expect the effect of *SLAC* on short-term policies to be weaker during the crisis spell. In contrast, the impact on long-term debt and dividend policy should be negligible given the brief duration of the shock. To test this prediction, we re-estimate equation (3) for leverage, the natural logarithm of one plus, short-term debt and long-term debt, and common dividends/total assets, and report the results in Panel C of Table 8.

Consistent with our prediction, the impact of *SLAC* on leverage is weaker during the hard drive crisis. Based on the coefficients in Column (1), a one-standard-deviation increase in *SLAC* relates to a 13.2% increase in leverage in the non-crisis period, and a 10.4% increase in leverage during the crisis period, relative to the sample mean. In Columns (2) and (3), we examine the use of short-term and long-term debt independently and find that moderating impact of the Thailand crisis is isolated to short-term debt policy. Column (4) of the table also shows that the Thailand crisis had an insignificant impact on dividend policy. Our results in Table 8 are robust to specifications excluding firms in the hard drive industry, as well as their customers and suppliers. In addition, the impact of Thailand flooding on the relation between *SLAC*, leverage and short-term debt is more pronounced for the subsample of firms that are heavily reliant on computers for automation.

5. Alternative Mechanisms

In this section, we address a number of alternative mechanisms that could potentially explain the observed link between *SLAC* and financial policy.

5.1 Automating or the option to automate?

One possibility is that instead of having the option to automate in the future, firms with high *SLAC* are actually in the process of automating. Investment in automated capital requires up-front costs of technology adoption and equipment purchases, which could result in lower cash balances and higher financial leverage. We note, however, that this is inconsistent with the positive relation between *SLAC* and dividends. We perform three tests to rule out a connection between *SLAC* and financial policies that is mechanically driven by the concurrent financing of automation.

First, we consider the marginal value of cash to establish that the negative relation between *SLAC* and cash holdings is driven by a precautionary demand for cash rather than a demand for cash to fund new investment in automation. If *SLAC* works as a latent hedge to operating leverage and reduces the need of precautionary cash reserve, we would expect the marginal value of cash to decline with *SLAC*. To test this hypothesis, we augment the Faulkender and Wang (2006) framework by introducing *SLAC*. Table IA.6 of the Internet Appendix summarizes the regression results. The dependent variables include the Fama and French (1993) size and market-to-book adjusted excess returns and the Fama and French (1997) 48 industry-adjusted excess returns. Consistent with our mechanism, we observe a statistically significant and negative impact of *SLAC* on the marginal value of cash. For example, based on the coefficient estimate in Column (1), the marginal value of cash, on average, is $0.086 lower for a one-standard-deviation increase in *SLAC*.

Second, we consider whether the relation between *SLAC* and financial policies is significantly weaker for firms that are not in the process of automating. If an industry is automating, *SLAC* should trend downward and firm-level capital-labor ratio should increase. We classify firms as not in the process of automating using two approaches. First, we restrict the sample to firms that observe an average declining capital-labor ratio in the last three years of data. Alternatively, we exclude firms that appear to be industry leaders in workplace automation. A firm is identified as an automation leader if it exhibits an average increasing capital-labor ratio in the last three years of data and its capital-labor ratio negatively correlates with the industry *SLAC* in the past three years. Table 9 reports the results. Using both approaches, we find that the relation between *SLAC* and financial policy (cash holdings, leverage, and payout) for firms not in the process of automation is equivalent to that observed in the baseline analyses in Tables 3 and 8.

[Table 9 about here]

As a final test, we find that the relation between *SLAC* and one to three years lagged financial variables (tabulated in Table IA.7) are essentially equivalent. Altogether, our evidence suggests that the contemporaneous relation between *SLAC* and financial policy is unlikely to be a byproduct of a concurrent investment in automation by high-*SLAC* firms.

5.2 Accounting for other labor-related characteristics

It is conceivable that the relation between *SLAC* and financial policies is the byproduct of other labor-related characteristics known to affect these same policies, such as capital intangibility, labor skill and mobility, unionization, the prevalence of low-paid employees, and the potential to offshore jobs. For example, Falato, Kadyrzhanova, Sim, and Steri (2021) show that intangible capital is associated with lower debt capacity and greater precautionary cash holdings, and Ghaly et al. (2017) find that the share of skilled workers increases the precautionary demand for cash. To address this issue, we control for capital intangibility, labor skill, labor mobility, union coverage, low-paid employee, and offshorability in our baseline regressions, and report the results in Table 10.[35] Our findings indicate that these labor-related variables do not subsume the relation between *SLAC* and financial policies, and that the potential to replace labor with automated capital is a first-order determinant of corporate financial decisions that is distinct from other labor-related aspects.

[Table 10 about here]

5.3 Bargaining power of unionized workers

A third possibility is that the option to automate and replace labor, weakens the ability of unionized workers to bargain for higher wages. Thus, the mechanism behind *SLAC* potentially obtains through firms' improved bargaining position to lower labor-induced operating leverage, allowing for more aggressive financial policies. If this mechanism is at work, we expect to find a

[35] We estimate capital intangibility following Peters and Taylor (2017), who augment the book value of intangible capital with knowledge and organization capital. As in Belo et al. (2017) we measure labor skill as the percentage of employees in occupations that require a high level of training and preparation. Labor mobility is constructed following Donangelo (2014), as a proxy for workers' flexibility to enter and exit an industry. Union coverage is the percentage of employed workers who are covered by a collective bargaining agreement in an industry by year, as in Hirsch and Macpherson (2003). Low-paid employee is the fraction of workers in an industry in a year with wage rates below the 10^{th} percentile of the entire distribution of wages in a given year, based on OES. Offshorability is the weighted average potential to offshore jobs across all occupational employment for a firm's primary industry.

more significant relation between *SLAC* and financial policies for firms with broad union coverage. This alternative, however, is not supported by the data. As observed in Table 6, our estimated effects of *SLAC* are significantly weaker for firms in industries with broader labor union coverage. This evidence is consistent with the notion that unions effectively resist workforce automation.

5.4 Accounting for market competition and other sources of heterogeneity

We consider the potential confounding effects associated with product market competition. Hoberg, Phillips, and Prabhala (2014) show that firms facing competitive threats adopt more conservative financial policies. Our tests, reported in Panel A of Table IA.8 in the Internet Appendix, show that the relation between *SLAC* and financial policies remains robust when we control for a host of competition measures, including the Hoberg et al. (2014) product market fluidity, the Herfindahl-Hirschman Index (HHI) by Fama and French 48 industry, the Irvine and Pontiff (2009) measure of industry turnover, and the inventory-to-sales ratio.

To mitigate the potential effects of heterogeneous selection, we conduct propensity score matching to control for observable firm differences. Specifically, we match above-median *SLAC* firms with below-median *SLAC* firms by year, industry (two-digit SIC codes), and the set of control variables used in our baseline specifications presented in Table 3 and Table 8. Our matching is performed using a nearest-neighbor-matching algorithm with replacement. The results presented in Panel B of Table IA.8 support the conclusion that above-median *SLAC* is reliably associated with lower cash holdings, higher financial leverage, and a higher dividend payout.

More generally, the relation between financial policies and the potential to automate may be confounded by unobservable firm or industry heterogeneity. To address this concern, we isolate common sources of heterogeneity by examining subsamples of similar firms. First, to assess whether our results are identified out of the subset of firms with high variability in *SLAC* over time, we exclude firms with an above-median standard deviation of *SLAC* during the sample period. Second, we examine the subsample of mature firms (above sample median firm age) to ensure that the results are not driven by young firms. Third, we note that firms differ in their potential to automate across economic sectors. For instance, the IFR data suggest a growing use of automation using robots in the manufacturing sector, and non-tradable sectors have seen an increasing emphasis on automation as opportunities for offshoring decline. The results in Panel C of Table IA.8, show that the coefficient estimates on *SLAC* remain significant for subsamples of similar firms, indicating that the negative relation between *SLAC* and financial policy is unlikely to be the byproduct of heterogeneity bias.

6. Conclusion

This paper provides new evidence that a firm's ability to substitute automated capital for labor reduces its need to hedge labor-induced operating leverage with conservative financial policies. Our findings reveal that firms with a higher substitutability of labor with automated capital (*SLAC*) robustly adopt more aggressive financial policies by holding less cash, using more financial leverage, and paying higher dividends. We reinforce the causal link between *SLAC* and corporate financial policies by exploiting the Thailand hard drive crisis of 2011–2012 as an exogenous shock to the cost of adopting automated capital.

We perform two distinct analyses that collectively support the mechanism that the ability to substitute automated capital for labor provides an option to lower operating leverage. First, we document a stronger relation between *SLAC* and cash holdings for (i) firms with greater labor-induced operating leverage and (ii) a lower expected cost of worker displacement. Second, we examine how firms with varying *SLAC* respond to large negative shocks to cash flow in the context of state corporate income tax hikes. Our analysis by exploiting this quasi-experiment yields novel findings. In the wake of state tax hikes, firms with higher *SLAC* actually add to their capital stock of equipment and software, increase their capital-labor ratio, reduce the use of production workers, and have lower labor costs. In keeping with the notion that the option to automate enhances operating flexibility, these high-*SLAC* firms show a decline in operating leverage after state tax rate increases. These findings support the notion that the automation of labor tasks can enhance operating flexibility, and allows for less conservative financial policies.

This study provides several insights in the context of automation. First, we provide new evidence that the impact of automation in reducing labor-induced operating leverage has important implications for first-order financial decisions. Second, we develop a measure of the potential to automate that uniquely captures prospective automation of both routine- and non-routine-task labor. Our measure yields substantial incremental predictive power for changes in employment by occupation relative to measures that account for only the substitution of routine tasks. In addition, our results derived using a measure of *SLAC* that accounts for the industry composition of multi-segment firms suggest that the potential to automate is closely tied to firm production. Finally, our evidence suggests that the impact of many labor frictions on corporate policies documented in the literature may vary with firms' ability to substitute automated capital for labor.

Our findings yield interesting implications for the relation between automation and aggregate investment. Recent evidence on the economic impact of automation raises concerns that the proliferation of automation technologies may result in a decline in employment and wages (e.g., Brynjolfsson and McAfee 2014; Acemoglu and Restrepo 2020). Our findings suggest that automation may also have a bright side in that it reduces financial conservatism, enabling the financing of additional investment opportunities. Whether or not the incremental investment gains from automation result in long-run gains in wages and employment remains an important question for further research.

