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Workplace Automation and Corporate Liquidity Policy[†]

Thomas W. Bates Fangfang Du Jessie Jiaxu Wang[*]

Abstract

Using an occupational probability of computerization, we measure a firm's ability to replace labor with automated capital. Our evidence suggests that the potential to automate a workforce enhances operating flexibility, allowing firms to hold less precautionary cash. To provide evidence for this mechanism, we exploit the 2011–2012 Thailand hard drive crisis as an exogenous shock to the cost of automation. In addition, the negative relation between prospective automation and cash holdings is greater for firms with a lower expected cost of worker displacement and greater labor-induced operating leverage.

JEL codes: G32, G35, J23, O33

Keywords: Automation; Operating flexibility; Corporate liquidity policy; Substitutability of labor with automated capital; Labor-induced operating leverage

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[*]Bates, thomas.bates@asu.edu, W. P. Carey School of Business, Arizona State University; Du, fangfangdu@fullerton.edu, Mihaylo College of Business and Economics, California State University, Fullerton; and Wang, jessiejiaxuw@gmail.com, Board of Governors of the Federal Reserve System and Arizona State University.

1. Introduction

Workplace automation has progressed dramatically over the past two decades. The use of automated capital has most notably included 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 also become 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 liquidity policies.

Labor is a critical input in production, but employing workers exposes a firm to labor market frictions. 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 often adopt conservative financial policies, such as precautionary cash holdings (e.g., Bates, Kahle, and Stulz 2009).

With widespread technology adoption, workplace automation provides a viable hedge to labor-induced operating leverage. Automation enhances operating flexibility by shifting the production function away from labor-intensive methods. 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. Thus, we expect that firms with a more automatable workforce are endowed with

[1] Using data compiled by the International Federation of Robotics (IFR), we estimate that more than 435,000 industrial and service robots were brought into service worldwide in 2021, increasing the stock of robots in production and services by 13% 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, 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).

an option to reduce labor-induced operating leverage.[4] The contribution of our paper is to test this hypothesis using a measure of a firm's ability to replace labor with automated capital as well as readily available data on corporate liquidity policies, and provide evidence on the mechanism.

We begin by constructing a novel measure of the proportion of an industry's existing employees that are susceptible to replacement by automation in a given year. We characterize this construct as the substitutability of labor with automated capital (*SLAC*). This measure is developed using Frey and Osborne's (2013, 2017) estimates 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 in the engineering sciences, such as machine learning and mobile robotics. In contrast to earlier methodologies designed to estimate the potential to automate only routine tasks, *SLAC* accounts for the potential to replace labor across a broad set of both routine and non-routine tasks. To validate our measure, we empirically confirm that *SLAC* is negatively correlated with changes in future employment, and positively correlated with the subsequent installation of industrial robots. We then match *SLAC* to Compustat firms according to their historical industry code.

Our primary analysis evaluates the relation between the substitutability of labor with automated capital and a first-order corporate policy, 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 5.43 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 26.9% decrease relative to the sample mean. Our results are robust to controlling for a suite of fixed effects, and to alternative measures of cash. We extend this analysis to several alternative measures of firm-level *SLAC* including: (i) time-invariant *SLAC* fixed to the 1999 estimate, (ii) *SLAC* using only an occupational employment weighting excluding wages, and (iii) segment sales-weighted *SLAC* that accounts for the industry composition of multi-segment firms.[5]

To pin down the mechanism behind the relation between *SLAC* and cash holdings, 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, leading to a shortage of drives and a spike in unit prices.

[4] Labor substitution reduces labor costs; however, automation itself entails costs including financing 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 a technology becomes accessible. Rather, we hypothesize that firms account for such a tradeoff and automate when the option to do so becomes in the money. We elaborate on this point in Section 2.

[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 using the segment sales-weighted firm-specific measure of *SLAC*.

Since hard drive prices are an important determinant of the cost of automation, this natural disaster was a negative shock to the potential to replace labor with automated capital that is orthogonal to omitted variables. Given this temporary increase in the cost of automation, we expect that the effect of *SLAC* on cash holdings will be weaker during the years 2011–2012 for firms that rely more on computers and peripheral equipment for automation. Our evidence supports these predictions.

We conduct a number of additional analyses that collectively support the notion that the ability to substitute automated capital for labor provides an option to lower operating leverage. Specifically, we document a stronger negative relation between *SLAC* and cash holdings for firms with (i) a lower expected cost of worker displacement and (ii) greater labor-induced operating leverage. For example, the relation between *SLAC* and cash is more pronounced for firms with lower union participation and for firms in states with more generous unemployment insurance.

We carefully evaluate the empirical relevance of a variety of alternative mechanisms that could conceivably explain the observed link between *SLAC* and corporate liquidity. One possibility is that firms with high *SLAC* are in the process of automating, and this investment is a drain on cash reserves. We test this conjecture using several approaches. First, we examine the relation between *SLAC* and cash for firms that are clearly not in the process of automating, such as those exhibiting a pronounced decline in the capital-labor ratio over time. We find that the negative relation between *SLAC* and cash for this subsample is similar to that observed for the full sample. Second, we consider whether the relation between *SLAC* and corporate liquidity extends to a firm's payout policy. To this point, we find that *SLAC* is associated with a higher rate of dividend payout, and a greater reliance on dividends relative to repurchases in their total distributions to shareholders. These findings suggest that firms with greater *SLAC* also adopt less flexible payout policies. Finally, we document that the marginal value of cash decreases in *SLAC*. This evidence is inconsistent with the notion that firms with high *SLAC* also have a greater demand for cash to invest in automation.

It is also possible that our measure of *SLAC* is correlated with one or more labor-related characteristics known to affect corporate financial policies. To address this alternative, we control for capital intangibility, labor skill, labor mobility, union coverage, the fraction of low-paid employees, and the ability to offshore labor into our baseline specifications. We continue to find that *SLAC* is a unique and economically substantial determinant of corporate liquidity. We also evaluate the incremental explanatory power of *SLAC* relative to routine-task intensity (*RTI*), which is constructed using Autor and Dorn (2013)'s occupational routine-task intensity and focuses solely on the potential to automate routine task labor. Consistent with *SLAC* and *RTI* overlapping in their estimation of prospective automation across the subset of routine tasks, we find that *RTI* is also negatively correlated with cash holdings. However, *SLAC* subsumes the explanatory power of *RTI* in regressions explaining cash holdings, and an orthogonal decomposition suggests that the substitutability of non-routine tasks accounts for about one-half of the impact of prospective automation on corporate liquidity policy. This indicates that *SLAC*, in keeping with the nature of its construction, is a significantly more comprehensive measure of the potential to automate a workforce relative to *RTI*.

A plausible alternative mechanism is that the threat of worker displacement from automation weakens the bargaining power of unionized workers, leading to lower labor costs. In contrast, our findings indicate that the estimated effects of *SLAC* on cash holdings are significantly stronger for firms in industries with lower labor union coverage. Finally, we consider whether the relation between *SLAC* and corporate liquidity can be explained by the confounding effects of competition, corporate governance, and other common sources of heterogeneity.

A key contribution of our research is the development of a novel, occupation-based measure of a firm's substitutability of labor with automated capital. Building on Autor and Dorn (2013), who consider the potential to automate only routine-task labor, our measure expands the definition of prospective automation to include certain non-routine tasks. Specifically, our measure is based on the probability of computerization developed by Frey and Osborne (2013, 2017). This probability uniquely accounts for technological innovation in various fields of the engineering sciences such as machine learning and mobile robotics that have enabled the automation of both routine and non-routine tasks. Our more comprehensive measure of prospective automation has strong predictive power for changes in future employment and the installation of industrial robots, and is an economically significant determinant for corporate liquidity decisions.

More broadly, this paper contributes to the growing literature on automation and its effect on the labor markets and firm outcomes. Much of this literature studies the replacement of routine-task jobs, and associated labor market dynamics such as job polarization (e.g., Acemoglu and Autor 2011; Autor and Dorn 2013; Goos, Manning, and Salomons 2014). Additional research in Zhang (2019) shows that the potential to automate routine-task labor reduces risk exposure and expected returns. Our study extends this line of research by studying the potential to automate both routine- and non-routine task labor, and focusing on the implications for a first-order corporate policy.

Finally, our research adds to the literature documenting the impact of labor market frictions on financial policies (e.g., Simintzi, Vig, and Volpin 2015; Serfling 2016; Ghaly, Dang, and Stathopoulos 2017; He, Tian, Yang, and Zuo 2020; Qiu, Wan, and Wang 2020; Kuzmina 2022). These studies examine labor market frictions from the perspective of changes in labor regulations or labor characteristics such as rigidity. We extend this line of inquiry in the context of prospective substitutability between labor and automated capital for a given production function. We present new evidence that a firm's (in)ability to substitute automated capital for labor is a unique labor-based friction that is a relevant determinant of financial policies.

The rest of the paper is organized as follows. Section 2 develops hypotheses. Section 3 describes the data and the construction of the *SLAC* measure. Section 4 estimates the relation between *SLAC* and liquidity policies 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 liquidity choice? 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, specifically, the use of precautionary cash holdings.

Labor market frictions are an important source of operating leverage. These frictions have been shown to obtain on a variety of dimensions. For example, Kahn (1997) provides evidence that wages are remarkably sticky, showing that firms are reluctant to cut wages even during periods of financial distress. Chen, Kacperczyk, and Ortiz-Molina (2011) and Favilukis and Lin (2016) document the significant impact of sticky wages on operating leverage. In addition, the costs of screening, training, and firing make labor a quasi-fixed factor (e.g., Oi 1962). 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. For example, firms hold cash to hedge against adverse cash flow shocks that would cause them to forego valuable investments when external financing is prohibitively costly. Consistent with this, Ghaly et al. (2017) show that firms with a high share of skilled workers hold more cash. All else equal, hedging operating leverage through flexible 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).

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 weigh the benefits of adopting automated capital against the costs of switching production technologies and will opt to automate when doing so appears valuable—for example, when the cost to automate 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 automate routine-task labor during economic downturns. Our paper's focus is also on a firm's option to replace a portion of its workforce through automation. 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 liquidity policies.

3. Data and Summary Statistics

3.1 Measuring the substitutability of labor with automated capital (*SLAC*)

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 substitutability between automated capital and labor, which, as we show, shapes firms' combination of factor inputs and financial policies.

To measure the prospective substitution of labor with automated capital, we develop our key variable, *SLAC*, using two primary data sources that we discuss in detail below: the occupational probability of computerization estimated by Frey and Osborne (2013, 2017), and the industry-level occupational employment and wage estimates from the Occupational Employment and Wage Statistics (OEWS) program.

Frey and Osborne's occupational probability of computerization quantifies the impact of technological progress in the 21st century on the potential to automate tasks performed by labor, extending prior work on 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; they argue that routine task labor is substitutable with computerized capital.[6] To estimate an occupation's susceptibility to automation, Autor and Dorn (2013) construct an occupational index of routine-task intensity. This index reflects the mix of tasks that can be described as routine, non-routine manual, and abstract for a given occupation, and quantifies the relative ease of automating a particular occupation based on its reliance on routine tasks.

The scope of what computers do has expanded, and computerization is no longer confined to routine tasks. Drawing on recent advances in a variety of fields in the engineering sciences, Frey and Osborne (2013, 2017) characterize a wide array of occupations by their susceptibility to automation using computer-controlled equipment.[7] Their model recognizes the technological developments that have enabled the automation of routine tasks have also turned many non-routine manual and cognitive tasks into well-defined algorithms. For example, non-routine manual tasks that can be defined using today's technologies include the operation of autonomous vehicles and warehouse picking using mobile robots. Examples of computerized non-routine cognitive tasks include deciphering handwriting on a personal check, medical diagnoses of radiological imaging diagnoses, and legal writing.[8]

More specifically, Frey and Osborne develop an extension of the task-based model of Autor et al. (2003) by redefining labor inputs that are not susceptible to substitution into three categories:

[6] 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.

