ROBOTS, LABOR MARKET FRICTIONS, AND CORPORATE FINANCIAL POLICIES

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DEDICATION

To my husband Hekun, mom, dad, and my family in China,

for their love, accompany, and support.

I love you.

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ABSTRACT

Using a novel dataset from the International Federation of Robotics (IFR), I find that robots can transform the labor market landscape and mitigate the impact of labor market frictions on financial policy decisions. Firms with more robots, which reduce labor adjustment costs and operational risk, have higher financial leverage and hold less cash. Such firms rely less on employees and attach less importance to gaining bargaining advantages over unions. The effects of robots on corporate financial policies are stronger for firms with more blue-collar workers. When facing greater foreign competition, firms with more robots are able to adopt less conservative financial policies. The effects of minimum wage increases on corporate financial policies are weaker for firms with more robots.

1. Introduction

Labor inputs have played an increasingly important role in economic growth. Labor market frictions are important factors in the corporate decision-making process (Agrawal and Matsa (2013)). Labor market frictions, such as labor adjustment expenses, firing costs, human costs of bankruptcy, and labor mobility can raise operational risk, crowd out financial leverage, hurt firm value, increase precautionary cash holdings, and refrain investments.[1] The rapid spread of robotics technologies, however, may transform the labor market landscape.

The fast spread of robot technologies could bring "technological unemployment," the loss of jobs caused by technological change (Keynes (1930)). The impressive advances in robotics and artificial intelligence in the 1990s and 2000s bring a renewed concern over these predictions (e.g., Ford (2015) and Brynjolfsson et al. (2014)). About 46,100 industrial robots were shipped to the United States in 2017 — 12% more than in 2016 — reaching a new peak for the seventh year in a row (IFR (2018)). The operational robot stock in the U.S. was about 323,600 units at the end of 2017. Production procedures are becoming more automated as robotic technologies progress. Workers can be substituted by new robots, which can perform complicated tasks, previously performed by humans, faster and more efficiently. Robots decrease the need for human labor and make firms' operations more flexible (Dauth et al. (2018)).

In this paper, I investigate how robots influence corporate financial policies. On one hand, greater penetration of robots may negatively affect wages and employment since robots take over tasks that workers were previously performing (Acemoglu and Restrepo (2017)). Compared to labor costs, robot prices have fallen, and robots have

[1] For example, see Simintzi et al. (2015), Ghaly et al. (2017), Klasa et al. (2009), and Serfling (2016).

more flexibility than human capital. Greater penetration of robots can reduce firms' dependence on workers, cut labor adjustment costs, and decrease the effect of labor market frictions on financial policy decisions. Firms with more robots can have lower operational risk and adopt more aggressive financial policies, such as higher financial leverage and lower cash holdings. On the other hand, greater penetration of robots can also positively affect wages and employment since the creation of new tasks may increase the demand for labor. The automation, especially of a range of low-skill and medium-skill occupations, may enable firms to create more new tasks for which labor has a comparative advantage. In this scenario, greater penetration of robots can amplify firms' reliance on workers. Firms with more robots have higher labor adjustment costs and adopt more conservative financial policies, such as lower financial leverage and higher cash holdings.

To examine the impact of robots on corporate financial policies empirically, I use a new dataset from the International Federation of Robotics (IFR). The IFR defines an industrial robot as "an automatically controlled, reprogrammable, and multipurpose manipulator" (IFR (2018)). A robot is an actuated mechanism with a degree of autonomy that does not need human intervention and that can be programmed to perform manual tasks such as welding, painting, assembling, handling materials, or packaging. Some machines, including textile looms, elevators, or transportation bands, are not industrial robots because they cannot be reprogrammed to perform other tasks, and/or they require human intervention. This definition hereby excludes other kinds of equipment and allows for an internationally and comparable measurement of "industrial robot" technologies. Moreover, these characteristics indicate that robots are different from earlier automation and from information and communication technologies (ICT), which left flexible three-dimensional movement to humans.

Using a sample of US public firms between 1993 and 2015, I first look at how changes in financial leverage are associated with changes in robot penetration and how changes in cash holdings are linked with variations in robot penetration. I start by conducting multivariate panel regressions of leverage and cash holdings on robot penetration. Using firm fixed effects to control for unobserved, time-invariant differences across firms in leverage, cash holdings, and robot penetration and using year fixed effects to control for common time trends, I find that firms with more robots have higher financial leverage and hold less cash. Given that firms facing greater labor frictions generally adopt more conservative financial policies, the results are consistent with the hypothesis that robots mitigate the impact of labor frictions on financial policy decisions. However, alternative explanations of these results may exist. For example, an omitted factor, such as firm characteristics, could affect both robot penetration and firms' financial policies. By introducing an instrumental variable drawing from Graetz et al. (2018) — replaceability — to estimate the causal effects of robot penetration on firms' financial policies, I confirm that more robots lead to higher financial leverage and less precautionary cash. Replaceability measures the portion of hours worked in each industry that can be replaced by robots. IFR robot data classify the robots' applications. I match these robot application data to U.S. occupations data in 1980 (before robots became widespread) and define occupations as "replaceable" if by 2017 their work could have been replaced by robots. [2] I then calculate the fraction of hours worked in each industry in 1980 that were performed by occupations that subsequently became susceptible to replacement by robots. In order for my instrument variable to predict robot penetration, there needs to be sufficient variation in replaceability among different firms. My data confirm the

[2] Since the extent of robot use in these tasks may be endogenous to industry characteristics, I don't use this information to construct the instrument.

existence of meaningful variation in replaceability. The validity of the instrumental variable approach rests on the feature that the robot capability is driven by technological supply factors, not by corporate financial policies. Although this instrument may not address all possible problems of omitted variables and reverse causality, it provides additional checks on my empirical approach. I acknowledge that the instrument is not perfect because it reflects variation across industries in terms of the fraction of tasks that could potentially be replaced by robots, which may be correlated with other changes over time, so I interpret my findings cautiously. These instrumental variable estimates are sometimes larger than my OLS estimates, consistent with the presence of measurement error in my measure of robot adoption.

To further support the hypothesis that robots mitigate the effect of labor market frictions on financial policy decisions, I examine the influence of robot penetration on the relationship between labor unionization and leverage and on the relationship between labor unionization and cash holdings. Firms in more unionized industries strategically have higher financial leverage and hold less cash to gain bargaining advantages over labor unions (Matsa (2010) and Klasa et al. (2009)). Since firms with robots rely less on employees and may attach less importance to gaining a bargaining advantage over unions, I expect that the positive relationship between corporate financial leverage and the union's bargaining power, as well as the negative relationship between corporate cash holdings and the union's bargaining power, are weaker for firms with more robots. Over the 1993-2015 period, I find strong support for this prediction. The results hold after controlling for profitability, leverage, and a number of other control variables.

My findings suggest that robots reduce firms' reliance on workers and mitigate the impact of labor frictions. The marginal value of an extra dollar of cash is declining, and cash holdings are less valuable in more unionized industries (Klasa et al. (2008)

and Faukendar et al. (2006)). If my hypothesis holds, I would expect that for firms with more robots, the negative relationship between unionization and the contribution of cash holdings to firm value is weaker. To test this hypothesis, I use the Faulkender and Wang (2006) methodology that relates changes in cash holdings to changes in the market value of a firm, measured by excess stock returns. The results are consistent with my hypothesis.

To better understand the effect of robot penetration on corporate financial policies, I also examine the impact of robot penetration on blue-collar workers and corporate financial policies. Many routine tasks that were traditionally performed by less-educated workers, such as assembly workers in a factory, are more likely to be replaced by robots (Autor et al. (2003) and Michaels et al. (2014)). Blue-collar workers are more likely to be replaced by robots (Rotman (2017)). I expect that the effects of robots on leverage and cash holdings are stronger for firms with more blue-collar workers. Following Klasa et al. (2009), I construct the blue-collar worker ratio and find strong evidence consistent with my hypothesis.

In further tests, I examine the impact of robots and foreign competition on corporate financial policies. The competitive threats faced by a firm threatens the stability of that company's future cash flows (Hoberg et al. (2014)). Firms will strategically take into account the competitive threats they face when deciding on their financial policies (Valta (2012) and Fresard (2010)). Firms experiencing increases in import competition tend to adopt conservative financial policies (Xu (2012)). Since firms with robots have less operational risk and might be able to avoid having to discharging workers if the firm experiences a temporary negative shock, I expect the effects of foreign competition on leverage and cash holdings to be weaker for firms with more robots. Similar to Xu (2012), Fresard and Valta (2016), and Srinivasan (2020), I measure increases in foreign competition using data on decreases in import tariffs. An advantage of using import tariffs to measure changes in industry competition structure is that a reduction in tariffs is an exogenous shock with respect to firms' financial policies. My findings indicate that for companies with more robots, the adverse connection between competitive threats, as reflected in decreases in import tariffs, and corporate financial leverage is weaker. Furthermore, I show that the positive relationship between competitive threats and cash holdings is smaller for firms with more robots.

Lastly, I examine the effects of minimum wage changes and robots on corporate financial policies. Minimum wage increases will increase factor prices, affect production costs, and raise a firm's operational risk (Gustafson and Kotter (2018), Aaronson et al. (2007), Cho (2018), and Bai et al. (2020)). Firms with more robots have less operational risk and rely less on minimum wage workers. Consistent with my hypothesis, I show that the effects of minimum wage increases on leverage and cash holdings are weaker for firms with more robots.

My paper brings attention to important changes in the labor market landscape over the last 50 years. As reported in Acemoglu et al. (2017), advances in robotics and artificial intelligence transform the labor market. I find evidence that robots mitigate the impact of labor frictions on financial policy decisions and that firms with more robots have higher financial leverage and hold less cash. I conduct a series of additional tests that show the robustness of my main results and offer more insights on the impact of robots on corporate financial policies. Firms with more robots rely less on workers and attach less importance to gaining a bargaining advantage over unions, and firms with more robots have more flexibility to adjust their labor demand in response to cash flow shocks.

My study makes four main contributions. Firstly, to the best of my knowledge, this paper is the first to provide empirical evidence on the effect of robots and automation on firms' financial policies. There is a particularly lively debate on the implications of the fast developments in robotics and closely-related technologies (see, e.g., Brynjolfsson et al. (2014), Autor (2015), Acemoglu et al. (2017), and Graetz et al. (2018)). During the period I analyze, industrial robots were used in just under a third of the economy, and service robots were still in their infancy. With the development of new robot capabilities, they can be used more intensively. This suggests that the impacts of robots on corporate financial policies may be substantial. By showing that robots can mitigate labor frictions and that firms with more robots have higher financial leverage and hold less precautionary cash, I add to the literature on the effect of labor market frictions on financial policy decisions (Matsa (2010), Agrawal and Matsa (2013), Klasa et al. (2009), Serfling (2016), Shen (2018), Xu (2018), Simintzi et al. (2015), and Klasa et al. (2017)).

Second, my study sheds further light on what determines corporate financial leverage. This paper also contributes to the broader industrial organization literature on strategic interactions between firms and other market participants, such as labor unions (Matsa (2010)). Robots can reshape the interaction between firms and labor unions. My paper proposes that firms with more robots rely less on workers and attach less importance to gaining a bargaining advantage over unions. Firms with more robots have higher financial leverage.

Third, my research is also related to recent work on what determines cash holdings and the contribution of cash holdings to firm value (Ghaly et al. (2017), Klasa et al. (2009), and Klasa et al. (2014)). My analysis identifies that firms with more robots have more flexibility to adjust their labor demand and hold less precautionary cash.

Finally, my paper adds to the existing product market competition literature (Hoberg et al. (2014), Maksimovic and Zechner (1991), and Mackay and Phillips

(2005)). In particular, it is related to Xu (2012) and Hoberg et al. (2014), who argue that firms facing more competitive threats tend to adopt conservative financial policies. My results suggest that firms with more robots have more flexibility to adjust their labor demand and can adopt less conservative financial policies when they face greater foreign competition.

The remainder of the paper is organized as follows. Section 2 reviews prior work, develops hypotheses, and discusses my empirical approach. Section 3 describes my sample and variables. Section 4 presents my empirical findings. Finally, section 5 concludes.

2. Literature review

2.1. Effect of labor market frictions on financial policy decisions

Labor inputs have become increasingly crucial for contemporary economic growth. Prior literature highlights the effect of labor frictions on corporate financial policies. Agrawal and Matsa (2013) claim that labor market frictions are significant factors in the corporate decision-making process.