Appendix A: Variable Definitions

Variable name	Description
<u>*SLAC*, other measures of automation, employment estimates from OES, and industrial robots from IFR</u>	
Probability of computerization	An occupational estimate, between zero and one, for the susceptibility of jobs to computerization for each detailed SOC occupation, estimated by Frey and Osborne (2013, 2017) based on occupational characteristics and technological developments.
SLAC: Substitutability of labor with automated capital	An industry-by-year measure, between zero and one, for the substitutability of labor with automated capital. This measure is constructed as the weighted average probability of computerization by Frey and Osborne across all occupational employment (weighted by wages) in that year using the employment and wage estimates from the OES.
Segment sales-weighted SLAC	A firm-year measure, between zero and one, for the substitutability of labor with automated capital. This measure is obtained by matching industry-year *SLAC* to firm-year using the primary industry code in Compustat for single-segment firms, and using the segment sales-weighted *SLAC* for multi-segment firms.
Routine-task intensity	An occupational index of routine-task intensity estimated by Autor and Dorn (2013). Using the crosswalk provided by Autor and Dorn, we map the index to the Census 2000 Occupational Classification System (OCC), which we then map to SOC occupation.
RTI	An industry-by-year measure of routine-task intensity, constructed as the weighted average routine-task intensity of Autor and Dorn across all occupational employment (weighted by wages) in that year using the employment and wage estimates from the OES.
Orthogonal SLAC	The residual from regressing *SLAC* on *RTI* controlling for industry and year fixed effects.
Employment growth	Percentage change in employment for each detailed SOC occupation from 2010 to 2018 in Panel B of Table 1, and the annual percentage change in employment for each detailed SOC occupation by four-digit NAICS industry between 2010 and 2018 in Panel C of Table 1.
Employment growth weighted by wage	Percentage change in employment weighted by wages for each detailed SOC occupation from 2010 to 2018 in Panel B of Table 1, and the annual percentage change in employment weighted by wages for each detailed SOC occupation by four-digit NAICS industry between 2010 and 2018 in Panel C of Table 1.
Total robot installations from 2010 to 2018	Total installations of industrial robots (in thousands) in the US by four-digit NAICS industry from 2010 to 2018 provided in the database maintained by the International Federation of Robotics (IFR). The IFR breaks down annual installations and operational stock of industrial robots by customer industry for six major sectors and 27 detailed manufacturing industries using the IFR industry classification scheme, which we map into the International SIC codes according to the data manual and further into the four-digit NAICS industry using the industry crosswalk provided by the Census Bureau.
Operational stock of robots in 2018	The operational stock of industrial robots (in thousands) in the US by four-digit NAICS industry in 2018. See the above item for our mapping method.
<u>Firm-level variables</u>	
Cash holdings	Cash and short-term investments (che), scaled by total assets (at).
Cash flow	Earnings after interest, dividends, and tax but before depreciation (oibdp − xint − txt − dvc), scaled by total assets (at).

Net working capital	Working capital (wcap) minus cash (che), scaled by total assets (at).
Capital expenditures	Capital expenditures (capx), scaled by total assets (at).
Leverage (Financial leverage)	Long-term debt (dltt) plus debt in current liabilities (dlc), scaled by total assets (at).
Acquisitions	Acquisitions (aqc), scaled by total assets (at).
Market to book	Book value of assets (at) plus the market value of equity (prcc_f × csho) minus the book value of equity (ceq), scaled by the book value of assets (at).
Size	The natural logarithm of the book value of assets (at) in 1999 dollars.
Ind. CF volatility	Industry cash flow volatility, calculated as the standard deviation of firm-level cash flow to assets for the previous five years, averaged within each two-digit SIC industry.
R&D expenditures	The ratio of R&D expenses (xrd) to net sales (sale) and is set equal to zero when R&D expenses (xrd) are missing.
Dividend payer	A dummy variable that takes the value of one in years in which a firm pays common dividends (dvc), and zero otherwise.
Equipment and software	Machinery and equipment at cost (fate) plus other equipment at cost (fato), scaled by total assets (at). This item represents the cost or valuation of equipment, machinery, capitalized software, and other items not classified as land or buildings.
Capital-labor ratio	The natural logarithm of the ratio between equipment and software (fate + fato) and the average of the current and lagged number of employees in thousands (emp).
Production workers	The natural logarithm of the number of production workers in thousands (prode). The data is from the NBER-CES Manufacturing Industry Database and is mapped to the Compustat manufacturing firms according to the six-digit NAICS code.
Production worker wage share	The ratio of the production worker wages (prodw) to total operating expenses (pay + matcost + energy). The data is from the NBER-CES Manufacturing Industry Database and is mapped to the Compustat manufacturing firms according to the six-digit NAICS code.
Operating leverage	The elasticity of net income plus depreciation (ni + dp) with respect to sales, estimated by regressing the log of net income plus depreciation on the log of sales for the past three years.
Tobin's q	Fiscal year-end closing price (prcc_f) times common shares outstanding (csho) + the liquidation value of preferred stock (pstkl) + long-term debt (dltt) + short-term debt (dlc) – deferred taxes and investment tax credits (txditc), scaled by total assets (at).
Tangibility	Net value of property, plant, and equipment (ppent), scaled by total assets (at).
Modified Z-score	The modified Altman's z-score: 1.2 × (wcap/at) + 1.4×(re/at) + 3.3×(ebit/at) + (sale/at).
Market leverage	Total debt (dltt + dlc) scaled by the sum of total debt and the market value of equity (prcc_f × csho).
Net leverage	Total debt (dltt + dlc) minus cash (che), scaled by total assets (at).

Log(1+ *total debt*)	The natural logarithm of one plus total debt (dltt + dlc) in 1999 dollars.
Log(1+*short-term debt*)	The natural logarithm of one plus short-term debt (dlc) in 1999 dollars.
Log(1+*long-term debt*)	The natural logarithm of one plus long-term debt (dltt) in 1999 dollars.
Common dividends/ total assets	Common dividends (dvc), scaled by total assets (at).
Total dividends/ total assets	Total dividends (dvc + dvp), scaled by total assets (at).
Common dividends/ total payout	Common dividends (dvc), over total payout (dvc + prstkc – pstkrv).
Log(1+*common dividends*)	The natural logarithm of one plus common dividends (dvc) in 1999 dollars.
Log(1+*total dividends*)	The natural logarithm of one plus total dividends (dvc + dvp) in 1999 dollars.
Capital intangibility	Intangible capital scaled by total capital (intangible capital + ppegt). To measure intangible capital, we follow Peters and Taylor (2017) and extend the variable to 2018.
Labor skill	An industry-year measure for the percentage of employees in occupations that require a high level of training and preparation. Belo et al. (2017) classify an occupation to be high skill if it requires more than two years of preparation based on information provided by the Dictionary of Occupational Titles (DOT). We follow their method and extend the variable to 2018.
Labor mobility	An industry-year measure for the flexibility of workers to walk away from an industry in response to better opportunities. The data are from Donangelo (2014) who computes labor mobility based on the average occupation dispersion of employed workers in an industry.
Union coverage	The percentage of employed workers of an industry in a given year who are covered by a collective bargaining agreement as constructed by Hirsch and Macpherson (2003). The data are provided by the 1990 Census Industry Code (CIC) up to 2002, by the 2002 CIC for the years 2003 to 2008, and by the 2007 CIC for the years 2009 to present. We use the crosswalk provided by the Census Bureau to map the CIC code into SIC industry code for 1999 to 2002 and into NAICS industry code for 2003 to present.
Low-paid employee	The fraction of employed workers in an industry with wage rates below the 10^{th} percentile of the entire wage distribution of employment in that year based on OES, following the method in Clemens et al. (2018).
Offshorability	An industry-year measure of labor offshorability constructed as the weighted average offshoring potential across all occupational employment (weighted by wages) in the industry that the firm belongs to. The occupational offshoring potential is from Autor and Dorn (2013).
Product market fluidity	The product market competitive threat of Hoberg et al. (2014), which assesses the degree of competitive threat and product market change surrounding a firm.

HHI	The Herfindahl-Hirschman Index, which assesses the static competition levels within each Fama and French 48 industry.
Industry turnover	A proxy for industry competition based on Irvine and Pontiff (2009). It is constructed by computing the market value of new entries plus the market value of exits divided by total industry market value for each Fama and French 48 industry.
Inventory-to-sales	The ratio of inventory (invt) to sales (sale).
Aggregate and state-level variables	
Labor market tightness	The monthly help-wanted index from Barnichon (2010) divided by the monthly unemployment rate from the Bureau of Labor Statistics, which is then converted to an annual time series.
Help-wanted index	The annualized help-wanted index of Barnichon (2010) which measures job opening rate.
Tax increase	A dummy variable that takes the value of one if the firm experiences an increase in the corporate income tax rate by at least 100 basis points in its state of major business operations in that year, and zero otherwise. We acquire state corporate income tax information for the period 1999–2012 from Giroud and Rauh (2019) and extend to 2018 using data from the Tax Foundation and *The Book of the States*. We use the state of major business operations based on Garcia and Norli (2012) to identify the most relevant state to which the tax rate is applied for 1999–2007. The historical headquarters state for post 2007 comes from the parsed 10-K data from Bill McDonald if available, and Compustat otherwise.
State unemployment rate	The unemployment rate of a state, obtained from the Bureau of Labor Statistics.
GSP growth rate	The real annual growth rate in gross state product (GSP) using data obtained from the Bureau of Economic Analysis.
Flooding	A dummy variable that takes the value of one for the years 2011 and 2012, which indicate the duration of the Thailand hard drive crisis caused by flooding in Thailand in 2011.

References

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

———. 2020. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128:2188–2244.

Agrawal, A., and D. Matsa. 2013. Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics* 108:449–470.

Arrow, K. J., H. B. Chenery, B. S. Minhas, and R. M. Solow. 1961. Capital-labor substitution and economic efficiency. *Review of Economics and Statistics* 43:225–250.

Atanassov, J., and X. Liu. 2020. Can corporate income tax cuts stimulate innovation? *Journal of Financial and Quantitative Analysis* 55:1415–1465.

Autor, D. H., and D. Dorn. 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103:1553–1597.

Autor, D. H., F. Levy, and R. J. Murnane. 2003. The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118:1279–1333.

Autor, D. H., and A. Salomons. 2018. Is automation labor share-displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity* 49:1–63.

Azar, J. A., J. Kagy, and M. C. Schmalz. 2016. Can changes in the cost of carry explain the dynamics of corporate "cash" holdings? *Review of Financial Studies* 29:2194–2240.

Baker, M., B. Mendel, and J. Wurgler. 2016. Dividends as reference points: A behavioral signaling approach. *Review of Financial Studies* 29:697–738.

Barnichon, R. 2010. Building a composite Help-Wanted Index. *Economics Letters* 109:175–178.

Bates, T. W., K. M. Kahle, and R. M. Stulz. 2009. Why do U.S. firms hold so much more cash than they used to? *Journal of Finance* 64:1985–2021.

Belo, F., J. Li, X. Lin, and X. Zhao. 2017. Labor-force heterogeneity and asset prices: The importance of skilled labor. *Review of Financial Studies* 30:3669–3709.

Belo, F., X. Lin, and S. Bazdresch. 2014. Labor hiring, investment, and stock return predictability in the cross section. *Journal of Political Economy* 122:129–177.

Bonaimé, A. A., K.W. Hankins, and J. Harford. 2014. Financial flexibility, risk management, and payout choice. *Review of Financial Studies* 27(4):1074–1101.

Booth, A. L., M. Francesconi, and J. Frank. 2002. Temporary jobs: Stepping stones or dead ends? *Economic Journal* 112(480):F189–F213.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt. 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics* 117:339–376.

Brynjolfsson, E., and A. McAfee. 2014. *The Second Machine Age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo. 2017. Customer-supplier relationships and corporate tax avoidance. *Journal of Financial Economics* 132(2):377–394.

Chen, H., M. Kacperczyk, and H. Ortiz-Molina. 2011. Labor unions, operating flexibility, and the cost of equity. *Journal of Financial and Quantitative Analysis* 46(1):25–58.

Chirinko, R. 2008. σ: The long and short of it. *Journal of Macroeconomics* 30:671–686.

Clemens, J., L. B. Kahn, and J. Meer. 2018. The minimum wage, fringe benefits, and worker welfare. NBER Working Paper No. 24635.

Cohen, L., and A. Frazzini. 2008. Economic links and predictable returns. *Journal of Finance* 63(4):1977–2011.

Crane, A. D., S. Michenaud, and J. P. Weston. 2016. The effect of institutional ownership on payout policy: Evidence from index thresholds. *Review of Financial Studies* 29:1377–1408.

