Labor-Capital Substitution and Capital Structure: Evidence from Automation

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Abstract

This paper presents evidence that the exposure to automation technologies has a positive impact on a firm's financial leverage. The effects are more pronounced in firms with greater labor costs, routine task intensity, firing costs, and union coverage. The results are robust when we instrument a firm's exposure to automation technologies using the robotics adoption in European countries. Our analysis suggests that the exposure to automation technologies creates a replacement threat that weakens workers' bargaining power, compressing their wage premiums for bearing financial distress risk and reducing wage rigidity, both of which allow firms to increase financial leverage.

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Abstract

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1. Introduction

Automation is the labor-saving technology that completes a process or procedure with minimal human intervention. Encompassing machine learning and artificial intelligence, automation has fundamentally reshaped how work is done—not only assembly-line types of repetitive tasks, but more recently, cognitive tasks with increasing sophistication. The impact of automation on many aspects of firm operations, such as production growth and efficiency, employment, composition of the labor force, and wage structures' of workers, has attracted great attention recently (e.g., Acemoglu and Restrepo 2018a, 2018b, 2018c, 2020; Graetz and Michaels 2017; Autor et al. 2003; Acemoglu and Autor 2011; Autor and Dorn 2013; Goos and Manning 2007), yet little is known about how automation shapes a firm's financing policy.

The importance of labor in a firm's capital structure decision has long been recognized and documented in the literature (e.g., Titman 1984; Berk, Stanton, and Zechner 2010; Agrawal and Matsa 2013, Gorton and Schmid 2004; Benmelech, Bergman, and Enriquez 2012). Matsa (2018) notes that, to understand the role of labor in a firm's capital structure decision, it is crucial to recognize that workers, unlike capital, cannot be owned (as a physical tangible asset), have their own preferences and can act strategically in response to the firm's decisions. More importantly, workers' bargaining power depends on the extent to which they can complete tasks that capital cannot. This insight suggests that, as automation technologies become more cost effective and readily available for firms, workers' bargaining power in influencing a firm's financing decision could be fundamentally reshaped. The purpose of this paper is to investigate this important insight by studying how the rising availability of automation technologies constitutes a replacement threat that can alter workers' incentives and bargaining position, and as a consequence, affect a firm's capital structure.

The replacement threat imposed by the increasing supply of automation technologies could affect the bargaining position of workers in two primary ways. First, the replacement threat could limit the wage premiums for financial distress demanded by workers. Prior literature shows that financial distress such as covenant violations (Falato and Liang 2016), bond defaults (Agrawal and Matsa 2013), maturity of long-term debt (Benmelech, Frydman, and Papanikolaou 2019), and bankruptcy (Graham et al. 2019) are often associated with dramatic labor cuts and wage losses.[1] To compensate the unemployment costs associated with financial distress, employees will demand a wage premium for bearing such risk, which raises the overall costs of debt financing and deters firms from increasing financial leverage (Titman 1984; Berk, Stanton and Zechner 2010; Agrawal and Matsa 2013).

However, demanding a higher wage could incentivize firms to accelerate the adoption of automation technologies to replace workers. Acemoglu and Restrepo (2020) show that the occurrence of worker replacement with automation technologies depends on the relative productivity-to-cost ratios of automation vs. labor: If the productivity-to-cost ratio of automation is higher than the productivity-to-wage ratio of workers, then it is in the firm's best interest to replace workers with automation technologies. As shown in the theoretical models of multi-sector search and wage bargaining by Leduc and Liu (2019) and Arnoud (2018), the automation threat shifts the bargaining power from workers toward firms. This finding suggests that the replacement threat posed by automation technology could weaken employees' incentive and bargaining power for demanding a higher wage for bearing financial distress risk, thereby allowing firms to increase financial leverage. We refer to this as the "wage compression" effect. Such an effect is expected

[1] Prior studies also show that laid-off workers experienced large wage cuts when they returned to work, found it more difficult to find jobs that matched their skills, or even experienced family and stress-related health issues (Gibbons and Katz, 1991; Farber, 2005; Mortensen, 1986; Mortensen and Pissarides, 1994; Lazear, 2009; Hsu, Matsa and Melzer, 2018; Charles and Stephens, 2004; Sullivan and von Wachter, 2009).

to be stronger among firms that are more susceptible to automation adoption (Autor and Dorn 2013; Autor, Dorn, and Hanson 2015; Acemoglu and Restrepo 2018a, 2018b).

Second, the replacement threat imposed by automation technologies could reduce wage rigidity, allowing firms to employ more financial leverage. Unlike capital, workers benefit from various labor market protections such as unions, employment protection regulations, and minimum wages. All of these impose labor-specific adjustment costs, which restrain a firm from flexibly cutting down employment and wages (Simintzi, Vig and Volpin 2015; Kuzmina 2013; Serfling 2016; Atanassov and Kim 2009; Chen, Kacperczyk, and Ortiz-Molina 2011; Gustafson and Kotter 2018). Wage rigidity is akin to an increase in operating leverage that limits a firm's use of financial leverage. Favilukis, Lin and Zhao (2019) demonstrate that wage rigidity can increase a firm's credit risk so that a firm tends to lower its financial leverage. The rising supply of automation technologies increases the productivity-to-cost ratio of automation, which could diminish the effectiveness of labor market protections. For example, the bargaining power of labor unions will diminish as they might be concerned that a tough stand in the negotiation could incentivize firms to accelerate the adoption of automation technologies. As such, by lowering wage rigidity, the availability of automation technologies allows a firm to increase its financial leverage. We refer to this as the "wage rigidity" effect.

Admittedly, besides affecting financial leverage through changing workers' incentives and bargaining position, the availability of automation technologies could affect financial leverage through other channels. For example, adopting automation technologies are expensive. It is possible that firms simply rely more on external financing to build up cash reserves in response to a greater exposure to automation technologies (e.g., Qiu and Chi 2015; Bloom, Schankerman, and Van Reenen 2013). Moreover, investing in automation technologies requires a high upfront fixed cost that could increase a firm's operating leverage, resulting in a lower financial leverage. It is also possible that the rising availability of automation technologies coincides with other industry structure changes (import competition from China (e.g., Xu 2012) or other capital deepening activities) that affect a firm's financial leverage. We will consider these alternative channels in our analysis.

We gauge a firm's exposure to automation technologies using two different measures. Our first measure builds on the patent textual analysis in Mann and Püttmann (2018, thereafter MP) who examine the texts of all 5 million U.S. patents granted from 1976 onwards and classify the patents as either automation or non-automation innovation using a supervised machine-learning method based on the naive Bayes algorithm. In essence, a patent is deemed automation-related if the patent text describes a new device (e.g., robots) or non-physical innovation (e.g., software and sophisticated algorithms) that carries out a task without requiring human intervention. An automation patent is then assigned to industries where the technology can be used. Using MP's classification, we define our firm-level proxy for automation exposure as the logarithm of the segment-sales-weighted sum of the stock of automation patents made available over the past five years across industries in which the firm operates (denoted as *AutoExpo*).

One advantage of using patent textual analysis to measure automation technologies is that it allows us to capture the availability of both technical and conceptual innovations in automation, of which the latter has gained increasing importance in the era of artificial intelligence. The second advantage is that we are able to separate the automation-related patents from non-automation-related patents which allows us to control for non-automation technologies in the analysis. This is important for the identification of the effect of automation exposure as non-automation innovations are likely to comove with automation innovations. Moreover, *AutoExpo* provides a direct and broad assessment of firm-level exposure to automation technologies that are readily available to a firm. It therefore is conceptually akin to the technological spillover measure by Bloom, Schankerman and Van Reenen (2013), but with a focus on automation technologies.

Our second measure of a firm's exposure to automation follows Acemoglu and Restrepo (2020). Denoted as the Adjusted Penetration of Robots in five European countries (*APR_EURO5*), this measure appraises U.S. firms' exposure to automation technologies as the segment-sales-weighted sum of the five-year changes in robotics adoption in five European countries that are ahead of the United States in robotics, including Denmark, Finland, France, Italy and Sweden. The benefit of using this measure as noted by Acemoglu and Restrepo (2020) is that the labor market outcomes of U.S. domestic markets (by extension, the financing policy of U.S. firms) cannot be driven by the penetration of robots in European countries that are ahead of the United States in robotics. In other words, the changes in capital structures of U.S. firms cannot be associated with the advancement of robotics in European countries other than via the exposure to the increasing supply of automation technologies.

We start our analysis by using the first measure of automation exposure (*AutoExpo)* to examine the impact of automation exposure on firm leverage. We find a strong and positive association between a firm's exposure to automation technologies (*AutoExpo*) and its leverage ratios. Our estimates suggest that a one-standard-within-deviation increase in *AutoExpo* increases book leverage by 1.3%. The results consistently hold for alternative measures of leverage, including book leverage, market leverage and their corresponding net measures (net of cash holdings).

We then present evidence that the replacement threat imposed by automation technologies affects workers' bargaining power in influencing a firm's capital structure decision. The "wage compression" effect suggests that the replacement threat from automation technologies reduces workers' bargaining power for demanding a higher wage for bearing the risk of financial distress and allows firms to increase financial leverage. Such a replacement threat is imminent for workers in firms that are more prone to automation adoption. We therefore expect that firms facing significant labor demand and stiff labor costs are more prone to adopt automation technologies, since automation has systematically shifted the comparative advantage away from low- and medium-skilled labor. Similarly, we expect that the replacement threat is more pressing among firms whose operations involve more routine tasks because repetitive and routine jobs are more likely to be replaced by robotics than non-routine jobs (e.g., jobs that require solving unstructured problems or creativity) (Autor, Levy, and Murnane 2003). Moreover, the innovative activities tend to be geographically concentrated (Jaffe, Trajtenberg, and Henderson 1993), and geographic proximity facilitates related technology transfer and lowers the rental costs of industrial robotics (Lychagin et al., 2016). Hence, we expect that the replacement threat is stronger among firms that are geographically close to robotic hubs.

In line with the "wage compression" effect, we find that the role of automation exposure in shaping a firm's capital structure is more salient in industries with a higher labor intensity (labor-to-capital ratio), a higher labor cost (extended labor share from Donangelo et al. 2019), a greater routine task intensity (Autor, Levy, and Murnane 2003), and among firms whose headquarters are located in the vicinity of the top 20 clusters of robot integrators (e.g., Boston, Chicago, and Detroit; Leigh and Kraft 2018).[2]

[2] A robot integrator is a company that engineers, builds and installs automation machinery for different industrial applications. A list of major robot integrators can be found at https://www.technavio.com/blog/top-21-companies-in-the-industrial-robotics-market.