Frictions in the labor market can influence corporate capital structure decisions. Labor market frictions can increase operating leverage, crowding out financial leverage. Labor-related considerations, such as human costs of bankruptcy (Berk, Stanton, and Zechner (2010)), strategic bargaining with labor unions (Matsa (2010)), firing costs (Serfling (2016)), unemployment risk (Agrawal and Matsa (2013)), labor market size (Kim (2015)), employment protection (Simintzi et al. (2015)), and labor adjustment costs (Ghaly et al. (2017)) can explain firms' leverage decisions.

Labor market frictions can also affect corporate cash holdings. Klasa, Maxwell, and Ortiz-Molina (2009) focus on the bargaining role of cash when firms deal with union pressures and show that a firm facing stronger unions will strategically hold less cash to improve its bargaining position. Schmalz (2015) claims that the interaction between unionization and cash holdings can be driven by an incentive to manage human capital risk. Labor adjustment costs can affect cash holdings, and firms with a greater proportion of skilled workers hold more precautionary cash (Ghaly et al. (2017)).

In addition, a growing theoretical and empirical body of literature examines the effects of labor market frictions on other corporate financial policies. Labor mobility can be detrimental to firm value (Balasubramanian et al. (2017), Jeffers (2017), and Klasa et al. (2017)). A firm's ability to hire skilled workers affects corporate investment (Xu (2018)). The negative relationship between firms' hiring rates and future stock returns is steeper in industries that rely more on high-skill workers than low-skill workers (Belo et al. (2017)). Minimum wage increases lead firms in minimum-wage-sensitive industries to scale down (Gustafson et al. (2018) and Cho (2018)).

The novelty of my paper is to focus on how corporate financial policy decisions are affected by robots that transform labor markets and reshape labor market frictions. My key insight is that greater penetration of robots can reduce firms' dependence on workers, cut labor adjustment costs, and decrease the effect of labor market frictions on financial policy decisions. Firms with more robots can have lower operational risk and adopt more aggressive financial policies, such as higher financial leverage and fewer cash holdings.

2.2. Literature on robots

The revolutionary advances in robotics and artificial intelligence bring a renewed concern over "technological unemployment" (e.g., Brynjolfsson et al. (2014) and Ford (2015)). Many routine tasks and blue-collar occupations traditionally performed by less educated workers, such as assembly workers in a factory, are more likely to be replaced by robots (Autor et al. (2003), Michaels et al. (2014), and Rotman (2017)). Production procedures are becoming more automated as robotic technologies progress. However, the effect of robots on the economy is under-explored and thus not clear.

Robots have contributed to wage inequality and employment polarization (e.g., Autor et al. (2003), Goos et al. (2007), Michaels et al. (2014), Dauth et al. (2017), and Graetz et al. (2018)). On one hand, greater penetration of robots may negatively affect wages and employment since robots directly take over tasks that workers were previously performing. Increasing the use of industrial robots may reduce employment and wages in the U.S. labor market (Acemoglu and Restrepo (2017)). Increasing the minimum wage significantly decreases the share of automatable employment held by low-skilled workers, with the largest effects being felt in manufacturing and by older, female, and black workers. On the other hand, greater penetration of robots can also positively affect wages and employment since the creation of new tasks may increase the demand for labor. The automation of a range of low-skill and medium-skill occupations may enable firms to create more new tasks for which labor has a comparative advantage. Mann and Puttmann (2017) analyze the effects of automation on employment using patent information and show that advances in national automation technology have a positive influence on employment in local labor markets.

Robots may be beneficial for growth. Automation creates productivity growth and pushes up the price of all factors in the long run. Finally, low-skill automation increases wage inequality, and high-skill automation reduces it (Acemoglu and Restrepo (2017)). Increasing automation productivity leads to a transfer of earlier offshore production back to the home economy without boosting low-skilled salaries and generating employment for low-skilled employees. A growing skill premium is associated with automation-induced reshoring (Krenz, Prettner, Strulik (2018)).

Furthermore, robots can affect corporate competitiveness (Enderwick (1989)). Robots can also affect corporate profits. The declining relative price of robots and the increase in factor substitutability causes the capital-to-labor ratio and corporate profits to rise. According to IFR's survey of managers, there are several reasons to use robots. Robots can reduce operating costs, improve product quality and consistency, increase flexibility in product manufacturing, save space in manufacturing areas, and improve quality of work for employees, complying with health and safety rules (IFR (2018)).

Last, robots can have a distinct impact on different firms. Firms with highly educated employees tend to expect beneficial impacts of AI-related technologies on their business, and firms with low-skill employees may be negatively affected. Larger firms and firms engaging in global markets tend to have favorable opinions on the impacts of AI-related innovation (Morikawa (2016)). However, there is no evidence examining the impacts of robots on corporate financial policies. This paper is motivated to fill the gap.

2.3. Hypothesis development and empirical predictions

My main hypothesis is that firms' financial policies are determined, at least in part, by robots' penetration. Labor market frictions can affect corporate financial policies (Agrawal and Matsa (2013)). Employment protection can increase operating leverage, crowding out financial leverage (Simintzi et al (2015)). Due to labor adjustment costs (LACs), a firm cannot adjust its labor demand without cost and has the incentive to minimize its labor turnover (Dixit (1997)). Firms with high labor adjustment costs have less flexibility to adjust their labor demand in response to cash flow shocks. Robots can affect firms' financial policies by affecting labor adjustment costs and operational risks.

On one hand, greater penetration of robots negatively affects wages and employment due to the displacement effect, as they directly replace workers. The increase in industrial robot usage may reduce employment and wages in the U.S. labor market (Acemoglu and Restrepo (2017)). Robot prices have fallen in comparison to labor costs, and robots have more flexibility than labor. Greater penetration of robots can reduce firms' dependence on workers, cut labor adjustment costs, and decrease the effect of labor market frictions on financial policy decisions. Firms with more robots can have lower operational risk and adopt more aggressive financial policies, such as higher financial leverage and lower cash holdings.

Hypothesis 1a. Firms with more robots that reduce labor adjustment costs and operational risk have higher financial leverage.

On the other hand, greater penetration of robots can also positively affect wages and employment since the creation of new tasks may increase the demand for labor. The automation of a range of low-skill and medium-skill occupations may enable firms to create more new tasks in which labor has a comparative advantage. In this scenario, greater penetration of robots can amplify firms' reliance on workers. Firms with more robots have higher labor adjustment costs and adopt more conservative financial policies, such as lower financial leverage and higher cash holdings.

Hypothesis 1b. Firms with more robots that increase labor adjustment costs have lower financial leverage.

My main hypothesis also suggests the following sub-hypotheses. These testable implications of my hypotheses can help to isolate the robot effect from other effects.

Second, firms with more robots hold less precautionary cash. The reason for this is that robots can reduce firms' reliance on workers and decrease operational risks. Firms with greater reliance on workers, and thus less flexibility in adjusting their labor demand in response to cash flow shocks, hold more precautionary cash (Ghaly et al. (2018)). It follows that firms with more robots have more flexibility in adjusting their labor demand when reacting to cash flow shocks and hold less precautionary cash.

Hypothesis 2. Firms with more robots hold less precautionary cash.

Third, for companies with more robots, the positive correlation between corporate financial leverage and the union's bargaining power is weaker. Since maintaining high levels of corporate liquidity can encourage workers to increase their wage demands, a firm with external finance constraints has a motivation to use cash flow requirements of debt service to enhance its bargaining position with workers (Matsa (2013)). Firms with more robots rely less on employees and attach less importance to gaining a bargaining advantage over unions. This suggests that the positive relationship between corporate financial leverage and the union's bargaining power is weaker for firms with more robots.

Hypothesis 3. The positive relationship between corporate financial leverage and the union's bargaining power is weaker for firms with more robots.

Fourth, the negative relationship between corporate cash holdings and the union's bargaining power is weaker for firms with more robots. Firms in more unionized industries strategically hold less cash to gain bargaining advantages over labor unions and to shelter corporate income from their demands (Klasa et al. (2009)). Firms with more robots rely less on workers and attach less importance to gaining a bargaining advantage over unions. Hence, the negative relationship between corporate cash holdings and the union's bargaining power is weaker for firms with more robots.

Hypothesis 4. The negative relationship between corporate cash holdings and the union's bargaining power is weaker for firms with more robots.

Fifth, the negative relationship between unionization and the contribution of cash holdings to firm value is weaker for firms with more robots. Larger cash holdings make it more difficult for firms to gain concessions from unions. Since large cash holdings are more costly for firms facing a strong union because they weaken the firm's bargaining position and allow labor to capture a larger fraction of profits, this should be reflected in the market's valuation of cash reserves. The marginal value of an extra dollar of cash is decreasing in a firm's industry unionization rate, and cash holdings are less valuable in more unionized industries (Klasa et al. (2008) and Faukender et al. (2006)). Firms with more robots have less reliance on workers and attach less importance to gaining a bargaining advantage over unions. This leads to my fifth hypothesis.

Hypothesis 5. The negative relationship between unionization and the contribution of cash holdings to firm value is weaker for firms with more robots.

Sixth, the effects of robots on leverage and cash holdings are stronger for firms with more blue-collar workers. Many routine tasks traditionally performed by less educated workers, such as assembly workers in a factory, are more likely to be replaced by robots (Autor et al. (2003) and Michaels et al. (2014)). Blue-collar jobs mainly involve routine tasks and relatively unskilled workers. These workers are more likely to be replaced by robots (Rotman (2017)). This suggests that the effects of robots on leverage and cash holdings are stronger for firms with more blue-collar workers.

Hypothesis 6. The effects of robots on leverage and cash holdings are stronger for firms with more blue-collar workers.

Seventh, the effects of foreign competition on leverage and cash holdings are weaker for firms with more robots. The competitive threat faced by a firm threatens the stability of a company's future cash flows (Hoberg et al. (2014)). Maintaining financial flexibility for a firm facing great competitive threats is crucial (Bolton et al. (1990) and Klasa et al. (2018)). Financial flexibility provided by lower financial leverage and more cash holdings allows firms to react to opportunistic behavior by their rivals (Bates et al. (2009), Campello (2003, 2006), and Khanna and Tice (2000, 2005)). Furthermore, firms will strategically take into account the competitive threats they face when deciding on their financial policies (Valta (2012) and Fresard (2010)). For example, firms experiencing increases in import competition significantly reduce their leverage ratios (Xu (2012)). In addition, firms can adopt several modes of restructuring, including downsizing, layoffs, and diversification, to survive industry shocks (Kang and Shivdasani (1997)). Since firms with robots have less operational risk and might be able to avoid discharging workers if firms experience a temporary negative shock, I expect the effects of foreign competition on leverage and cash holdings to be weaker for firms with more robots.

Hypothesis 7. The effects of foreign competition on leverage and cash holdings are weaker for firms with more robots.

Eighth, the effects of minimum wage increases on leverage and cash holdings are weaker for firms with more robots. Minimum wage increases raise factor prices, affect production costs, and reduce optimal production (Gustafson et al. (2018) and Aaronson et al. (2007)). Minimum wage increases can raise a firm's operating leverage and operational risk because the firm cannot reduce wages when output falls during bad times (Cho (2018), and Bai et al. (2018)). Firms faced with greater operational risk tend to adopt more conservative financial policies. Minimum wage increases will have greater impacts on firms that rely more on minimum wage workers, who are mainly low-wage and less-educated workers. However, these workers can be replaced by robots (Rotman (2017)). Firms with more robots have less operational risk and less reliance on minimum wage workers. Therefore, the effects of minimum wage increases on leverage and cash holdings are weaker for firms with more robots.

Hypothesis 8. The effects of minimum wage increases on leverage and cash holdings are weaker for firms with more robots.

3. Data and summary statistics

3.1. Sample selection and variables

My primary source of data on robots is the International Federation of Robotics (IFR) dataset, which collects data on industrial robots from the national federations of robot manufacturers. The IFR refers to an "industrial robot" as defined by ISO 8373: an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications" (IFR (2018))[3]. Each element of the definition is crucial for a machine to be considered an industrial robot. For instance, some machines, including textile looms, elevators, or transportation bands, are not

[3] see also ISO definitions at https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en

industrial robots because they cannot be reprogrammed to perform other tasks, and/or they require human intervention.

Common applications of industrial robots include handling, welding, dispensing, processing, and assembling, which are prevalent in manufacturing industries. Other applications include harvesting (used in agriculture) and inspecting of equipment and structures (used in power plants). The IFR offers data on the number of robots delivered to each industry in each country and year. Based on Graetz et al. (2018), I build the stock of robots based on deliveries using the perpetual inventory method, assuming a depreciation rate of 10 percent. I have data for the use of robots in seven broad industries: manufacturing; agriculture, forestry, and fishing; mining; utilities; construction; education, research and development; and services. Within the manufacturing sector, I have consistent data on the use of robots for 13 more disaggregated industries: food and beverages; textiles (including apparel); wood and furniture; paper and printing; plastic and chemicals; minerals, glass, and ceramics; basic metals; metal products; industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing (e.g. production of jewelry and toys). I use this industry classification throughout the paper and refer to it as the IFR industries.