Cunha, I., and J. M. Pollet. 2020. Why do firms hold cash? Evidence from demographic demand shifts. *Review of Financial Studies* 33:4102–4138.

Curtis, E. M., and R. A. Decker. 2018. Entrepreneurship and state taxation. Working Paper, Federal Reserve Board.

Custodio, C. 2014. Mergers and acquisitions accounting and the diversification discount. *Journal of Finance* 69:219–240.

D'Acunto, F., L. Ryan, C. Pflueger, and M. Weber. 2018. Flexible prices and leverage. *Journal of Financial Economics* 129(1): 46–68

Dittmar, A., and J. Mahrt-Smith. 2007. Corporate governance and the value of cash holdings. *Journal of Financial Economics* 83:599–634.

Donangelo, A. 2014. Labor mobility: Implications for asset pricing. *Journal of Finance* 69:1321–1346.

Donangelo, A., F. Gourio, M. Kehrig, and M. Palacios. 2019. The cross-section of labor leverage and equity returns. *Journal of Financial Economics* 132:497–518.

Dowrick, S., and B. J. Spencer. 1994. Union attitudes to labor-saving innovation: when are unions Luddites? *Journal of Labor Economics* 12(2):316–344.

Falato, A., D. Kadyrzhanova, J. W. Sim, and R. Steri. 2021. Rising intangible capital, shrinking debt capacity, and the US corporate savings glut. *Journal of Finance,* forthcoming.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

———. 1997. Industry costs of equity. *Journal of Financial Economics* 43:153–193.

Faulkender, M., and R. Wang. 2006. Corporate financial policy and the value of cash. *Journal of Finance* 61:1957–1990.

Favilukis, J., and X. Lin. 2016. Wage rigidity: A quantitative solution to several asset pricing puzzles. *Review of Financial Studies* 29:148–192.

Favilukis, J., X. Lin, and X. Zhao. 2020. The elephant in the room: The impact of labor obligations on credit markets. *American Economic Review* 110:1673–1712.

Frank, M., and V. Goyal. 2009. Capital structure decisions: Which factors are reliably important? *Financial Management* 38:1–37.

Frey, C. B., and M. A. Osborne. 2013. The future of employment: How susceptible are jobs to computerisation? Working Paper, University of Oxford.

———. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114:254–280.

Garcia, D., and Ø. Norli. 2012. Geographic dispersion and stock returns. *Journal of Financial Economics* 106:547–565.

Ghaly, M., V. A. Dang, and K. Stathopoulos. 2017. Cash holdings and labor heterogeneity: The role of skilled labor. *Review of Financial Studies* 30:3636–3668.

Giroud, X., and J. Rauh. 2019. State taxation and the reallocation of business activity: Evidence from establishment-level data. *Journal of Political Economy* 127:1262–1316.

Goos, M., A. Manning, and A. Salomons. 2014. Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104:2509–2526.

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

Harford, J. 1999. Corporate cash reserves and acquisitions. *Journal of Finance* 54:1969–1997.

Harford, J., S. Mansi, and W. Maxwell. 2008. Corporate governance and firm cash holdings in the US. *Journal of Financial Economics* 87:535–555.

He, J., X. Tian, H. Yang, and L. Zuo. 2020. Asymmetric cost behavior and dividend policy. *Journal of Accounting Research* 58:989–1021.

Heider, F., and A. Ljungqvist. 2015. As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes. *Journal of Financial Economics* 118:684–712.

Hicks, J. 1932. *The Theory of Wages*. London: Macmillan and Co.

Hirsch, B. T., and D. A. Macpherson. 2003. Union membership and coverage database from the Current Population Survey: Note. *Industrial and Labor Relations Review* 56:349–354.

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

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

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

Irvine, P. J., and J. Pontiff. 2009. Idiosyncratic return volatility, cash flows, and product market competition. *Review of Financial Studies* 22:1149–1177.

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

Jaimovich, N., and H. E. Siu. 2020. Job polarization and jobless recoveries. *Review of Economics and Statistics* 102:129–147.

Kahl, M., J. Lunn, and M. Nilsson. 2019. Operating leverage and corporate financial policies. Working Paper.

Kahn, S. 1997. Evidence of nominal wage stickiness from microdata. *American Economic Review* 87(5):993–1008.

Knesl, J. 2019. Automation and the displacement of labor by capital: Asset pricing theory and empirical evidence. Working Paper.

Kuehn, L. A., M. Simutin, and J. J. Wang. 2017. A labor capital asset pricing model. *Journal of Finance* 72:2131–2178.

Kuzmina, O. 2018. Operating flexibility and capital structure: Evidence from a natural experiment. Working Paper, New Economic School.

Ljungqvist, A., L. Zhang, and L. Zuo. 2017. Sharing risk with the government: How taxes affect corporate risk taking. *Journal of Accounting Research* 55(3):669–707.

Lucas, R. E. 1969. Labor-capital substitution in U.S. manufacturing. In A. Harberger and M. J. Bailey, eds., *The Taxation of Income from Capital*. Washington, DC: The Brookings Institution, pp. 223–274.

Mandelker, G. N., and S. G. Rhee. 1984. The impact of the degrees of operating and financial leverage on systematic risk of common stock. *Journal of Financial and Quantitative Analysis* 19(1):45–57.

Mukherjee, A., M. Singh, and A. Žaldokas. 2017. Do corporate taxes hinder innovation? *Journal of Financial Economics* 124:195–221.

Organization for Economic Development and Cooperation (OECD). 2002. *Employment Outlook*. Available at www.oecd.org/els/emp/oecdemploymentoutlook2002.htm

Oi, W. Y. 1962. Labor as a quasi-fixed factor. *American Economic Review* 70(6):538–555.

Peters, R. H., and L. A. Taylor. 2017. Intangible capital and the investment-q relation. *Journal of Financial Economics* 123:251–272.

Rajan, R., and L. Zingales. 1995. What do we know about capital structure? Some evidence from international data. *Journal of Finance* 50:1421–1460.

Reinartz, S. J., and T. Schmid. 2016. Production flexibility, product markets, and capital structure decisions. *Review of Financial Studies* 29(6):1501–1548.

Serfling, M. 2016. Firing costs and capital structure decisions. *Journal of Finance* 71:2239–2286.

Simintzi, E., V. Vig, and P. Volpin. 2015. Labor protection and leverage. *Review of Financial Studies* 28:561–591.

Topel, R. H. 1983. On layoffs and unemployment insurance. *American Economic Review* 73(4):541–559.

Tuzel, S., and M. B. Zhang. 2020. Economic stimulus at the expense of routine-task jobs. *Journal of Finance*, forthcoming.

Webb, M. 2020. The impact of artificial intelligence on the labor market. Working Paper.

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

Figure 1. Validation of *SLAC* using employment outcomes and installations of industrial robots

This figure summarizes the relation between *SLAC* and realized employment outcomes and installations of industrial robots. Panel A shows binned scatter plots of the occupational employment growth from 2010 to 2018 relative to the occupational probability of computerization by Frey and Osborne, and the occupational routine-task intensity by Autor and Dorn. Panel B shows the binned scatter plots of the total robot installations from 2010 to 2018 relative to industry-level *SLAC* in 2010, and industry-level *RTI* in 2010. The definitions of all variables are provided in Appendix A.

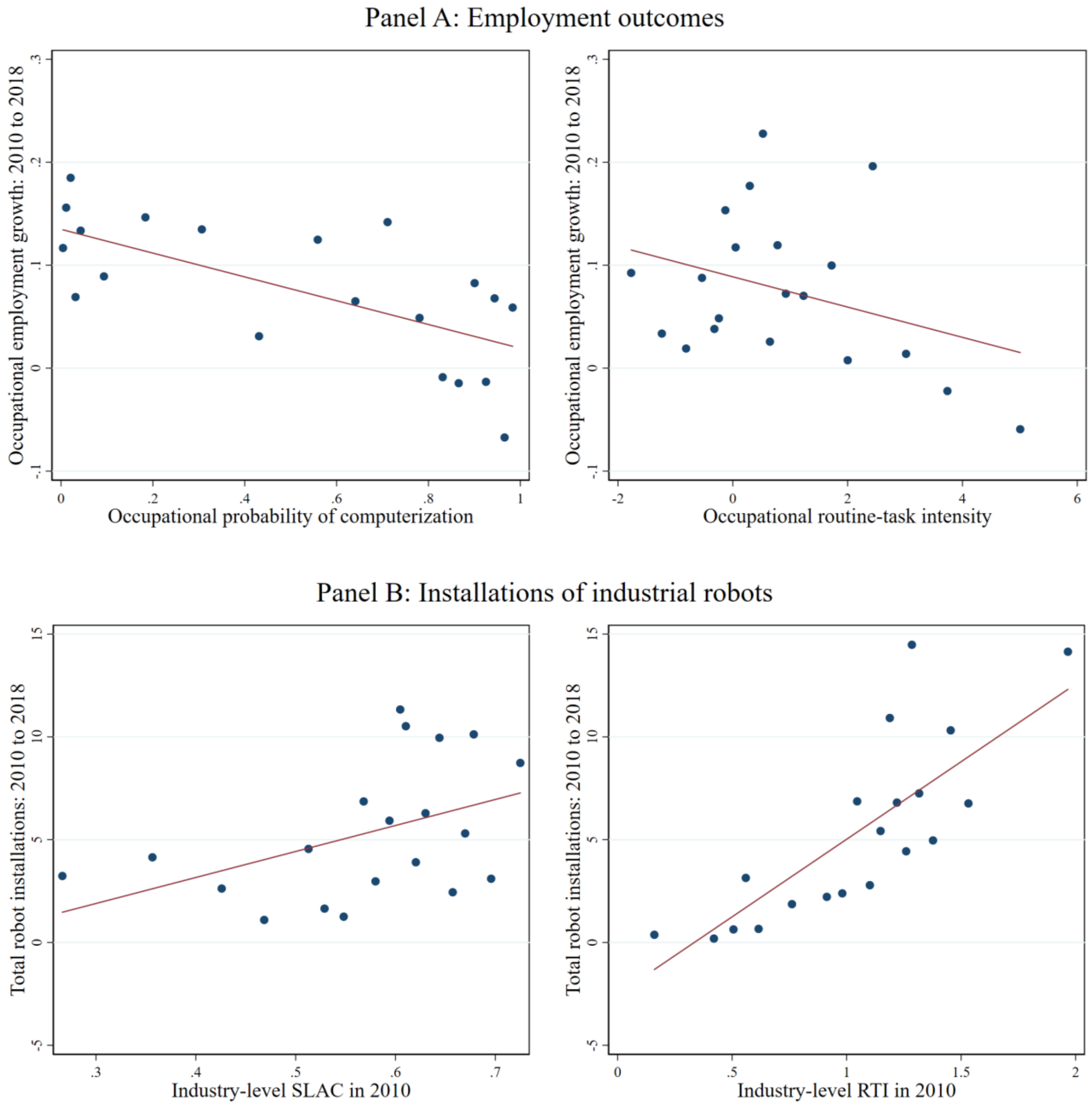
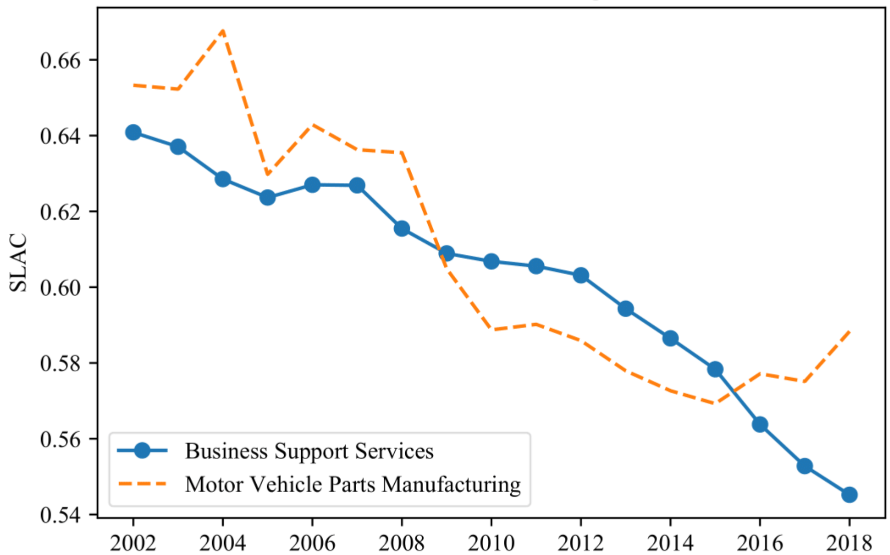