The "wage rigidity" effect of automation exposure on capital structure indicates that the replacement threat imposed by the rising availability of automation technologies makes wages less rigid by weakening the labor market protection, leading to a higher use of financial leverage. Such an effect is expected to be greater for firms that are subject to stronger protection by labor unions or market regulation and norms, i.e., those firms facing a greater firing cost and covered by broader union coverage. Consistent with these conjectures, we find that the role of automation exposure in shaping a firm's capital structure is more evident in firms facing a higher firing cost and a high union coverage. Taken together, our findings provide strong evidence that the replacement threat imposed by automation exposure affects a firm's financial leverage by changing workers' bargaining power.

To further sharpen the causal inference, we use the second measure of automation exposure constructed from Acemoglu and Restrepo (2020) to analyze the relation between the exposure to automation technologies and financial leverage. Since *APR_EURO5* captures the changes in robotics adoption in European countries that are ahead of robotics technologies in the United States, we follow Acemoglu and Restrepo (2020) and construct the *APR_EURO5* as the segment-sales-weighted sum of the five-year adjusted penetration of robots from five European countries using the robotic and employment data from 1995 to 2015.[3] Then we instrument the automation exposure to U.S. firms using the firm-level segment-sales-weighted sum of the adjusted penetration of robots in five European countries. We find consistent evidence that automation exposure has a significant and positive impact on U.S. firms' financial leverage.

[3] Acemoglu and Restrepo (2020) construct the average adjusted penetration of robots from 1993 to 2007 and use it in cross-sectional regressions. We extend their measure and use a five-year moving window to capture time-series dynamics of adjusted penetration of robots.

Importantly, we also consider in our analysis other potential explanations for the impact of automation exposure on financial leverage. First, we include asset tangibility in all regressions to control for the possibility that a firm's exposure to automation technologies could increase its asset tangibility, which could lead to a higher financial leverage. Second, we use two measures of net leverage (i.e., book leverage net of cash holdings and market leverage net of cash holdings) as alternative measures of financial leverage to address the concern that a greater exposure to automation technologies could incentivize firms to raise debt and increase their cash reserves for adopting new technologies. Third, automation adoption generally requires a significant upfront fixed cost that could increase a firm's operating leverage and correspondingly reduce a firm's financial leverage. Our results show that automation exposure increases a firm's financial leverage, which is inconsistent with the fixed cost explanation. Nevertheless, we include a variable *NonAutoExpo* that captures a firm's exposure to non-automation technologies as a control variable. Investing in non-automation technologies might require a significant upfront fixed cost but does not impose a replacement threat on workers. Our results show that *NonAutoExpo* is negatively or insignificantly related to financial leverage, while *AutoExpo* remains positive and statistically significant, suggesting that automation exposure has a distinct effect on financial leverage from non-automation technology exposure that imposes no "replacement threat." Fourth, to address the concern that the rising availability of automation technologies could coincide with the increasing import competition from China, we further control for the import competition from China and again find robust results. Lastly, we include industry capital stock, industry IT capital expenditure, and total industry value added to control for the effect of industry capital deepening and other technologies on a firm's financial leverage. We show that the capital deepening and other technological changes that cannot generate a replacement threat have no impact on financial leverage, which indicates that the effect of automation exposure on financial leverage is not driven by other concurrent technological changes.

Our paper adds to the literature that examines the relation between labor and capital structure decisions, including unemployment risks (Agrawal and Matsa 2013; Berk et al. 2010; Titman 1984; Falato and Liang 2016), labor market protections (Simintzi et al. 2015; Kuzmina 2013; Serfling 2016), and operating leverage (Donangelo et al., 2019). Differing from this line of inquiry, we focus on how the replacement threat from automation technologies affects workers' bargaining power in influencing corporate financing policies. We investigate the insight by Matsa (2018) that the extent to which capital could replace labor is the key factor in determining workers' bargaining power in influencing corporate decision. Our analyses show that the exposure to automation technologies significantly alters the bargaining power of workers and consequently affects the firm's capital structure decision.[4]

Our paper also adds to the literature that examines the impact of automation on a firm's real outcomes such as productivity, wages, and the composition of jobs (Acemoglu and Restrepo 2018a, 2018b, 2018c, 2020; Graetz and Michaels 2017; Autor et al. 2003; Acemoglu and Autor 2011; Autor and Dorn 2013; Goos and Manning 2007). Our findings show that the availability of automation technologies not only affects a firm's real activities, but also its financing policy, which could influence its ability to undertake investment opportunities.

[4]Our paper is related to a contemporaneous study by Bates et al. (2020) but differs in two important ways. First, Bates et al. (2020) measure a firm's automation threat using an industry-level occupational susceptibility to computerization. Our study uses both patent textual analysis and robot penetration from European countries to measure automation exposure, which allows us to capture both the physical and conceptual innovations of automation technologies at the firm level, and more importantly, directly address the endogenous concerns. Second, Bates et al. (2020) explore the relationship between automation and different financial policies with a focus on cash holdings. Our study focuses on the effect of automation exposure on financial leverage and explores the specific underlying mechanisms following the implications by Matsa (2018).

The remainder of the paper proceeds as follows. Section 2 details the construction of key variables and data sources. Section 3 empirically investigates the effect of automation exposure on capital structure. Section 4 provides further analyses using the adjusted penetration of robots from Acemoglu and Restrepo (2020). Section 5 concludes.

2. Data and Variables

In this section, we describe data and samples, measurement of firm-level automation exposure, and the construction of variables used in our empirical analysis.

2.1. Data and samples

We obtained the financial information of U.S. public firms from COMPUSTAT from 1976 to 2014, during which automation and non-automation patent classification is available from MP (2018). We excluded the financial and utilities industries (SIC codes 6000-6999 and 4900-4999), as well as firms with missing or negative total assets or total sales. Our final sample contains 130,231 firm-year observations for 23,323 unique U.S. public firms.

2.2. Measurements of automation exposure

We describe the first firm-level measure of automation exposure in this subsection and provide further details on the construction of the second measure *APR_EURO5* in Section 4.

We construct our first measure of automation exposure, *AutoExpo*, based on MP's (2018) classification of U.S. utility patents.[5] MP (2018) define an automation patent as "*a device that carries out a process independently,*" including "*a physical machine, a combination of machines,*

[5] The automation patents from MP (2018) is obtained from https://github.com/lpuettmann/automation-patents.

an algorithm or a computer program." The examples of automation patents include industrial robots or automatic taco machines (physical device) or automated email activity management (a program). Based on this definition, MP (2008) extract the patent description texts of approximately 5 million U.S. utility patents granted between 1976 and 2014 and classify the utility patents into either automation or non-automation innovation using a naïve Bayes algorithm. Each patent is then assigned to relevant industries where the technology can be potentially used. This feature considers an important fact that the terminal user of the technology may not necessarily be the assignee (i.e., creator) of a patent.[6]

To measure a firm's exposure to automation technologies, for each industry *j* in year *t*, we compute an industry-level sum of automation patents made available over the past five years (denoted as $AutoPatent_{j,t}$) to quantify the automation-related knowledge pool available to industry *j*.[7] We compute firm *i*'s exposure to automation technologies in year *t*, $AutoExpo_{i,t}$, as a logarithm of the segment-sales-weighted sum of the stock of automation patents across all four-digit SIC industries in which the firm operates as follows,

$$AutoExpo_{i,t} = \log(\sum_{j=1}^{N} s_{i,j,t} AutoPatent_{j,t}), \tag{1a}$$

where $s_{i,j,t}$ is firm *i*'s percentage of segment sales in four-digit SIC industry *j* in year *t* obtained from the COMPUSTAT historical segment data.

Similarly, we provide an analogous measures of the firm-level exposure to non-automation technologies: $NonAutoExpo_{i,t}$. $NonAutoExpo_{i,t}$ is calculated as the logarithm of the segment-sales-

[6] For example, a software company might own many patents that are not used in the computer industry, but by companies in the manufacturing or in the retail sector.

[7] MP (2018) conducts various tests to validate this novel patent-level classification method and demonstrate the usefulness of their industry-level automation proxy. For instance, they found that their measure is correlated to routine-task intensity, computer investment and the number of robots used in an industry.

weighted sum of the number of non-automation patents (besides chemical and pharmaceutical patents) in the four-digit SIC industry in which the firm operates:

$$NonAutoExpo_{i,t} = \log(\sum_{j=1}^{N} s_{i,j,t} NonAutoPatent_{j,t}) . \quad (1b)$$

It is important to control for a firm's exposure to non-automation technologies as the availability of both automation and non-automation technologies has increased considerably over time.

In addition, since the patents in the chemical and pharmaceutical industries are classified neither as automation patents nor as non-automation patents, we further control for a firm's exposure to the technologies available in those industries.[8] Specifically, we construct a variable *Chem&Pharm* defined as the logarithm of the segment-sales-weighted sum of the number of chemical and pharmaceutical patents available in the past five years.

2.3. Summary statistics of automation exposure

Figure 1 plots the time series of the number of automation patents and non-automation patents of our sample firms over the period of 1976 – 2014. The blue (red) line denotes the time-series of the number of automation (non-automation) patents. The green line indicates the time-series of patent numbers in the chemical and pharmaceutical industries. It observes a steady increase of automation (non-automation) patents from approximately 4.7×10^4 (1.6×10^4) to more than 16.3×10^4 (9.0×10^4) over the sample period. The number of patents in the chemical and pharmaceutical industries stay relatively stable over the sample period. In particular, the growth rate of automation patents accelerates after 2002 and, since then, the number of automation patents

[8] Those patents fall into the USPC technology classes: 127, 252, 423, 424, 435, 436, 502, 510-585, 800, 930, 987. As detailed in MP (2018), most chemical and pharmaceutical patents are not classified as automation patents, and words like "automatic" are often used with a different meaning in these patents.

granted in a year has surpassed that of non-automation patents. At the beginning of the sample period in 1976, automation patents only accounted for 23.2% of the total patents; in 2014, its share increased to 57.2%, which is more than double of that at the beginning of the sample in 1976. These observations indicate that automation technologies play an increasingly important role in our economy.

[Figure 1 about here]

In panel A of Table 1, we report mean, median, the 25th, the 75th percentiles, and standard deviation of our automation and non-automation exposure measure. The average value of our firm-level automation exposure measure is 4.64 with a standard deviation of 2.14. This implies that on average, there are 104 automation patents granted in the past five years available to a firm (Exp(4.64) = 104). Similarly, the average value of the non-automation exposure measure is 5.08 with a standard deviation of 2.06, which indicates that on average, a firm has access to 161 non-automation patents granted in the past five years ((Exp(5.08) = 161).

[Table 1 about here]

2.4. Other firm-level variables

We construct four measures of financial leverage. The first two measures, book leverage and market leverage, are computed as the ratio of long-term debt plus current liability over total assets and the ratio of long-term debt plus current liability over market value of assets (i.e., book value of debt plus market value of equity), respectively. Note that market leverage is more closely related to the theoretical prediction of the optimal debt level; however, as shown by Welch (2004), a large portion of variation in market leverage is driven by the variation of the market value of equity rather than changes in debt values.