My second major source of data is EUKLEMS (Timmer et al. (2007)). These data include information on inputs, outputs, and prices at the industry-country-year level. I use data from the EUKLEMS 2017 update for hours worked to calculate robot penetration. IFR and EUKLEMS data use different industry classifications at different levels of aggregation. Dollar values are expressed in 2010 dollars.

The third dataset is the merged CRSP-Compustat database. Consistent with the extant literature, I also exclude financial firms and utilities (i.e., firms with SIC codes between 6000 and 6999 or between 4900 and 4999). My sample consists of all firms headquartered in the U.S. for which I can construct the variables used in my main tests. The sample period is 1993-2015. The first year of my analysis is 1993 (the first year covered in the IFR data), and the last year I use is 2015 (the last year covered in EUKLEM 2017). The final sample has 81,212 observations.

The main regressor in my empirical analysis is ROB and is based on my measure of robot density, which I define as the number of robots per million hours worked. I use hours to normalize the number of robots since workers can differ in the number of hours that they work. Due to robot data limitation, ROB is an industry-level measure with a mean of 4.001. ROB is very small and positive in my sample period.

My main dependent variables are the corporate financial policy variables, including financial leverage and cash holdings. I mainly use *Financial leverage* to measure leverage. However, my results are robust to alternative measures of leverage. *Financial leverage* is the book value of long-term debt plus debt in current liabilities divided by book value of assets. In terms of the control variables in the financial leverage analysis, I follow Xu (2012) and Klasa et al. (2018) and include standard control variables in capital structure tests (*Log book assets, Market-to-book assets, Return on assets, Fixed assets/assets, and Dividend dummy).* To measure cash holdings, I mainly use *Cash ratio*. *Cash ratio* is the ratio of cash and short-term investments to total assets. I follow Bates, Kahle, and Stulz (2009) and add standard control variables in cash holdings tests (*Market-to-book assets, Log book assets, Cash flow, Net working capital, Capital expenditures/assets, Financial leverage, RD/sales, Dividend dummy, Acquisition/assets*, *Fixed assets/assets* and *Industry cash flow risk).* I winsorize these variables at the 1st and 99th percentiles of their distributions.

3.2. Potential endogeneity and instrumental variable

To identify the impact of robot penetration on firms' capital structure choices, robot penetration should be exogenous to domestic firms' capital structure choices. However, potential endogeneity concerns arise. For example, an omitted factor such as firm characteristics could affect both robot penetration and firms' financial policies, including capital structure. Another endogeneity concern comes from the possibility of reverse causality from firms' financial policies to increase robot adoption.

In order to mitigate endogeneity concerns including omitted factors and possible reverse causality, I use an instrumental variable to capture exogenous variations in robot density. My instrument for robot density is an industry-level measure called replaceability. The replaceability values represent an upper bound to the share of hours that is replaceable by robots. I construct this instrument based on Graetz and Michaels (2018) using data from IFR on robot applications, the U.S. census occupational classifications, and the distribution of hours across occupations and industries from the 1980 U.S. Census (Ruggles et al. (2010)). The IFR distinguishes different applications of robots, including welding, painting, and assembling (IFR (2018)). I use the 2000 Census three-digit occupational classification and assign a replaceability value of one to an occupation if its name corresponds to at least one of the IFR application categories and zero otherwise. Then, I map my replaceability measure into the 1990 Census occupational classification. While several 2000 occupations map into one 1990 occupation, I assign the 1990 occupation a replaceability value of one if and only if at least one of the corresponding 2000 occupations has a value of one.

To construct my industry-level replaceability measure, I first assign these variables to each individual in the 1980 IPUMS Census based on their reported 1990 occupation. Next, I assign each individual one of 28 EUKLEMS industries based on a crosswalk to the 1990 Census industry classification. I calculate the fraction of replaceable hours for each robot-using industry by dividing the sum product of replaceability and annual hours worked by the total sum of hours worked. I apply person weights when computing both the numerator and the denominator. The replaceability values are an upper limit to the number of hours that can be replaced since occupations are classified as replaceable as long as part of their work can be replaced by robots.

The robotic capability is mainly influenced by technological supply factors, not by industries' job requirements that may represent omitted variables and reverse causality. To construct this instrument, I assess the extent to which industries used occupations replaceable by robots. The instrumental variable, replaceability, satisfies the exclusion condition because it is arguably not related to firm-level financial policies through any channels other than the robot channel.

3.3. The regression model and the ordinary least squares specification

To study the effects of robot penetration on corporate financial policies, I use the following linear regression model:

$$Y_{it} = \alpha_1 ROB_{jt} + X_{it}\beta + v_i + W_t + \varepsilon_{it}. \quad (1)$$

Y_{it} represents the corporate financial policies variables, such as financial leverage or cash holdings at firm i and year t. ROB_{jt} is the robot density in year t for the industry j in which firm i operates. The regression analysis focuses on the coefficient for ROB_{jt}, α_1. X_{it} is a vector of explanatory variables. v_i stands for the firm fixed effects, which absorb firm-specific and time-invariant components in corporate financial policies and alleviate time series correlations in leverage due to firm fixed effects (Petersen (2009)). W_t stands for year fixed effects, used to control for common time trends in financial leverage or cash holdings across all industries and firms. ε_{it} is a random error term. I cluster standard errors at the firm level.[4]

4. Empirical results

4.1. Univariate findings

Table 1 reports the summary statistics and results of univariate tests of the relation between robot density and corporate financial policies. The results reveal important (cross-sectional) variation in ROB. Over my sample period, mean and median financial leverage are 0.304 and 0.172, respectively. Mean and median robot density are 4.001 and 1.219, respectively. The robot density distribution has a long right tail, which makes fitting a linear model challenging and indicates the measurement error in the measure of robot adoption. Figure 1 shows the quality-adjusted price indices of robots reported by surveyed firms. The price of robots dropped sharply around the world from 1990 to 2005.[5] Figure 2 Panel A depicts the operational stock of robots in the United States, United Kingdom, Italy, Germany, and China from 1993 to 2015. The United States and Germany have the most robots stock. Robot stock in China has grown rapidly in recent years. Figure 2 panel B is the robots stock shares of these five countries in the world. The United States has around 18% of robots in the world, and Germany has about 12% of robots.

I restrict my attention to the United States. Figure 3 illustrates the geographic distribution of robots of the United States in 2015, which clearly shows that the robot density is relatively low in many parts of the United States and that there is some geographic variation in the distribution of robots. Figure 4 shows the United States robot distribution by industry. Among the six broad industries, manufacturing has

[4] My results are robust to clustering at industry level.
[5] IFR reports quality-adjusted prices until 2006.

the most operational robots. Within the manufacturing industry, the automation industry has the most operational robots, followed by the electronics industry.

4.2. OLS regressions for the effects of robots on leverage and cash

Table 2 reports the effects of robots on financial leverage using ordinary least squares (OLS) estimates. The findings in Column 1 show a significantly positive correlation between robot density and leverage. The results are consistent with my prediction. Robots can lower labor costs, make production more stable, and reduce operational risks. Firms with greater robot density will have higher leverage.

Column 1 in Table 3 examines the impact of robots on cash holdings using ordinary least squares (OLS) estimates. The findings show a negative association between robot density and cash holdings. Greater penetration of robots can reduce firms' dependence on workers, cut labor adjustment costs, and decrease the effect of labor market frictions on financial policy decisions. The results support my hypothesis that firms with more robots will hold less precautionary cash.

4.3. The instrument variable specification

To identify the causal effect of robot density on leverage ratios, I estimate instrumental variable (IV) regressions using replaceability to instrument for robot density. After confirming that the instruments used in leverage and robot density models are valid, I estimate the 2SLS estimators.[6] The IV regressions are conducted

[6] To determine the validity of using 2SLS, I examined the suitability of the instruments in the leverage and robots equations and the appropriateness of using an instrumental variables approach. The results of these analyses are as follows. First, the weak instrument test, which is the Sanderson Windmeijer F test, shows that the instruments in the leverage and robots equations are significant in explaining the endogenous variables and that the instrument is valid. Second, the weak instrument robust inference (Anderson Rubin Wald test) shows that the instrument does not have a weak instrument problem and is valid. Third, the results of tests for whether I have underidentification or weak instrument problem reject the hypothesis that the instrument in the equations suffer from such problems. Finally, I ran a Sargan test and found that the leverage and robots equation does not suffer from overidentification problems. I note that I use the same method to determine the validity of using 2SLS and the suitability of the instruments in all other 2SLS models in the paper.

in two stages. In the first stage, I regress robot density on replaceability, firm controls, and fixed effects. In the second stage, I estimate the regression model in Eq. (1) while replacing robot density by the predicted value of robot density from the first-stage regression. The regression results are summarized in Table 2, Column 2. In this section and the following sections, I refer to the IV regressions based on Eq. (1) as the baseline IV regressions of leverage and the results reported herein as the baseline IV regression results of leverage.

The second column of Table 2 displays the IV estimates of the effects of robot density on financial leverage. The estimated coefficient is positive and statistically significant. The results are consistent with the OLS results while supporting a causal interpretation of the impact of robot density on capital structure. The effects are economically significant as well. A coefficient of 0.113 (Column 2) implies that a 10% increase in robot density for an average firm leads to a 4.3% increase in financial leverage. Noticeably, both estimates are much greater in magnitude than the estimates from the OLS models. The magnitudes of these effects are comparable to those reported in prior work on how shocks affect firms' debt ratios. For example, Xu (2012) finds that a 2% increase in an industry's import penetration ratio (a 10% increase over its mean) leads to an 8%-9% decrease in firms' leverage. Klasa et al. (2018) show that the recognition of the Inevitable Disclosure Doctrine leads to a 5.2% increase in book leverage ratios.

To identify the causal effects of robot density on cash ratios, I estimate IV regressions using replaceability to instrument for robot density. After confirming that the instruments used in the cash holdings and robot density models are valid, I estimate the 2SLS estimators. The IV regressions are conducted in two stages. In the first stage, I regress robot density on replaceability, firm controls, and fixed effects. In the second stage, I estimate the regression model in Eq. (1) while replacing robot density by the predicted value of robot density from the first-stage regression. The regression results are summarized in Table 3 Column 2.

The second column of Table 3 displays the IV estimates of the effects of robot density on *Cash Ratio*. The estimated coefficient is negative and statistically significant. The results are consistent with the OLS results while supporting a causal interpretation of the impact of robot density on cash holdings. The effects are economically significant as well. The coefficient of -0.024 (Column 2) implies that a 10% increase in robot density for an average firm leads to a 1% decrease in the cash ratio. Notably, both estimates are much greater in magnitude than the estimates from the OLS models.

4.4. Robots, unionization, and corporate financial policies

I now augment my main specification and interact *ROB* with variables that affect firms' financial policies. These tests of the cross-sectional predictions developed in Section 2 shed further light on the economic mechanism behind my results. The tests also provide further evidence that my main results are causal, i.e., if a variable omitted from my main regression model were to drive the results in Table 2 and Table 3, then such a variable would also have to explain the cross-sectional results I report here. To support the labor friction hypothesis that firms with more robots rely less on workers and that they are less likely to use the cash flow demands of debt service to improve their bargaining position with workers, I examine the effects of robot density on the relationship between labor unionization and corporate financial policies. After confirming that the instruments used in the robots, unionization, and leverage models are valid, I estimate the 2SLS estimators. Table 4 Column 1 examines the IV estimates of the effect of robots on the impact of labor unions on financial leverage.

Table 4 Column 1 demonstrates that there is a positive relationship between leverage and industry unionization rates, which is consistent with Matsa (2010). Because keeping high levels of corporate liquidity can encourage workers to raise their wage demands, a firm with external finance constraints has an incentive to use the cash flow demands of debt service to improve its bargaining position with workers. Union bargaining power leads firms to increase financial leverage. Since firms with more robots rely less on workers, they are less likely to use the cash flow demands of debt services to improve their bargaining position with workers. Consistent with my prediction, Table 4 Column 1 shows a statistically significant negative coefficient on the interaction between a firm's industry unionization rate and robots densities. Thus, the positive relation between unionization rates and leverage is weaker for firms with robots. The relation is not only statistically significant, but also economically significant. I find that a one-standard deviation increase in unionization leads to a 4.7% increase in the firm's book leverage. To determine the economic importance of robots on the relationship between leverage and unionization, I investigate how a one-standard deviation increase in robot density impacts the effect of changes in unionization on leverage. By multiplying the standard deviation of robot density, the standard deviation of labor unionization rate of 0.097, and the coefficient of this interaction term (-0.059), I find that a one-standard deviation increase in unionization would lead to a 4.5% smaller increase in a firm's leverage. Thus, the positive relation between unionization rates and leverage is weaker for firms with robots.