Figure 2. The evolution of *SLAC* for selected industries

This figure plots the yearly measure of *SLAC* for selected industries. In Panel A, we plot the time series of industries with relatively high-*SLAC* values, including Business Support Services (NAICS code 5614) and Motor Vehicle Parts Manufacturing (NAICS code 3363). In Panel B, we plot the time series of industries with relatively low *SLAC* values, including Child Day Care Services (NAICS code 6244), Home Health Care Services (NAICS code 6216), and Architectural, Engineering, and Related Services (NAICS code 5413). For consistency, we include only data from 2002 through 2018 constructed using a uniform four-digit NAICS definition.

Panel A: Industries with high SLAC



Panel B: Industries with low SLAC

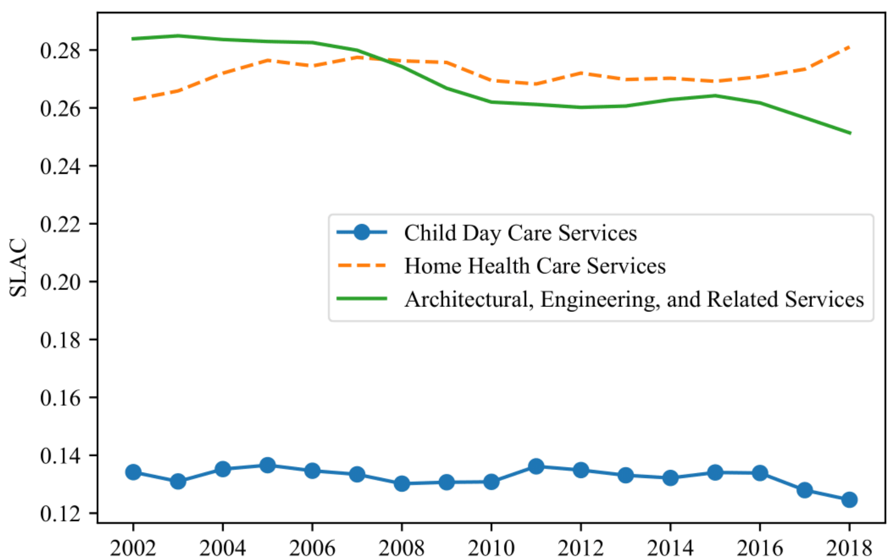
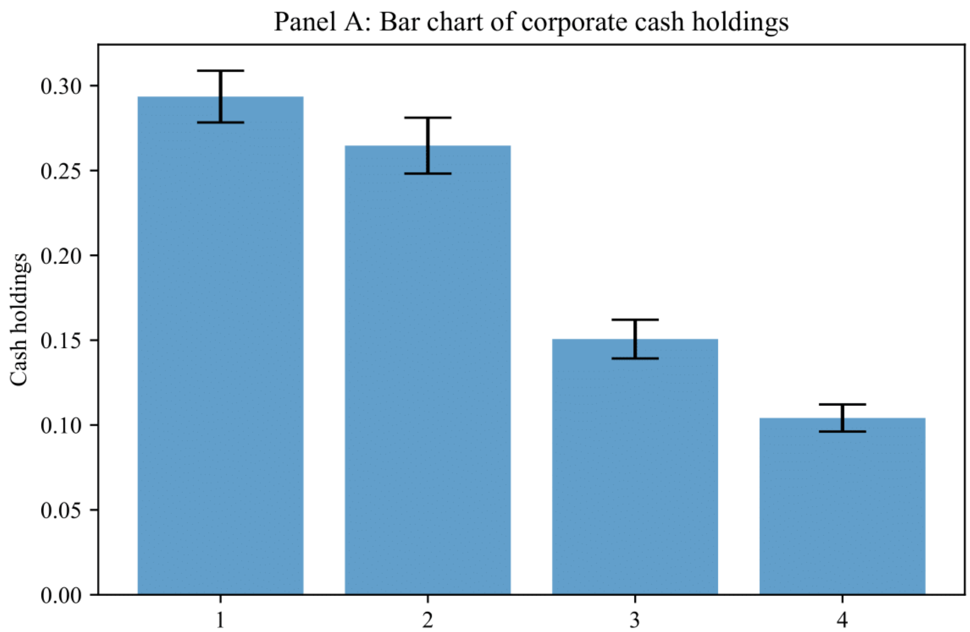


Figure 3. *SLAC* and cash holdings

The figure reports average cash holdings (y-axis), defined as cash and short-term investments scaled by total assets, for groups of firms with increasing *SLAC*. Panel A presents a bar chart with the average cash holdings pooled across the sample period of 1999–2018. For each bin, the graph illustrates 95% confidence intervals around the average. Panel B presents the time series of cash holdings for firms with low (below-median) *SLAC* and high (above-median) *SLAC*. The gray dashed curves are 95% confidence intervals.



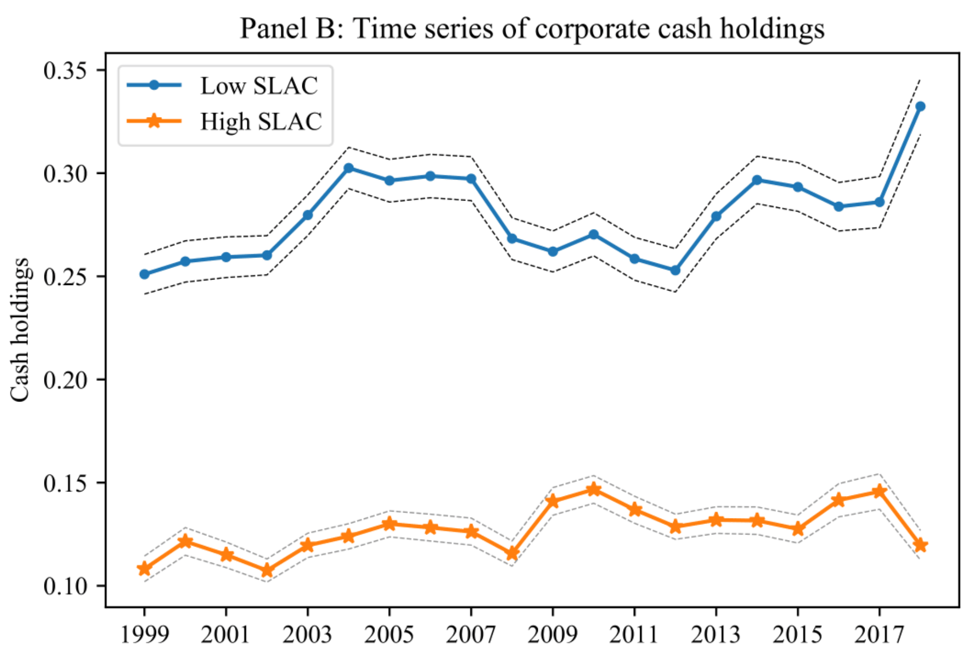


Figure 4. The 2011–2012 Thailand hard drive crisis as a shock to the cost of automation

The figure plots the price for hard disk drives between 2009 and 2015. The time series of global hard disk drive prices are expressed in the unit of 0.01 cents in USD per megabyte. The shaded bar highlights the period characterized as the 2011–2012 Thailand hard drive crisis when prices spiked due to flooding.

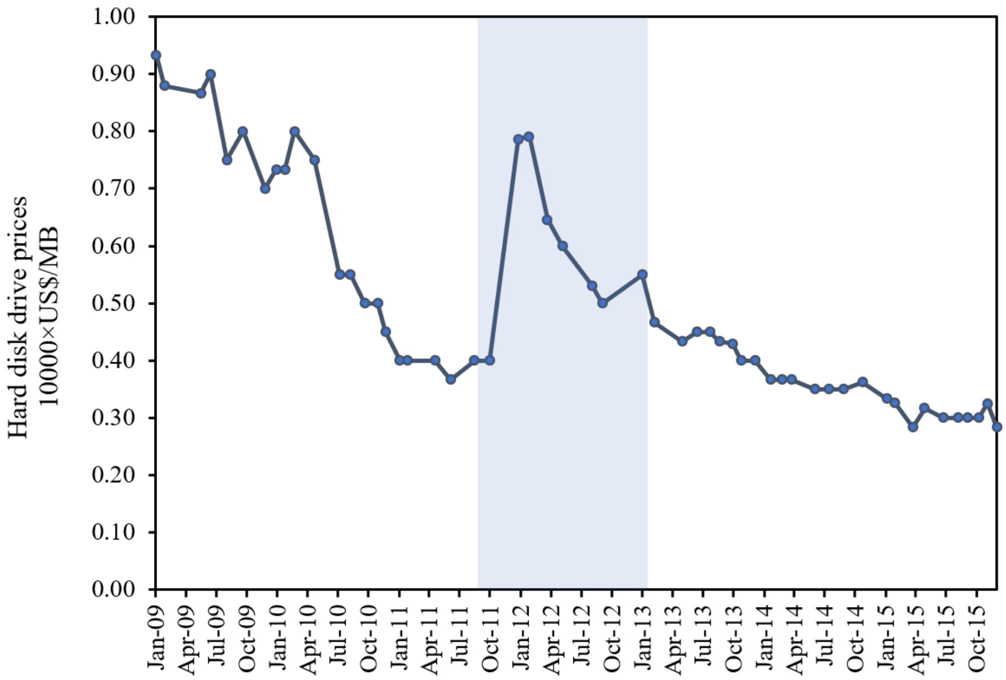


Table 1. Measuring *SLAC*: The substitutability of labor with automated capital

This table lists industries with the lowest and highest values for *SLAC*, and provides evidence to validate the measure. In Panel A, we compute the *SLAC* of each industry averaged across our sample period and report the bottom and top 15 industries defined by four-digit NAICS. Panel B examines the relation between occupational employment growth from 2010 to 2018 and the probability of computerization by Frey and Osborne and the routine-task intensity by Autor and Dorn. We use the employment data starting from 2010 because the probability of computerization is estimated for the 2010 SOC occupations. Panel C examines the relation between the annual industry-level occupational employment growth and the industry-year measures of *SLAC* and *RTI* for 2010–2018. Panel D examines the relation between total robot installations from 2010 to 2018 and the operational stock of robots in 2018, and the industry-level measures of *SLAC* and *RTI* in 2010. Heteroscedasticity-robust standard errors are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A: Industries with the lowest and highest *SLAC*