[7] Specifically, advances in the fields of machine learning, including data mining, machine vision, computational statistics and other sub-fields of artificial intelligence, as well as mobile robotics.

[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).

perception and manipulative tasks, creative intelligence tasks, and social intelligence tasks. Occupations involving these aspects of labor require algorithms that are difficult or impossible to fully computerize using current machine learning and robotics technologies, leading the authors to conclude that they are unlikely to be substitutable with automated capital over the next decade or two. With these boundaries to the scope of computerization, Frey and Osborne estimate the probability of automation for occupations defined by the 2010 Standard Occupational Classification (SOC) system using the task content of occupation as provided by the O*NET database.[9] For example, the O*NET task keywords "fine arts" and "originality" reflect aspects of creative intelligence that are impossible to automate with the current computerized technologies. As such, the Frey and Osborne probability is derived solely from the standpoint of technological capabilities and is not related to employment growth, factor input costs, expenditures on automation, or firm financial policies. A lower probability implies that the occupation is less likely to be automated. For example, the occupation "Recreational Therapists" has the lowest estimated probability of computerization (0.0028), while "Telemarketers" has the highest probability (0.99).

Our second data source is the time-varying industry-level occupational employment and wage estimates from the OEWS program. Maintained by the Bureau of Labor Statistics (BLS), the OEWS program collects data on wage and salary workers in nonfarm establishments and produces estimates of occupational employment and wages. We use the industry-level occupational employment and wage data for 1999–2018.[10] The OEWS data used the 2000 SOC occupation definitions for 1999–2009 and the 2010 SOC definitions after. We link the 2000 SOC codes to the 2010 SOC codes using the crosswalk table provided by the BLS.[11] 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.

[9] The methodology of Frey and Osborne (2013, 2017) builds upon work in Blinder (2009), which adopts a subjective approach to indexing occupational offshorability, as well as Jensen and Kletzer (2005), who create objective rankings of offshorability based on standardized and measurable O*NET variables. First, the automatability of a wide range of tasks was assessed by a group of researchers in the engineering sciences and used to subjectively hand-label 70 occupations, which the researchers were most confident about whether or not the occupation was definitely automatable with state-of-the-art computer-controlled equipment. Second, they identified objective O*NET variables corresponding to the defined engineering bottlenecks to computerization related to tasks that involve perception and manipulation, creativity, and social intelligence. Finally, they implemented a probabilistic classification algorithm to compute the automatability for all detailed occupations using the training data from the 70 occupations and a Gaussian process classifier.

[10] Our sample starts in 1999 because the OEWS occupational estimates are based on the SOC taxonomy from 1999.

[11] The crosswalk table can be obtained at www.bls.gov/soc/soc_2000_to_2010_crosswalk.xls.

We map the occupational probability of computerization to the OEWS occupational employment and wage data using the SOC occupation codes.[12] Our measure of the substitutability of labor with automated capital for each industry in each year ($SLAC_{j,t}$) is constructed as:

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

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 for 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-year using the annual wages of workers in that occupation to reflect labor's impact on cash flows.[13] 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 an industry-year can be replaced with automated capital according to technological capabilities, 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 industry-level *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 occupations that rely on highly skilled labor, such as research and development, but also occupations that utilize lower-skilled labor, such as child care services. This observation highlights that *SLAC* measures an occupational characteristic that is distinct from labor skill.[14] 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.[15]

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[12] The six-digit 2010 SOC system has 840 occupations in total. The Frey and Osborne estimates include 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 calculated as the average of "Clergy" (SOC 21-2011) and "Directors, Religious Activities and Education" (SOC 21-2021).
[13] Our results are essentially unchanged when we construct *SLAC* using only employment data in Equation (1).
[14] 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.
[15] 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

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. If the probability of computerization truly reflects the potential to automate occupations, and automation-based substitution for labor shapes employment outcomes, then the probability should predict occupational changes in employment over time. For example, Frey and Osborne estimate that telemarketers can be easily displaced by automated interaction strategies such as chatbots. Indeed, the total employment for the "telemarketer" occupation declined by 45% from 2010 to 2018 (283,460 to 156,100 workers). To formally test this prediction, we use the OEWS employment and wage data and compute changes in employment from 2010 to 2018 for each 2010 SOC occupation (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 illustrates a negative relation between the probability of computerization and employment growth by occupation from 2010 to 2018. For comparison, the scatter plot on the right uses Autor and Dorn's (2013) occupational routine-task intensity and illustrates the decline of employment in routine-intensive occupations. Panel B of Table 1 reports the ordinary least squares (OLS) estimation results. The estimates in Column (1) suggest that a one-standard-deviation increase in the probability of computerization by Frey and Osborne is associated with a 4.4 percentage point decline in employment growth across occupations. The same increase in occupational routine-task intensity by Autor and Dorn 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. These estimates reveal a consistent pattern: Occupations with a high probability of computerization experience robustly lower employment growth, with or without controlling for routine-task intensity.

We next validate our *SLAC* measure using data on the use of industrial robots, which are a common form of automated capital, particularly for occupations involving routine manual tasks. As a benchmark, we also construct the industry-year measure of routine-task intensity (which we denote as *RTI*) by replacing $Prob_o$ in Equation (1) with occupational routine-task intensity by Autor and Dorn. The International Federation of Robotics (IFR) provides a breakdown of annual installations and the operational stock of industrial robots for six major sectors and 27 manufacturing industries. We match

Restaurants Replace Humans with Technology?" *QSR*, January 2019, www.qsrmagazine.com/outside-insights/should-restaurants-replace-humans-technology.

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 robot installations by industry between 2010 and 2018. Similarly, the OLS estimates in Panel C of Table 1 indicate that both *SLAC* and *RTI* independently can explain the installation and stock of robots; however, *RTI* absorbs the explanatory power of *SLAC* when both measures are included. This result follows from the fact that the IFR data primarily covers manufacturing industries where routine-task labor is most common. Since by construction, *SLAC* and *RTI* overlap in measuring the ability to automate routine tasks, we consider the relative explanatory power of *RTI* in models explaining corporate liquidity choice in Section 5.

[Figure 2 about here]

In Figure 2 we present the evolution of *SLAC* for various industries over time. Industries with high *SLAC* tend to show a downward trend in *SLAC*, consistent with their gradual adoption of automated capital to replace labor that is highly susceptible to computerization. For example, Panel A illustrates that Business Support Services, the industry that employs telemarketers, experiences a marked decline in *SLAC* over time. 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 illustrates that for low-*SLAC* industries, such as Child Day Care Services, *SLAC* 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.[16] We use $SLAC_{i,t}$ to denote the substitutability of labor with automated capital mapped to the firm-year panel in order to differentiate from the industry-year variable $SLAC_{j,t}$ in Equation (1).

[Table 2 about here]

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

The dependent variable 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: cash flow, net working capital, capital expenditures, leverage, acquisitions, market-to-book ratio, size, industry cash flow volatility, R&D expenditures, 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. (2009). The mean and standard deviation of *SLAC* are 0.464 and 0.150, respectively, and the 10^{th} and 90^{th} percentiles of the distribution are 0.266 and 0.662.

3.3 The persistence of firm-level *SLAC*

Figure 3 presents evidence that *SLAC* is highly persistent over time. In Panel A, we plot the evolution of average *SLAC* across four portfolios in event time. For each year from 1999 through 2008 (the latest year that allows us to track the portfolios for the next 10 years), we sort all sample firms into four portfolios based on their *SLAC* that year and then compute the average *SLAC* for each portfolio year, fixed in composition, over the subsequent 10 years. We then average *SLAC* by "event time" across the original sorting years of 1999 to 2008 to obtain the bold lines in the figure. The plot shows the high persistence of *SLAC* over time, as well as its substantial cross-sectional dispersion. Consistent with observations in Figure 2 based on industry-level *SLAC*, Panel A also shows that average *SLAC* declines over time for the top three portfolios but is essentially unchanged for the bottom portfolio.

[Figure 3 about here]

We calculate the transition matrix for firms moving from one portfolio to another after ten years, following the approach in Gao (2021). In Panel B of Figure 3, the x-axis (width) shows the partitions based on *SLAC* in the current year (t), and the y-axis (depth) shows the partitions based on *SLAC* 10 years later (t+10). The height of the columns indicates the likelihood of transition from one group to another, averaged across the original sorting years of 1999 to 2008. The diagonal columns average around 73.5% and are significantly higher than off-diagonal columns. This figure suggests that firm-level *SLAC* evolves slowly, with the vast majority of firms remaining in their original portfolio 10 years after their initial sort. Overall, the evidence suggests that firm-level *SLAC* is quite stable over time, and thus is unlikely to be changed by individual firms' cash policies.

4. Empirical Tests and Main 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 corporate liquidity policy. In Section 4.2, we outline analyses that collectively support the mechanism that the prospective substitution of labor with automated capital enhances operating flexibility.

4.1 *SLAC* and cash holdings

Our initial analysis evaluates the relation between *SLAC* and liquidity policy reflected in cash holdings. Figure 4 summarizes the 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 quartile of *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 4.

[Figure 4 and Table 3 about here]

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

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

where $Y_{i,t}$ is cash holdings, $SLAC_{i,t}$ is our measure of the substitutability of labor with automated capital mapped to the firm-year panel, and X is a vector of firm-level control variables following the specification in Bates et al. (2009).[17] 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, two-digit SIC industry-by-year fixed effects, 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, and size 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 (3), which includes industry-by-year fixed effects to control for unobserved time-

[17] Our main results are robust to alternative measures of cash, such as cash and short-term investments scaled by total assets net of cash.

varying heterogeneity across industries, a one-standard-deviation increase in *SLAC* is associated with a 5.43 percentage points (=0.15×0.362) reduction in *Cash holdings*. This effect is economically significant, suggesting a 26.9% (=5.43/20.2) reduction relative to the sample mean. The results are similar when we control for industry and year fixed effects in Column (1) and industry-specific time trends in Column (2). While we find that *SLAC* is persistent over time, we also incorporate firm fixed effects in the model in Column (4) to address the concern that unobserved time-invariant firm heterogeneity may lead to a spurious correlation between *SLAC* and cash. In this specification, the coefficient estimate suggests a 4.0% (=0.15×0.054/0.202) reduction in *Cash holdings* relative to the sample mean for a one-standard-deviation increase in *SLAC*. While economically important, the relation between *SLAC* and *Cash holdings* is less pronounced in this specification, 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-by-year fixed effects. This approach allows us to focus on the cross-sectional relation between *SLAC* and corporate liquidity policy, controlling for broad time-varying industry heterogeneity.

Next, we consider the potential for an endogenous relation between the substitutability of labor with automated capital and corporate liquidity policies. The *SLAC* measure is calculated as the weighted average of the probability of computerization across occupations, with the weight being the total wage expenses allocated to each occupation in the primary industry that a firm belongs to. One advantage of *SLAC* in this regard is that it is based on an occupational characterization of the technological capability to automate. Neither the occupational susceptibility of jobs to computerization, nor the industry-level occupational employment, are likely endogenous to individual firm characteristics or policies. Nevertheless, industry-level wage expenses could be correlated with the financial strength of an industry (e.g., Benmelech, Bergman, and Enriquez 2012), raising the concern of reverse causality, where *SLAC* is influenced by firms' liquidity policies.