After confirming that the instruments used in the robots, unionization, and cash holdings models are valid, I estimate the 2SLS estimators. Table 4 Column 2 examines the IV estimates of the effect of robots and labor unions on cash holdings. I find that there is a negative relation between cash holdings and industry unionization rates. The coefficient on *ROB×High industry unionization rate* is positive and statistically significant. For Table 4 Column 2, I find that a one-standard deviation increase in unionization leads to a 1.0% decrease in the firm's cash ratio. To determine the economic importance of robots on the relationship between cash holdings and unionization, I estimate how a one-standard deviation increase in robot density impacts the effect of changes in unionization on cash holdings. As a result of such an increase in robot density, a one-standard deviation increase in unionization would lead to a 0.9% smaller decrease in a firm's cash holdings. Thus, the negative relation between unionization rates and cash holdings is weaker for firms with more robots. In sum, the results of Table 4 Column 2 support the prediction that the negative relationship between unionization and cash holdings is weaker for firms with more robots. These results also suggest that firms with more robots hold less precautionary cash since robots can reduce firms' reliance on workers.

My results thus far suggest that robots can reduce firms' reliance on workers and mitigate labor market frictions. Larger cash holdings make it harder for firms to gain concessions from unions. Since large cash holdings are more costly for firms facing a strong union because they weaken the firm's bargaining position and allow workers to acquire a larger fraction of profits, this should be reflected in the market's valuation of cash reserves. The marginal value of an extra dollar of cash is decreasing in a firm's industry unionization rate, and cash holdings are less valuable in more unionized industries (Klasa et al. (2008) and Faukendar et al. (2006)). Firms with more robots rely less on workers and attach less importance to gaining a bargaining advantage over unions. Thus, I predict that the negative relationship between unionization and the contribution of cash holdings to firm value is weaker for firms with more robots. To examine the impact of robots on the contribution of cash holdings to firm value, I follow the methodology developed by Faulkender and Wang

(2006) and use excess stock returns to determine how a change in cash holdings leads to a change in the market value of a firm.

Table 5 provides the results of the analysis. The dependent variable in columns of the Table 5 model is a firm's current fiscal year excess stock return, defined as the firm's annual stock return minus the firm's matched Fama and French 5×5 portfolio return. The independent variables in the first model in Table 5 are the change in current year cash holdings (defined as cash and short-term investments), the firm's industry unionization rate, robot density, the difference-in-difference-in-difference estimator of the firm's industry unionization rate, robot the change in current year cash holdings, and a set of control variables. Except for market leverage and a firm's industry unionization rate, all of the independent variables are scaled by the lagged market value of equity. Also, as in Faulkender and Wang (2006), all of the independent variables are winsorized at their 1st and 99th percentiles.

The results for the first model in Table 5 show that the coefficient on the change in current year cash holdings variable is significant and positive, which, not surprisingly, indicates that the marginal value of an extra dollar of cash is positive. The coefficient on $Industry\ unionization\ rate \times \Delta Cash\ holdings_t$ is significantly negative, which is consistent with Klasa et al. (2008) and indicates that cash holdings are less valuable in more unionized industries. Interestingly, I find that the coefficient on $ROB \times Industry\ unionization\ rate \times \Delta Cash\ holdings_t$ is significantly positive. This result supports the prediction that the negative relationship between unionization and the contribution of cash holdings to firm value is weaker for firms with more robots.

The second model of Table 5 further shows that the coefficient on the change in current year cash holdings is significant and positive, which indicates that the marginal value of an extra dollar of cash is positive. The coefficient on the interaction of a firm's industry unionization rate with the change in current year cash holdings is significantly negative, i.e. -0.876. This indicates that the marginal value of an extra dollar of cash is decreasing in a firm's industry unionization rate and suggests that cash holdings are less valuable in more unionized industries. The coefficient of *Industry unionization rate*$\times \Delta C_t$ is -0.876, indicating that an extra dollar of cash in a firm with zero labor union coverage is worth $0.0876 more to shareholders than an extra dollar in a firm with 10% labor union coverage. The coefficient of *ROB*$\times$*Industry unionization rate*$\times \Delta C_t$ is 0.123. Thus, the results are consistent with my prediction that the negative relation between unionization rates and the marginal value of an extra dollar of cash is weaker for firms with more robots.

I calculate the marginal value of a dollar of cash for the average firm in the sample using regression coefficients from the second model of Table 5 and the mean values of several independent variables. The mean firm has labor union coverage of 10.6%, robot density of 4, leverage of 17.1%, and cash holdings as a percentage of the market capitalization of equity at the beginning of the fiscal year of 15.2%. Therefore, the marginal value of cash to shareholders in the mean firm is $1.214 ($= \$1.569 + (-0.876 \times 0.106) + (-0.009 \times 4) + (0.123 \times 4 \times 0.106) + (-0.627 \times 0.152) + (-1.063 \times 0.171)$). This value is close to the marginal value of a dollar of cash for the average firm in the Faulkender and Wang (2006) sample of 0.940.

4.5. Robots, blue-collar workers, and corporate financial policies

To further investigate the labor friction hypothesis that firms with more robots rely less on workers, have less operational risk, and adopt more aggressive financial policies, I examine the effects of robot density on blue-collar workers and financial leverage. After confirming that the instruments used in the robots, blue-collar workers, and leverage models are valid, I estimate the 2SLS estimators. Table 6

Column 1 examines the IV estimates of the effect of robots on blue-collar workers and financial leverage. I follow Klasa et al. (2009) to calculate the blue-collar worker rate. From the division of Occupational Employment Statistics of the Bureau of Labor Statistics (BLS), I obtained data for three-digit SIC industries (I converted NAICS codes to SIC codes after 2001) on the number of workers employed in approximately 800 different occupations. For each industry, I examined the title of each occupation and, following the definition used by the BLS, I classified all non-office occupations as blue-collar occupations. *High blue-collar* is an indicator variable equal to one if the industry's blue-collar worker rate is above the mean of the sample, and zero otherwise.

Table 6 Column 1 displays the IV estimates. Blue-collar jobs mainly involve routine tasks and relatively unskilled workers. These workers are more likely to be replaced by robots (Rotman (2017)). The coefficient of *ROB*×*High blue-collar* is positive and significant, which is consistent with my prediction that the effects of robots on leverage are stronger for firms with more blue-collar workers.

After confirming that the instruments used in the robots, blue-collar workers, and cash holdings models are valid, I estimate the 2SLS estimators. Table 6 Column 2 examines the IV estimates of the effects of robots on blue-collar workers and cash holdings. The coefficient of *ROB*×*High blue-collar* is negative and significant, which is consistent with my prediction that the negative relationship between robots and cash holdings is stronger for firms with more blue-collar workers.

4.6. Robots, foreign competition, and corporate financial policies

Greater foreign competition reduces price-cost margins (Katics and Petersen (1994)), results in asset reallocation (Bertrand et al. (2007)), and may force firms to discharge workers to survive industry shocks (Kang and Shivdasani (1997)). The competitive threats faced by a firm threatens the stability of a company's future cash flows (Hoberg et al. (2014)), and firms faced with greater foreign competition are more likely to use conservative financial policies (Xu (2012) and Fresard (2010)). Since firms with robots have less operational risk and might be able to avoid discharging workers if firms experience a temporary negative shock, I expect the effects of foreign competition on leverage and cash holdings to be weaker for firms with more robots. I followed Srinivasan (2020) to measure the increase in foreign competition. Data on import tariffs at the 6-digit NAICS level are from the United States International Trade Commission's (USITC) website. I collected data on collected duties and dutiable import values by industry year aggregated across all MFN countries and products within the NAICS industry. Then, I calculated the change in the import tariffs faced by an industry each year as the percentage change in the ad-valorem duty rate from the prior year. *Decdummy* is an indicator variable equal to one for a tariff reduction of 2% or more, and zero otherwise.

After confirming that the instruments used in the robots, foreign competition, and leverage models are valid, I estimate the 2SLS estimators. Table 7 Column 1 reports the IV estimates of the effect of robots on foreign competition and leverage. The variable of main interest is the interaction between robot density and *Decdummy*. Table 7 Column 1 shows that firms faced with greater foreign competition adopt more conservative financial policies. Firms faced with greater foreign competition have lower financial leverage. The coefficient on *ROB×Decdummy* is positive and significant for the financial leverage model, which indicates that robots improve operational flexibility and that the effects of foreign competition on leverage are weaker for firms with more robots.

After confirming that the instruments used in the robots, foreign competition, and cash holdings models are valid, I estimate the 2SLS estimators. Table 7 Column 2 displays the IV estimates of the effect of robots on foreign competition and cash holdings. The variable of main interest is the interaction between robot density and *Decdummy*. Table 7 Column 2 shows that firms faced with greater foreign competition have more cash holdings. The coefficient on *ROB*×*Decdummy* is negative and significant for the cash holding model, which indicates that robots improve operational flexibility and that firms with more robots have a smaller need to adopt more conservative financial policies when foreign competition is greater.

4.7. Exposure to minimum wage changes, robots, and corporate financial policies

Minimum wage increases will increase factor prices and reduce optimal production (Gustafson et al. (2018)). Minimum wage increases can raise a firm's operating leverage and operational risk because the firm cannot reduce wages when output falls during bad times (Cho (2018), and Bai et al. (2018)). Firms with more robots have less operational risk and rely less on minimum wage workers. Therefore, I expect that the effects of minimum wage increases on leverage and cash holdings are weaker for firms with more robots.

To test this prediction, I follow Gustafson and Kotter (2018) and adopt a Difference-in-Difference-in-Difference method as the identification strategy. *Bound* measures a firm's exposure to states that are bound (i.e. have a state minimum wage less than or equal to the federal minimum wage) as of the end of the firms' fiscal year. ΔMW is the percentage change in the nominal federal minimum wage over the firm's prior fiscal year. The coefficient on the triple interaction term $Bound \times \Delta MW \times ROB$ represents the differential effect of minimum wages on firms with more robots and firms with fewer robots across bound and unbound states.[7]

[7] The Bound and ΔMW variables are measured as of each firm's fiscal year end, so including year and firm fixed effects does not absorb the coefficient on Bound or the interaction of Bound*ΔMW. Since these coefficients are identified off differences in fiscal years, it is not clear that they have any meaningful economic interpretation (Gustafson and Kotter (2018)).

Table 8 reports the effect of minimum wage change and robots on financial leverage. Column 1 reports the main regression results, and Column 2 reports the timing test results. In Column 1, the coefficient of *Bound*×Δ*MW*×*High ROB* is positive and significant, which indicates that firms with more robots can adopt less conservative financial policies when the minimum wage increases. In Column 2, the coefficient of interest is the triple interaction *Bound*×*Post*×*High ROB*. *Post* equals zero for three years before the federal minimum wage increase and equals one for the two years of the federal minimum wage increase. The significantly positive coefficient of this interaction suggests that firms with more robots adopt less conservative financial policies following federal minimum wage changes.

Table 9 reports the effect of minimum wage change and robots on cash holdings. Column 1 reports the main regression results, and Column 2 reports the timing test results. In Column 1, the coefficient of *Bound*×Δ*MW*×*ROB* is negative and significant, which indicates that firms with more robots can adopt less conservative financial policies when the minimum wage increases. In Column 2, the coefficient of interest is the triple interaction *Bound*×*Post*×*ROB*. *Post* equals zero for three years before the federal minimum wage increase and equals one for the two years of the federal minimum wage increase. The significantly negative coefficient of this interaction suggests that firms with more robots adopt less conservative financial policies following federal minimum wage changes.

5. Additional investigation

I now briefly discuss the results of additional investigations, which are contained and more extensively discussed in the Appendix.

First, I show that firms with more robots have less operational risk (see Table A1) and invest more in risky R&D activities (see Table A2). Second, I show that robots reduce firms' cost of bank debt (see Table A3) and have a negative and significant impact on corporate foreign currency hedging (see Table A4). This is further support for the proposition that robots reduce firms' operational risk.

Third, I provide evidence that firms with robots can adopt less conservative payout policies. Firms might refrain from making payouts until their product markets mature, as payout conservatism can strengthen the firm's competitive positioning. Firms with more robots have greater flexibility and less operational risk. These firms can adopt less conservative payout policies (see Table A5).