We also consider two alternative measures, net book leverage and net market leverage, which are defined as net debt (i.e., total debt minus cash and other marketable securities) over total assets and net debt over the market value of assets, respectively. As discussed earlier, our measure of a firm's exposure to automation technologies is akin to Bloom et al.'s (2013) measure of technology spillovers but focuses on automation technologies. Qiu and Wan (2015) show that technological spillovers could increase a firm's precautionary cash holdings. Given adopting automation technologies is costly, firms could increase their cash reserve through debt financing when their exposure to automation technologies increases. Net book leverage and Net market leverage allow us to control for this effect.

In our regression analysis, we include a set of firm-level control variables that determine firm leverage following the prior literature (e.g., Rajan and Zingales 1995; Serfling 2016; Simintzi et al. 2015): Firm size (*Size*) is defined as the logarithm of a firm's total assets, which controls for diversification and the risk of default; the market-to-book ratio (*M*/*B*) is computed as the ratio of the market value of equity plus book value of debt over the book value of debt plus equity, which works as an indicator of growth opportunities; profitability is measured by the return on assets (*ROA*) (i.e., the ratio of EBIT over total assets) as a proxy for the level of internal funds; cash flow volatility (*Cash flow volatility*) is defined as the standard deviation of income before extraordinary items plus depreciation and amortization to book assets over the past five years; Cuñat and Melitz (2012) argue that firms with more volatile cash flows are more likely to adjust labor inputs in response to economic conditions, and hence, cash flow volatility should be considered as a factor for a firm's use of debt; dividend payment (*Dividend*) is an indicator for whether the firm paid a common dividend as a proxy for financial constraints; R&D (*R&D*), defined as research and development expenditure scaled by total assets, captures the internal research potential of a firm.

Importantly, we also control for tangibility (*Tangibility*) which is calculated as net property, plant and equipment scaled by total assets. The rising availability of automation technologies could be associated with a greater asset tangibility by increasing pledgeable collateral assets, resulting in higher borrowing capacity. Including asset tangibility allows us to control for this effect of automation exposure on financial leverage.

In panel B of Table 1, we report mean, median, the 25th, the 75th percentiles, and standard deviation of leverage ratios and its relevant control variables. All the variables are winsorized at 1st and 99th percentiles. The distribution of leverage ratios and control variables of our sample firms are comparable to those reported in prior studies (Serfling 2016; Simintzi et al. 2015): the average book (market) leverage is about 26% (19%); on average, a firm holds 148 million in total assets and has a market-to-book ratio of 2.0; the average tangibility of a firm is 29.6%; on average, 34.6% of firm-years are where dividends are paid; the mean of ROA and cash flow volatility is 4.7% and 10.2%, respectively, in our sample.

3. Automation exposure and financial leverage

This section provides the empirical findings based on the firm-level measure of automation exposure. Section 3.1 analyzes the impact of automation exposure on employment risk. Section 3.2 examines the overall effect of a firm's exposure to automation technologies on financial leverage. Section 3.3 and Section 3.4 investigate the mechanism through which automation exposure affects capital structure.

3.1. Automation exposure and employment risk

Previous studies generally find that automation has a negative impact on manufacturing employment risk using industry-level proxies for automation such as the investment in computer capital or the use of robots (Autor et al., 2008; Autor et al. 2015; Acemoglu and Restrepo, 2017). We first extend this literature by investigating whether our firm-level measure of automation exposure is associated with firm-level employment risk.

To implement this test, we follow the empirical work of Falato and Liang (2016) and construct three measures of firm-level employment risk: (i) logarithm of number of employees (*Empl size*), (ii) an indicator variable *Layoffs* which indicates the firm-year observations in which there is a layoff announcement; and (c) an indicator variable *Part-time* that identifies a firm-year in which the firm reports having seasonal and part-time employees in its total workforce. Then we examine whether a firm's automation exposure leads to a higher employment risk by estimating the following three specifications:

$$EmplRisk_{i,t} = \delta_0 + \delta_1 AutoExpo_{i,t-1} + \delta_2 NonAutoExpo_{i,t-1} + \delta_3 Chem\,\&\,Pharm_{i,t-1} + \varphi X_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t} \tag{2}$$

where the dependent variables are as described above. $AutoExpo_{i,t-1}$ denotes a firm's exposure to its available automation technologies, $NonAutoExpo_{i,t-1}$ denotes a firm's exposure to its available technologies that are defined as non-automation related, and $Chem\&Pharm_{i,t-1}$ is the logarithm of a firm's segment-sales weighted number of patents in chemical and pharmaceutical industries over the past five years. The vector $\mathbf{X}_{i,t-1}$ includes all firm-level control variables as described in section 2.4. The dependent variables $EmplRisk_{i,t}$ include *Empl size*, *Layoffs*, and *Part-time*. We also include a firm fixed effect (α_i) to control for any time-invariant, unobservable firm-level characteristics that are relevant to a firm's employment risk and year fixed effect (τ_t) to control for time-varying macroeconomic conditions. Standard errors are clustered at industry level to control for the correlated unobserved shocks that affect firms in an industry.

[Table 2 about here]

The results are presented in Table 2. We find that the coefficients for automation exposure are consistently significant across all three measures of employment risk. A firm's automation exposure is highly indicative of an increase in employment risk: the higher the automation exposure faced by a firm, the lower its employment size, the higher its layoffs and use of part-time and seasonal workers. This implies that the threat of automation diminishes a firm's size of employment, increases the likelihood of major layoffs and the use of seasonal and part-time employees. The results are consistent with previous industry-level findings that automation leads to higher employment risk (Autor et al., 2008; Autor et al. 2015; Acemoglu and Restrepo, 2017).

3.2. Baseline results

We first examine the overall effect of automation exposure on a firm's financial leverage by estimating the following regression:

$$LEV_{i,t} = \beta_0 + \beta_1 AutoExpo_{i,t-1} + \beta_2 NonAutoExpo_{i,t-1} + \beta_3 Chem\,\&\,Pharm_{i,t-1} + \gamma X_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t} \tag{3}$$

where $LEV_{i,t}$ denotes firm i's leverage ratio in year t, which can refer to one of the four leverage ratios (i.e., book leverage, market leverage, net book leverage, and net market leverage). $AutoExpo_{i,t-1}$ denotes a firm's exposure to its available automation technologies, $NonAutoExpo_{i,t-1}$ denotes a firm's exposure to its available technologies that are defined as non-automation related, and $Chem\&Pharm_{i,t-1}$ is the logarithm of a firm's segement-sales-weighted sum of number of patents in chemical and pharmaceutical industries over the past five years. The vector $\mathbf{X}_{i,t-1}$

includes all the observable firm characteristics that determine firm i's leverage (i.e., firm size, book-to-market ratio, ROA, tangibility, cash flow volatility, dividend payment and R&D intensity). We also include a firm fixed effect (α_i) to control for any time-invariant, unobservable firm-level characteristics that are relevant to a firm's capital structure and year fixed effect (τ_t) to control for time-varying macroeconomic conditions. Standard errors are clustered at the industry level to control for correlated unobserved shocks that affect firms within an industry.

[Table 3 about here]

Table 3 reports the main results on the relation between automation exposure and capital structure. The results show positive and significant coefficients on automation exposure measures across all four different measures of firm leverage. As a firm fixed effects model relies on within firm variation to estimate the coefficients, the results show that an increase of one standard deviation of within firm variation in automation exposure (0.76) leads to an increase of book leverage (market leverage) by 1.3% (0.39%).[9] In contrast, the coefficients associated with a firm's exposure to non-automation related technologies show a negative impact on firm leverage. One concern is that the positive relation between automation exposure and leverage might simply capture the fact that firms with a greater exposure to new technologies (either automation-related or non-automation-related) tend to raise more capital in order to adopt the new technologies, resulting in a higher financial leverage. The finding that a firm's exposure to non-automation-related technology is negative may suggest that non-automation-related technology are more likely to be intangible assets, which decrease a firm's ability to borrow and reduce its leverage. Importantly, the fact that the effect of *AutoExpo* on financial leverage is robust by controlling for

[9] The total stand deviation of automation exposure can be decomposed into within standard deviation 0.76 and between standard deviation 2.07.

non-automation-related technologies indicates that our results are not simply driven by a firm's exposure to newly available technologies.

3.3. Replacement threat: wage compression effect and financial leverage

In this subsection, we explore the first effect of the replacement threat imposed by automation technologies, that it can compress the wage premium demanded by workers arising from the use of financial leverage and allow firms to increase leverage. To examine this mechanism, we test the cross-sectional variation in the positive effect of automation on financial leverage across a few firm/industry characteristics that are indicative of high susceptibility of automation technology adoption.

3.3.1 Labor intensity

Since automation has systematically shifted the comparative advantage away from low-skilled labor, we expect that firms facing great labor demand and stiff labor costs are more prone to adopt automation technologies (Acemoglu and Restrepo 2018b). We construct two measures of labor costs, i.e., labor-to-capital ratio and extended labor share, both of which capture a firm's dependence on labor inputs. The first measure of labor costs, labor-to-capital ratio, is computed as the total employment divided by the gross property, plant, and equipment as in Knesl (2019). The second measure of labor costs, the extended labor share, is computed as the imputed labor expenses divided by the value added of a firm as in Donangelo et al. (2019). The firm-level imputed labor expense is calculated based on an industry average labor costs per employee (e.g., total staff expense divided by value added, i.e., the operating income before depreciation plus the change in inventory) multiplied by the number of employees in a firm.

Table 4 panel A (panel B) shows the subsample results based on the labor-to-capital ratio (extended labor share). We report the test of difference between the coefficient estimates in high- vs. low- labor-to-capital ratio (extended labor share) at the end of panel A (panel B). Consistent with the wage compression effect, we observe that firms with high labor-to-capital ratio significantly increase their leverage ratios, while firms with low labor-to-capital ratio do not change their leverage ratios. For example, the coefficient for automation exposure in firms with high labor share (column 1 of Panel A) is positive and highly significant while the coefficient for automation exposure in firms with low labor share (column 5 of Panel A) shows insignificant relation between automation exposure and book leverage. The test of coefficient difference shows that the difference between the two estimates for automation exposure is highly significant. The results are consistent across alternative definitions of leverage in columns 2 – 4 and columns 6 – 8, including market leverage and leverage measures net of cash holdings. Furthermore, panel B shows robust results using the extended labor share from Donangelo et al. (2019). The coefficients for automation exposure measures are consistently positive and significant for firms with higher extended labor share while either weakly positive or insignificant for firms with low extended labor share. The test of coefficient difference again shows that difference between the two estimates is highly significant in three out of the four leverage ratios.