Lowest *SLAC*	*SLAC* (%)	Rank
Child Day Care Services	13.41	1
Outpatient Care Centers	20.69	2
Specialty (except Psychiatric and Substance Abuse) Hospitals	21.12	3
Psychiatric and Substance Abuse Hospitals	21.23	4
Offices of Physicians	22.13	5
General Medical and Surgical Hospitals	22.38	6
Other Residential Care Facilities	23.10	7
Computer Systems Design and Related Services	23.34	8
Software Publishers	23.68	9
Technical and Trade Schools	23.73	10
Scientific Research and Development Services	23.88	11
Offices of Other Health Practitioners	25.11	12
Computer and Peripheral Equipment Manufacturing	26.52	13
Home Health Care Services	26.97	14
Educational Support Services	27.07	15
Highest *SLAC*	***SLAC* (%)**	**Rank**
Full-Service Restaurants	82.07	1
Restaurants and Other Eating Places	81.46	2
Limited-Service Eating Places	80.97	3
School and Employee Bus Transportation	78.97	4
Drinking Places (Alcoholic Beverages)	76.60	5
Gasoline Stations	75.90	6
Support Activities for Crop Production	75.21	7
Offices of Real Estate Agents and Brokers	74.08	8
Special Food Services	73.78	9
Logging	73.73	10
Used Merchandise Stores	73.40	11
Clothing Stores	73.23	12
Fiber, Yarn, and Thread Mills	72.60	13
Jewelry, Luggage, and Leather Goods Stores	72.42	14
Vending Machine Operators	71.96	15

Panel B: Occupational employment growth from 2010 to 2018

	Employment growth			*Employment growth weighted by wage*		
	(1)	(2)	(3)	(4)	(5)	(6)
Probability of computerization by Frey and Osborne	-0.116***		-0.106***	-0.139***		-0.122***
	(0.032)		(0.036)	(0.038)		(0.041)
Routine-task intensity by Autor and Dorn		-0.015**	-0.006		-0.020**	-0.011
		(0.007)	(0.008)		(0.008)	(0.009)
Constant	0.135***	0.089***	0.135***	0.322***	0.267***	0.323***
	(0.019)	(0.013)	(0.019)	(0.023)	(0.016)	(0.023)
Observations	759	759	759	704	704	704
R-squared	0.017	0.005	0.017	0.018	0.008	0.020

Panel C: Annual industry-level occupational employment growth for 2010–2018

	Employment growth			*Employment growth weighted by wage*		
	(1)	(2)	(3)	(4)	(5)	(6)
SLAC	-0.276***		-0.265***	-0.297***		-0.280***
	(0.056)		(0.062)	(0.059)		(0.065)
RTI		-0.039**	-0.007		-0.045***	-0.011
		(0.016)	(0.017)		(0.016)	(0.018)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	266,980	266,980	266,980	259,704	259,704	259,704
R-squared	0.010	0.010	0.010	0.010	0.010	0.010

Panel D: Installations and operational stock of industrial robots

	Total robot installations from 2010 to 2018			*Operational stock of robots in 2018*		
	(1)	(2)	(3)	(4)	(5)	(6)
SLAC in 2010	12.646**		1.720	17.574**		3.908
	(6.044)		(4.099)	(7.351)		(4.818)
RTI in 2010		7.544***	7.367***		9.467***	9.056***
		(1.909)	(1.737)		(2.371)	(2.145)
Constant	-1.895	-2.523	-3.315	-3.356	-3.206	-4.990
	(3.036)	(1.54)	(2.975)	(3.608)	(1.901)	(3.547)
Observations	124	124	124	119	119	119
R-squared	0.029	0.146	0.146	0.038	0.157	0.159

Table 2. Summary statistics of main variables

This table reports the summary statistics for the firm-year observations of our main sample. The definitions of all variables are provided in Appendix A.

Variable	N	Mean	Median	SD	P10	P90
SLAC (%)	96,039	46.432	45.538	14.996	26.561	66.249
RTI	96,039	0.881	0.841	0.481	0.257	1.416
Orthogonal SLAC	96,039	0.000	-0.006	0.070	-0.062	0.085
Cash holdings	96,039	0.202	0.106	0.234	0.008	0.576
Cash flow	96,039	-0.216	0.048	1.030	-0.537	0.147
Net working capital	96,039	-0.183	0.007	1.164	-0.320	0.261
Capital expenditures	96,039	0.057	0.032	0.075	0.004	0.137
Leverage	96,039	0.337	0.203	0.635	0.000	0.629
Acquisitions	96,039	0.022	0.000	0.061	0.000	0.068
Market to book	96,039	3.273	1.537	6.958	0.859	5.162
Size	96,039	5.022	5.133	2.619	1.627	8.343
Ind. CF volatility	96,039	1.553	0.847	1.917	0.063	4.392
R&D expenditures	96,039	0.558	0.000	2.887	0.000	0.329
Dividend payer	96,039	0.277	0.000	0.447	0.000	1.000
Market leverage	96,039	0.236	0.152	0.255	0.000	0.639
Net leverage	96,039	0.136	0.091	0.704	-0.497	0.552
Log(1+*total debt*)	96,039	3.244	2.851	2.736	0.000	7.148
Log(1+*short-term debt*)	96,038	1.671	0.912	1.967	0.000	4.748
Log(1+*long-term debt*)	96,039	2.868	2.099	2.824	0.000	7.002
Common dividends/total assets	96,039	0.009	0.000	0.024	0.000	0.029
Total dividends/total assets	95,985	0.014	0.000	0.041	0.000	0.037
Common dividends/total payout	50,004	0.373	0.000	0.439	0.000	1.000
Log(1+*common dividends*)	96,038	0.910	0.000	1.756	0.000	3.936
Log(1+*total dividends*)	95,984	0.983	0.000	1.765	0.000	3.975

Table 3. Substitutability of labor with automated capital (*SLAC*) and cash holdings

This table reports OLS regression estimates of the relation between firms' *SLAC* and their cash holding policy. We estimate the following specification:

$$Y_{i,t} = \beta_0 + \beta_1 SLAC_{i,t} + \gamma' X + B_t + \mu_j + \varepsilon_{i,t},$$

where $Y_{i,t}$ is cash holdings; $SLAC_{i,t}$ is our measure for the substitutability of labor with automated capital of firm i in year t; vector X is the set of firm-level control variables commonly included in the literature; B_t and μ_j are a full set of year and industry/firm fixed effects (or other varieties). Column (1) includes year fixed effects; Column (2) includes year and industry fixed effects; Column (3) includes year and industry fixed effects, as well as industry-specific time trends; Column (4) includes year and firm fixed effects. Standard errors clustered at the two-digit SIC industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings			
	(1)	(2)	(3)	(4)
SLAC	-0.366***	-0.344***	-0.353***	-0.054**
	(0.048)	(0.074)	(0.074)	(0.021)
Cash flow	0.010***	0.010***	0.010***	0.017***
	(0.003)	(0.002)	(0.002)	(0.005)
Net working capital	-0.025***	-0.025***	-0.025***	-0.012**
	(0.007)	(0.006)	(0.006)	(0.005)
Capital expenditures	-0.445***	-0.300***	-0.308***	-0.211***
	(0.076)	(0.067)	(0.068)	(0.040)
Leverage	-0.121***	-0.114***	-0.114***	-0.055***
	(0.009)	(0.009)	(0.009)	(0.007)
Acquisitions	-0.434***	-0.397***	-0.399***	-0.226***
	(0.068)	(0.059)	(0.059)	(0.040)
Market to book	0.005***	0.005***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.010***	-0.007***	-0.007***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.004)
Ind. CF volatility	0.004	-0.000	-0.001	-0.000
	(0.004)	(0.001)	(0.001)	(0.000)
R&D expenditures	0.019***	0.016***	0.016***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Dividend payer	-0.038**	-0.037**	-0.037**	0.011***
	(0.015)	(0.014)	(0.014)	(0.002)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No
Industry-specific time trends	No	No	Yes	No
Firm fixed effects	No	No	No	Yes
Observations	96,039	96,039	96,039	96,039
R-squared	0.311	0.366	0.370	0.785

Table 4. Causal evidence from the 2011–2012 Thailand hard drive crisis

In this table, we estimate the following difference-in-differences model by exploiting variation in the cost of automation caused by the 2011–2012 Thailand hard drive crisis:

$$Y_{i,t} = \beta_0 + \beta_1\, Flooding_t \times SLAC_{i,t} + \beta_2\, SLAC_{i,t} + \gamma'\, X + B_t + \mu_j + \varepsilon_{i,t},$$

where $Y_{i,t}$ is cash holdings; $Flooding_t$ is a dummy variable that takes the value of one for the years 2011 and 2012, representing the duration of the Thailand hard drive crisis; $SLAC_{i,t}$ is the substitutability of labor with automated capital of firm *i* in year *t*. The table presents estimation results for: (i) the full sample, (ii) a subsample that excludes firms in the hard drive industry (NAICS code 3341, Computer and Peripheral Equipment Manufacturing) and their major customers and suppliers identified from the Compustat Segment Customer database, and (iii) a subsample of firms that heavily rely on computers for automation. The last subsample contains firms in the top tercile of industries based on the ratio of investment in computers and peripheral equipment to total investment in equipment and machinery according to the 1997 capital flow table by the Bureau of Economic Analysis. Standard errors clustered by industry are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings			
	(1)	(2)	(3)	(4)
Full sample				
SLAC × Flooding	0.065***	0.062***	0.041**	0.032***
	(0.022)	(0.018)	(0.017)	(0.008)
SLAC	-0.372***	-0.350***	-0.357***	-0.057***
	(0.048)	(0.074)	(0.074)	(0.020)
Observations	96,039	96,039	96,039	96,039
R-squared	0.311	0.366	0.370	0.785
Subsample excluding firms in the hard drive industry and their major customers and suppliers				
SLAC × Flooding	0.062***	0.058***	0.036**	0.027***
	(0.023)	(0.019)	(0.018)	(0.008)
SLAC	-0.367***	-0.331***	-0.338***	-0.059***
	(0.052)	(0.082)	(0.082)	(0.020)
Observations	92,639	92,639	92,639	92,639
R-squared	0.312	0.369	0.372	0.787
Subsample of firms that heavily rely on computers for automation				
SLAC × Flooding	0.080***	0.074***	0.048**	0.036***
	(0.020)	(0.023)	(0.020)	(0.009)
SLAC	-0.392***	-0.334***	-0.338***	-0.033
	(0.049)	(0.054)	(0.051)	(0.026)
Observations	27,968	27,968	27,968	27,968
R-squared	0.260	0.333	0.339	0.796
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No
Industry-specific time trends	No	No	Yes	No
Firm fixed effects	No	No	No	Yes

Table 5. Routine-task intensity (RTI), *SLAC*, and cash holdings

This table reports OLS regression estimates for the relation between firms' routine-task intensity (*RTI*) and their cash holding policy, and contrasts the explanatory power of this variable with that of *SLAC*. Column (1) includes only *RTI* in the regression; Column (2) includes both *RTI* and *SLAC* in the regression; Column (3) instead includes *Orthogonal SLAC*, which is the residual from regressing *SLAC* on *RTI* controlling for industry and year fixed effects. We include the same set of firm-level controls as in Table 3. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

		Cash holdings	
	(1)	(2)	(3)
SLAC		-0.334***	
		(0.091)	
RTI	-0.056***	-0.004	
	(0.016)	(0.013)	
Orthogonal SLAC			-0.331***
			(0.116)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	96,039	96,039	96,039
R-squared	0.356	0.366	0.359