Fourth, I find that firms with more robots have higher acquirer announcement returns (see Table A6). This is further support for the proposition that robots mitigate the impact of labor market frictions on firms. Labor market frictions have negative impacts on the value of acquisition activities (Dessaint et al. (2017)). Robots reduce labor adjustment costs, and firms with more robots have higher synergy gains.

6. Conclusion

I investigate the impact of robots on corporate financial policies. Specifically, I find that firms with more robots have higher financial leverage and hold less cash. These results suggests that greater penetration of robots can reduce firms' reliance on workers, mitigate the impact of labor frictions, and decrease operational risks. As a result, firms with more robots have more flexibility in adjusting their labor demand in response to cash flow shocks, have higher financial leverage, and hold less cash.

Supporting the notion that robots mitigate the impact of labor frictions, I find that the positive relationship between corporate financial leverage and the union's bargaining power is weaker for firms with more robots, and the negative relationship between corporate cash holdings and the union's bargaining power is weaker for firms with more robots. In addition, I document that the negative relationship between unionization and the value of cash is weaker for firms with more robots. Since blue-collar occupations are more likely to be replaced by robots, I provide further evidence that the effects of robots on corporate financial policies are stronger for firms with more blue-collar workers.

Robots can affect firms' financial situations and ultimately firms' competitive positions in product markets. Since firms with robots have less operational risk and might be able to avoid discharging workers, firms with more robots can adopt less conservative financial policies when they face greater competitive threats. I examine the effects of foreign competition on robots and corporate financial policies and show that the effects of foreign competition on leverage and cash holdings are weaker for firms with more robots.

Lastly, I examine the effects of minimum wage change and robots on corporate financial policies and show that firms with more robots can adopt less conservative financial policies when the minimum wage increases. Overall, my results imply that robots mitigate the impacts of labor frictions on corporate financial policies.

Figure 1. Robots price, 1990-2005

The figure shows the quality-adjusted price indices of robots reported by surveyed firms. The indices of robot prices (1990=100) are from the International Federation of Robotics. The figure shows robot price indices for four countries: United States, United Kingdom, Italy, and Germany. The mean is the average robot price indices of these four countries.

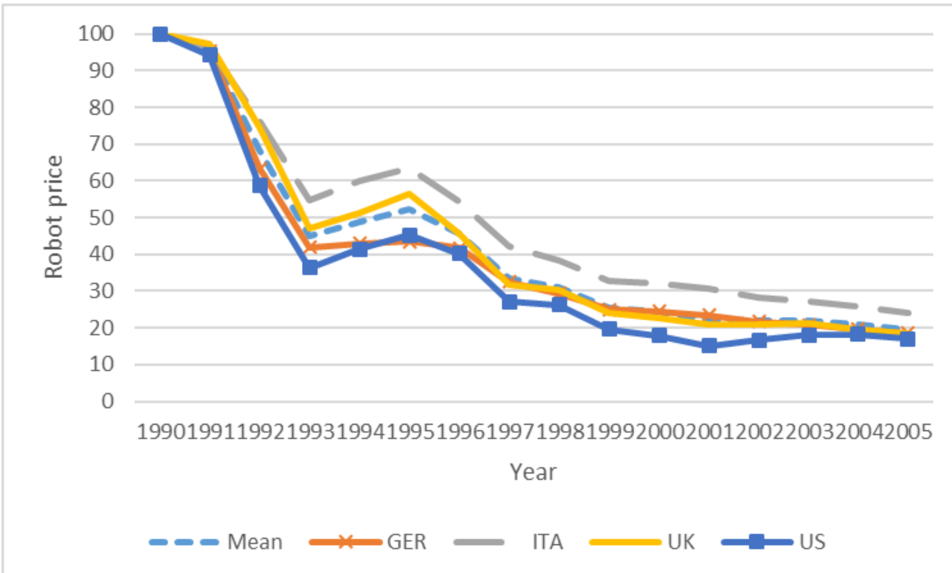
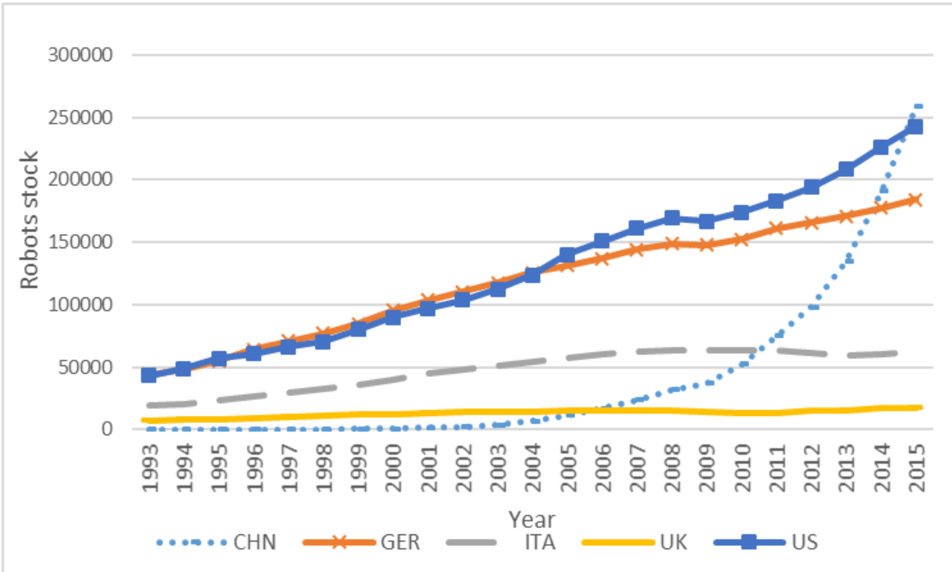


Figure 2. Robots stock, 1993-2015

The figure shows the operational stock of robots in five countries from 1993-2015. The five countries are United States, United Kingdom, Italy, Germany, and China. For data confidentiality reasons, the exact value of robot density was censored.

Panel A. Robots stock



Panel B. Robots stock percentage

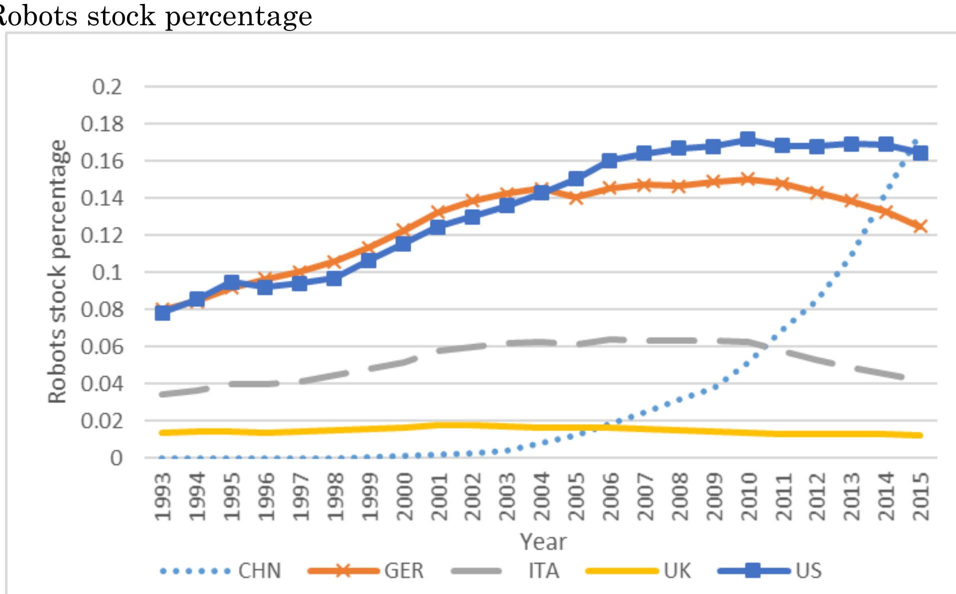


Figure 3. Geographic distribution of robots

The figure shows the robot density of the United States in 2015. Robot density is defined as the number of robots per million hours worked. For data confidentiality reasons, the exact value of robot density was censored.

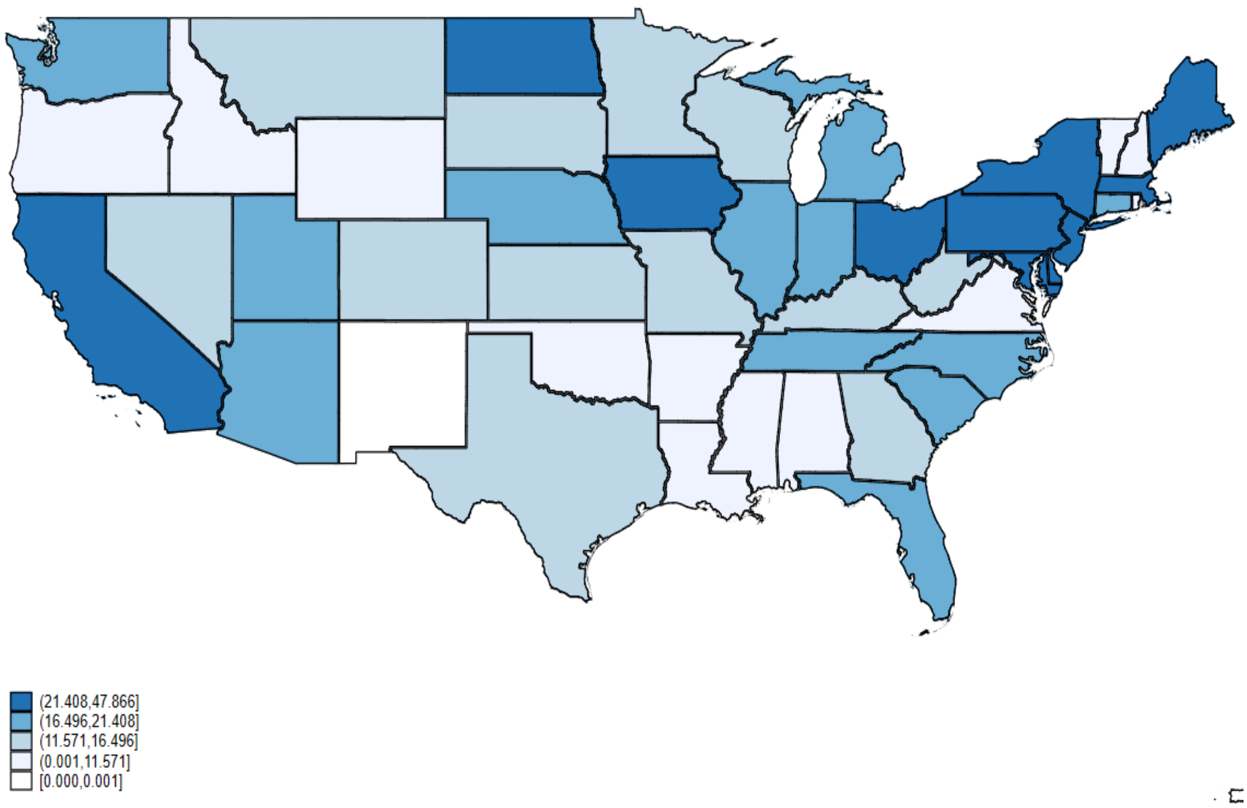
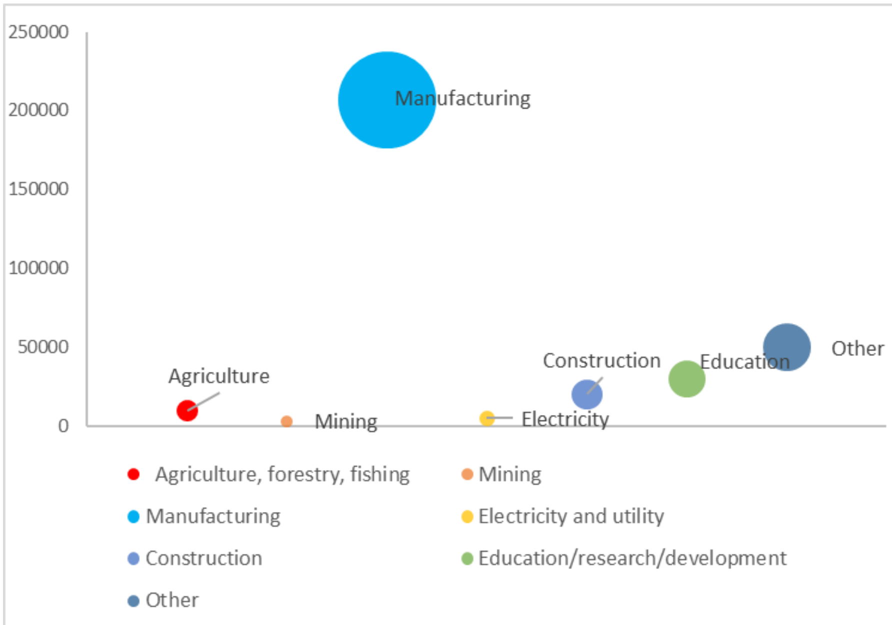


Figure 4. Robots distribution by industries

The figure shows the operational stock of robots in the United States in 2015. For data confidentiality reasons, the exact value of robot density was censored.