[Table 4 about here]

3.3.2 Routine vs. non-routine tasks

Second, the replacement threat imposed by automation technologies is more imminent among the firms whose operation involves more routine tasks since repetitive and routine jobs are more likely to be replaced by robotics than non-routine jobs (e.g., jobs requiring solving unstructured problems or creativity) (Autor et al. 2003). Therefore, we expect that the positive effect of automation exposure on leverage to be more pronounced among industries with a greater routine task intensity.

To measure routine task intensity, we construct two measures of routine task intensity based on the routine tasks classified by Autor et al. (2003).[10] Using data on task compositions from the Directory of Occupational Titles (DOT) from 1960 and 1998, Autor et al. (2003) show that computerization is associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of non-routine cognitive tasks.[11] We focus on four DOT categories provided by Autor et al. (2003): (i) STS (set limits, tolerances, or standards): a measure of routine cognitive activity defined as adaptability to work requiring the precise attainment of set limits, tolerances, or standards; (ii) FINGDEX: a measure of routine manual activity defined as finger dexterity, i.e., the ability to move fingers and manipulate small objects with fingers, rapidly or accurately, (iii) DCP (Direction, Control, and Planning): a measure of non-routine interactive tasks of activities such as adaptability to accepting responsibility for the direction, control, and planning of an activity, and (iv) MATH: a measure of non-routine analytical tasks that require mathematics and general quantitative reasoning. The first measure of routine tasks combines routine manual and routine cognitive tasks and defines the industries with above-median values for the fraction of FINGDEX and STS tasks out of total industry task inputs as routine industries. The second measure of routine tasks combines non-routine interactive and analytical tasks and defines the industries with below-median values for the fraction of DCP and MATH tasks out of total industry

[10] As defined by Autor et al. (2003): a routine task is "a task if it can be accomplished by machines following explicit programmed rules. Because these tasks require methodical repetition of an unwavering procedure, they can be exhaustively specified with programmed instructions and performed by machines." A task is defined as "non-routine" as those "for which the rules are not sufficiently well understood to be specified in computer code and executed by machines."
[11] Additional evidence on the threat of automation for jobs held by unskilled workers is provided in Autor and Dorn (2013) and Autor et al. (2015).

task inputs as routine industries. These two measures capture the extent of automatable jobs that are more easily replaced by automation technologies in an industry.

Table 4 panel C (panel D) presents the subsample results in routine vs. non-routine task industries using the routine task intensity measure based on FINGDEX + STS (DCP + MATH). We report the test of difference between the coefficient estimates in routine vs. non-routine task industries at the end of each panel. The results show that the coefficients associated with automation exposure are consistently positive and significant in the subsample of high-routine task industries, while the coefficients for automation exposure are mostly insignificant in the subsample of low-routine task industries. For example, the coefficient associated with automation exposure is 0.029 and significant at 1% level in the subsample of high routine task industries (column 1 of panel C) while the coefficient for automation exposure is 0.003 and statistically insignificant in the subsample of low routine task industries (column 5 of panel C). We find consistent evidence using the alternative definition of routine task industries based on the fraction of DCP and MATH tasks out of total industry task inputs in panel D. The test of coefficient difference indicates that seven out of eight subsamples show statistically different coefficient estimates between the routine vs. non-routine task industries. Taken together, our findings imply that the increase of availability of automation technologies have the most significant impact on the industries that are more susceptible to automation threats.

3.3.3. Geographic proximity

Innovative activities tend to be geographically concentrated (Jaffe et al. 1993), and geographic proximity is conducive to technology spillover (Lychagin et al. 2016). Hence, being geographically close to a robotic hub facilitates related technology transfer and lowers the rental costs of industrial robotics. Put differently, the replacement effect of automation is stronger among firms whose headquarters are located near the robotic clustering regions like Boston or Chicago. We hereby explore the cross-sectional variation among firms located close to or further from robotic industry hubs. We identify 20 key robotic regions following Leigh and Kraft (2018), such as Detroit-Warren-Dearborn (MI), Chicago-Naperville-Elgin (IL-IN-WI), and Boston-Cambridge-Newton (MA-NH). We then analyze whether the effect of automation exposure on leverage is more evident for firms whose headquarters are in these key robotic regions.

The results are reported in Table 4 panel E. We report the test of difference between the coefficient estimates in robotic vs. non-robotic regions at the end of panel E. The results show that the coefficients associated with automation exposure in the subsample of firms located in the automation hubs are consistently positive and significant while the coefficients for automation exposure in the subsample of firms that do not locate in the automation hubs are either insignificant or weakly significant. The finding is consistent with our conjecture that the wage compression effect of automation exposure on leverage is more evident in firms whose headquarters are located in the robotic regions.

All findings in section 3.3 indicate that automation exposure has a more pronounced effect on leverage in firms that are highly susceptible to automation (i.e., firms dependent more on labor inputs and routine tasks or firms more accessible to automation technologies), consistent with the wage compression effect imposed by the replacement threat.

3.4. Replacement threat: wage rigidity effect and financial leverage

In this subsection, we explore the implications related to the second effect of the replacement threat: automation exposure reduces the wage rigidity arising from labor market protections and leads to a higher use of financial leverage. Prior literature shows that firms are less likely to discharge workers or lower wages and experience higher wage rigidity if employment protection regulation is tightened or unionization is more intense (Simintzi et al. 2015; Kuzmina 2013; Serfling 2016; Atanassov and Kim 2009; Chen et al. 2011). The rising supply of automation technologies increases productivity-to-cost ratio of automation that can diminish the effectiveness of labor market protections. We thus explore whether the effect of automation exposure on financial leverage is more pronounced in states facing high firing costs and more intense union coverage.

We follow Serfling (2016) to denote firms as having a high firing cost if they operate in states that adopted the Wrongful Discharge Laws (WDLs) over the period 1967 to 1995. WDLs significantly increase firing costs as documented by the prior literature (e.g., Jung 1997; Boxold 2008; Dertouzos and Karoly 1992; Autor et al. 2007). Next, we obtain the state-level union information from the publicly available Union Membership and Coverage Database, which provides private and public sector labor union membership, coverage and density estimates across U.S. states compiled by Hirsch and Macpherson (2003) from the monthly household Current Population Survey (CPS).[12] The state-level unionization is measured as the share of employees in a state that are members of a union or covered by a collective bargaining agreement.

The results are presented in Table 5. Panel A (Panel B) shows the subsample results based on firing costs (union coverage). We report the test of difference between the coefficient estimates in high- vs. low- firing costs (union coverage) at the end of panel A (panel B). We observe that firms with high firing costs significantly increase their financial leverage, while firms with low

[12] See the details of this dataset at http://www.unionstats.com. Economy-wide estimates are provided beginning in 1973; estimates by state, detailed industry and detailed occupation begin in 1983; and estimates by metropolitan area begin in 1986. This database constructed by Barry Hirsch and David Macpherson was created in 2002 and is updated annually.

firing costs do not change their leverage ratios. For a one standard deviation increase in the within variation of automation exposure, the book leverage increases by 2.1% (0.028 x 0.76 = 2.1) in firms facing high firing costs. In contrast, the automation exposure has an insignificant impact on a firm's leverage in firms facing low firing costs. The test of coefficient difference shows that the two estimates for automation exposure are statistically different in two subsamples. This implies that a given increase of automation exposure leads to a higher increase in book leverage of firms subject to high firing costs relative to firms subject to low firing costs.

Panel B of Table 5 shows that the automation exposure has a positive and significant impact on financial leverage among firms with high union coverage and an insignificant impact among firms with low union coverage. For example, the coefficient for automation exposure in firms with high union coverage (column 1 Panel B) is positive and highly significant, while the coefficient for automation exposure is insignificant in firms with low union coverage. The results are similar using other measures of leverage.

[Table 5 about here]

Taken together, the results on the cross-sectional variation in the effect of automation exposure on financial leverage support our story that the replacement threat imposed by automation technologies creates a "wage compression" and a "wage rigidity" effect, leading to a higher use of financial leverage.

4. Adjusted penetration of robots and financial leverage

Although we control for unobservable time invariant firm characteristics using a firm fixed effects model, one may still wonder whether our identification strategy provides a causal relationship between automation exposure and financial leverage since that relationship can be driven by some unobservable time variant industry or firm characteristics that affect both variables. For example, an unobserved time variant industry shock such as product market competition or changes in labor demand may be related to both a firm's exposure to automation technologies and a firm's use of financial leverage. Alternatively, it may be that the changes in a firm's corporate governance practice is correlated with both a firm's increasing adoption of automation technologies to gain a more competitive advantage over competitors and a firm's higher borrowing capacity. To provide further corroborating evidence and mitigate the endogeneity concerns, we present the results using our second proxy for automation exposure following Acemoglu and Restrepo (2020) in this section.

4.1. Measurement of penetration of robots

We adopt the approach in Acemoglu and Restrepo (2020) and measure the U.S. firms' exposure to automation technologies using the changes in robots used in European countries. Acemoglu and Restrepo (2018c) show that a shortage of production workers encourages the rapid development and adoption of robotic technologies in European countries, and these automation technologies subsequently transfer to the U.S. They point out that the difference in automation technology advancement between the U.S. and European countries has been driven primarily by demographic differences rather than any time-varying economic or industry shocks. As such, Acemoglu and Restrepo (2020) identify the causal effect of automation on employment outcomes using the penetration of robots in European countries as an instrument for U.S. firms' exposure to automation technologies. Borrowing this strategy, we proxy U.S. firms' exposure to automation technologies using the robotic penetration in European countries.

Specifically, for each industry *j*, we measure the average of adjusted penetration of robots ($APR\_EURO5_{j,(t_0,t_1)}$) across five European countries (Denmark, Finland, France, Italy and Sweden) that are ahead of the U.S. in automation technologies as follows,[13]

$$APR\_EURO5_{j,(t_0,t_1)} = \frac{1}{5} \sum_{k \in EURO5} \left[\frac{M^k_{j,t_1} - M^k_{j,t_0}}{L^k_{j,1995}} - g^k_{j,(t_0,t_1)} \frac{M^k_{j,t_0}}{L^k_{j,1995}} \right] \tag{4}$$

where *k* indicates one of the five European countries (i.e., Denmark, Finland, France, Italy and Sweden), $M^k_{j,t}$ is the number of robots in industry *j* in country *k* at time *t* from the International Federation of Robotics (IFR) which provides information on the stock and new adoption of industrial robots by industry, country and year, $g^k_{j,(t_0,t_1)}$ is the growth rate of output of industry *j* in country *k* between t_0 and t_1 from EUKLEMS which provides data on Productivity and Growth Accounts at industry level across European countries, and $L^k_{j,1995}$ is the baseline employment level in industry *j* in country *k* in 1995 from EUKLEMS. The first term measures the increase in robot density (i.e., changes in robots per employment) in each industry. The second term is an adjustment factor for the fact that some industries expand faster than others.[14]

The adjusted penetration of robots across five European countries satisfies the two primary criteria of selecting an instrumental variable: (i) The changes in the use of industrial robots across European countries is correlated with the U.S. firm's adoption of industrial robots since the robotic technologies are more advanced in the European countries; (ii) The U.S. firms' financial policy cannot be driven by the changes in adoption of industrial robots in European countries other than through its effect on the adoption of robots in the U.S.