To address this issue, we consider alternative measures of *SLAC*. First, we replace the time-varying *SLAC* with ex-ante time-invariant *SLAC* computed at the beginning of the sample period, $SLAC_{i,1999}$. Second, to alleviate concerns about the potential effect of corporate liquidity policies on the wage rate, we reconstruct *SLAC* using only occupational employment data as the weights in Equation (1), excluding wages, as *SLAC weighted by employment*. The results presented in Panel B of Table 3 indicate that our conclusions are robust to these alternative measures of *SLAC*.

Our baseline analysis utilizes a measure of *SLAC* derived for a firm's primary line of business. We also estimate a firm-specific *SLAC* that reflects 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* accounting for their constituent industries.[18] Results in Panel B of Table 3 illustrate that segment-based *SLAC* improves the explanatory power of the model relative to our baseline estimates in Panel A, suggesting that firm-specific *SLAC* better approximates production in multi-segment firms. To provide additional support for the notion that *SLAC* reflects the true nature of a firm's production, in Table IA.1 in the Internet Appendix, we focus on the subsample of multi-segment firms and compare the results between *SLAC* and the alternative measure *Segment sales-weighted SLAC.* In the top panel of the table we summarize the relation between *SLAC* and cash holdings using only the primary line of business for multi-segment firms. The second panel evaluates the impact of using the firm-specific segment sales-weighted *SLAC*. Consistent with a reduction in measurement error, *Segment sales-weighted SLAC* has a significantly greater impact on cash holdings, relative to *SLAC* estimated using the primary line of business.

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 1979 to 1998. 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 27% of the magnitude documented in Table 3. For observations from 1979 through 1989, the magnitude declines to about 16%.

4.2 Evidence on the mechanism

Our results in Section 4.1 show that a firm's ability to replace labor with automated capital is a novel factor that shapes corporate liquidity policy. Our proposed mechanism is that the potential to automate acts as a latent hedge to operating leverage, allowing firms to adopt more aggressive liquidity policies. In this section, we provide evidence to support this mechanism.

[18] Our approach of identifying segments with distinct industry codes 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*.

4.2.1 The Thailand hard drive crisis

We exploit a novel event, the 2011–2012 Thailand hard drive crisis, as an exogenous shock to the cost of workplace automation. Specifically, we examine how the effect of *SLAC* on cash holdings changed during the hard drive crisis for firms that rely more on computers and peripheral equipment for automation.

Thailand is the second-largest producer of hard disk drives, with approximately 40% of the world's production. Severe flooding in the country during the 2011 monsoon season caused widespread damage to the production facilities of hard drive manufacturers, including those of Western Digital and Seagate Technology. The resulting global shortage of hard disk drives led to a spike in prices, the effects of which rippled into the production of PC, chip, server, and memory products. Figure 5 plots the price for hard disk drives from 2009 to 2015 at a unit price of 0.01 cents in USD per megabyte.[19] As observed in the figure, hard drive prices nearly doubled in the fall of 2011, and gradually returned to the pre-crisis level by mid-year 2013.

[Figure 5 about here]

While technological advances have made workplace automation increasingly feasible, adopting automated technology is costly leading firms to consider the cost of replacing labor with automated capital when evaluating the net benefit of automation. A higher 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 resulted in an exogenous change in the cost of workplace automation that is orthogonal to potential omitted variables. We expect *SLAC* to have a more muted impact on cash holdings during the hard drive crisis.

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

$$Y_{i,t} = \beta_0 + \beta_1\, Flooding_t \times SLAC_{i,2010} + \beta_2\, SLAC_{i,2010} + \gamma'\, X + \mu_{j,t} + \varepsilon_{i,t}, \qquad (3)$$

where $Y_{i,t}$ is cash holdings; $Flooding_t$ is a dummy variable equal to one for the years 2011 and 2012, representing the duration of the Thailand hard drive crisis; and $SLAC_{i,2010}$ is the substitutability of labor with automated capital for firm *i* in year 2010. We fix the measure of *SLAC* in year 2010, immediately prior to the event date of the hard drive crisis, to isolate it from the dynamic response of an industry's

[19] 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.

wage expenditures to changes in hardware prices. X is the same set of control variables used in Table 3; $\mu_{j,t}$ is a full set of industry-by-year fixed effects, which absorbs the dummy variable $Flooding_t$.

Not all firms suffer from an increased cost of automation amid a shortage of hard disk drives. Hence, for our test, we focus on those firms that rely heavily on computers for automation, and thus are particularly sensitive to the change in hard drive prices. 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 for our sample.[20] Our coefficient of interest is β_1, the coefficient of the interaction term, $Flooding_t \times SLAC_{i,2010}$. We expect that the negative relation between *SLAC* and cash holdings is weaker during the hard drive crisis for firms that utilize a higher proportion of computers and peripheral equipment, resulting in a positive coefficient on β_1.

[Table 4 about here]

Consistent with our prediction, the results in Panel A of Table 4 show that the impact of *SLAC* on cash holdings is indeed significantly weaker during the Thailand crisis. Column (1) presents baseline estimates showing that a one-standard-deviation increase in *SLAC* translates to a 24.7% (=0.15×0.332/0.202) decline in cash holdings relative to the sample mean in the non-crisis period. In contrast, a one-standard-deviation increase in *SLAC* yields only a 19.2% reduction in cash holdings during the crisis. Our use of a flooding indicator variable in the baseline specification captures the extensive margin of the cost to automate. In Column (2), we also consider the intensive margin by examining changes in the price of hard disk drives. Specifically, we replace the dummy variable $Flooding_t$ in Equation (3) with $Hard\ drive\ price_t$, the deviations from a linear trend in the natural logarithm of annual unit price of hard drives from 1999 to 2018. Our findings are robust to this alternative specification. Our results are essentially unchanged in Columns (3) and (4) where we replace $SLAC_{i,2010}$ with the time-varying $SLAC_{i,t}$.[21]

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 are

[20] The BEA capital flow data 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 unreported results, we consider the temporal dynamics of the Thailand hard drive crisis in more detail. Our findings confirm that the effect of *SLAC* on cash holdings did not change in the years preceding the flooding event. In addition, the moderating impact of the flooding event is lost after 2012, consistent with hard drive prices returning to pre-crisis level by mid-year 2013.

customers and suppliers of the industry, such as Advanced Micro Devices, Dell Technologies, and NetApp. 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 address this issue, we eliminate from the sample those 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 re-estimate Equation (3). The results, reported in Panel B of Table 4, are largely equivalent to those presented in Panel A.[22] Overall, our evidence developed in the context of the Thailand hard drive crisis supports the mechanism that the potential to automate a firm's workforce alleviates the need to maintain high cash balances as a hedge to labor induced operating leverage.

4.2.2 The benefits and costs of worker displacement by automation

To provide additional evidence on the mechanism, we examine the cross-section of our sample to characterize the moderating effects of the benefits and costs of worker displacement on the relation between *SLAC* and cash holdings. Workplace automation is achieved by the adoption of automated capital and the displacement of human workers, thereby reducing the impact of labor costs on operating leverage. In this framework, we expect to find a stronger relation between *SLAC* and cash holdings for firms with a lower cost of worker displacement, and for firms with greater labor-induced operating leverage.

We start by examining the cross-sectional implications of heterogeneous costs of worker displacement. If the effect of *SLAC* on cash holdings obtains through the net benefits of automation, 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 the cost of worker displacement—labor unionization and unemployment insurance.

Labor unionization presents a significant obstacle to displacing workers (e.g., Dowrick and Spencer 1994; Chen et al. 2011). There are many examples of unions resisting automation; more generally, collective bargaining agreements often constrain firms' ability to lay off workers.[23] Accordingly, we expect that firms in industries with broader union coverage face a greater barrier to

[22] 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).

[23] 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.

prospective automation. We obtain industry-year data on labor union membership from the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003), based on the Current Population Survey. We calculate *Union coverage* as the percentage of employed workers who are covered by a collective bargaining agreement in an industry each year, and map this industry-year variable to Compustat firms according to their historical industry code.

Another important factor contributing to the cost of worker displacement is the unemployment insurance (UI) benefits provided by a state. The unemployment insurance system in the US provides temporary income to eligible workers who lose their jobs. Topel (1983) documents that employers' willingness to lay off workers increases with a state's unemployment insurance benefits, making automation more feasible. Hence, we expect the effect of *SLAC* on cash holdings will be stronger for firms whose primary business operations are located in states with more generous UI 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 construct the variable *UI benefits* annually using the product of the maximum weekly benefit amount and the maximum benefit duration in weeks. To map *UI benefits* to our firm-year panel, we identify a firm's state in a year 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.

Columns (1) and (2) of Table 5 summarize the result of regressions that incorporate terms that interact *SLAC* with the variables *Union coverage* and *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. Our findings related to labor union coverage are particularly salient in ruling out employee bargaining power as an alternative mechanism. Specifically, it is possible that the option to automate and replace labor weakens the ability of unionized workers to bargain for higher wages, resulting in lower labor-induced operating leverage and more aggressive financial policies. For example, Qiu et al. (2020) argue that the threat to replace labor with automated capital weakens workers' bargaining power and enables firms to use greater financial leverage. If this mechanism is at work, we would expect to find a more significant relation between *SLAC* and liquidity policies for firms with broader union coverage. This alternative is not supported by the data. As observed in Table 5, our estimated effects of *SLAC* are significantly weaker for firms in industries with broader labor union coverage, consistent with the notion that unions effectively resist workforce automation.

We next examine the heterogeneous effect of *SLAC* on cash holdings for the cross-section of firms delineated by labor-induced operating leverage. If *SLAC* boosts operational flexibility by alleviating the reliance on labor, firms that rely more on labor in the production process will benefit more. To test this prediction, we measure *Labor intensity* as the ratio of selling, general & administrative (SG&A) expenses to sales. Another way to measure the significance of labor in the production process is through the lens of wages and labor contracts. 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), and thus contribute less to firm operating leverage relative to other employees. Accordingly, the value of the option to automate is lower 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 OEWS data.[24] We map the industry-year *Low-paid employee* to Compustat firms according to their historical industry code.

[Table 5 about here]

As predicted, results in Columns (3) and (4) show that firms with higher labor intensity exhibit a stronger relation between *SLAC* and cash holdings, whereas firms with a greater fraction of low-paid employees exhibit a weaker relation between *SLAC* and cash holdings.

While the occupational probability of computerization is independent of the firm, industry, or state level characteristics, the construction of *SLAC* utilizes the employment and wage information of an industry, thus potentially overlapping with the information used to construct *Union coverage* and *Low-paid employee*. To rule out a mechanical relationship between *SLAC* and these cross-sectional characteristics, we conduct two robustness checks. First, we repeat the regressions in Table 5 by replacing *SLAC* with the alternative measure *SLAC weighted by employment*, which is constructed using only occupational employment counts (excluding wages). Second, we replace the time-varying *SLAC* with ex-ante time-invariant *SLAC* fixed to the year 2010. The results, summarized in Table IA.3 in the Internet Appendix, are robust to these alternative specifications, helping to rule out concerns

[24] A concern may arise if the fraction of low-paid employees is highly correlated with *SLAC*, for example, if low-paid employees mainly engage in automatable tasks. To address this concern, we find that the correlation between industry-level *Low-paid employee* and *SLAC* is 0.23, suggesting only a moderate level of overlap between the two characteristics. Second, a closer look at the data suggests that, contrary to the prior that low-paid employees are mainly associated with routine tasks and automatable jobs, many industries that are ranked high in the fraction of low-paid employees actually have low *SLAC*. These include Child Day Care Services, Home Health Care Services, Individual and Family Services, Motion Picture and Video Industries, Civic and Social Organizations, Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly.

associated with reverse causality or potential non-linear interactions between *SLAC* and the cross-sectional characteristics.