Panel A. Robots distribution by broad industries



Panel B. Robots distribution within the manufacturing industry

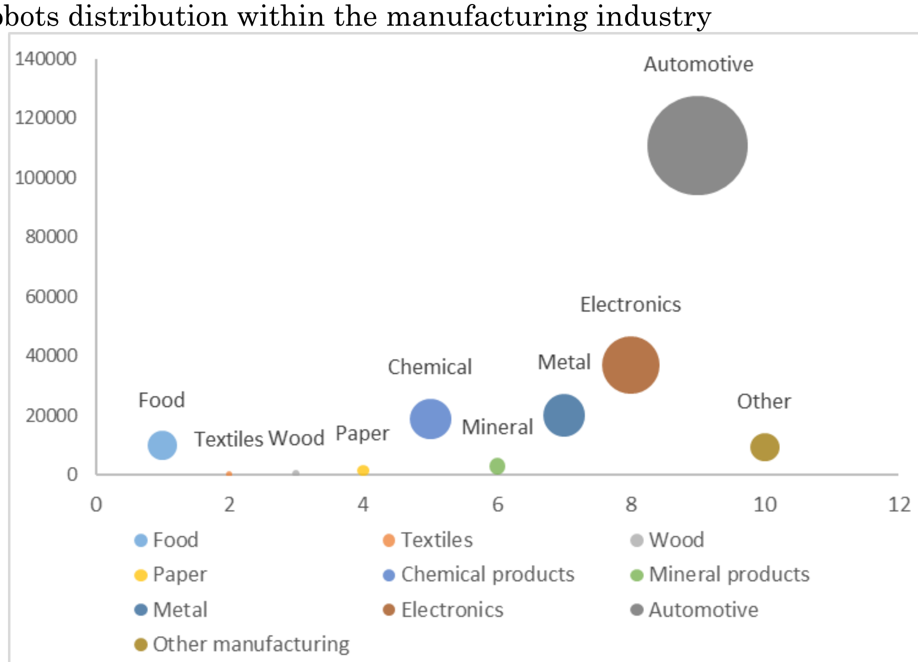


Table 1: Summary statistics for variables in main tests

This table reports summary statistics for the variables used in my main tests in Table 2 and Table 3. The sample spans the 1993-2015 period. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *ROB* is robot density, which is defined as the number of robots per million hours worked. *Replaceability* measures the share of hours that is replaceable by robots. *Log book assets* is the natural logarithm of total asset (at). *Market-to-book assets* is the market value of assets (*prcc_f*×*csho* + *at* - *ceq*) divided by the book value of assets (*at*). *Return on asset* is the return on assets for firm or industry *i* in year *t*, measured as operating income(*pi-xi*) scaled by asset *(at)*. *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *Cash flow* is earnings after interest, dividends, and tax but before depreciation (oibdp − xint −txt−dvc), scaled by the book value of total assets (at). *Net working capital* is measured as working capital (wcap) minus cash (che), scaled by total assets (at). *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). *RD/sales* is the ratio of research and development expense to sales. *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Industry cash flow risk* is the mean of the standard deviations of cash flow/assets over 10 years for firms in the same industry, as defined by the two-digit SIC code. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Mean	Std.Dev	25%	Median	75%
ROB	4.001	8.008	0.015	1.219	4.621
Financial leverage	0.304	0.799	0.015	0.172	0.346
Log book assets	4.717	2.416	3.120	4.632	6.349
Replaceability	0.273	0.088	0.205	0.298	0.325
Market-to-book assets	3.569	14.902	1.130	1.597	2.680
Return on assets	-0.155	1.210	-0.085	0.086	0.156
Fixed assets/assets	0.296	0.258	0.091	0.214	0.434
Dividend dummy	0.252	0.434	0.000	0.000	1.000
Cash ratio	0.224	0.264	0.023	0.116	0.336
Cash flow	-0.436	2.334	-0.179	0.034	0.094
Net working capital	-0.288	2.549	-0.067	0.023	0.157
Capital expenditures/assets	0.073	0.098	0.016	0.038	0.085
RD/sales	0.431	1.788	0.000	0.000	0.078
Acquisition/assets	0.015	0.593	0.000	0.000	0.001
Industry cash flow risk	0.922	0.930	0.157	0.578	1.537

Table 2: Effects of robots on financial leverage, ordinary least squares (OLS) and instrumental variable (IV) estimates

This table reports results from OLS and IV regressions of financial leverage on robots. The sample spans the 1993-2015 period. The dependent variables is *Financial leverage.* Column 1 reports the OLS regression results. Column 2 reports the second-stage regression results. Column 3 reports first-stage regression results using an industry-level measure called *Replaceability* as the instrument. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *ROB* is robot density, which is defined as the number of robots per thousand hours worked. *Replaceability* measures the share of hours that is replaceable by robots. *Log book assets* is the natural logarithm of total asset (at). *Market-to-book assets* is the market value of assets (*prcc_f*×*csho* + *at* - *ceq*) divided by the book value of assets (*at*). *Return on asset* is the return on assets for firm or industry *i* in year *t*, measured as operating income(*pi-xi*) scaled by asset (*at*). Fixed assets/assets is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	OLS	Second-stage Estimation	First-stage Estimation
	(1)	(2)	(3)
VARIABLES	Financial leverage	Financial leverage	ROB
ROB	0.001*	0.113***	
	(1.71)	(2.69)	
Replaceability			0.014***
			(3.56)
Log book assets	-0.091***	-0.094***	0.001
	(-8.24)	(-7.96)	(0.43)
Market-to-book assets	0.010***	0.009***	0.001
	(7.66)	(7.54)	(1.17)
Return on assets	-0.203***	-0.207***	0.001
	(-13.65)	(-13.89)	(1.53)
Fixed assets/assets	0.330***	0.357***	-0.001
	(6.15)	(6.26)	(-0.83)
Dividend dummy	-0.019***	0.002	-0.001
	(-2.68)	(0.13)	(-1.61)
First-stage F-statistic		88.22***	
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Observations	81,212	81,212	81,212

Table 3: Effects of robots on cash holdings, ordinary least squares (OLS) and instrumental variable (IV) estimates

This table reports results from OLS and IV regressions of cash holding on robots. The sample spans the 1993-2015 period. The dependent variables is *Cash ratio*. Column 1 reports OLS regression results. Column 2 reports second-stage regression results. Column 3 reports first-stage regression results using an industry level measure called *Replaceability*. *Replaceability* measures the share of hours that is replaceable by robots. *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *ROB* is robot density, which is defined as the number of robots per million hours worked. *Log book assets* is the natural logarithm of total asset(at). *Market-to-book assets* is the market value of assets (*prcc_f×csho + at - ceq*) divided by the book value of assets (*at*). *Cash flow* is earnings after interest, dividends, and tax but before depreciation (oibdp − xint −txt−dvc), scaled by the book value of total assets (at). *Net working capital* is measured as working capital (wcap) minus cash (che), scaled by total assets (at). *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). *Financial leverage* is long-term debt (dltt) plus debt in current liabilities (dlc), scaled by total assets (at). *RD/sales* is the ratio of research and development expense to sales. *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Industry cash flow Risk* is the mean of the standard deviations of cash flow/assets over 10 years for firms in the same industry, as defined by the two-digit SIC code. *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	OLS	Second-stage Estimation	First-stage Estimation
	(1)	(2)	(3)
VARIABLES	Cash ratio	Cash ratio	ROB
ROB	-0.001***	-0.024**	
	(-3.26)	(-2.50)	
Replaceability			0.014***
			(3.31)
Market-to-book assets	0.001***	0.001***	0.001
	(6.73)	(6.25)	(0.79)
Log book assets	-0.004***	-0.003*	0.001
	(-2.58)	(-1.77)	(0.79)
Cash flow	0.004***	0.004***	0.001
	(4.15)	(3.66)	(0.71)
Net working capital	-0.004***	-0.003**	0.001*
	(-3.57)	(-2.35)	(1.31)
Capital expenditures/assets	0.022**	0.064***	0.001***
	(2.32)	(3.08)	(5.89)
Financial leverage	-0.023***	-0.019***	0.001**
	(-8.16)	(-5.82)	(1.97)
RD/sales	0.006***	0.008***	0.001***
	(7.96)	(6.36)	(2.92)
Dividend dummy	0.012***	0.008*	-0.001
	(4.08)	(1.76)	(-1.35)
Acquisition/assets	0.001	0.001	0.001***
	(0.34)	(0.84)	(2.70)
Industry cash flow risk	0.002	0.005*	0.001
	(1.35)	(1.79)	(1.54)
Fixed assets/assets	-0.586***	-0.596***	-0.001
	(-57.74)	(-50.15)	(-1.49)
First-stage F-statistic		73.34***	
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Observations	72,043	72,043	72,043

Table 4: The effect of robots on the impact of labor unions on financial leverage and cash holdings, instrumental variable (IV) estimates

This table reports results from 2SLS regressions of financial leverage and cash holdings on robots and industry unionization rates. Column 1 reports 2SLS regression results of financial leverage. Column 2 reports 2SLS results of cash holdings. The sample spans the 1993-2015 period. The dependent variables are *Financial leverage* and *Cash ratio*. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *ROB* is robot density, which is defined as the number of robots per million hours worked. *High industry unionization rate* is an indicator variable equal to one if industry unionization rate is above 50% of the sample, and zero otherwise. *Industry unionization rates* are for 3-digit CIC industries and represent the fraction of total workers in an industry that are represented by unions in the collective bargaining with the firm. *Log book assets* is the natural logarithm of total asset (at). *Market-to-book assets* is the market value of assets (*prcc_f*×*csho* + *at* - *ceq*) divided by the book value of assets (*at*). *Return on asset* is the return on assets for firm or industry *i* in year *t*, measured as operating income (*pi-xi*) scaled by asset *(at)*. *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. *Cash flow* is earnings after interest, dividends, and tax but before depreciation (oibdp − xint −txt−dvc), scaled by the book value of total assets (at). *Net working capital* is measured as working capital (wcap) minus cash (che), scaled by total assets (at). *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). *RD/sales* is the ratio of research and development expense to sales. *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Industry cash flow risk* is the mean of the standard deviations of cash flow/assets over 10 years for firms in the same industry, as defined by the two-digit SIC code. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Continued.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Financial leverage	Cash ratio
ROB	0.157**	-0.033**
	(2.46)	(-2.28)
ROB×High industry unionization rate	-0.059**	0.012*
	(-2.21)	(1.92)
High industry unionization rate	0.481**	-0.101**
	(2.25)	(-2.01)
Log book assets	-0.096***	-0.003
	(-7.75)	(-1.22)
Market-to-book assets	0.011***	0.001***
	(7.63)	(5.56)
Return on assets	-0.207***	
	(-13.69)	
Fixed assets/assets	0.356***	-0.596***
	(6.07)	(-48.35)
Dividend dummy	0.007	0.008
	(0.37)	(1.56)
Cash flow		0.005***
		(3.57)
Net working capital		-0.004***
		(-2.59)
Capital expenditures/assets		0.065***
		(2.89)
Financial leverage		-0.020***
		(-5.31)
RD/sales		0.009***
		(5.27)
Acquisition/assets		0.002
		(1.10)
Industry cash flow risk		0.004
		(1.51)
First-stage F-statistic	28.96***	24.31***
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	81,102	71,946

Table 5: The effect of robots on the impact of unionization on the valuation of cash holdings using excess returns