[13] Acemoglu and Restrepo (2020) argue that Germany is excluded from the baseline measure of APR because Germany is too far ahead of the other countries and might be less relevant for U.S. firms.

[14] Acemoglu and Restrepo (2020) show that 96 percent of the variation in the adjusted penetration of robots across industries is driven by the first term, and the adjustment term is not quantitatively important for their findings.

Based on the average of adjusted penetration of robots ($APR\_EURO5_{j,(t_0,t_1)}$) proposed by Acemoglu and Restrepo (2020), we use a five-year moving window to compute the adjusted penetration of robots to capture the dynamics of the robotic adoption in the time-series (e.g., t_0 +4 = t_1).[15] In other words, for the average adjusted penetration of robots in year t, we use the industry-level robotic stocks from IFR and industry output growth rates from EUKLEMS from year t – 4 to year t. For industry j in year t – 1, the average of adjusted penetration of robots ($APR\_EURO5_{j,(t-5,t-1)}$) is constructed as follows,

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

Since we attempt to identify the effect of a firm-level exposure to automation technologies on financial leverage, we extend the Acemoglu and Restrepo's (2020) measure by aggregating the industry-level adjusted penetration of robots across European countries to a firm-level automation exposure measure using the segment sales as weights. This approach is similar to our construction for *AutoExpo* using MP's (2018) patent classification. For firm i that operates across N industries in year t – 1, firm i's average adjusted penetration of robots ($APR\_EURO5_{i,t-1}$) is equal to the segment-sales-weighted sum of average adjusted penetration of robots in year t – 1 across N industries in which firm i operates,

$$APR\_EURO5_{i,t-1} = \sum_{j=1}^{N} s_{i,j,t-1} APR\_EURO5_{j,(t-5,t-1)}, \tag{5b}$$

where $s_{i,j,t-1}$ denotes firm i's percentage of segment sales in four-digit SIC industry j in year t – 1 and *Euro5* include five countries that are ahead of the United States in robotics excluding Germany: Denmark, Finland, France, Italy, and Sweden. Alternatively, we also compute two analogous

[15] Acemoglu and Restrepo (2020) estimate the average of adjusted penetration of robots from 1993 to 2007 and use it in the cross-sectional regressions.

measures ($APR\_EURO6_{i,t-1}$ or $APR\_EURO9_{i,t-1}$) using the robotics data from six European countries (*Euro6)* including Denmark, Finland, France, Italy, Sweden, and Germany, and nine European countries (*Euro9*) including Germany, Denmark, Finland, France, Italy, Sweden, Norway, Spain, and the UK. Two alternative measures are defined analogous to $APR\_EURO5_{i,t-1}$.

Following Acemoglu and Restrepo (2020), we use $APR\_EURO5_{i,t-1}$ in two forms, one as a direct proxy for automation exposure for U.S. firms (reduced-form estimation) and the other as the instrument variable for automation exposure for U.S. firms (instrumental variable estimation).

4.2. Reduced-Form Estimation

As a first step, we use $APR\_EURO5_{i,t-1}$ as a direct proxy to analyze the effect of automation exposure on financial leverage using the following specification:

$$LEV_{i,t} = \kappa_0 + \kappa_1 APR\_EURO5_{i,t-1} + \kappa_2 X_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t} \qquad (6)$$

where $LEV_{i,t}$ denotes firm *i*'s leverage ratios in year *t*, which can refer to one of the four leverage ratios defined in Section 2.4 (i.e., book leverage, market leverage, net book leverage, or net market leverage), $APR\_EURO5_{i,t-1}$ is average adjusted automation penetration for firm i in year $t-1$ constructed as in equation (5b), and the vector $\mathbf{X}_{i,t}$ includes all the observable firm characteristics that determine firm *i*'s leverage, including firm size, book-to-market ratio, ROA, tangibility, cash flow volatility, dividend payment and R&D intensity. We also include a firm fixed effect (α_i) to control for any time-invariant, unobservable firm-level characteristics that are relevant to a firm's capital structure and year fixed effect (τ_t) to control for time-varying macroeconomic conditions. The main coefficient of interest is κ_1 which measures the effect of automation exposure of U.S.

firms on financial leverage. We conduct inference from the standard errors clustered at the industry level.

The results are presented in Table 6. Panel A (Panel B or Panel C) shows the results from the reduced-form panel regression using the firm-level average adjusted penetration of robots constructed across five European countries (six European countries or nine European countries). The results in panel A show that the coefficients associated with $APR\_EURO5_{i,t-1}$ are positive and statistically significant at 1% level across all columns, ranging from 0.003 to 0.006.

[Table 6 about here]

As a robustness check, we then re-estimate two analogous average adjusted penetration of robots measures using $APR\_EURO6_{i,t-1}$ or $APR\_EURO9_{i,t-1}$. The results are presented in panel B for $APR\_EURO6_{i,t-1}$ and panel C for $APR\_EURO9_{i,t-1}$, respectively. As shown in panels B and C, our results remain robust using two alternative definitions of adjusted pentration of robots.

Taken together, these findings are consistent with the prior results using the first firm-level measure of automation exposure based on the patent classification by MP (2018). These findings indicate that an increase in the improvements in robotics technologies available to U.S. firms leads to a higher use of financial leverage.

4.3. Instrumental Variable Estimation

We then use $APR\_EURO5_{i,t-1}$ as an instrument for the improvement in robotics technologies available to U.S. firms and re-estimate our results using the IV two-stage, least-square estimation. Similar to the construction of firm-level average adjusted penetration of robots from five European countries in equation (5a), we estimate the industry-level adjusted penetration of robots in the U.S. using a five-year moving window as follows:

$$APR\_US_{j,(t-5,t-1)} = \frac{M^{US}_{j,t-1} - M^{US}_{j,t-5}}{L^{US}_{j,1995}} - g^{US}_{j,(t-5,t-1)} \frac{M^{US}_{j,t-5}}{L^{US}_{j,1995}} \tag{7a}$$

where $M^{US}_{j,t}$ is the number of robots in industry *j* in the U.S. at time *t* from IFR, $g^{US}_{j,(t-5,t-1)}$ is the growth rate of output of industry *j* in the U.S. between *t* – 1 and *t* – 5, and $L^{US}_{j,1995}$ is the baseline employment level in industry *j* in the U.S. in 1995. For firm *i* that operates across *N* industries in year *t* – 1, a firm *i*'s average adjusted penetration of robots ($APR\_US_{i,t-1}$) is equal to the segment-sales-weighted sum of average adjusted penetration of robots in year *t* – 1 across *N* U.S. industries in which firm *i* operates,

$$APR\_US_{i,t-1} = \sum_{j=1}^{N} s_{i,j,t-1} APR\_US_{j,(t-5,t-1)}, \tag{7b}$$

Due to the limited industry coverage of U.S. robots before 2004 in IFR, we can only construct $APR\_US_{i,t-1}$ from 2004 to 2015. Then we implement the two-stage instrumental variable estimation as follows,

$$APR\_US_{i,t-1} = \lambda_0 + \lambda_1 APR\_EURO5_{i,t-1} + \lambda_2 X_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t}, \tag{8a}$$

$$LEV_{i,t} = \theta_0 + \theta_1 \widehat{APR\_US}_{i,t-1} + \theta_2 X_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t}. \tag{8b}$$

Table 7 reports the results from the IV two-stage least square regression. Panel A (Panel B or Panel C) reports the IV estimation results using $APR\_EURO5_{i,t-1}$ ($APR\_EURO6_{i,t-1}$ or $APR\_EURO9_{i,t-1}$) as an instrument variable. The first column of each panel reports the first-stage estimation and the corresponding F-statistics. The results in Panel A show that the adjusted penetration of robots using U.S. robotic data is highly correlated with the average adjusted penetration of robots in five European countries (Coef. = 0.171, *t*-stat = 10.30). The F-statistics for the significance of the instrument in the first stage regression is approximately 105, which shows that $APR\_EURO5_{i,t-1}$ is not a weak instrument. Columns (2) to (5) report the second-stage estimation using four different measures of leverage ratios, including book leverage, market leverage, net book leverage and net market leverage. The results in Panel A show that the coefficients associated with the instrumented $APR\_US_{i,t-1}$ are positive and significant in three out of four leverage measures, ranging from 0.008 to 0.011. In terms of the economic effect, it indicates that one within-standard-deviation increase in the average adjusted penetration of robots across five European countries leads to a 0.9% increase in book leverage during the period of 1995 – 2015.[16] The economic magnitude is comparable to what we documented in Section 3.1 (1.3%) using our first automation exposure measure constructed from MP's (2018) automation vs. non-automation patent classification, which implies that the two constructed measures using different approaches yield similar findings.

In addition, the results in panel B (panel C) where $APR\_US_{i,t-1}$ is instrumented using the adjusted penetration of robots across six (nine) European countries are consistent with the results in panel A.

[Table 7 about here]

Overall, the results from the IV two-stage least square estimation are quantitatively similar to the results using a reduced-form least square estimation in Section 4.2. All the results provide strong evidence that an increase in automation exposure leads to a higher use of financial leverage. Our IV estimation further suggests that the positive relation between automation exposure and financial leverage is unlikely to be driven by unobserved industry shocks or any omitted firm characteristics.

[16] The economic significance is computed as 0.964 x 0.0096 = 0.93% for book leverage.

4.4 Import Competition

One concern is that the industries that have been adopting more robots over the past decades in both the U.S. and European countries could have been on an upward trend in leverage because of international competition that affects labor demand in some industries over the same period. For example, the impact of import competition from China may intensify both the labor and product market competition in the U.S. that affects the financial leverage of U.S. firms.

To address this concern, we include the industry-level Chinese imports (*China*) to control for the secular trend of Chinese import competition, and we measure the industry-level Chinese import competition as the industry-level change in the share of U.S. imports from China.[17] Controlling for potentially confounding changes in trade patterns ensures that our estimation is not driven by the correlated trade patterns that occur during the same time period. We follow the specification in equation (6) and add the Chinese import competition (*China*) as the additional control variable.