In sum, consistent with the proposed mechanism, the results in Table 5 indicate that *SLAC* has a stronger impact on cash holdings for firms with (i) a lower expected cost of worker displacement, and (ii) greater labor-induced operating leverage.

5. Alternative Mechanisms

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

5.1 Automating or the option to automate?

One possibility is that instead of having the option to automate, firms with high *SLAC* are in the process of automating and are using cash to finance it. For example, Cheng, Lyandres, Zhou, and Zhou (2022) find that investment in industrial robots in Chinese firms leads to higher leverage and a lower cost of debt. In the context of our study, investment in automated capital requires up-front expenditures on technology adoption and equipment, which might result in us observing lower cash balances. We perform several tests to consider whether the connection between *SLAC* and liquidity policies is mechanically driven by concurrent financing of automation.

Under the alternative explanation, the *SLAC*-cash relation should be significantly weaker for firms that are not in the process of automating. We classify firms as not in the process of automating using several complementary approaches. Firms that automate should see an increase in capital relative to labor, so we restrict the sample to firms that exhibit a declining capital-labor ratio in the most recent three years. Similarly, firms that automate their workforce should see a net decline in *SLAC* as occupations that are highly susceptible to computerization are replaced by machines. With this in mind, we restrict the sample to firms that experience an increase in *SLAC* over the most recent three years of data. Our final approach is to exclude firms that are industry leaders in workplace automation, which we identify in two ways. First, a firm is classified as an automation leader if it exhibits an increase in the capital-labor ratio coupled with a decrease in *SLAC* over the last three years. Second, a firm is defined as a leader if its capital-labor ratio increases in the last three years and is negatively correlated with industry *SLAC* over the same period. In Panel A of Table 6 we report the results of regressions estimating the relation between *SLAC* and *Cash holdings* for these four subsamples of firms identified as not in the process of automating. The results indicate that the relation between *SLAC* and cash for these non-automating firms is equivalent to that observed in the baseline results in Table 3.[25]

[Table 6 about here]

To further rule out the possibility that our results are a byproduct of contemporaneous investment in automation by high *SLAC* firms, we consider the relation between a firm's potential to automate and its payout policy. While our main findings focus on how a firm's cash policy relates to labor's susceptibility to replacement by automated capital, cash is likely just one facet of a firm's liquidity policies affected by labor-induced operating leverage. For example, He et al. (2020) find that firms reduce dividends in response to close-call union elections. If the potential to substitute labor with automated capital reduces the impact of labor-based operating leverage for firms, *SLAC* should be negatively correlated with financial conservatism more broadly, as evidenced by a firm's payout policy. Specifically, firms with a greater *SLAC* will be more likely to pay dividends. Bonaimé, Hankins, and Harford (2014) also note that financial flexibility allows firms to tilt to dividend payout relative to share repurchases; hence, we expect firms with greater *SLAC* will rely more on dividends relative to repurchases in their distributions to shareholders.

Following He et al. (2020), we measure a firm's dividend payout using common dividends scaled by total assets, and the fraction of total payout (including repurchases) distributed as common dividends (e.g., Fried and Wang 2019). Following Crane, Michenaud, and Weston (2016), we also estimate dividends using the natural logarithm of common dividends and the natural logarithm of total dividends paid. We control for a broad set of firm characteristics known to affect payout policy, including firm size, cash flow, Tobin's *q*, leverage, as well as asset tangibility as in Jagannathan, Stephens, and Weisbach (2000).

Panel B of Table 6 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) yield similar conclusions for the reliance on dividends in payout policy and alternative measures of dividend payout. This result of high-*SLAC* firms paying out more dividends is inconsistent with those firms using cash to finance automation.

[25] We also find that the relation between *SLAC* and one to three years lagged cash holdings (tabulated in Table IA.4) is essentially equivalent to the baseline results.

Finally, we estimate the marginal value of cash. If *SLAC* works as a latent hedge to operating leverage reducing the need for cash reserves, we expect the marginal value of cash to decline with *SLAC*. Alternatively, if high-*SLAC* firms are financing automation using cash, the marginal value of cash will increase with *SLAC*. To test these alternatives, we augment the Faulkender and Wang (2006) framework by introducing *SLAC* as an explanatory variable. Table IA.5 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 $0.081 lower for a one-standard-deviation increase in *SLAC*. In sum, the evidence presented in Section 5.1 suggests that the relation between *SLAC* and liquidity policy is unlikely to be the byproduct of concurrent investment in automation by high-*SLAC* firms.

5.2 Other labor-related characteristics

In this subsection, we consider the possibility that the relation between *SLAC* and financial policies can be attributed to other labor-related characteristics. We begin by accounting for features of labor and production that have been shown to affect financial policies. For example, Falato, Kadyrzhanova, Sim, and Steri (2022) 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. In Panel A of Table 7, we summarize regressions relating *SLAC* to cash holdings as in our baseline regressions in Table 3, with added controls for capital intangibility, labor skill, labor mobility, union coverage, low-paid employees, and offshorability.[26] Our findings indicate that these labor-related variables do not subsume the relation between *SLAC* and cash holdings. These results confirm our conclusion that prospective automaton is a first-order determinant of corporate liquidity policies that is distinct from other labor-related characteristics.

[Table 7 about here]

[26] 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* and *Low-paid employee* are identical to the variables used in Table 5 and discussed in Section 4.2.2. *Offshorability* is the weighted average potential to offshore jobs across all occupational employment for a firm's primary industry. We map the industry-year variables to our firm-year panel according to firms' historical industry code.

Our measure of the substitutability of labor with automated capital (*SLAC*) accounts for the potential to automate both routine and non-routine tasks. As such, *SLAC* can be viewed as an extension of the routine-task intensity (*RTI*), which is constructed upon Autor and Dorn (2013)'s occupational routine-task intensity and focuses solely on the potential to automate aspects of routine task labor. Given that, by construction, *SLAC* and *RTI* have some overlap in estimating the potential to computerize routine tasks, we consider the relative explanatory power of *RTI* in models explaining corporate cash holdings. Specifically, we map the industry-year measure of *RTI* to our firm-year panel according to the firms' historical industry code and include it in our baseline models in Table 3. Panel B of Table 7 summarizes the results.

Column (1) of Panel B presents 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 point estimate implies that a one-standard-deviation increase in *RTI* translates to a 2.84 percentage point decrease in *Cash holdings*.[27] 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 Panel B includes both *RTI* and *SLAC* as explanatory variables. *SLAC* is a significant factor in determining cash policy, and statistically subsumes *RTI*, indicating that *SLAC* is a more comprehensive construct of the potential to automate the workforce. To assess the relative significance of the substitutability of routine and non-routine-task labor, we regress the firm-year *SLAC* on the firm-year *RTI*, controlling for industry-by-year fixed effects to obtain a residual variable which we denote as *Orthogonal SLAC*. This residual, which is orthogonal to *RTI* by construction, captures the substitutability of only non-routine-task labor. The coefficient estimate on *Orthogonal SLAC* in Column (3) indicates that a one-standard-deviation increase in *Orthogonal SLAC* translates to a 2.37 percentage point decrease in *Cash holdings*. The estimated economic magnitude of the effect is comparable to that of *RTI* in Column (1), suggesting that the substitutability of non-routine-task labor accounts for about one-half of *SLAC*'s total effect on corporate liquidity policy.

5.3 Competition, governance, and other sources of heterogeneity

In this subsection, we consider the potential confounding effects of market competition, corporate governance, and other sources of heterogeneity on the relation between *SLAC* and liquidity policy. We first examine the impact of product market competition as Hoberg, Phillips, and Prabhala

[27] 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.

(2014) document that firms facing competitive threats adopt more conservative financial policies. Our tests, reported in Table IA.6 in the Internet Appendix, show that the relation between *SLAC* and cash holdings remains robust when we control for a host of proxies for market competition including the Hoberg et al. (2014) measure of product market fluidity, the Herfindahl-Hirschman Index (HHI) estimated for the Fama-French 48 industries, the Irvine and Pontiff (2009) measure of industry turnover, and the inventory-to-sales ratio.

We also evaluate the possibility that a firm's governance structures may be correlated with both its potential to automate and its cash holdings. The findings of Harford, Mansi, and Maxwell (2008) suggest that the quality of corporate governance is correlated with cash holdings. To account for any confounding effect of corporate governance on our empirical results, we control for several aspects of governance, including two indices of antitakeover provisions: the Gompers, Ishii, and Metrick (2003) index of twenty-four antitakeover provisions (*G-index*), and the Bebchuk, Cohen, and Ferrell (2009) entrenchment index based on a subset of these provisions (*E-index*). We also control for the number of directors on the board (*Board size*) and the proportion of independent directors on the board (*Board independence*). The results presented in Panel B of Table IA.6 indicate that the relation between *SLAC* and cash holdings remains statistically significant with these controls.

More generally, the relation between financial policies and the potential to automate may be confounded by unobservable firm or industry heterogeneity. 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 industry-year (two-digit SIC) and the set of control variables used in our baseline specifications in Table 3. Our matching is performed using a nearest-neighbor-matching algorithm with replacement. The results in Panel C of Table IA.6 support the conclusion that above-median *SLAC* is reliably associated with lower cash holdings.

We also isolate common sources of heterogeneity by examining subsamples of similar firms in Panel D of Table IA.6. First, to assess whether our results are identified out of the subset of firms with high variation in *SLAC* over time, we exclude firms with an above-median standard deviation of *SLAC* during the sample period. Second, we isolate 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 example, the IFR data suggest a rise in automation using robots in the manufacturing sector, and non-tradable sectors have seen an increasing emphasis on automation as opportunities for offshoring have declined. Our results 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 primary findings indicate that firms with higher substitutability of labor with automated capital (*SLAC*) hold significantly less cash. Our results obtain after controlling for a suite of fixed effects, and are robust to the use of alternative measures of *SLAC*, including *SLAC* fixed to the 1999 value; *SLAC* estimated using only an occupational employment weighting excluding wages; and segment-weighted *SLAC* that accounts for the industry composition of multi-segment firms.

To pin down the mechanism behind the relation between *SLAC* and cash holdings, we exploit the 2011–2012 flooding in Thailand. This natural disaster resulted in a marked increase in the cost of hard drives, an exogenous negative shock to the cost of automation that was orthogonal to omitted variables. Given this temporary increase in the cost of automation, we expect that the effect of *SLAC* on cash holdings will be weaker during the Thailand flooding for firms that rely heavily on computers and peripheral equipment for automation. Our evidence supports these predictions.

We reinforce the proposed mechanism with evidence that the empirical relation between *SLAC* and cash holdings is stronger for firms with a lower expected cost of worker displacement, and greater labor-induced operating leverage. These findings collectively support the notion that the prospective automation of labor tasks allows for less conservative financial policies such as precautionary cash holdings. Our analysis also provides evidence that, on average, firms with greater *SLAC* pay greater total dividends and are more reliant on dividends relative to share repurchases in their payout policy.