This table reports results from OLS regressions of changes in firm value on robots and industry unionization rates, changes in cash holdings, interaction terms among robots, unionization, and changes in cash holdings, and control variables. The sample spans the 1993-2015 period. The dependent variable is the firm's excess stock return with excess return defined as the firm's annual fiscal year stock return minus the matched Fama and French 5×5 portfolio's return. The firm-level independent variables are: *ROB* is robot density, which is defined as the number of robots per million hours worked. *Industry unionization rates* are for 3-digit CIC industries and represent the fraction of total workers in an industry that are represented by unions in the collective bargaining with the firm. *Cash holdings* (cash and short term investments), *Earnings* (earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits), *Net assets* (total assets minus cash holdings), *Research & development expenses*, *Interest expenses, Dividends* (common dividends paid), *Market leverage* (total debt divided by the total debt plus the market value of equity), *Net financing* (total equity issuance minus repurchases plus debt issuance minus debt redemption), and *Repurchase* (the percentage of distributions to shareholders that occur in the form of repurchases). These independent variables, except leverage, are divided by the lagged market value of equity. A delta (Δ) reflects the variable is calculated as the change from year t-1 to t. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Continued.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
ROB	-0.003***	-0.003***	-0.001
	(-5.83)	(-5.82)	(-1.24)
Industry unionization rate	0.041	0.037	-0.042
	(1.42)	(1.29)	(-1.36)
ΔCash holdings$_t$	1.212***	1.569***	1.332***
	(22.16)	(22.82)	(11.99)
ROB×Industry unionization rate	0.032***	0.032***	0.021***
	(6.63)	(6.78)	(4.51)
Industry unionization rate×ΔCash holdings$_t$	-1.615***	-0.876***	-1.034***
	(-5.21)	(-2.71)	(-2.75)
ROB×ΔCash holdings$_t$	-0.009*	-0.009*	-0.019***
	(-1.76)	(-1.70)	(-2.97)
ROB×Industry unionization rate×ΔCash holdings$_t$	0.128**	0.123**	0.212***
	(2.50)	(2.45)	(3.63)
ΔEarnings$_t$	0.640***	0.628***	0.674***
	(24.82)	(24.30)	(15.35)
ΔNet assets$_t$	0.303***	0.307***	0.271***
	(21.11)	(21.16)	(12.54)
ΔResearch&development expenses$_t$	1.189***	1.164***	0.964**
	(5.65)	(5.58)	(2.57)
ΔInterest expense$_t$	-2.425***	-2.315***	-2.277***
	(-9.68)	(-9.14)	(-6.08)
ΔDividends$_t$	2.924***	2.829***	3.298***
	(5.44)	(5.26)	(5.82)
Cash holdings$_{t-1}$	0.189***	0.152***	0.103***
	(10.06)	(8.19)	(3.88)
Market leverage$_t$	-0.443***	-0.449***	-0.394***
	(-31.94)	(-32.16)	(-22.18)
Net financing$_t$	-0.096***	-0.126***	-0.179***
	(-3.50)	(-4.57)	(-4.39)
Cash holdings$_{t-1}$ × ΔCash holdings$_t$		-0.627***	-0.546***
		(-6.04)	(-3.10)
Market leverage$_t$ × ΔCash holdings$_t$		-1.063***	-0.799***
		(-8.18)	(-4.48)
Repurchase$_t$			-0.035***
			(-4.99)
Repurchase$_t$ × ΔCash holdings$_t$			-0.020
			(-0.21)
Constant	0.011*	0.012**	0.041***
	(1.83)	(2.19)	(5.36)
Observations	30,660	30,660	16,823
Adjusted R-squared	0.172	0.179	0.159

Table 6: The effect of robots on the impact of blue-collar workers on financial leverage and cash holdings, instrumental variable (IV) estimates

This table reports results from 2SLS regressions of financial leverage and cash holdings on robots and blue-collar workers. Column 1 reports 2SLS regression results of financial leverage. Column 2 reports 2SLS results of cash holdings. The sample spans the 1993-2015 period. The dependent variables are *Financial leverage* and *Cash ratio*. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *ROB* is robot density, which is defined as the number of robots per million hours worked. *High blue-collar* is an indicator variable equal to one if industry blue-collar worker rate is above the mean of the sample, and zero otherwise. *Log book assets* is the natural logarithm of total asset (at). *Market-to-book assets* is the market value of assets (*prcc_f*×*csho* + *at* - *ceq*) divided by the book value of assets (*at*). *Return on asset* is the return on assets for firm or industry *i* in year *t*, measured as operating income (*pi-xi*) scaled by asset *(at*). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. *Cash flow* is earnings after interest, dividends, and tax but before depreciation (oibdp − xint −txt−dvc), scaled by the book value of total assets (at). *Net working capital* is measured as working capital (wcap) minus cash (che), scaled by total assets (at). *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). *RD/sales* is the ratio of research and development expense to sales. *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Industry cash flow risk* is the mean of the standard deviations of cash flow/assets over 10 years for firms in the same industry, as defined by the two-digit SIC code. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Continued.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Financial leverage	Cash ratio
ROB	0.082**	-0.015**
	(2.51)	(-2.28)
ROB×High blue-collar	0.041**	-0.009**
	(1.99)	(-2.08)
High blue-collar	-0.204**	0.039*
	(-2.03)	(1.78)
Log book assets	-0.111***	-0.004**
	(-8.55)	(-2.38)
Market-to-book assets	0.009***	0.001***
	(7.38)	(5.99)
Return on assets	-0.202***	
	(-13.45)	
Fixed assets/assets	0.373***	-0.602***
	(6.29)	(-51.51)
Dividend dummy	0.008	0.008*
	(0.45)	(1.77)
Cash flow		0.004***
		(3.93)
Net working capital		-0.002**
		(-2.28)
Capital expenditures/assets		0.052***
		(2.79)
Financial leverage		-0.018***
		(-5.66)
RD/sales		0.007***
		(7.16)
Acquisition/assets		0.001
		(0.86)
Industry cash flow risk		0.002
		(0.86)
First-stage F-statistic	46.53***	39.52***
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	68,314	60,636

Table 7: The effect of robots on the impact of foreign competition on financial leverage and cash holdings, instrumental variable (IV) estimates

This table reports results from 2SLS regressions of financial leverage and cash holdings on robots and foreign competition. Column 1 reports 2SLS regression results of financial leverage. Column 2 reports 2SLS results of cash holdings. The sample spans the 1993-2015 period. The dependent variables are *Financial leverage* and *Cash ratio*. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *ROB* is robot density, which is defined as the number of robots per million hours worked. *Decdummy* takes a value of one for a tariff reduction of 2% or more, and zero otherwise. *Log book assets* is the natural logarithm of total asset (at). *Market-to-book assets* is the market value of assets (*prcc_f*csho + at - ceq*) divided by the book value of assets (*at*). *Return on asset* is the return on assets for firm or industry *i* in year *t*, measured as operating income (*pi-xi*) scaled by asset *(at*). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. *Cash flow* is earnings after interest, dividends, and tax but before depreciation (oibdp − xint −txt−dvc), scaled by the book value of total assets (at). *Net working capital* is measured as working capital (wcap) minus cash (che), scaled by total assets (at). *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). *RD/sales* is the ratio of research and development expense to sales. *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Industry cash flow risk* is the mean of the standard deviations of cash flow/assets over 10 years for firms in the same industry, as defined by the two-digit SIC code. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7

Continued.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Financial leverage	Cash ratio
ROB	0.123*	-0.023*
	(1.90)	(-1.78)
ROB×Decdummy	0.037**	-0.007**
	(2.15)	(-2.04)
Decdummy	-0.267**	0.048**
	(-2.17)	(1.99)
Log book assets	-0.108***	-0.004*
	(-6.49)	(-1.82)
Market-to-book assets	0.009***	0.001***
	(6.04)	(4.81)
Return on assets	-0.208***	
	(-10.97)	
Fixed assets/assets	0.394***	-0.594***
	(4.95)	(-35.51)
Dividend dummy	0.006	0.008
	(0.26)	(1.52)
Cash flow		0.004***
		(2.68)
Net working capital		-0.002
		(-1.55)
Capital expenditures/assets		0.045**
		(2.17)
Financial leverage		-0.018***
		(-4.12)
RD/sales		0.006***
		(3.98)
Acquisition/assets		-0.150***
		(-6.11)
Industry cash flow risk		0.001
		(0.47)
First-stage F-statistic	22.01***	18.48***
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	50,104	44,328

Table 8: Exposure to minimum wage changes, robots, and financial leverage

This table reports results from OLS regressions of exposure to minimum wage changes, robots, and financial leverage. The sample spans the 1993-2015 period. The dependent variables are *Financial leverage.* Column 1 reports OLS regression results and Column 2 reports the timing test results. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *High ROB* is an indicator variable equal to one if the robot density is above sample median, and zero otherwise. The explanatory variable of interest is the triple interaction between a bound state, a federal minimum wage change, and robot density. *Bound* is an indicator for a firm year that begins with the state minimum wage being equal to or less than the federal minimum wage. ΔMW *is* the percentage change in the federal minimum wage over the firm's prior year. *Post* equals to zero for three years before federal minimum wage increase and one for the two years of the federal minimum wage increase. Control variables include *Log book assets, Market-to-book assets, Return on asset, Fixed assets/assets, Dividend dummy, Log market capitalization, Industry cash flow Risk*, and *Cash flow.* Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Financial leverage	(2) Financial leverage
Bound×ΔMW×High ROB	0.490*	
	(1.84)	
Bound×ΔMW	-0.150	
	(-0.77)	
Bound×High ROB	-0.034	-0.032
	(-1.50)	(-1.31)
ΔMW×High ROB	-0.647***	
	(-2.80)	
Bound	0.013	0.007
	(0.68)	(0.39)
High ROB	0.047**	0.047**
	(2.08)	(2.04)
Bound×Post× High ROB		0.048*
		(1.65)
Bound×Post		-0.003
		(-0.17)
Post× High ROB		-0.066***
		(-2.58)
Post		-0.022
		(-0.15)
Control variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	48,236	48,236
Adjusted R-squared	0.718	0.718

Table 9: Exposure to minimum wage changes, robots, and cash holdings

This table reports results from OLS regressions of exposure to minimum wage changes, robots, and cash holdings. The sample spans the 1993-2015 period. The dependent variables are *Cash Ratio.* Column 1 reports OLS regression results and Column 2 reports the timing test results. *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *ROB* is robot density, which is defined as the number of robots per million hours worked. The explanatory variable of interest is the triple interaction between a bound state, a federal minimum wage change, and robot density. *Bound* is an indicator for a firm year that begins with the state minimum wage being equal to or less than the federal minimum wage. ΔMW *is* the percentage change in the federal minimum wage over the firm's prior year. *Post* equals to zero for three years before federal minimum wage increase and one for the two years of the federal minimum wage increase. Control variables include *Log book assets, Market-to-book assets, Fixed assets/assets, Dividend dummy, Financial leverage, Net working capital, Capital expenditures/assets, RD/sales, Acquisition/assets, Industry cash flow Risk,* and *Cash flow.* Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
VARIABLES	Cash ratio	Cash ratio
Bound×ΔMW×ROB	-0.006*	
	(-1.78)	
Bound×ΔMW	0.061	
	(1.37)	
Bound×ROB	0.001	0.001
	(0.24)	(0.26)
ΔMW×ROB	0.004*	
	(1.81)	
Bound	0.001	0.001
	(0.24)	(0.01)
ROB	-0.001	-0.001
	(-1.48)	(-1.56)
Bound×Post×ROB		-0.001*
		(-1.93)
Bound× Post		0.009**
		(2.14)
Post×ROB		0.001*
		(1.99)
Post		-0.001
		(-0.01)
Control variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	49,205	49,205
Adjusted R-squared	0.776	0.776

APPENDIX A: Effects of robots on overall firm risk, instrumental variable (IV) estimates

Table A1: Effects of robots on overall firm risk, instrumental variable (IV) estimates

This table reports results from IV regressions of operating leverage on robots. The sample spans the 1993-2015 period. The dependent variable is *Operating Leverage. Operating Leverage* is the percentage change in operating income for a percentage change in sales and is estimated using quarterly data from year t to year t+2. *High robot density* is an indicator variable equal to one if robot density is above sample median, and zero otherwise. *Labor-to-capital* is the number of employees (emp) to the real book value of property, plant, and equipment (ppent). *Log(#of employees)* is the natural logarithm of the number of employees (emp). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Industry cash flow Risk* is the mean of the standard deviations of cash flow/assets over 10 years for firms in the same industry, as defined by the two-digit SIC code. *Log firm age* is the natural log of one+firm age. *Negative earning* is an indicator variable equal to one if a firm reports negative earnings in a given year and is zero otherwise. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Operating Leverage	Operating Leverage
High robot density	-2.447*	-2.466*
	(-1.69)	(-1.70)
Labor-to-capital	-0.026	-0.026
	(-0.91)	(-0.91)
log(#of employees)	0.143***	0.153***
	(5.25)	(5.57)
Fixed assets/assets	-0.342	-0.329
	(-1.55)	(-1.49)
Industry cash flow risk	-0.005	-0.001
	(-0.15)	(-0.04)
Negative earning	-1.061***	-1.059***
	(-18.52)	(-18.51)
Log firm age		-0.123**
		(-1.96)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	65,465	65,465

APPENDIX B: Effects of robots on innovation, instrumental variable (IV) estimates

Table A2: Effects of robots on innovation, instrumental variable (IV) estimates

This table reports results from IV regressions of innovation on robots. The sample spans the 1993-2010 period. The dependent variables are *R&D* (models 1)*, R&D intensity* (models 2*), CW innovation value (*model3*), and Patents per capita (*model 4*). R&D* is the firm R&D expenses divided by book value of assets. *R&D intensity* is the firm R&D expenses divided by the sum of book value of assets and capital expenditures. *Citation-weighted innovation value* is the citation-weighted dollar value of innovation produced by a given firm in the year and is from Kogan et al. (2017). Patents per capita is the number of patents divided by the number of employees. Internal cash flow is income before extraordinary items plus depreciation and amortization divided by book value of assets. *High robot density* is an indicator variable equal to one if robot density is above sample median, and zero otherwise. *Tobin's Q* is the market value of equity plus book value of assets minus book value of equity minus deferred taxes divided by book value of assets. *Internal cash flow* is income before extraordinary item plus depreciation and amortization divided by book value of assets. *Financial leverage* is the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by book value of assets (*at*). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Market-to-book assets* is the market value of assets (*prcc_f*×*csho* + *at* - *ceq*) divided by the book value of assets (*at*). *Cash flow* is earnings after interest, dividends, and tax but before depreciation (oibdp − xint −txt−dvc), scaled by the book value of total assets (at). *Cash flow volatility* is the standard deviation of a firm's *Return on assets* over the previous five years (firms are required to have at least three years of data during the prior five years to enter the sample). *Labor-to-capital* is the number of employees (emp) to the real book value of property, plant, and equipment (ppent). *Log(#of employees)* is the natural logarithm of the number of employees (emp). *Negative earning* is an indicator variable equal to one if a firm reports negative earnings in a given year and is zero otherwise. *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A2

Continued.