[Table 8 about here]

The results are reported in Table 8. Consistent with Acemoglu and Restrepo (2020), the industries that adopt more robotic technologies are not those industries that experience more intense import competition from China (corr. = -0.208). As indicated in Panel A of Table 8, the coefficients with the firm-level adjusted penetration of robots across five European countries remain positive and significant across four measures of leverage ratios while the changes in Chinese import competition are not related to the firm-level financial leverage. Furthermore, panel B and panel C show that the coefficients associated with two alternative measures of the firm-level average adjusted penetration of robots across six or nine European countries are again positive and

[17] The data on exposure to Chinese imports are obtained from Autor, Dorn and Hanson (2013).

significant across all measures of leverage ratios after controlling for the changes in Chinese import competition. The results indicate that the positive association between the adjusted penetration of robots and financial leverage is not driven by the confounding changes in trade patterns but rather by the firm's adjustment in financial policies in response to the increase in availability of automation technology.

4.5 Capital Deepening and Other Technologies

We have shown in Section 3 that automation exposure has a distinct effect from non-automation exposure on financial leverage, supporting the argument that automation exposure imposes a replacement threat that non-automation technologies do not have, which allows firms to employ higher financial leverage. To provide further evidence that automation exposure on financial leverage is different from the effect of other concurrent technological changes, in this subsection, we further investigate the effect of other types of capital deepening and technological changes that cannot generate the replacement threat by automating tasks previously performed by labor.

To capture capital deepening and other technological changes, we obtain the industry-level output data from Integrated Industry-Level Production Account (KLEMS) from 1995 to 2015 and construct three measures.[18] The first measure for capital deepening is the "exposure to capital" which is constructed as the logarithm of the industry capital stock for each industry-year where the industry capital stock includes the capital investment in fixed assets such as machinery, equipment etc. The second measure for capital deepening is the "exposure to IT capital" which is

[18] The integrated industry-level production account (ILPA) contains industry-level data related to changes in factors of production, including capital, labor, intermediate inputs, and multifactor productivity. These accounts are often referred to as "KLEMS" accounts that represent the datasets merged between the Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA).

calculated as the logarithm of industry IT capital expenditure for each industry-year, where the industry IT capital refers to computers, communications, and other information technology related investments of an industry. The last measure for capital deepening is the total industry value added for each industry-year where the industry value added is the total industry gross output less the total intermediate inputs (i.e., materials or energy used in the production). If our measure of adjusted penetration of robots simply mimics the effect of these technological changes, then we should find that our effect has been subsumed by the effect of other technological changes.

[Table 9 about here]

The results are reported in Table 9. Panel A shows that the coefficients for the exposure to industry capital are either negative or insignificant while the coefficients for our firm-level APR measure are consistently positive and significant, implying that the exposure to industry capital has little effect on the effect of APR on financial leverage. Panel B shows that the coefficients for the exposure to industry IT capital are significant in the regressions, however, the effect of APR on financial leverage remains robust and significant after controlling for the effect of industry IT capital. This result suggests that while the industry IT capital is related to firm's use of financial leverage, but the effect of industry IT capital on a firm's use of leverage does not subsume our effect of APR. Lastly, panel C reports the results by controlling for the total industry value added. The results show that coefficients for the total industry value added are mostly insignificant and again our estimates are robust by including the control for the total industry value added.

The results show that the effect of automation exposure on financial leverage is distinct from capital deepening and other types of technological changes that increase industry value-added. The findings are consistent with the argument in Acemoglu and Restrepo (2020) that automation technologies differ from other technologies in that automation technologies impose a replacement threat to workers, which affects a firm's financial leverage through changes in workers' bargaining power.

5. Conclusion

This paper provides robust evidence that a firm's exposure to automation technologies has a significant, positive effect on its leverage ratios. Using a firm-level measure of automation exposure that captures the automation technologies accessible to a firm based on textual analysis of U.S. utility patents, we find that the effect of automation exposure on a firm's leverage is economically meaningful: An increase of one standard deviation of automation exposure leads to an increase of a firm's book leverage by 1.3%. Our findings further show that the effect of automation exposure on leverage is more pronounced for firms with higher labor costs, involving more routine task, facing higher firing costs and greater union coverage. Furthermore, we conduct the analysis using the adjusted penetration of robots from five European countries as an instrumental variable for automation exposure to U.S. firms and find consistent evidence that an increase in automation exposure to U.S. firms leads to a higher use of financial leverage. We provide further evidence that the effect of automation exposure on a firm's use of financial leverage is not driven by the effect of other types of capital deepening and technological changes over the same period. The findings are consistent with the notion that automation threat changes workers' incentives and bargaining power which in turn compresses their wage premium for financial distress and reduces wage rigidity, both of which allow firms to increase financial leverage.

We conclude that automation technologies not only have a significant impact on labor market outcomes like employment, real wages, and aggregate productivity, but also play an important role in shaping a firm's corporate financial policy. Our findings imply that the improvement in the availability of automation technologies could allow firms to adopt a more aggressive capital structure and therefore increase their capacity to undertake more investment opportunities. In general, we believe that recognizing the importance of the interactions between automation technologies, labor markets and corporate policies is a fruitful area for future research.

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Figure 1. Time trend of automation patents

This figure plots the time-series of the number of automation patents, non-automation patents, and chemical and pharmaceutical patents over the period between 1976 and 2014 (in 10,000). The three categories of patents constitute all utility patents granted by the USPTO.

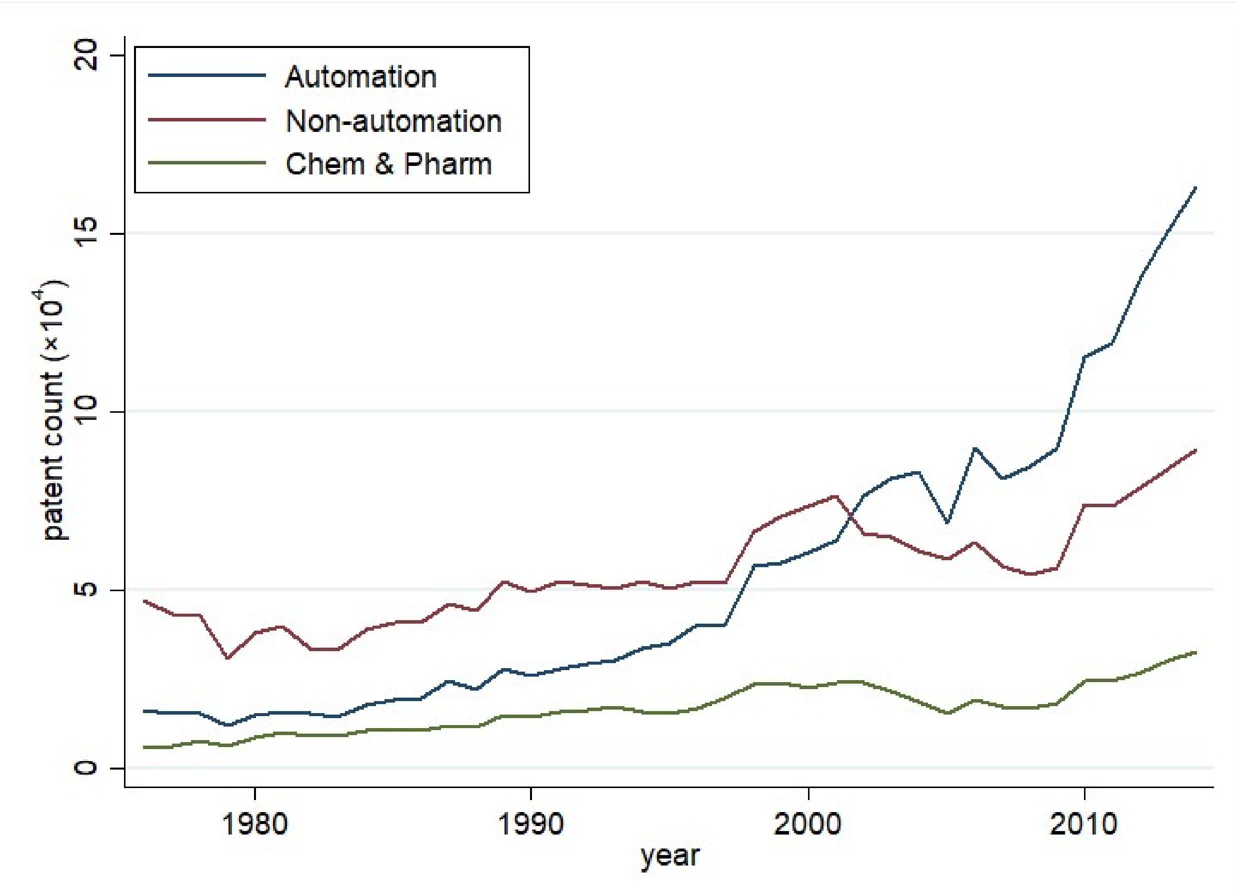

Table 1. Descriptive statistics

This table presents summary statistics of our sample, which consists of 130,231 firm-year observations for 23,323 unique nonfinancial U.S. public firms between 1981 and 2014. Panel A presents the descriptive statistics of the automation and non-automation exposure measures. Panel B presents the descriptive statistics of the dependent variables and control variables.

The automation exposure, denoted as *AutoExpo*, is computed as the logarithm of segment-sales-weighted sum of number of automation patents made available in the past five years across industries in which a firm operates in a given year.[19] The non-automation measure (*NonAutoExpo*) is computed as the logarithm of segment-sales-weighted sum of number of non-automation patents made available in the past five years across industries in which it operates in a given year. Similarly, *Chem & Pharm* is the logarithm of segment-sales-weighted sum of number of chemical and pharmaceutical patents made available in the past five years in a given year.[20]

Book leverage (*Book*) and market leverage (*Market*) are computed as the ratio of long-term debt plus current liability over total assets and the ratio of long-term debt plus debt in current liability over market value of assets (i.e., book value of debt plus market value of equity) respectively. Net book leverage (*Net book*) and net market leverage (*Net market*) are defined as net debt (i.e., total debt minus cash and other marketable securities) over total assets and net debt over the market value of assets, respectively.

The control variables are defined as follows: firm size (*Size*) is defined as the logarithm of firms' total asset; the market-to-book ratio (*M/B*) is computed as the ratio of the market value of equity plus book value of debt over the book value of debt plus equity; the return on assets (*ROA*) is computed as the ratio of EBIT over total assets; *Tangibility* is calculated as net property, plant, and equipment scaled by total assets; *Cash flow volatility* is defined as the standard deviation of the income before extraordinary items plus depreciation and amortization to book assets over the past five years; dividend payment (*Dividend*) is an indicator for whether the firm paid a common dividend in a firm-year; *R&D* is calculated as research and development expenditure scaled by the total assets.

[19] Lev and Sougiannis (1996) document that technology cycles measured by the duration of the benefits of R&D outlays are about five years.