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 is an important determinant of a first-order corporate policy. 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. 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. Finally, our findings yield interesting implications for corporate 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 prospective automation may also have a bright side in that it reduces financial conservatism, enabling the financing of investment opportunities. Whether 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 OEWS, 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	A time-varying measure, between zero and one, for the substitutability of labor with automated capital. The industry-year measure $SLAC_{j,t}$ is constructed as the weighted average probability of computerization by Frey and Osborne across all occupational employment (weighted by wages) of an industry in a year using the employment and wage estimates from the OEWS. We map the industry-year measure $SLAC_{j,t}$ to Compustat firms according to their historical industry code to obtain the firm-year variable $SLAC_{i,t}$.
SLAC weighted by employment	A time-varying measure, between zero and one, for the substitutability of labor with automated capital. The industry-year measure is constructed as the weighted average probability of computerization by Frey and Osborne across all occupational employment of an industry in a year using only occupational employment (excluding wages) from the OEWS. We map the industry-year measure to Compustat firms according to their historical industry code to obtain the firm-year variable.
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 $SLAC_{j,t}$ 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	A time-varying measure of routine-task intensity, constructed as the weighted average occupational routine-task intensity of Autor and Dorn across all occupational employment (weighted by wages) of an industry in a year using the employment and wage estimates from the OEWS. We map the industry-year measure $RTI_{j,t}$ to Compustat firms according to their historical industry code to obtain the firm-year $RTI_{i,t}$.
Orthogonal SLAC	The residual from regressing firm-year $SLAC_{i,t}$ on firm-year $RTI_{i,t}$ controlling for industry-by-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	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.
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).
Common dividends/ total assets	Common dividends (dvc), 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 firm-year 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. We map the data to the firm-year panel according to firms' historical industry code.
Labor mobility	The flexibility of workers to walk away from an industry in a year 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. We map the data to the firm-year panel according to firms' historical industry code.
Union coverage	The percentage of employed workers of an industry in a year who are covered by a collective bargaining agreement. The data are obtained from the Union Membership and Coverage Database constructed by Hirsch and Macpherson (2003). The data are provided by the 1990 Census Industry Code (CIC) up to 2002, the 2002 CIC for the years 2003 to 2008, and the 2007 CIC for the years 2009 to present. We use the Census Bureau crosswalk to map the CIC code into three-digit SIC industry for 1999 to 2002 and four-digit NAICS industry for 2003 to 2018, and further map to the firm-year panel according to firms' historical industry code.
UI benefits	The maximum unemployment insurance benefits provided by a state in a year. 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 calculate *UI benefits* using the product of the maximum weekly benefit amount and the maximum benefit duration in weeks. To map the data to the firm-year panel, we identify a firm's state in a year 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.
Labor intensity	The ratio of selling, general and administrative expenses (xsga) to sales (sale).
Low-paid employee	The fraction of employed workers in an industry in a year with wage rates below the 10^{th} percentile of the entire wage distribution of employment in that year based on OEWS, following the method in Clemens et al. (2018). We map the data to the firm-year panel according to firms' historical industry code.
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). We map the data to the firm-year panel according to firms' historical industry code.
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-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-French 48 industry.
Inventory-to-sales	The ratio of inventory (invt) to sales (sale).

E-index	An index of six entrenchment provisions developed by Bebchuk, Cohen, and Ferrell (2009). Data come from Lucian Bebchuk's website.
G-index	An index of antitakeover provisions developed by Gompers, Ishii, and Metrick (2003). Data come from Andrew Metrick's website.
Board size	The number of directors on the board.
Board independence	The percentage of independent directors over the total number of directors.
Hard drive crisis variables	
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.
Hard drive price	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.

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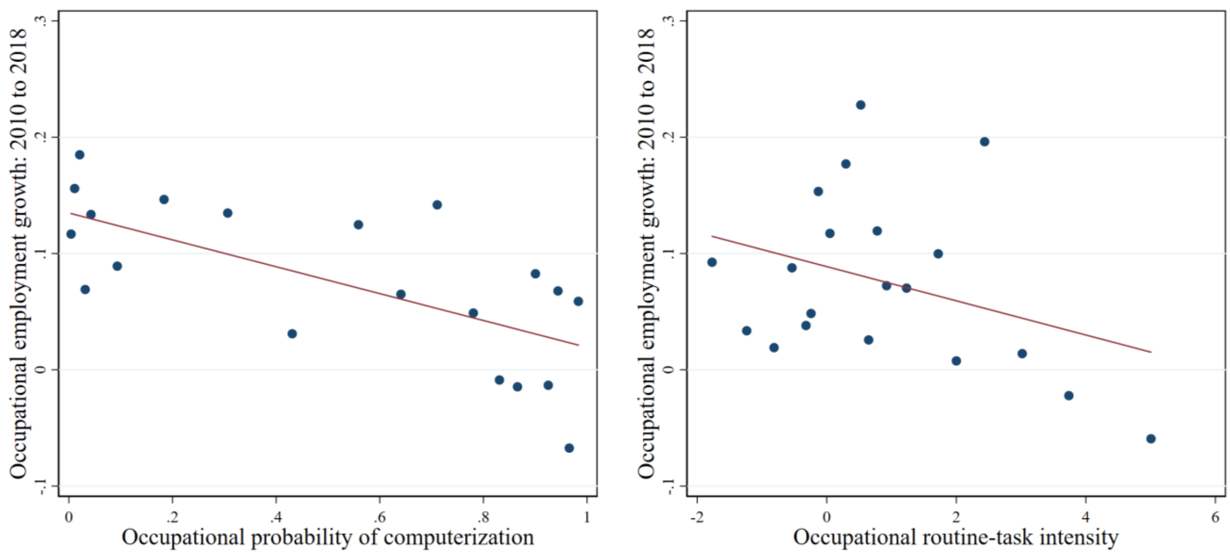
Figure 1. Validation of *SLAC* using employment outcomes and installations of industrial robots

This figure provides evidence to validate both the occupational probability of computerization and the industry-year *SLAC* measure. Panel A shows the binned scatter plots of the occupational employment changes from 2010 to 2018 relative to the occupational probability of computerization by Frey and Osborne (on the left), and the occupational routine-task intensity by Autor and Dorn (on the right). The unit of observation is at the 2010 SOC occupation level (o). Panel B shows the binned scatter plots of the total robot installations from 2010 to 2018 relative to industry-level *SLAC* in 2010 (on the left), and industry-level *RTI* in 2010 (on the right). The unit of observation is at the four-digit NAICS industry level (j). The definitions of all variables are provided in Appendix A.

Panel A: Employment outcomes



Panel B: Installations of industrial robots

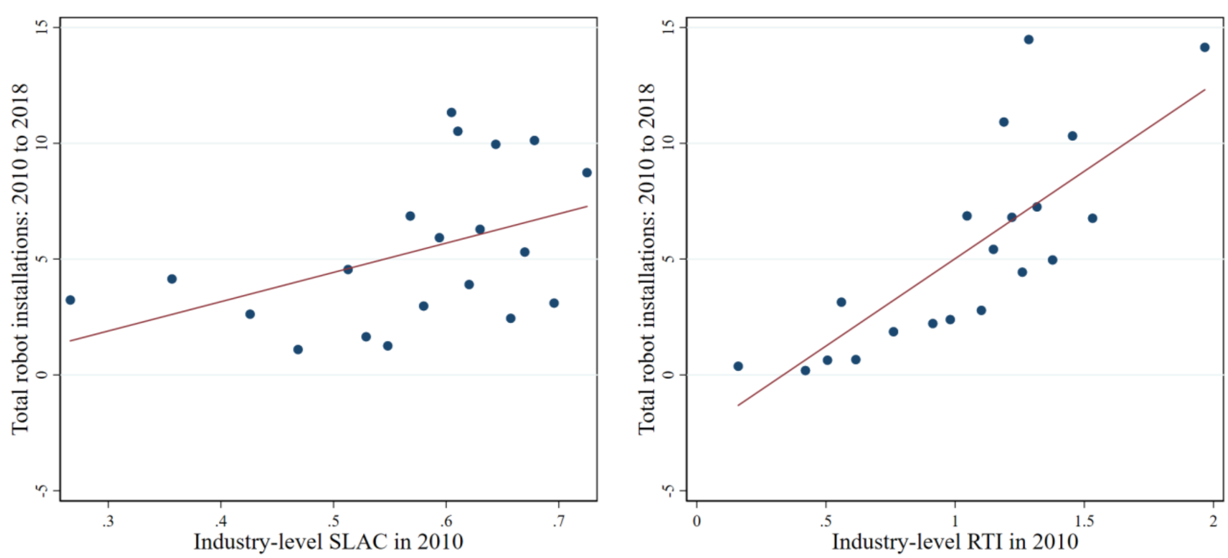
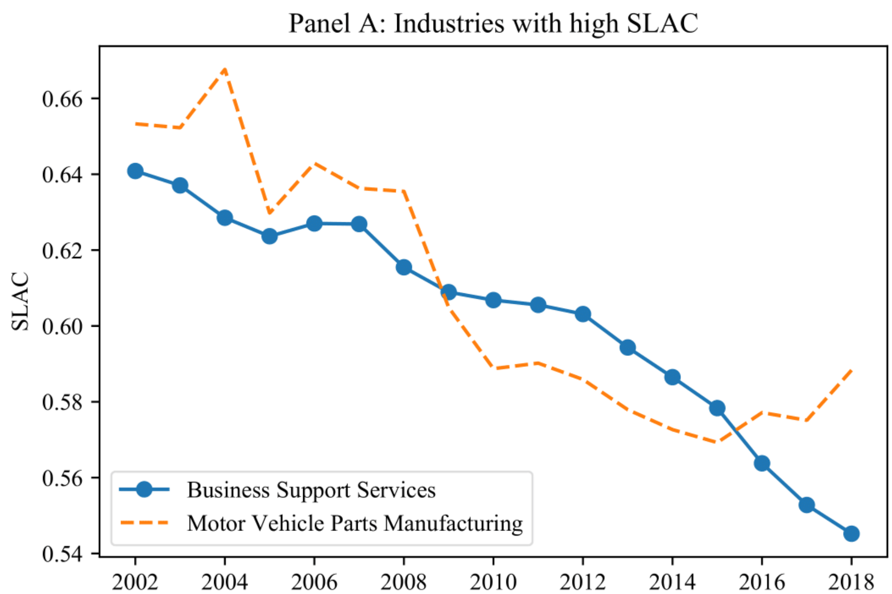


Figure 2. The evolution of *SLAC* for selected industries

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.