Table 6. The benefits and costs of automation

This table summarizes the moderating effect of various benefits and costs of automation on the empirical relation between *SLAC* and cash holdings. In Columns (1)–(2), we augment the baseline model in Table 3 with time series variables that proxy for firms' hiring costs: *Labor market tightness* and *Help-wanted index*. *Labor market tightness* is computed as the monthly *Help-wanted index* from Barnichon (2010) divided by the monthly unemployment rate from the Bureau of Labor Statistics. We convert the monthly series to annual frequency by taking the average. We do not include the time series variables independently in the regressions because they are subsumed by the year fixed effects. In Columns (3)–(5), we augment the baseline model with cross-sectional characteristics: *High low-paid employee*, *High union coverage*, and *High UI benefits*. *High low-paid employee* is a dummy variable that takes the value of one if the percentage of low-paid employees (those below the 10th percentile of the entire wage distribution based on OES) is above the sample mean in that year, and zero otherwise. *High union coverage* is a dummy variable that takes the value of one if the percentage of employed workers who are covered by a collective bargaining agreement is above the sample mean in that year, and zero otherwise. *High UI benefits* is a dummy variable that takes the value of one if the maximum unemployment insurance (UI) benefits provided by the state is above the sample mean in that year, and zero otherwise. Following Agrawal and Matsa (2013), we measure the generosity of each state's annual UI benefits using the product of the maximum weekly benefit amount and the maximum benefit duration in weeks. We identify a firm's state using the most mentioned state in a firm's 10-K reports based on data from Garcia and Norli (2012) if available; otherwise, we use the historical headquarters state. We include the same set of firm-level controls as in Table 3, year fixed effects, and industry fixed effects. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings				
	(1)	(2)	(3)	(4)	(5)
SLAC	-0.289***	-0.268***	-0.394***	-0.341***	-0.333***
	(0.071)	(0.068)	(0.091)	(0.048)	(0.082)
SLAC × *Labor market tightness*	-0.120***				
	(0.043)				
SLAC × *Help-wanted index*		-0.030**			
		(0.013)			
SLAC × *High low-paid employee*			0.218***		
			(0.075)		
High low-paid employee			-0.145***		
			(0.040)		
SLAC × *High union coverage*				0.183**	
				(0.076)	
High union coverage				-0.127**	
				(0.052)	
SLAC × *High UI benefits*					-0.059**
					(0.024)
High UI benefits					0.036***
					(0.013)
Controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	88,455	88,455	96,039	95,880	69,465
R-squared	0.357	0.357	0.367	0.371	0.362

Table 7. *SLAC*, automation, and operating leverage: Evidence from state corporate tax increases

In this table, we estimate the following difference-in-differences model exploiting shocks to cash flow caused by large increases in state corporate income tax rates:

$$Y_{i,t+s} = \beta_0 + \beta_1 Tax\ Increase_{i,t} \times SLAC_{i,t} + \beta_2 SLAC_{i,t} + \beta_3 Tax\ Increase_{i,t} + \gamma' X + B_t + \mu_j + \sigma_k + \varepsilon_{i,t},$$

where *i* indexes firm, *t* indexes year, and *s* is equal to one, two, or three years. The dependent variable $Y_{i,t+s}$ takes the value of *Equipment and software*, *Capital-labor ratio*, *Production workers*, *and Production worker wage share* in Panel A, and *Operating leverage* and *Financial leverage* in Panel B. The dummy variable, $Tax\ Increase_{i,t}$, takes the value of one if firm *i* experiences an increase in the corporate income tax rate by at least 100 basis points in its state of major business operations in year *t*, and zero otherwise. We identify a firm's state using the most mentioned state in a firm's 10-K reports based on data from Garcia and Norli (2012) if available; otherwise, we use the historical headquarters state. $SLAC_{i,t}$ is the substitutability of labor with automated capital of firm *i* in year *t*; *X* is the set of control variables suppressed in the tables. The controls include *Size*, *Cash holdings*, *Cash flow*, and *Tobin's q* in Panel A, and *Size*, *Tangibility*, *Cash flow*, *Tobin's q*, *Ind. CF volatility*, *Dividend payer*, *Modified Z-score*, *State unemployment rate*, and *GSP growth rate* in Panel B; B_t, μ_j, and σ_k are a full set of year, industry, and state fixed effects. For each variable, the three columns each presents the dependent variables leading by *s* = 1, 2, or 3 years. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A: The use of automated capital, the capital-labor ratio, and labor share

	Equipment and software			*Capital-labor ratio*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
SLAC	0.197**	0.205**	0.209**	-0.115	-0.081	-0.025
	(0.080)	(0.085)	(0.089)	(0.422)	(0.429)	(0.447)
SLAC × Tax increase	0.179***	0.175**	0.267***	0.824***	0.613**	0.592**
	(0.060)	(0.085)	(0.095)	(0.272)	(0.277)	(0.252)
Tax increase	-0.119***	-0.113**	-0.151***	-0.576***	-0.427***	-0.400***
	(0.031)	(0.046)	(0.054)	(0.131)	(0.137)	(0.135)
Observations	40,700	35,176	30,418	39,197	33,922	29,365
R-squared	0.224	0.220	0.221	0.349	0.353	0.358
	Production workers			*Production worker wage share*		
	t+1	t+2	t+3	t+1	t+2	t+3
SLAC	0.447	0.499	0.543	0.079	0.077	0.075
	(1.361)	(1.386)	(1.405)	(0.076)	(0.075)	(0.075)
SLAC × Tax increase	-0.821***	-0.928***	-0.924***	-0.049**	-0.055**	-0.050**
	(0.286)	(0.250)	(0.248)	(0.023)	(0.021)	(0.019)
Tax increase	0.377***	0.442***	0.446***	0.021*	0.023**	0.021**
	(0.117)	(0.091)	(0.099)	(0.011)	(0.009)	(0.008)
Observations	26,712	25,494	24,203	26,712	25,494	24,203
R-squared	0.143	0.140	0.137	0.321	0.317	0.313
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Operating leverage and financial leverage

	Operating leverage			*Financial leverage*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
SLAC	-0.184	-0.463	-1.149	0.166**	0.121*	0.120
	(0.648)	(0.873)	(0.760)	(0.066)	(0.069)	(0.072)
SLAC × Tax increase	1.602	-2.875	-8.380**	0.080	0.271**	0.347**
	(2.966)	(2.428)	(3.810)	(0.123)	(0.130)	(0.168)
Tax increase	-0.911	0.996	4.555**	-0.022	-0.138**	-0.167*
	(1.617)	(1.198)	(2.106)	(0.059)	(0.058)	(0.089)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,346	33,249	29,554	54,974	47,679	41,387
R-squared	0.005	0.006	0.007	0.391	0.319	0.272

Table 8. *SLAC*, financial leverage, and payout policy

This table reports results on the relation between a firm's *SLAC*, its use of financial leverage, and its payout policy. Panel A reports the results on financial leverage. The dependent variable is *Leverage* in Column (1), *Market leverage* in Column (2), *Net leverage* in Column (3), Log(1+*total debt*) in Column (4), Log(1+*short-term debt*) in Column (5), and Log(1+*long-term debt*) in Column (6). All dollar variables are deflated to 1999 dollars. Panel B reports the results on payout policy. We measure payout policy using *Common dividends/total assets* in Column (1), *Total dividends/total assets* in Column (2), Log(1+*common dividends*) in Column (3), Log(1+*total dividends*) in Column (4), and *Common dividends/total payout* in Column (5). All dollar variables are deflated to 1999 dollars. Panel C reports the results estimating a difference-in-differences model exploiting variation in the cost of automation caused by the 2011–2012 Thailand hard drive crisis. *Flooding* is a dummy variable that takes the value of one for the years 2011–2012, representing the duration of the Thailand hard drive crisis. We tabulate the estimation results for: (i) the full sample, (ii) a subsample that excludes firms in the hard drive industry (NAICS code 3341, Computer and Peripheral Equipment Manufacturing) and their major customers and suppliers identified from the Compustat Segment Customer database, and (iii) a subsample of firms that heavily rely on computers for automation. The last subsample contains firms in the top tercile of industries based on the ratio of investment in computers and peripheral equipment to total investment in equipment and machinery according to the 1997 capital flow table by the Bureau of Economic Analysis. Firm-level controls, industry fixed effects, and year fixed effects are included across all the tests. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A: *SLAC* and financial leverage

	Leverage	*Market leverage*	*Net leverage*	Log(1+ *total debt*)	Log(1+*short-term debt*)	Log(1+*long-term debt*)
	(1)	(2)	(3)	(4)	(5)	(6)
SLAC	0.291***	0.234***	0.623***	1.426***	0.867***	1.210***
	(0.076)	(0.050)	(0.144)	(0.350)	(0.210)	(0.305)
Size	0.017***	0.015***	0.025***	0.901***	0.493***	0.905***
	(0.003)	(0.003)	(0.004)	(0.036)	(0.034)	(0.041)
Tangibility	0.253***	0.230***	0.592***	1.300***	0.627**	1.201***
	(0.041)	(0.025)	(0.092)	(0.194)	(0.244)	(0.209)
Cash flow	-0.141***	-0.023***	-0.145***	-0.235***	-0.175***	-0.199***
	(0.011)	(0.005)	(0.015)	(0.018)	(0.019)	(0.016)
Tobin's q	0.010***	-0.010***	0.006***	0.001	-0.004	0.010**
	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)	(0.004)
Ind. CF volatility	-0.001	0.002	-0.002	-0.002	-0.010	0.001
	(0.001)	(0.001)	(0.002)	(0.006)	(0.007)	(0.007)
Dividend payer	-0.053***	-0.099***	-0.022	-0.030	0.166*	0.080
	(0.012)	(0.013)	(0.025)	(0.093)	(0.094)	(0.091)
Modified Z-score	-0.013***	-0.002***	-0.014***	-0.018***	-0.012***	-0.017***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,542	94,541	94,542	94,542	94,542	94,542
R-squared	0.493	0.242	0.438	0.722	0.453	0.696

Panel B: *SLAC* and payout policy

	Common dividends/ total assets	*Total dividends/ total assets*	Log(1+*common dividends*)	Log(1+*total dividends*)	*Common dividends/ total payout*
	(1)	(2)	(3)	(4)	(5)
SLAC	0.013***	0.012**	0.842***	0.832***	0.454***
	(0.003)	(0.005)	(0.284)	(0.280)	(0.112)
Size	0.002***	0.001***	0.422***	0.430***	0.040***
	(0.000)	(0.000)	(0.035)	(0.035)	(0.003)
Tangibility	0.002	0.002	-0.031	-0.025	0.153***
	(0.002)	(0.002)	(0.175)	(0.166)	(0.051)
Cash flow	-0.000	-0.004***	-0.240***	-0.249***	-0.022***
	(0.000)	(0.001)	(0.025)	(0.025)	(0.005)
Tobin's q	0.000***	0.000**	0.027***	0.025***	0.003***
	(0.000)	(0.000)	(0.005)	(0.005)	(0.001)
Ind. CF volatility	-0.000*	-0.000	-0.014*	-0.014*	-0.002
	(0.000)	(0.000)	(0.008)	(0.007)	(0.002)
Leverage	-0.002***	-0.002***	-0.081*	-0.058	-0.088***
	(0.000)	(0.001)	(0.041)	(0.035)	(0.018)
Cash holdings	0.001	0.003	-0.459***	-0.431***	-0.130***
	(0.002)	(0.003)	(0.150)	(0.150)	(0.040)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	96,015	95,961	96,014	95,960	49,994
R-squared	0.118	0.041	0.421	0.424	0.193

Panel C: Causal evidence from the 2011–2012 Thailand hard drive crisis

	Leverage	Log(1+ *short-term debt*)	Log(1+ *long-term debt*)	*Common dividends/ total assets*
	(1)	(2)	(3)	(4)
Full sample				
SLAC × *Flooding*	-0.063**	-0.255**	-0.067	0.000
	(0.027)	(0.101)	(0.146)	(0.002)
SLAC	0.297***	0.892***	1.216***	0.013***
	(0.077)	(0.210)	(0.308)	(0.003)
Observations	94,542	94,542	94,542	96,015
R-squared	0.493	0.453	0.696	0.118
Subsample excluding firms in the hard drive industry and their major customers and suppliers				
SLAC × *Flooding*	-0.068**	-0.277***	-0.134	-0.001
	(0.029)	(0.098)	(0.149)	(0.002)
SLAC	0.279***	0.842***	1.086***	0.013***
	(0.087)	(0.234)	(0.346)	(0.003)
Observations	91,147	91,147	91,147	92,615
R-squared	0.493	0.451	0.698	0.118
Subsample of firms that heavily rely on computers for automation				
SLAC × *Flooding*	-0.097**	-0.432***	-0.321	0.003
	(0.037)	(0.109)	(0.253)	(0.003)
SLAC	0.374***	0.619	1.280***	0.011***
	(0.094)	(0.475)	(0.477)	(0.004)
Observations	27,383	27,383	27,383	27,955
R-squared	0.490	0.385	0.635	0.140
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Table 9. Are high-*SLAC* firms in the process of automating?