[20] Those patents fall into the USPC technology classes: 127, 252, 423, 424, 435, 436, 502, 510-585, 800, 930, and 987. As detailed in MP (2018), most chemical and pharmaceutical patents are not classified as automation patents, and words like "automatic" are often used with a different meaning in these patents.

Panel A: Descriptive statistics of automation exposure

	N	Mean	SD	p25	p50	p75
AutoExpo	130231	4.6376	2.1372	3.3244	4.7460	6.0185
NonAutoExpo	130231	5.0778	2.0564	3.7970	5.6733	6.4582
Chem & Pharm	130231	3.2162	2.2541	1.2158	3.3339	4.5349

Panel B: Descriptive statistics of other variables

	N	Mean	SD	p25	p50	p75
Dependent variables:						
Book leverage	130231	0.2600	0.2844	0.0483	0.2081	0.3718
Market leverage	130231	0.1902	0.1891	0.0251	0.1395	0.2969
Net book leverage	130231	0.0953	0.3909	-0.1282	0.1139	0.3123
Net market leverage	130231	0.0873	0.2602	-0.0635	0.0735	0.2467
Control variables:						
Size	130231	5.0163	2.2949	3.2998	4.8755	6.5790
M/B	130231	2.0019	3.8736	1.0418	1.3757	2.0833
ROA	130231	0.0466	0.2961	0.0268	0.1074	0.1685
Cash flow volatility	130231	0.1018	0.2621	0.0248	0.0468	0.0948
Dividend	130231	0.3459	0.4757	0.0000	0.0000	1.0000
R&D	130231	0.0497	0.1167	0.0000	0.0000	0.0507
Tangibility	130231	0.2956	0.2347	0.1062	0.2337	0.4293

Table 2. Automation and employment risk

This table presents regression results of a firm's exposure to automation threat and employment risk. The variable of interest is *AutoExpo*, which is computed as the logarithm of segment-sales-weighted sum of number of automation patents made available in the past five years across industries in which a firm operates in a given year. *NonAutoExpo* is computed as the logarithm of segment-sales-weighted sum of number of non-automation patents made available in the past five years across industries in which it operates in a given year. *Chem & Pharm* is the logarithm of segment-sales-weighted sum of number of chemical and pharmaceutical patents made available in the past five years in a given year. All control variables are as described in Table 1 and are lagged one year.

The dependent variable of column 1 is the logarithm of total number of employees (*Empl Size*). In column 2, the dependent variable is a layoff dummy indicating a firm-year in which there is a layoff announcement in a firm (*Layoffs*). The dependent variable of column 3 is an indicator that identifies a firm-year in which the firm reports having seasonal and part-time employees in its total workforce (*Part-time*). All regressions include control variables, the firm fixed effect, and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	(1) Empl Size	(2) Layoffs	(3) Part-time
AutoExpo	**-0.0118****	**0.0161*****	**0.0087***
	(-1.97)	**(3.19)**	**(1.69)**
NonAutoExpo	0.0019	-0.0129**	-0.0112*
	(0.29)	(-2.24)	(-1.85)
Chem & Pharm	0.0093**	0.0059*	0.0032
	(2.25)	(1.67)	(0.96)
Size	-0.0466***	0.0391***	-0.0062**
	(-15.10)	(16.07)	(-2.41)
M/B	0.0221***	0.0008	0.0001
	(5.86)	(1.48)	(0.15)
ROA	0.2560***	-0.0024	0.0094
	(17.05)	(-0.38)	(1.42)
Cash flow volatility	0.0265***	-0.0130**	0.0046
	(2.80)	(-2.54)	(0.59)
Dividend	0.0209***	0.0058	-0.0030
	(3.15)	(1.15)	(-0.64)
R&D	-0.0749**	0.0980***	0.0037
	(-1.99)	(3.90)	(0.19)
Tangibility	-0.1572***	0.0473***	0.0251*
	(-8.54)	(3.67)	(1.72)
Firm FE	Y	Y	Y
Time FE	Y	Y	Y
N	130231	130231	130231
Adj. R^2	0.250	0.626	0.714

Table 3. Automation and capital structure: Baseline Results

This table presents regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables. The dependent variables are the different forms of leverage ratios, including book leverage, market leverage, book leverage net of cash holdings and market leverage net of cash holdings as described in Table 1. The variable of interest is *AutoExpo*, which is computed as the logarithm of segment-sales-weighted sum of number of automation patents made available in the past five years across industries in which a firm operates in a given year. *NonAutoExpo* is computed as the logarithm of segment-sales-weighted sum of number of non-automation patents made available in the past five years across industries in which it operates in a given year. *Chem & Pharm* is the logarithm of segment-sales-weighted sum of number of chemical and pharmaceutical patents made available in the past five years in a given year. All control variables are as described in Table 1 and are lagged one year. All regressions include the firm fixed effect and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)
AutoExpo	**0.0174*****	**0.0051****	**0.0211*****	**0.0069***
	(3.86)	**(2.03)**	**(3.74)**	**(1.90)**
NonAutoExpo	-0.0228***	-0.0071**	-0.0272***	-0.0120***
	(-4.85)	(-2.58)	(-4.53)	(-3.10)
Chem & Pharm	0.0073**	0.0030*	0.0061*	0.0040*
	(2.45)	(1.87)	(1.66)	(1.80)
Size	0.0113***	0.0338***	0.0306***	0.0384***
	(4.27)	(24.37)	(9.78)	(20.06)
M/B	-0.0022*	-0.0062***	-0.0061***	-0.0009*
	(-1.83)	(-7.24)	(-5.60)	(-1.83)
ROA	-0.1466***	-0.0779***	-0.1506***	-0.0556***
	(-12.08)	(-17.31)	(-11.59)	(-10.60)
Cash flow volatility	0.0160	0.0091**	0.0135	0.0141***
	(1.43)	(2.54)	(1.14)	(2.62)
Dividend	-0.0220***	-0.0231***	-0.0272***	-0.0219***
	(-6.75)	(-9.25)	(-6.58)	(-6.85)
R&D	-0.0196	-0.0598***	-0.0285	0.0175
	(-0.58)	(-5.42)	(-0.75)	(1.24)
Tangibility	0.2193***	0.1598***	0.4594***	0.3205***
	(13.55)	(18.58)	(23.95)	(26.72)
Firm FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
N	130231	130231	130231	130231
Adj. R^2	0.613	0.685	0.681	0.690

Table 4. Automation and capital structure: wage compression effect

This table presents regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables in subsamples of firms with different susceptibility of automation adoption. The dependent variables are the different forms of leverage ratios, including book leverage, market leverage, book leverage net of cash holdings and market leverage net of cash holdings as described in Table 1. The variable of interest is *AutoExpo*, which is computed as the logarithm of segment-sales-weighted sum of number of automation patents made available in the past five years across industries in which a firm operates in a given year. *NonAutoExpo* is computed as the logarithm of segment-sales-weighted sum of number of non-automation patents made available in the past five years across industries in which it operates in a given year. *Chem & Pharm* is the logarithm of segment-sales-weighted sum of number of chemical and pharmaceutical patents made available in the past five years in a given year.

Panel A columns 1 – 4 (columns 5 – 8) show the subsample results of firms with high- (low-) labor to capital ratios. Panel B columns 1 – 4 (columns 5 – 8) show the subsample results of firms with high- (low-) extended labor shares. The extended labor share is computed as the imputed labor expenses divided by the value added of a firm as in Donangelo et al. (2019). The firm-level imputed labor expense is calculated based on an industry average labor costs per employee and then time the number of employees of a firm.

Panel C columns 1 – 4 (columns 5 – 8) show the subsample results of firms that operate in industries with high- (low-) shares of routine-task inputs based on the sum of value of FINGDEX and STS. The share of routine task inputs is an industry-level measure of the fraction of routine task inputs out of total industry task inputs using 1980 Census data paired with Dictionary of Occupational Titles (DOT) task measures following Autor, Levy, and Murnane (2003). Panel D columns 1 – 4 (columns 5 – 8) show the subsample results of firms that operate in industries with high- (low-) shares of routine-task inputs based on the sum of value of DCP and MATH.

Panel E Columns 1 – 4 (columns 5 – 8) show the subsample results of firms that (do not) have headquarters located in the top 20 key robotic regions. The top 20 key robotic regions are identified following Leigh and Kraft (2018), including the following areas, Detroit-Warren-Dearborn (MI), Chicago-Naperville-Elgin (IL-IN-WI), Boston-Cambridge-Newton (MA-NH).

All control variables are as described in Table 1 and are lagged one year. All regressions include control variables, the firm fixed effect, and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Labor to capital ratio

	Book (1)	Market (2)	Net book (3)	Net market (4)	Book (5)	Market (6)	Net book (7)	Net market (8)
AutoExpo	**0.0265*****	**0.0097*****	**0.0286*****	**0.0134****	**0.0098**	**0.0030**	**0.0168****	**0.0070**
	(4.26)	**(2.72)**	**(3.58)**	**(2.56)**	**(1.40)**	**(0.79)**	**(1.97)**	**(1.31)**
NonAutoExpo	-0.0258***	-0.0087**	-0.0258***	-0.0134**	-0.0235***	-0.0069*	-0.0340***	-0.0168***
	(-3.84)	(-2.17)	(-2.99)	(-2.36)	(-3.61)	(-1.65)	(-3.98)	(-2.94)
Chem & Pharm	0.0055	0.0029	0.0042	0.0044	0.0139***	0.0039	0.0150***	0.0069**
	(1.40)	(1.25)	(0.83)	(1.33)	(3.24)	(1.58)	(2.83)	(2.09)
Test: High – Low	[0.001]	[0.008]	[0.004]	[0.371]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	54162	54162	54162	54162	61257	61257	61257	61257
Adj. R^2	0.648	0.704	0.712	0.715	0.663	0.733	0.731	0.739

Panel B: Extended labor share

	Book (1)	Market (2)	Net book (3)	Net market (4)	Book (5)	Market (6)	Net book (7)	Net market (8)
AutoExpo	**0.0211*****	**0.0069****	**0.0239*****	**0.0102****	**0.0112***	**0.0043**	**0.0174****	**0.0065**
	(3.29)	**(1.97)**	**(3.03)**	**(1.96)**	**(1.66)**	**(1.27)**	**(2.07)**	**(1.36)**
NonAutoExpo	-0.0247***	-0.0084**	-0.0303***	-0.0168***	-0.0193***	-0.0069*	-0.0265***	-0.0116**
	(-3.69)	(-2.08)	(-3.59)	(-2.89)	(-2.73)	(-1.85)	(-2.90)	(-2.23)
Chem & Pharm	0.0070*	0.0034	0.0064	0.0053*	0.0109**	0.0043*	0.0135**	0.0069**
	(1.76)	(1.49)	(1.32)	(1.66)	(2.34)	(1.95)	(2.30)	(2.21)
Test: High – Low	[0.037]	[0.000]	[0.512]	[0.000]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	59253	59253	59253	59253	54875	54875	54875	54875
Adj. R^2	0.648	0.702	0.710	0.718	0.651	0.738	0.721	0.735