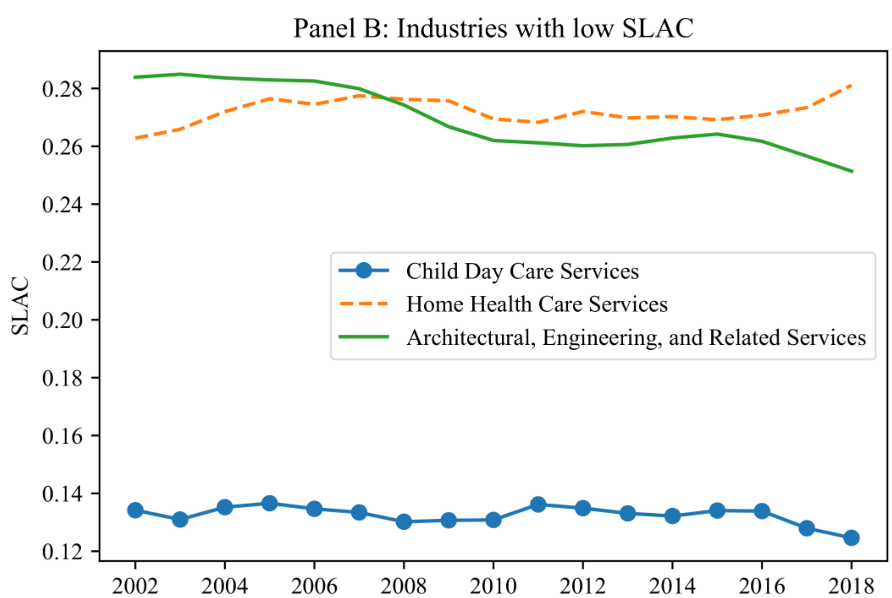
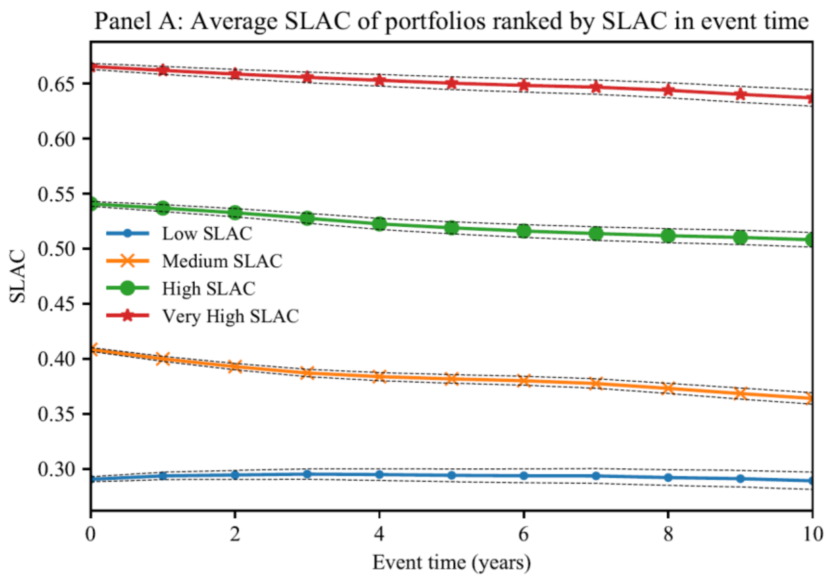


Figure 3. The persistence of *SLAC* over time

This figure presents evidence of the persistent nature of firm-level *SLAC*. Panel A plots the average *SLAC* of four portfolios in event time, where year zero is the portfolio formation period. For each calendar year from 1999 to 2008, we rank all firms into four portfolios based on their *SLAC* in that year. Holding the portfolios fixed for the next 10 years, we compute the average *SLAC* every year for each portfolio. We then average the average *SLAC*s by "event time" to obtain the bold lines in the figure. The surrounding dashed lines represent 95% confidence intervals. Panel B plots the transition matrix of firm-level *SLAC* over time. For each year, we rank all firms into four portfolios based on their *SLAC* in that year. We compute the transitional probability from one portfolio to another portfolio 10 years later, and average the transitional probability matrixes across 1999 to 2008. The height of the columns indicates the transitional probability from one group to another group. The x-axis (width) shows the partitions based on a current year and the y-axis (depth) shows the partitions based on 10 years later.



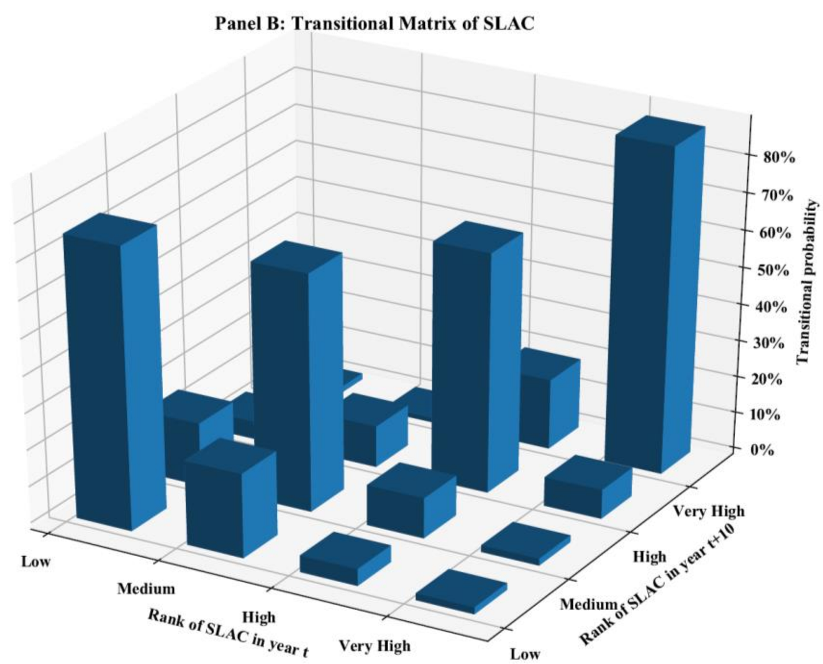


Figure 4. *SLAC* and cash holdings

This 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.

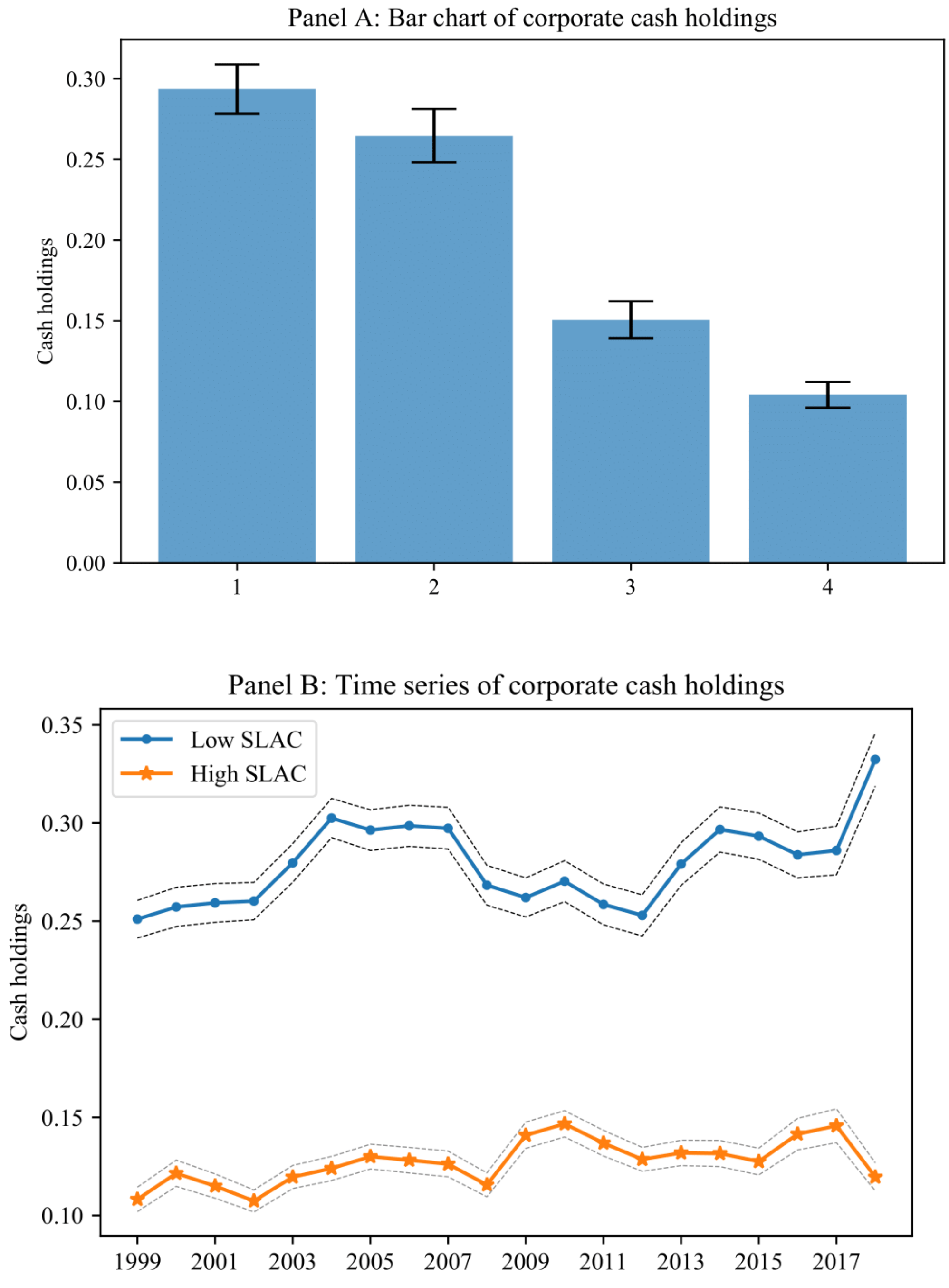


Figure 5. The 2011–2012 Thailand hard drive crisis as a shock to the cost of automation

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.

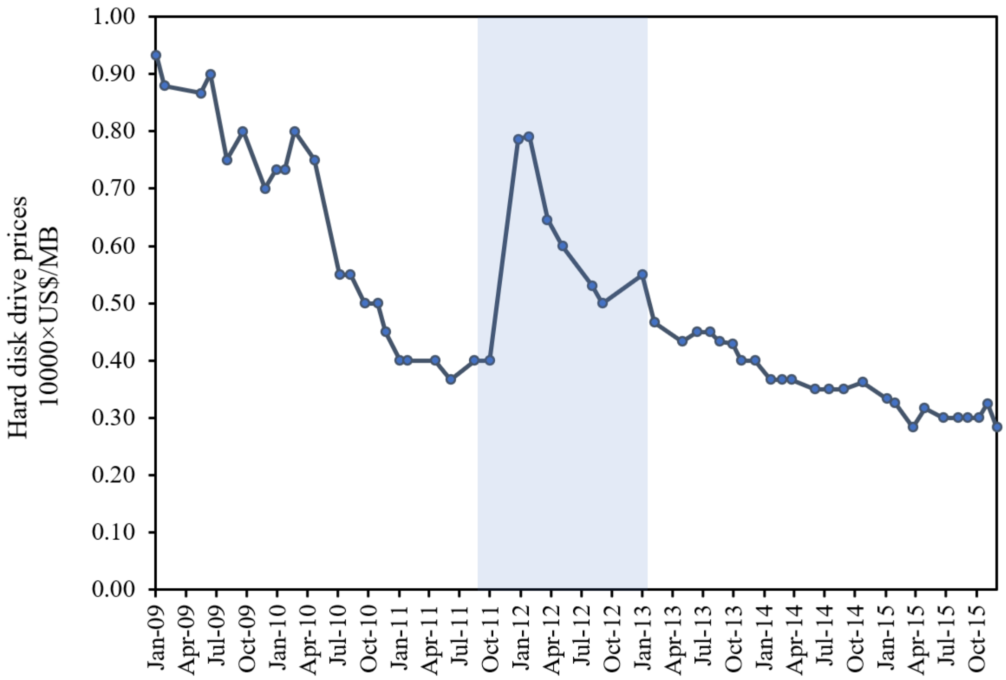


Table 1. Measuring *SLAC*: The substitutability of labor with automated capital

This table lists industries with the lowest and highest *SLAC* and provides evidence to validate both the occupational probability of computerization and the industry-year *SLAC* measure. Panel A lists the bottom and top 15 industries (defined by four-digit NAICS) sorted by average industry-level *SLAC* over our sample period. Panel B examines the relation between occupational employment changes from 2010 to 2018 and the probability of computerization by Frey and Osborne and the routine-task intensity by Autor and Dorn, both at the occupation level. The unit of observation is at the 2010 SOC occupation level (o). We use the employment data starting from 2010 for this panel because the probability of computerization is estimated for the 2010 SOC occupations. Panel C examines the relation between total robot installations from 2010 to 2018 and the operational stock of robots in 2018 of an industry, and the industry-level *SLAC* and *RTI* in 2010. The unit of observation is at the four-digit NAICS industry level (j). 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$_o$	-0.116***		-0.106***	-0.139***		-0.122***
	(0.032)		(0.036)	(0.038)		(0.041)
Routine-task intensity by Autor and Dorn$_o$		-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: Installations and operational stock of industrial robots