This table presents evidence that the connection between *SLAC* and financial policy does not appear to be driven by firms in the process of automation. Panel A restricts the sample to firms that experience an average declining capital-labor ratio based on the most recent three years of data. Panel B drops firms that are possibly industry leaders in workplace automation. A firm is identified as an automation leader if it experiences an average increasing capital-labor ratio and its capital-labor ratio negatively correlates with the industry *SLAC* based on the most recent three years of data. The dependent variable is *Cash holdings* in Column (1), *Leverage* in Column (2), and *Common dividends/total assets* in Column (3). We include the same set of firm-level controls as in Table 3 and Table 8, year fixed effects, and industry fixed effects. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings	*Leverage*	*Common dividends/ total assets*
	(1)	(2)	(3)
Panel A: Firms with a declining capital-labor ratio			
SLAC	-0.363***	0.264***	0.011***
	(0.082)	(0.073)	(0.004)
Observations	15,561	15,460	15,561
R-squared	0.358	0.536	0.107
Panel B: Excluding industry leaders in workplace automation			
SLAC	-0.356***	0.316***	0.013***
	(0.075)	(0.081)	(0.003)
Observations	66,625	65,223	66,604
R-squared	0.369	0.509	0.121
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes

Table 10. Controlling for other labor-related characteristics

This table reports the OLS regression estimates on the relation between *SLAC* and firms' financial policies, controlling for other labor-related characteristics. We estimate capital intangibility following Peters and Taylor (2017), who augment the book value of intangible capital with knowledge and organization capital. As in Belo et al. (2017) we measure labor skill as the percentage of employees in occupations that require a high level of training and preparation. Labor mobility is constructed following Donangelo (2014), as a proxy for workers' flexibility to enter and exit an industry. Union coverage is the percentage of employed workers who are covered by a collective bargaining agreement in an industry by year, as in Hirsch and Macpherson (2003). Low-paid employee is the fraction of workers in an industry in a year with wage rates below the 10th percentile of the entire distribution of wages in a given year, based on OES. Offshorability is the weighted average potential to offshore jobs across all occupational employment for a firm's primary industry. We include the same set of firm-level controls as in Table 3 and Table 8, year fixed effects, and industry fixed effects. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings	*Leverage*	*Common dividends/ total assets*
	(1)	(2)	(3)
SLAC	-0.213**	0.157**	0.020**
	(0.085)	(0.077)	(0.008)
Capital intangibility	0.130**	-0.018	-0.008***
	(0.050)	(0.029)	(0.002)
Labor skill	0.006	-0.039	0.009
	(0.066)	(0.062)	(0.006)
Labor mobility	-0.017	0.014	0.001**
	(0.011)	(0.010)	(0.001)
Union coverage	-0.045	0.011	-0.007
	(0.066)	(0.072)	(0.005)
Low-paid employee	-0.043	-0.011	0.000
	(0.031)	(0.036)	(0.003)
Offshorability	0.043***	-0.053***	-0.002
	(0.015)	(0.015)	(0.002)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	75,933	75,051	75,933
R-squared	0.374	0.492	0.106

Internet Appendix

Table IA.1. *SLAC* and cash holdings: Segment sales-weighted *SLAC* for multi-segment firms

This table reports OLS regressions of the relation between firms' *SLAC* and their cash holdings using segment sales-weighted *SLAC* for multi-segment firms. A firm is identified as multi-segment in a given year if it has positive sales in more than one business segment defined by distinct three-digit SIC codes before 2002 and four-digit NAICS codes afterward. We report the results for multi-segment firms using, respectively, the primary industry code in Compustat to match the industry-year *SLAC* to firm-year, and the firm-specific segment sales-weighted *SLAC*. We also report the results for estimating the full sample when we incorporate the firm-specific segment sales-weighted *SLAC* for multi-segment firms. We include the same set of firm-level controls and fixed effects as in Table 3. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings			
	(1)	(2)	(3)	(4)
Multi-segment firms using primary line of business				
SLAC	-0.185***	-0.209***	-0.216***	-0.053**
	(0.044)	(0.053)	(0.052)	(0.021)
Observations	18,866	18,866	18,866	18,866
R-squared	0.253	0.284	0.290	0.788
Multi-segment firms using the segment sales-weighted *SLAC*				
Segment sales-weighted SLAC	-0.218***	-0.259***	-0.267***	-0.079**
	(0.049)	(0.055)	(0.054)	(0.034)
Observations	18,866	18,866	18,866	18,866
R-squared	0.257	0.288	0.294	0.788
Full sample using the segment sales-weighted *SLAC*				
Segment sales-weighted SLAC	-0.378***	-0.363***	-0.373***	-0.055**
	(0.049)	(0.076)	(0.076)	(0.025)
Observations	96,039	96,039	96,039	96,039
R-squared	0.312	0.367	0.371	0.785
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No
Industry-specific time trends	No	No	Yes	No
Firm fixed effects	No	No	No	Yes

Table IA.2. *SLAC* and cash holdings: Placebo test

This table reports the results of OLS regressions of the relation between firms' *SLAC*, fixed to its value in 1999, and their cash holdings at various sample periods. The sample consists of Compustat firms from 1979–1998 in Column (1), 1979–1989 in Column (2), and 1999–2018 in Column (3). The Chi-squared test and the p-value to test for equal coefficient estimates between Columns (1) and (3), and between Columns (2) and (3) are also reported. We include the same set of firm-level controls as in Table 3, year fixed effects, and industry fixed effects. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings		
	1979–1998	1979–1989	1999–2018
	(1)	(2)	(3)
SLAC in 1999	-0.102***	-0.058**	-0.251***
	(0.035)	(0.027)	(0.076)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	88,883	44,176	91,499
R-squared	0.414	0.352	0.347
Chi-squared test of equal coefficients	11.5***	8.26***	
P-value of the Chi-squared test	[0.001]	[0.004]	

Table IA.3. *SLAC* and cash holdings: Alternative *SLAC* measures

This table reports robustness checks to Table 3 when we replace *SLAC* with its one-year lagged value, and an ex-ante time-invariant measure fixed in 1999, the initial year of our sample period. We include the same set of firm-level controls and fixed effects as in Table 3. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings			
	(1)	(2)	(3)	(4)
Lagged SLAC	-0.364***	-0.338***	-0.347***	-0.034**
	(0.048)	(0.073)	(0.073)	(0.016)
Observations	89,889	89,889	89,889	89,889
R-squared	0.307	0.365	0.368	0.790
SLAC in 1999	-0.275***	-0.251***	-0.253***	-0.129***
	(0.060)	(0.076)	(0.077)	(0.031)
Observations	91,499	91,499	91,499	91,499
R-squared	0.291	0.347	0.350	0.782
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No
Industry-specific time trends	No	No	Yes	No
Firm fixed effects	No	No	No	Yes

Table IA.4. Causal evidence from the Thailand hard drive crisis: Price of hard disk drives

This table reports robustness checks to Table 4 and Panel C of Table 8 using an alternative specification to equation (3). Specifically, we replace the dummy variable *Flooding* with *Hard drive price*, which is an annual series representing the deviations from a linear trend in the natural logarithm of the annual unit price of hard disk drives in 1999–2018. The model is as follows:

$$Y_{i,t} = \beta_0 + \beta_1\, Hard\ drive\ price_t \times SLAC_{i,t} + \beta_2\, SLAC_{i,t} + \gamma' X + B_t + \mu_j + \varepsilon_{i,t},$$

The dependent variable is *Cash holdings* in Panel A, and *Leverage*, Log(1+*short-term debt*), Log(1+*long-term debt*), and *Common dividends/total assets* in Panel B. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A: Causal evidence from the Thailand hard drive crisis on cash holdings

	Cash holdings			
	(1)	(2)	(3)	(4)
Full sample				
SLAC × Hard drive price	0.077***	0.072***	0.046**	0.043***
	(0.020)	(0.019)	(0.018)	(0.008)
SLAC	-0.368***	-0.346***	-0.354***	-0.055***
	(0.048)	(0.074)	(0.074)	(0.021)
Observations	96,039	96,039	96,039	96,039
R-squared	0.311	0.366	0.370	0.785
Excluding firms in the hard drive industry and their major customers and suppliers				
SLAC × Hard drive price	0.074***	0.067***	0.040**	0.039***
	(0.022)	(0.021)	(0.020)	(0.009)
SLAC	-0.363***	-0.327***	-0.335***	-0.058***
	(0.052)	(0.082)	(0.082)	(0.020)
Observations	92,639	92,639	92,639	92,639
R-squared	0.312	0.369	0.372	0.787
Subsample of firms that heavily rely on computers for automation				
SLAC × Hard drive price	0.095***	0.088***	0.055**	0.043***
	(0.029)	(0.030)	(0.027)	(0.014)
SLAC	-0.386***	-0.329***	-0.334***	-0.031
	(0.048)	(0.052)	(0.049)	(0.026)
Observations	27,968	27,968	27,968	27,968
R-squared	0.260	0.333	0.339	0.796
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No
Industry-specific time trends	No	No	Yes	No
Firm fixed effects	No	No	No	Yes

Panel B: Causal evidence from the Thailand hard drive crisis on leverage and payout policy

	Leverage	Log(1+ *short-term debt*)	Log(1+ *long-term debt*)	*Common dividends/ total assets*
	(1)	(2)	(3)	(4)
Full sample				
SLAC × Hard drive price	-0.072**	-0.371***	-0.074	0.005
	(0.029)	(0.109)	(0.115)	(0.003)
SLAC	0.293***	0.877***	1.212***	0.013***
	(0.076)	(0.210)	(0.304)	(0.003)
Observations	94,542	94,542	94,542	96,015
R-squared	0.493	0.453	0.696	0.118
Excluding firms in the hard drive industry and their major customers and suppliers				
SLAC × Hard drive price	-0.081**	-0.378***	-0.127	0.004
	(0.031)	(0.109)	(0.123)	(0.003)
SLAC	0.274***	0.825***	1.077***	0.013***
	(0.086)	(0.234)	(0.341)	(0.003)
Observations	91,147	91,147	91,147	92,615
R-squared	0.493	0.451	0.698	0.118
Subsample of firms that heavily rely on computers for automation				
SLAC × Hard drive price	-0.115***	-0.462***	-0.272	0.006
	(0.031)	(0.121)	(0.200)	(0.004)
SLAC	0.367***	0.585	1.254***	0.011***
	(0.091)	(0.470)	(0.460)	(0.004)
Observations	27,383	27,383	27,383	27,955
R-squared	0.491	0.385	0.635	0.140
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Table IA.5. *SLAC*, automation, and operating leverage: Robustness checks