	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
VARIABLES	R&D	R&D intensity	CW innovation value	Patents per capita
High robot density	0.071*	0.333***	0.097*	25.50*
	(1.67)	(3.90)	(1.65)	(1.70)
Tobin's Q	0.001	-0.001**	-0.002	0.129
	(0.47)	(-2.53)	(-1.38)	(0.41)
Internal cash flow	-0.018***	-0.004***	0.001	0.496
	(-13.07)	(-6.15)	(0.28)	(0.62)
Financial leverage			-0.012**	-0.979
			(-2.56)	(-1.44)
Fixed assets/assets			0.053***	-0.461
			(2.82)	(-0.21)
Market-to-book assets			0.001	-0.215
			(0.96)	(-0.66)
Cash flow			-0.014**	-0.328
			(-2.33)	(-0.37)
Cash Flow Volatility			-0.001	-0.136
			(-0.67)	(-1.41)
Capital expenditures/assets			-0.003	-4.297**
			(-0.19)	(-2.23)
Negative earning			0.012***	0.290
			(2.92)	(1.01)
Labor-to-capital				-0.789
				(-1.47)
log(#of employees)				-4.467***
				(-5.91)
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	79,232	76,483	51,147	44,916

APPENDIX C: The effect of robots on the cost of bank debt, instrumental variable (IV) estimates

Table A3: The effect of robots on the cost of bank debt, instrumental variable (IV) estimates

This table reports results from IV regressions of the cost of bank debt on robots. The dependent variable in columns (1) and (2) is the weighted average cost of private bank loans of firm i in year t and the dependent variable in columns (3) and (4) is the log (loan spread). *ROB* is robot density, which is defined as the number of robots per million hours worked. *Log book assets* is the natural logarithm of total asset(at). *Market-to-book assets* is the market value of assets (*prcc_f*×*csho* + *at* - *ceq*) divided by the book value of assets (*at*). *Return on asset* is the return on assets for firm or industry *i* in year *t*, measured as operating income (*pi-xi*) scaled by asset (*at*). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Log loan size* is the natural logarithm of the loan amount (in millions). *Log loan maturity* is the natural logarithm of the number of months until the loan matures. *Financial leverage* is long-term debt (dltt) plus debt in current liabilities (dlc), scaled by total assets (at). *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Cash flow volatility* is the standard deviation of a firm's *Return on assets* over the previous five years (firms are required to have at least three years of data during the prior five years to enter the sample). *Log market capitalization* is the natural logarithm of market capitalization. *Log sale growth* is the natural logarithm of sale growth. *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. Log age is the natural logarithm of 1 + firm age. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (z-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
VARIABLES	Weighted average cost of debt	Weighted average cost of debt	Log(spread)	Log(spread)
ROB	-0.042*	-0.046*	-0.061*	-0.065*
	(-1.65)	(-1.69)	(-1.81)	(-1.78)
Log book assets	0.052*	0.057**	0.041	0.048
	(1.82)	(2.01)	(1.23)	(1.43)
Market-to-book assets	0.006	0.004	0.012	0.010
	(0.51)	(0.32)	(0.81)	(0.63)
Return on assets	0.013	0.006	-0.155	-0.155
	(0.07)	(0.04)	(-0.86)	(-0.85)
Fixed assets/assets	-0.503***	-0.498***	-0.366**	-0.365**
	(-3.63)	(-3.59)	(-2.16)	(-2.13)
Log loan size	-0.085***	-0.083***	-0.086***	-0.085***
	(-4.99)	(-4.85)	(-4.75)	(-4.61)
Log loan maturity	0.103***	0.099***	0.083***	0.083***
	(5.27)	(5.01)	(3.63)	(3.59)
Financial leverage	0.468***	0.474***	0.354***	0.371***
	(5.33)	(5.35)	(3.78)	(3.84)
Acquisition/assets	0.427***	0.428***	0.253***	0.249**
	(5.32)	(5.19)	(2.60)	(2.45)
Cash flow volatility	-0.425**	-0.470**	-0.464*	-0.506*
	(-2.04)	(-2.14)	(-1.77)	(-1.79)
Log market capitalization	-0.150***	-0.140***	-0.123***	-0.114***
	(-8.48)	(-7.94)	(-6.30)	(-5.74)
Log age	-0.488***	-0.472***	-0.417***	-0.398***
	(-6.78)	(-6.48)	(-4.61)	(-4.36)
Log sale growth	0.017	0.019	0.008	0.011
	(0.77)	(0.83)	(0.33)	(0.38)
Dividend		-0.196***		-0.201***
		(-5.48)		(-4.35)
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	7,436	7,436	12,870	12,870

APPENDIX D: The effect of robots on risk management, instrumental variable (IV) estimates

Table A4: The effect of robots on risk management, instrumental variable (IV) estimates

This table reports results from IV regressions of risk management on robots. The dependent variable in columns (1) and (2) is *Ln(1+FX_hedge_num)* and is the natural logarithm of 1 plus a firm's total mentions of foreign currency hedging contracts in its annual report in a year. *ROB* is robot density, which is defined as the number of robots per million hours worked. *Log market capitalization* is the natural logarithm of market capitalization. *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Ln(1+CO_hedge_num)* is the natural logarithm of 1 plus a firm's total mentions of commodity derivatives in its annual report in a year. *Ln(1+IR_hedge_num)* is the natural logarithm of 1 plus a firm's total mentions of interest rate derivatives in its annual report in a year. *Blue-collar worker rate* is the industry blue-collar worker rate. *Market-to-book assets* is the market value of assets (*prcc_f×csho + at - ceq*) divided by the book value of assets (*at*). *Capital expenditures/assets* is the ratio of capital expenditures (capx) to total assets (at). *Financial leverage* is long-term debt (dltt) plus debt in current liabilities (dlc), scaled by total assets (at). *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (z-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Log(1+FX_hedge_num)	Log(1+FX_hedge_num)
ROB	-0.023**	-0.023**
	(-2.12)	(-2.09)
Log market capitalization	0.011	0.011
	(1.56)	(1.50)
Fixed assets/assets	-0.050**	-0.043
	(-2.21)	(-1.13)
Log(1+CO_hedge_num)	0.073	0.069
	(1.50)	(1.43)
Log(1+IR_hedge_num)	-0.043	-0.041
	(-1.48)	(-1.41)
Blue-collar worker rate	0.221	0.235
	(0.78)	(0.83)
Market-to-book assets	0.001	0.001
	(0.95)	(0.94)
Capital expenditures/assets	0.146***	0.145***
	(2.96)	(2.95)
Financial leverage	-0.001	-0.001
	(-0.29)	(-0.25)
Cash ratio		0.009
		(0.23)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	6,397	6,395

APPENDIX E: The effect of robots on payout policy, instrumental variable (IV) estimates

Table A5: The effect of robots on payout policy, instrumental variable (IV) estimates

This table reports results from IV regressions of payout policy on robots. The dependent variable in columns (1) and (2) is *Payout* and is the sum of repurchases and dividends divided by the book value of assets *(at)*. *High ROB* is an indicator variable equal to one if robot density is above the median of the sample, and zero otherwise. *Log(#of employees)* is the natural logarithm of the number of employees (emp). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Cash flow volatility* is the standard deviation of a firm's *Return on assets* over the previous five years (firms are required to have at least three years of data during the prior five years to enter the sample). *Log firm age* is the natural log of one+firm age. *Log market* capitalization is the natural logarithm of market capitalization. *Market leverage* is total debt divided by the total debt plus the market value of equity). *Net working capital* is measured as working capital (wcap) minus cash (che), scaled by total assets (at). *Acquisition/assets* is defined as the ratio of acquisitions (aqc) to total assets (at). *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (z-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Payout	Payout
High ROB	0.091*	0.093*
	(1.69)	(1.70)
log(#of employees)	-0.022**	-0.022**
	(-2.12)	(-2.10)
Fixed assets/assets	0.029	0.034
	(1.06)	(1.26)
Cash flow volatility	0.008	0.008
	(1.26)	(1.26)
Log firm age	0.023***	0.024***
	(2.78)	(2.80)
Market leverage	-0.006	-0.005
	(-0.84)	(-0.73)
Log market capitalization	0.002	0.002
	(1.29)	(1.16)
Net working capital	0.001	0.001
	(0.81)	(0.80)
Acquisition/assets	-0.004	-0.003
	(-0.55)	(-0.34)
Cash ratio		0.009
		(1.37)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Observations	61,560	61,560

APPENDIX F: The effect of robots on acquisition activities, instrumental variable (IV) estimates

Table A6: The effect of robots on acquisition activities, instrumental variable (IV) estimates

This table reports results from IV regressions of acquisition synergies on robots. The dependent variable in columns (1) and (2) is the Acquirer CAR and is calculated as the acquirer three-day CARs. *High ROB* is an indicator variable equal to one if robot density is above the median of the sample, and zero otherwise. *Log book assets* is the natural logarithm of total asset (at). *Blue-collar worker rate* is the industry blue-collar worker rate. *Financial leverage* is long-term debt (dltt) plus debt in current liabilities (dlc), scaled by total assets (at). *Fixed assets/assets* is the book value of property, plant, and equipment (*ppent*) divided by the book value of assets (*at*). *Dividend dummy* is an indicator variable equal to one if a firm pays common dividends (*dvc*), and zero otherwise. *State Per Capita GDP* is a state's GDP (in thousands) divided by its total population. *Cash ratio* is the ratio of cash and short-term investments (*che*) to total assets (*at*). *Related deal* is an indicator variable equal to one if both the target and the acquirer are from the same industry and zero otherwise. *Percent equity* is the percent of the deal value paid in equity. *Relative size* is the deal value, scaled by acquirer's market value. *Financial Constrained* is set to one for firms that depend on external capital, which are those whose capital expenditures exceed operating cash flows. Dollar values are expressed in 2010 dollars. Continuous variables, except state-level variables, are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at firm level (z-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	2SLS	2SLS
	(1)	(2)
VARIABLES	Acquirer CAR	Acquirer CAR
High ROB	0.097*	0.097*
	(1.71)	(1.72)
Log book assets	-0.007***	-0.007***
	(-3.78)	(-3.77)
Blue-collar worker rate	0.044	0.044
	(0.98)	(0.97)
Financial leverage	0.033**	0.032**
	(2.10)	(2.09)
Fixed assets/assets	0.036	0.035
	(1.33)	(1.32)
Dividend dummy	-0.006	-0.006
	(-0.92)	(-0.91)
Log(State Per Capita GDP)	-0.031	-0.031
	(-1.39)	(-1.41)
Cash ratio	-0.025	-0.025
	(-1.10)	(-1.11)
Related deal	-0.007	-0.007
	(-1.40)	(-1.38)
Percent equity	-0.001***	-0.001***
	(-2.97)	(-2.99)
Relative size	0.036**	0.036**
	(1.98)	(1.98)
Financial constrained		0.001
		(0.33)
Industry-year Fixed Effects	Yes	Yes
Observations	2,716	2,716

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