	Total robot installations from 2010 to 2018$_j$			*Operational stock of robots in 2018$_j$*		
	(1)	(2)	(3)	(4)	(5)	(6)
$SLAC_{j,2010}$	12.646**		1.720	17.574**		3.908
	(6.044)		(4.099)	(7.351)		(4.818)
$RTI_{j,2010}$		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
$SLAC_{i,t}$	96,039	0.464	0.455	0.150	0.266	0.662
$SLAC_{i,1999}$	91,499	0.492	0.499	0.130	0.281	0.649
SLAC weighted by employment$_{i,t}$	96,039	0.573	0.581	0.142	0.368	0.742
Segment sales-weighted SLAC$_{i,t}$	96,039	0.464	0.458	0.147	0.269	0.659
$SLAC_{i,2010}$	92,654	0.453	0.420	0.155	0.228	0.667
RTI	96,039	0.881	0.841	0.481	0.257	1.416
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
Common dividends/total assets	96,039	0.009	0.000	0.024	0.000	0.029
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:

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

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; $\mu_{j,t}$ represents various sets of fixed effects detailed as follows. The unit of observation is at the firm(*i*)-year(*t*) level. Column (1) includes industry (two-digit SIC) and year fixed effects; Column (2) includes industry-specific time trends; Column (3) includes a full set of industry-by-year fixed effects; Column (4) includes firm and year fixed effects. Panel A reports the baseline estimates. Panel B reports robustness checks to Panel A when we replace $SLAC_{i,t}$ with three alternative measures: (1) an ex-ante time-invariant measure fixed in year 1999 (the initial year of our sample period), (2) *SLAC* weighted by employment where we reconstruct *SLAC* using only occupational employment data as the weights in Equation (1) without wage data, and (3) the segment sales-weighted *SLAC* where we incorporate the firm-specific segment sales-weighted *SLAC* for multi-segment firms. 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.

Panel A: Baseline estimates

	Cash holdings			
	(1)	(2)	(3)	(4)
$SLAC_{i,t}$	-0.344***	-0.353***	-0.362***	-0.054**
	(0.074)	(0.074)	(0.076)	(0.021)
Cash flow	0.010***	0.010***	0.010***	0.017***
	(0.002)	(0.002)	(0.002)	(0.005)
Net working capital	-0.025***	-0.025***	-0.026***	-0.012**
	(0.006)	(0.006)	(0.005)	(0.005)
Capital expenditures	-0.300***	-0.308***	-0.316***	-0.211***
	(0.067)	(0.068)	(0.068)	(0.040)
Leverage	-0.114***	-0.114***	-0.113***	-0.055***
	(0.009)	(0.009)	(0.009)	(0.007)
Acquisitions	-0.397***	-0.399***	-0.405***	-0.226***
	(0.059)	(0.059)	(0.058)	(0.040)
Market to book	0.005***	0.005***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.007***	-0.007***	-0.007***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.004)
Ind. CF volatility	-0.000	-0.001		-0.000
	(0.001)	(0.001)		(0.000)
R&D expenditures	0.016***	0.016***	0.016***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Dividend payer	-0.037**	-0.037**	-0.037**	0.011***
	(0.014)	(0.014)	(0.014)	(0.002)
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	96,039	96,039	95,965	96,039
R-squared	0.366	0.370	0.374	0.785

Panel B: Alternative measures of *SLAC*

	Cash holdings			
	(1)	(2)	(3)	(4)
$SLAC_{i,1999}$	-0.251***	-0.253***	-0.253***	-0.129***
	(0.076)	(0.077)	(0.077)	(0.031)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	91,499	91,499	91,439	91,499
R-squared	0.347	0.350	0.353	0.782
SLAC weighted by employment$_{i,t}$	-0.333***	-0.341***	-0.349***	-0.046*
	(0.066)	(0.065)	(0.068)	(0.023)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	96,039	96,039	95,965	96,039
R-squared	0.364	0.367	0.372	0.785
Segment sales-weighted SLAC$_{i,t}$	-0.363***	-0.373***	-0.381***	-0.055**
	(0.076)	(0.075)	(0.078)	(0.025)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	96,039	96,039	95,965	96,039
R-squared	0.367	0.371	0.376	0.785

Table 4. Evidence on the mechanism: 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:

$$Y_{i,t} = \beta_0 + \beta_1\, Flooding_t \times SLAC_{i,2010} + \beta_2\, SLAC_{i,2010} + \gamma'\, X + \mu_{j,t} + \varepsilon_{i,t},$$

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; $SLAC_{i,2010}$ is the substitutability of labor with automated capital of firm *i* in year 2010. The unit of observation is at the firm(*i*)-year(*t*) level. Column (1) presents the baseline estimates. In column (2), we replace the dummy variable $Flooding_t$ with $Hard\ drive\ price_t$, 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. In columns (3) and (4), we conduct robustness checks by replacing $SLAC_{i,2010}$ with the time-varying $SLAC_{i,t}$. In panel A, the estimates are performed on the sample of firms that heavily rely on computers for automation, i.e., 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. In panel B, we exclude 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. 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.

Panel A: Baseline estimates

	Cash holdings			
	(1)	(2)	(3)	(4)
$SLAC_{i,2010} \times Flooding_t$	0.074**			
	(0.029)			
$SLAC_{i,2010} \times Hard\ drive\ price_t$		0.109***		
		(0.029)		
$SLAC_{i,t} \times Flooding_t$			0.087***	
			(0.023)	
$SLAC_{i,t} \times Hard\ drive\ price_t$				0.113***
				(0.023)
$SLAC_{i,2010}$	-0.332***	-0.326***		
	(0.053)	(0.051)		
$SLAC_{i,t}$			-0.344***	-0.337***
			(0.051)	(0.049)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	26,455	26,455	27,797	27,797
R-squared	0.343	0.343	0.345	0.345

Panel B: Excluding firms in the hard drive industry and their major customers and suppliers

	Cash holdings			
	(1)	(2)	(3)	(4)
$SLAC_{i,2010} \times Flooding_t$	0.065**			
	(0.030)			
$SLAC_{i,2010} \times Hard\ drive\ price_t$		0.103***		
		(0.032)		
$SLAC_{i,t} \times Flooding_t$			0.079***	
			(0.023)	
$SLAC_{i,t} \times Hard\ drive\ price_t$				0.107***
				(0.026)
$SLAC_{i,2010}$	-0.327***	-0.322***		
	(0.054)	(0.052)		
$SLAC_{i,t}$			-0.339***	-0.333***
			(0.051)	(0.049)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	24,074	24,074	25,395	25,395
R-squared	0.349	0.349	0.350	0.350

Table 5. 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. We augment the baseline model with cross-sectional characteristics using the following specification:

$$Y_{i,t} = \beta_0 + \beta_1\, SLAC_{i,t} + \beta_2\, Characteristic_{i,t} \times SLAC_{i,t} + \beta_3\, Characteristic_{i,t} + \gamma'\, X + \mu_{j,t} + \varepsilon_{i,t},$$

where *Characteristics* includes *Union coverage*, *UI benefits*, *Labor intensity*, and *Low-paid employee*; the unit of observation is at the firm (i)-year (t) level. *Union coverage* is the percentage of employed workers of an industry in a year who are covered by a collective bargaining agreement obtained from the Union Membership and Coverage Database. We map the data from the Census Industry Code (CIC) to three-digit SIC industry for 1999 to 2002 and four-digit NAICS industry for 2003 to 2018 using the Census Bureau crosswalk. *UI benefits* is the maximum unemployment insurance (UI) benefits provided by a state in a year. To map the data to the firm-year level, 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. *Labor intensity* is the ratio of Selling, general and administrative (SG&A) expense to sales at the firm-year level from Compustat. *Low-paid employee* is the fraction of employed workers in an industry in a year with wage rates below the 10th percentile of the entire wage distribution of employment in that year based on OEWS. We include the same set of firm-level controls as in Table 3 and the full set of industry-by-year 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)
$SLAC_{i,t}$	-0.428***	0.017	-0.355***	-0.370***
	(0.072)	(0.141)	(0.051)	(0.077)
$SLAC_{i,t}$ × *Union coverage*	1.554***			
	(0.487)			
Union coverage	-0.995***			
	(0.350)			
$SLAC_{i,t}$ × *UI benefits*		-0.161**		
		(0.069)		
UI benefits		0.113***		
		(0.038)		
$SLAC_{i,t}$ × *Labor intensity*			-0.078***	
			(0.023)	
Labor intensity			0.086***	
			(0.012)	
$SLAC_{i,t}$ × *Low-paid employee*				0.920***
				(0.206)
Low-paid employee				-0.637***
				(0.145)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	95,806	69,395	85,222	95,965
R-squared	0.377	0.373	0.302	0.375

Table 6. Are high-*SLAC* firms in the process of automating?

This table presents evidence that the connection between *SLAC* and cash holdings does not appear to be driven by firms in the process of automation. In panel A, we drop firms that are possibly in the process of automation. Column (1) restricts the sample to firms that experience an average declining capital-labor ratio based on the most recent three years of data. Column (2) restricts the sample to firms that experience an average increasing *SLAC* based on the most recent three years of data. Columns (3) and (4) drop firms that are possibly industry leaders in workplace automation. In column (3), a firm is identified as an automation leader if it experiences an average increasing capital-labor ratio and an average decreasing *SLAC* based on the most recent three years of data. In column (4), 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. We include the same set of firm-level controls as in Table 3 and the full set of industry-by-year fixed effects. Panel B reports results on the relation between a firm's *SLAC* and its payout policy. We measure payout policy using *Common dividends/total assets* in Column (1), *Common dividends/total payout* in Column (2), Log(1+*common dividends*) in Column (3), and Log(1+*total dividends*) in Column (4). The dollar variables in columns (3) and (4) are deflated to 1999 dollars. 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: Estimates for subsamples of firms that are not in the process of automating

	Cash holdings			
	(1)	(2)	(3)	(4)
$SLAC_{i,t}$	-0.375***	-0.362***	-0.375***	-0.369***
	(0.085)	(0.077)	(0.085)	(0.077)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	15,452	23,506	35,638	66,562
R-squared	0.375	0.400	0.388	0.379

Panel B: *SLAC* and payout policy

	Common dividends/ total assets	*Common dividends/ total payout*	Log(1+*common dividends*)	Log(1+*total dividends*)
	(1)	(2)	(3)	(4)
$SLAC_{i,t}$	0.013***	0.505***	0.989***	0.947***
	(0.004)	(0.129)	(0.352)	(0.345)
Size	0.002***	0.041***	0.427***	0.435***
	(0.000)	(0.004)	(0.036)	(0.036)
Tangibility	0.002	0.193***	0.129	0.123
	(0.002)	(0.048)	(0.192)	(0.185)
Cash flow	-0.000	-0.022***	-0.239***	-0.247***
	(0.000)	(0.006)	(0.027)	(0.027)
Tobin's q	0.000***	0.002*	0.024***	0.022***
	(0.000)	(0.001)	(0.005)	(0.005)
Leverage	-0.002***	-0.075***	-0.039	-0.017
	(0.001)	(0.019)	(0.045)	(0.037)
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	95,941	49,904	95,940	95,886
R-squared	0.134	0.210	0.428	0.431

Table 7. Controlling for other labor related characteristics and routine-task intensity (RTI)