This table presents several robustness checks to Table 7. First, we set the dummy variable, *Tax increase*, equal to one for the year of, and one year after, the rate increase. Second, we identify a firm's state according to its historical headquarters state for the entire sample period. Third, we use the initial *SLAC* in 1999 instead of the time-varying *SLAC*. Fourth, we control for state-specific time trends in addition to state, year, and industry fixed effects. We include the same set of firm-level controls, state, year, and industry fixed effects as in Table 7. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A: The use of automated capital, the capital-labor ratio, and labor share

	Equipment and software			*Capital-labor ratio*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
Tax increase lasting for two years						
SLAC × *Tax increase*	0.191***	0.224**	0.255***	0.785***	0.683**	0.601**
	(0.067)	(0.088)	(0.087)	(0.272)	(0.263)	(0.237)
Historical headquarters state						
SLAC × *Tax increase*	0.133**	0.118	0.193**	0.570**	0.341	0.335
	(0.055)	(0.087)	(0.096)	(0.241)	(0.265)	(0.253)
Initial *SLAC* in 1999						
SLAC in 1999 × *Tax increase*	0.228***	0.230**	0.304***	0.917***	0.707**	0.532**
	(0.068)	(0.092)	(0.095)	(0.316)	(0.293)	(0.225)
Controlling for state-specific time trends						
SLAC × *Tax increase*	0.184***	0.178**	0.270***	0.837***	0.616**	0.593**
	(0.061)	(0.084)	(0.096)	(0.283)	(0.283)	(0.264)
	Production workers			*Production worker wage share*		
	t+1	t+2	t+3	t+1	t+2	t+3
Tax increase lasting for two years						
SLAC × *Tax increase*	-0.899***	-0.946***	-0.939***	-0.059**	-0.059***	-0.060***
	(0.258)	(0.240)	(0.249)	(0.022)	(0.020)	(0.019)
Historical headquarters state						
SLAC × *Tax increase*	-0.701**	-0.799***	-0.778***	-0.038*	-0.043**	-0.039**
	(0.277)	(0.252)	(0.262)	(0.021)	(0.019)	(0.017)
Initial *SLAC* in 1999						
SLAC in 1999 × *Tax increase*	-1.349***	-1.226***	-1.254***	-0.084***	-0.086***	-0.075***
	(0.359)	(0.359)	(0.391)	(0.028)	(0.027)	(0.026)
Controlling for state-specific time trends						
SLAC × *Tax increase*	-0.805***	-0.888***	-0.876***	-0.044**	-0.048**	-0.042**
	(0.260)	(0.226)	(0.224)	(0.021)	(0.018)	(0.016)

Panel B: Operating leverage and financial leverage

	Operating leverage			*Financial leverage*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
<u>Tax increase lasting for two years</u>						
SLAC × Tax increase	-0.908	-5.535**	-2.220	0.136	0.301**	0.292
	(2.055)	(2.402)	(2.149)	(0.130)	(0.146)	(0.185)
<u>Historical headquarters state</u>						
SLAC × Tax increase	2.938	-2.465	-9.009***	0.105	0.231*	0.354**
	(2.942)	(2.276)	(3.129)	(0.119)	(0.121)	(0.150)
<u>Initial *SLAC* in 1999</u>						
SLAC in 1999 × Tax increase	2.172	-2.013	-8.604**	0.019	0.231	0.355*
	(3.360)	(2.764)	(4.234)	(0.139)	(0.154)	(0.204)
<u>Controlling for state-specific time trends</u>						
SLAC × Tax increase	1.245	-3.323	-8.814**	0.076	0.270**	0.346**
	(3.132)	(2.501)	(3.721)	(0.117)	(0.124)	(0.162)

Table IA.6. *SLAC* and the marginal value of cash holdings

This table reports the marginal value of cash derived from the following specification:

$$r_{i,t} - R_{i,t}^{B} = \beta_0 + \beta_1 \Delta Cash_{i,t} + \beta_2 SLAC_{i,t} \times \Delta Cash_{i,t} + \beta_3 SLAC_{i,t} + \gamma' X + B_t + \mu_j + \varepsilon_{i,t},$$

where $r_{i,t} - R_{i,t}^{B}$ is the excess stock return of firm *i* during fiscal year *t*; $SLAC_{i,t}$ is the substitutability of labor with automated capital of firm *i* in year *t*; vector *X* is the set of firm-level control variables described in Faulkender and Wang (2006); B_t and μ_j are a full set of year and industry fixed effects. The dependent variable is the Fama and French (1993) size and market-to-book adjusted excess returns in Columns (1)–(2), and the Fama and French (1997) 48 industry-adjusted excess returns in Columns (3)–(4). Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Size and M/B-adjusted annual excess stock returns		Industry-adjusted annual excess stock returns	
	(1)	(2)	(3)	(4)
Δ *Cash*	1.831***	1.587***	1.714***	1.521***
	(0.102)	(0.098)	(0.109)	(0.099)
SLAC × Δ *Cash*	-0.570***		-0.452*	
	(0.213)		(0.253)	
SLAC	0.140***		0.147***	
	(0.047)		(0.052)	
Δ *Earnings*	0.184***	0.183***	0.179***	0.178***
	(0.029)	(0.029)	(0.030)	(0.030)
Δ *Net assets*	0.158***	0.158***	0.147***	0.147***
	(0.014)	(0.014)	(0.014)	(0.014)
Δ *R&D*	-0.357	-0.332	-0.349	-0.327
	(0.350)	(0.349)	(0.327)	(0.327)
Δ *Interest*	-0.525***	-0.531***	-0.521**	-0.526**
	(0.191)	(0.193)	(0.201)	(0.202)
Δ *Dividends*	1.582***	1.583***	1.604***	1.606***
	(0.280)	(0.280)	(0.266)	(0.265)
Lag cash	0.325***	0.319***	0.343***	0.337***
	(0.020)	(0.020)	(0.019)	(0.019)
Net financing	-0.108***	-0.106***	-0.107***	-0.106***
	(0.036)	(0.036)	(0.036)	(0.036)
Mkt leverage	-0.649***	-0.641***	-0.560***	-0.551***
	(0.034)	(0.035)	(0.029)	(0.029)
Δ *Cash* × *Lag cash*	-0.397***	-0.389***	-0.392***	-0.387***
	(0.062)	(0.062)	(0.061)	(0.061)
Mkt leverage × Δ *Cash*	-1.149***	-1.230***	-1.058***	-1.119***
	(0.177)	(0.190)	(0.178)	(0.183)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	32,007	32,007	33,345	33,345
R-squared	0.189	0.188	0.196	0.195

Table IA.7. *SLAC* and lagged financial policies

This table presents additional evidence relating *SLAC* to lagged measures of cash holdings, leverage, and dividend payout. Columns (1)–(3) each present the dependent variable lagging by 1, 2, or 3 years. We include the same set of firm-level controls as in Table 3 and Table 8, year fixed effects, and industry fixed effects. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Cash holdings		
	One-year lagged	Two-year lagged	Three-year lagged
	(1)	(2)	(3)
SLAC	-0.353***	-0.371***	-0.378***
	(0.079)	(0.086)	(0.088)
Observations	93,935	76,407	66,148
R-squared	0.339	0.329	0.320
	Leverage		
	One-year lagged	Two-year lagged	Three-year lagged
SLAC	0.288***	0.295***	0.290***
	(0.072)	(0.080)	(0.074)
Observations	92,396	75,367	65,303
R-squared	0.317	0.261	0.222
	Common dividends/total assets		
	One-year lagged	Two-year lagged	Three-year lagged
SLAC	0.013***	0.014***	0.013***
	(0.003)	(0.003)	(0.004)
Observations	88,245	76,394	66,139
R-squared	0.118	0.117	0.114
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes

Table IA.8. Accounting for market competition and other sources of heterogeneity

This table presents additional evidence on the relation between *SLAC* and financial policies. Panel A controls for various measures of market competition including *Product market fluidity*, *HHI*, *Industry turnover*, and *Inventory-to-sales*. Panel B reports the results of a propensity score matching analysis. We match above-median *SLAC* firms with below-median *SLAC* firms on year, industry (two-digit SIC), and the firm-level controls included in Table 3 and Table 8. Matching is based on nearest-neighbor-matching with a caliper of 0.01, and with replacement. Standard errors in parentheses are bootstrapped based on 500 replications with replacement. Panel C examines the relation between *SLAC* and financial policies for subsamples. Column (1) excludes firms with above-median variability of *SLAC*, which is computed as the standard deviation of *SLAC* over the sample period; Column (2) includes only the mature firms with above-median firm age; Column (3) includes only firms that belong to the manufacturing sector (SIC codes 2000–3999); Column (4) excludes firms that belong to the tradable sector (agriculture, manufacturing, and mining). We include the same set of firm-level controls as in Table 3 and Table 8, as well as year and industry fixed effects. Standard errors clustered at the industry level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A: Controlling for market competition

	Cash holdings	*Leverage*	*Common dividends/ total assets*
	(1)	(2)	(3)
SLAC	-0.213***	0.182***	0.009***
	(0.046)	(0.058)	(0.003)
Product market fluidity	0.016***	-0.006**	-0.001***
	(0.004)	(0.002)	(0.000)
HHI	-0.111*	-0.010	0.007
	(0.057)	(0.089)	(0.007)
Industry turnover	0.040**	0.005	-0.000
	(0.016)	(0.030)	(0.002)
Inventory-to-sales	-0.120***	-0.013	-0.007***
	(0.030)	(0.026)	(0.001)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	54,667	53,891	54,666
R-squared	0.517	0.228	0.124

Panel B: Propensity score matching

	Cash holdings	*Leverage*	*Common dividends/ total assets*
	(1)	(2)	(3)
Above median – Below median	-0.062***	0.049***	0.003***
Bootstrapped standard errors	(0.002)	(0.006)	(0.002)
Observations	93,019	91,452	92,996

Panel C: Subsample analysis

	Cash holdings			
	Non-volatile *SLAC*	Mature firms	Manufacturing	Nontradable
	(1)	(2)	(3)	(4)
SLAC	-0.257***	-0.289***	-0.445***	-0.271***
	(0.057)	(0.079)	(0.144)	(0.086)
Observations	46,027	45,725	46,606	38,323
R-squared	0.324	0.347	0.396	0.287
	Leverage			
	Non-volatile *SLAC*	Mature firms	Manufacturing	Nontradable
SLAC	0.213**	0.204***	0.261**	0.296**
	(0.101)	(0.054)	(0.117)	(0.114)
Observations	45,240	45,456	46,402	37,691
R-squared	0.528	0.467	0.495	0.502
	Common dividends/total assets			
	Non-volatile *SLAC*	Mature firms	Manufacturing	Nontradable
SLAC	0.011***	0.017***	0.013**	0.013***
	(0.004)	(0.003)	(0.005)	(0.004)
Observations	46,009	45,723	46,600	38,311
R-squared	0.099	0.118	0.126	0.099