This table presents evidence that the connection between *SLAC* and cash holdings is not driven by other labor related characteristics. Panel A reports OLS regression estimates on the relation between *SLAC* and cash holdings, 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* and *Low-paid employee* are defined the same as in Table 5. *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 the full set of industry-by-year fixed effects. Panel B 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-by-year fixed effects. We include the same set of firm-level controls as in Table 3 and the full set of industry-by-year 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 other labor-related characteristics

	Cash holdings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$SLAC_{i,t}$	-0.317***	-0.295**	-0.358***	-0.343***	-0.361***	-0.293***	-0.272**
	(0.059)	(0.123)	(0.072)	(0.066)	(0.078)	(0.085)	(0.109)
Capital intangibility	0.127***						0.130**
	(0.045)						(0.050)
Labor skill		0.054					-0.035
		(0.060)					(0.087)
Labor mobility			-0.011				-0.019
			(0.013)				(0.014)
Union coverage				-0.185*			-0.029
				(0.106)			(0.068)
Low-paid employee					-0.016		-0.036
					(0.045)		(0.039)
Offshorability						0.043***	0.048***
						(0.015)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind×Year	Ind×Year	Ind×Year	Ind×Year	Ind×Year	Ind×Year	Ind×Year
Observations	94,411	92,194	76,573	95,806	95,965	95,965	75,872
R-squared	0.376	0.369	0.365	0.376	0.374	0.376	0.381

Panel B: Differentiating from routine-task intensity (RTI)

	Cash holdings		
	(1)	(2)	(3)
$SLAC_{i,t}$		-0.353***	
		(0.096)	
$RTI_{i,t}$	-0.059***	-0.004	
	(0.016)	(0.015)	
Orthogonal $SLAC_{i,t}$			-0.349***
			(0.123)
Controls	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year
Observations	95,965	95,965	95,965
R-squared	0.364	0.374	0.367

Workplace Automation and Corporate Liquidity Policy

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 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				
$SLAC_{i,t}$	-0.209***	-0.216***	-0.217***	-0.053**
	(0.053)	(0.052)	(0.053)	(0.021)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	18,866	18,866	18,761	18,866
R-squared	0.284	0.290	0.308	0.788
Multi-segment firms using the segment sales-weighted *SLAC*				
Segment sales-weighted $SLAC_{i,t}$	-0.259***	-0.267***	-0.269***	-0.079**
	(0.055)	(0.054)	(0.054)	(0.034)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	18,866	18,866	18,761	18,866
R-squared	0.288	0.294	0.312	0.788
Chi-squared test of equal coefficients	12.10***	11.88***	11.07***	2.01
P-value of the Chi-squared test	[0.001]	[0.001]	[0.001]	[0.156]

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 upper panel reports results derived from the sample of Compustat firms from 1979–1998, and the lower panel for 1979–1989. We include the same set of firm-level controls and fixed effects as in Table 3. We also report the Chi-squared test and the p-value to test for equal coefficient estimates between each panel and the baseline tests 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)
Sample of 1979–1998				
$SLAC_{i,1999}$	-0.102***	-0.099***	-0.099***	-0.012
	(0.035)	(0.035)	(0.035)	(0.027)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	88,883	88,883	88,850	88,883
R-squared	0.414	0.417	0.423	0.751
Chi-squared test of equal coefficients	11.5***	10.81***	10.56***	10.27***
P-value of the Chi-squared test	[0.001]	[0.001]	[0.001]	[0.001]
Sample of 1979–1989				
$SLAC_{i,1999}$	-0.058**	-0.058**	-0.058**	0.003
	(0.027)	(0.028)	(0.028)	(0.021)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind + Year	Ind-trends	Ind × Year	Firm + Year
Observations	44,176	44,176	44,163	44,176
R-squared	0.352	0.355	0.362	0.754
Chi-squared test of equal coefficients	8.26***	8.02***	7.92***	15.14***
P-value of the Chi-squared test	[0.004]	[0.005]	[0.005]	[0.000]

Table IA.3. The benefits and costs of automation: Robustness checks

This table presents robustness checks to Table 5. In Panel A, we replace $SLAC_{i,t}$ with *SLAC weighted by employment*, constructed using only occupational employment weights (excluding wages). In Panel B, we replace $SLAC_{i,t}$ with $SLAC_{i,2010}$. 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* weighted by employment

	Cash holdings			
	(1)	(2)	(3)	(4)
SLAC weighted by employment	-0.380***	-0.037	-0.323***	-0.352***
	(0.058)	(0.158)	(0.052)	(0.069)
SLAC weighted by employment × *Union coverage*	0.844*			
	(0.486)			
Union coverage	-0.747**			
	(0.359)			
SLAC weighted by employment × *UI benefits*		-0.132*		
		(0.071)		
UI benefits		0.115**		
		(0.047)		
SLAC weighted by employment × *Labor intensity*			-0.056**	
			(0.023)	
Labor intensity			0.083***	
			(0.013)	
SLAC weighted by employment × *Low-paid employee*				0.841***
				(0.223)
Low-paid employee				-0.658***
				(0.171)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	95,806	69,395	85,222	95,965
R-squared	0.375	0.370	0.341	0.372

Panel B: *SLAC* fixed in year 2010

	Cash holdings			
	(1)	(2)	(3)	(4)
$SLAC_{i,2010}$	-0.428***	-0.030	-0.377***	-0.383***
	(0.078)	(0.119)	(0.050)	(0.082)
$SLAC_{i,2010}\times$ *Union coverage*	1.374***			
	(0.449)			
Union coverage	-0.886***			
	(0.299)			
$SLAC_{i,2010}\times$ *UI benefits*		-0.149**		
		(0.067)		
UI benefits		0.105***		
		(0.036)		
$SLAC_{i,2010}\times$ *Labor intensity*			-0.094***	
			(0.022)	
Labor intensity			0.092***	
			(0.012)	
$SLAC_{i,2010}\times$ *Low-paid employee*				0.773***
				(0.218)
Low-paid employee				-0.520***
				(0.155)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	92,420	66,799	82,323	92,578
R-squared	0.384	0.381	0.348	0.382

Table IA.4. *SLAC* and lagged financial policies

This table presents additional evidence relating *SLAC* to lagged measures of cash holdings. 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 the full set of industry-by-year 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)
$SLAC_{i,t}$	-0.372***	-0.384***	-0.388***
	(0.081)	(0.087)	(0.090)
Controls	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year
Observations	93,861	76,326	66,067
R-squared	0.349	0.337	0.327

Table IA.5. *SLAC* and the marginal value of cash holdings

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

$$r_{i,t} - R^B_{i,t} = \beta_0 + \beta_1 \Delta Cash_{i,t} + \beta_2 SLAC_{i,t} \times \Delta Cash_{i,t} + \beta_3 SLAC_{i,t} + \gamma' X + \mu_{j,t} + \varepsilon_{i,t},$$

where $r_{i,t} - R^B_{i,t}$ 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); $\mu_{j,t}$ are a full set of industry-by-year 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*	1.749***	1.520***	1.691***	1.516***
	(0.110)	(0.102)	(0.107)	(0.102)
$SLAC_{i,t}$ × Δ *Cash*	-0.538**		-0.412*	
	(0.213)		(0.234)	
$SLAC_{i,t}$	0.122**		0.146***	
	(0.049)		(0.052)	
Δ *Earnings*	0.177***	0.176***	0.174***	0.173***
	(0.030)	(0.030)	(0.030)	(0.030)
Δ *Net assets*	0.153***	0.152***	0.150***	0.150***
	(0.015)	(0.015)	(0.015)	(0.015)
Δ *R&D*	-0.323	-0.299	-0.389	-0.367
	(0.358)	(0.357)	(0.330)	(0.329)
Δ *Interest*	-0.531***	-0.536***	-0.551***	-0.555***
	(0.194)	(0.196)	(0.203)	(0.204)
Δ *Dividends*	1.694***	1.695***	1.688***	1.690***
	(0.230)	(0.231)	(0.236)	(0.236)
Lag cash	0.316***	0.310***	0.341***	0.335***
	(0.020)	(0.019)	(0.020)	(0.019)
Net financing	-0.095**	-0.093**	-0.103***	-0.101***
	(0.036)	(0.036)	(0.036)	(0.036)
Mkt leverage	-0.591***	-0.583***	-0.546***	-0.537***
	(0.036)	(0.035)	(0.032)	(0.031)
Δ *Cash* × *Lag cash*	-0.380***	-0.373***	-0.397***	-0.392***
	(0.062)	(0.061)	(0.061)	(0.061)
Mkt leverage × Δ *Cash*	-1.117***	-1.194***	-1.061***	-1.116***
	(0.176)	(0.187)	(0.178)	(0.182)
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	31,951	31,951	33,290	33,290
R-squared	0.249	0.249	0.241	0.241

Table IA.6. Accounting for market competition, governance, and other sources of heterogeneity

This table presents additional evidence that the connection between *SLAC* and cash holdings is not driven by market competition, corporate governance, and other sources of heterogeneity. Panel A controls for various measures of market competition including *Product market fluidity*, *HHI*, *Industry turnover*, and *Inventory-to-sales*. Panel B controls for a set of measures of corporate governance including *E-index* developed by Bebchuk, Cohen, and Ferrell (2009), *G-index* developed by Gompers, Ishii, and Metrick (2003), *Board size* defined as the number of directors on the board, and *Board independence* which is the percentage of independent directors over the total number of directors. Panel C 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. Matching is based on nearest-neighbor-matching with a caliper of 0.01, and with replacement. Panel D reports results 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); Control (5) restricts the sample period to 2002 and after. We include the same set of firm-level controls as in Table 3 and the full set of industry-by-year fixed effects. Standard errors are either bootstrapped or clustered at the industry level. ***, **, 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				
	(1)	(2)	(3)	(4)	(5)
$SLAC_{i,t}$	-0.222***	-0.370***	-0.362***	-0.350***	-0.214***
	(0.047)	(0.080)	(0.076)	(0.071)	(0.048)
Product market fluidity	0.017***				0.017***
	(0.005)				(0.004)
HHI		-0.170**			-0.128**
		(0.083)			(0.060)
Industry turnover			0.028		0.047
			(0.026)		(0.029)
Inventory-to-sales				-0.146***	-0.120***
				(0.034)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	55,564	84,093	95,576	95,232	54,614
R-squared	0.519	0.365	0.375	0.384	0.523

Panel B: Controlling for corporate governance

	Cash holdings				
	(1)	(2)	(3)	(4)	(5)
$SLAC_{i,t}$	-0.316***	-0.376***	-0.213***	-0.220***	-0.177***
	(0.065)	(0.082)	(0.042)	(0.044)	(0.053)
E-index	-0.006*				-0.002
	(0.003)				(0.004)
G-index		-0.004**			-0.003
		(0.002)			(0.002)
Board size			-0.006***		-0.010***
			(0.002)		(0.003)
Board independence				0.001	0.018
				(0.011)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	3,687	3,032	16,256	16,256	2,133
R-squared	0.577	0.515	0.525	0.521	0.600

Panel C: Propensity score matching

	Firms with above-median *SLAC*	Matched firms with below-median *SLAC*	Difference (bootstrapped standard errors)	Difference (standard errors clustered at industry level)
Cash holdings				
Mean	0.147	0.208	-0.060***	-0.060***
Observations	26,798	26,798		

Panel D: Subsample analysis

	Cash holdings				
	Non-volatile *SLAC*	Mature firms	Manufacturing	Nontradable	2002 and after
	(1)	(2)	(3)	(4)	(5)
$SLAC_{i,t}$	-0.299***	-0.298***	-0.465***	-0.285***	-0.371***
	(0.061)	(0.082)	(0.152)	(0.082)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	45,947	45,643	46,604	38,289	78,917
R-squared	0.339	0.354	0.400	0.295	0.380