Panel C: Routine vs. non-Routine manual activities – FINGER + STS

	Book	Market	Net book	Net market	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AutoExpo	**0.0298*****	**0.0098*****	**0.0328*****	**0.0090***	**0.0036**	**0.0011**	**0.0037**	**0.0010**
	(4.70)	**(2.81)**	**(4.18)**	**(1.88)**	**(0.46)**	**(0.25)**	**(0.38)**	**(0.16)**
NonAutoExpo	-0.0314***	-0.0107***	-0.0329***	-0.0110**	-0.0150*	-0.0047	-0.0131	-0.0053
	(-4.81)	(-2.79)	(-3.98)	(-2.09)	(-1.94)	(-0.92)	(-1.32)	(-0.75)
Chem & Pharm	0.0089**	0.0014	0.0061	0.0027	0.0043	0.0036	-0.0006	-0.0005
	(2.13)	(0.68)	(1.18)	(0.94)	(0.97)	(1.20)	(-0.11)	(-0.13)
Test: High – Low	[0.001]	[0.002]	[0.011]	[0.135]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	57550	57550	57550	57550	51558	51558	51558	51558
Adj. R^2	0.594	0.669	0.672	0.683	0.618	0.696	0.684	0.695

Panel D: Routine vs. non-Routine manual activities – DCP + MATH

	Book	Market	Net book	Net market	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AutoExpo	**0.0262*****	**0.0112*****	**0.0295*****	**0.0125****	**0.0096**	**0.0006**	**0.0095**	**-0.0008**
	(3.45)	**(2.78)**	**(3.23)**	**(2.30)**	**(1.53)**	**(0.15)**	**(1.15)**	**(-0.14)**
NonAutoExpo	-0.0353***	-0.0136***	-0.0362***	-0.0160***	-0.0137**	-0.0028	-0.0135	-0.0033
	(-4.62)	(-2.89)	(-3.75)	(-2.65)	(-2.09)	(-0.68)	(-1.58)	(-0.56)
Chem & Pharm	0.0083**	0.0031	0.0036	0.0025	0.0067	0.0022	0.0046	0.0017
	(1.99)	(1.39)	(0.66)	(0.78)	(1.43)	(0.82)	(0.81)	(0.48)
Test: High – Low	[0.001]	[0.029]	[0.002]	[0.093]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	55102	55102	55102	55102	54006	54006	54006	54006
Adj. R^2	0.593	0.693	0.685	0.699	0.619	0.672	0.663	0.677

Panel E: Geographic proximity to robotics hubs

	Book	Market	Net book	Net market	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AutoExpo	**0.0210*****	**0.0060***	**0.0270*****	**0.0084***	**0.0117***	**0.0037**	**0.0124**	**0.0045**
	(3.58)	**(1.81)**	**(3.70)**	**(1.77)**	**(1.68)**	**(0.95)**	**(1.44)**	**(0.83)**
NonAutoExpo	-0.0254***	-0.0078**	-0.0311***	-0.0128**	-0.0185***	-0.0058	-0.0213**	-0.0108*
	(-3.95)	(-2.10)	(-3.81)	(-2.44)	(-2.72)	(-1.40)	(-2.45)	(-1.87)
Chem & Pharm	0.0052	0.0026	0.0053	0.0050*	0.0091**	0.0032	0.0071	0.0030
	(1.32)	(1.23)	(1.04)	(1.68)	(2.08)	(1.35)	(1.32)	(0.87)
Test: High – Low	[0.042]	[0.186]	[0.058]	[0.380]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	63784	63784	63784	63784	64840	64840	64840	64840
Adj. R^2	0.585	0.675	0.676	0.690	0.616	0.682	0.667	0.678

Table 5. Automation and capital structure: wage rigidity effect

This table presents regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables in subsamples of firms facing different forms of labor market protection. The dependent variables are the different forms of leverage ratios, including book leverage, market leverage, book leverage net of cash holdings and market leverage net of cash holdings as described in Table 1. The variable of interest is *AutoExpo*, which is computed as the logarithm of segment-sales-weighted sum of number of automation patents made available in the past five years across industries in which a firm operates in a given year. *NonAutoExpo* is computed as the logarithm of segment-sales-weighted sum of number of non-automation patents made available in the past five years across industries in which it operates in a given year. *Chem & Pharm* is the logarithm of segment-sales-weighted sum of number of chemical and pharmaceutical patents made available in the past five years in a given year.

Panel A columns 1 – 4 (columns 5 – 8) show the subsample results of firms with high- (low-) firing costs. The firms operating in states that passed the Wrongly Discharge Laws (WDLs) in the period 1967 to 1995 are classified as high-firing cost firms and the remaining firms are classified as low-firing cost firms. Panel B columns 1 – 4 (columns 5 – 8) show the subsample results of firms that operate in states with high- (low-) intensity of union coverage. The state-level union information is obtained from the publicly available Union Membership and Coverage Database, which provides private and public sector labor union membership, coverage, and density estimates by state compiled by Hirsch and Macpherson (2003) from the monthly household Current Population Survey (CPS). The state-level union coverage is measured as the share of employees in a state that are members of a union or covered by a collective bargaining agreement.

All control variables are as described in Table 1 and are lagged one year. All regressions include the control variables, the firm fixed effect, and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Firing cost

	Book (1)	Market (2)	Net book (3)	Net market (4)	Book (5)	Market (6)	Net book (7)	Net market (8)
AutoExpo	**0.0280*** **	**0.0107*** **	**0.0367*** **	**0.0180*** **	**0.0052**	**-0.0003**	**0.0083**	**0.0000**
	(3.87)	**(2.87)**	**(3.94)**	**(3.14)**	**(0.82)**	**(-0.09)**	**(1.10)**	**(0.00)**
NonAutoExpo	-0.0259***	-0.0092**	-0.0323***	-0.0188***	-0.0145**	-0.0029	-0.0191**	-0.0064
	(-3.12)	(-2.09)	(-3.04)	(-2.93)	(-2.35)	(-0.76)	(-2.50)	(-1.28)
Chem & Pharm	0.0070	0.0015	0.0055	0.0058*	0.0058	0.0021	0.0044	0.0020
	(1.31)	(0.67)	(0.87)	(1.72)	(1.53)	(0.87)	(0.95)	(0.65)
Test: High – Low	[0.003]	[0.065]	[0.119]	[0.353]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	59934	59934	59934	59934	68409	68409	68409	68409
Adj. R^2	0.615	0.696	0.692	0.702	0.642	0.704	0.692	0.709

Panel B: Labor union coverage

	Book (1)	Market (2)	Net book (3)	Net market (4)	Book (5)	Market (6)	Net book (7)	Net market (8)
AutoExpo	**0.0167*** **	**0.0076*** **	**0.0199*** **	**0.0070*** **	**0.0030**	**-0.0009**	**0.0025**	**-0.0040**
	(6.01)	**(4.22)**	**(5.38)**	**(2.74)**	**(1.10)**	**(-0.45)**	**(0.68)**	**(-1.46)**
NonAutoExpo	-0.0235***	-0.0106***	-0.0287***	-0.0125***	-0.0123***	-0.0038*	-0.0154***	-0.0060*
	(-7.30)	(-5.06)	(-6.71)	(-4.23)	(-3.99)	(-1.65)	(-3.77)	(-1.94)
Chem & Pharm	0.0074***	0.0043***	0.0092***	0.0074***	0.0063***	0.0027**	0.0029	0.0021
	(3.93)	(3.49)	(3.65)	(4.24)	(3.54)	(2.02)	(1.22)	(1.17)
Test: High – Low	[0.179]	[0.000]	[0.306]	[0.089]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	48985	48985	48985	48985	49245	49245	49245	49245
Adj. R^2	0.651	0.725	0.739	0.730	0.676	0.713	0.734	0.711

Table 6. Penetration of robots and capital structure: baseline results

This table presents regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables using an alternative measure of automation exposure as in Acemoglu and Restrepo (2020). Panel A shows the long-difference regression results using *APR_Euro5* as proxy for automation exposure. Panel B shows the regression results using *APR_Euro6* as proxy for automation exposure. Panel C shows the regression results using *APR_Euro9* as proxy for automation exposure.

The industry-level automation exposure variable ($APR\_EURO5_{j,(t-5,t-1)}$) is constructed in a five-year window using the European robotics data from 1995 to 2015 as in Acemoglu and Restrepo (2020). The firm-level automation exposure variable ($APR\_EURO5_{i,t-1}$) is aggregated as the segment-sales-weighted sum of industry-level automation exposure across *N* industries in which a firm operates in a given year,

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

$$APR\_EURO5_{i,t-1} = \sum_{j=1}^{N} s_{i,j,t-1} APR\_EURO5_{j,(t-5,t-1)},$$

where $M^k_{j,t}$ is the number of robots in industry *j* in country *k* at time *t* from the IFR, $g^k_{j,(t-5,t-1)}$ is the growth rate of output of industry *j* in country *k* between $t-5$ and $t-1$ obtained from EUKLEMS, and $L^k_{j,1995}$ is the baseline employment level in industry *j* in country *k* in 1995 from EUKLEMS. Assuming the firm *i* operates across *N* industries, $APR\_EURO5_{i,t-1}$ is constructed as the segment-sales-weighted sum of $APR\_EURO5_{j,(t-5,t-1)}$ in the past five years across *N* industries in which firm *i* operates in a given year.

Euro5 include five countries that are ahead of the United States in robotics excluding Germany: Denmark, Finland, France, Italy, and Sweden. As alternative measures, we also use *Euro6*, which include Denmark, Finland, France, Italy, Sweden, and Germany. *Euro9* include nine European countries, i.e., Germany, Denmark, Finland, France, Italy, Sweden, Norway, Spain, and the UK. Two alternative measures are defined analogous to *APR_EURO5*.

All control variables are as described in Table 1 and are lagged one year. All regressions include the firm fixed effect and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: APR_EURO5 and leverage

	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)
APR_EURO5	**0.0006*****	**0.0004*****	**0.0004*****	**0.0003*****
	(4.83)	**(4.97)**	**(3.23)**	**(2.81)**
Size	0.0083	0.0356***	0.0288***	0.0371***
	(1.39)	(8.65)	(3.78)	(4.73)
M/B ratio	0.0017	-0.0038***	-0.0015	0.0013*
	(0.70)	(-5.57)	(-0.61)	(1.73)
ROA	-0.1553*	-0.0346***	-0.1683**	-0.0268***
	(-1.77)	(-3.35)	(-2.07)	(-3.69)
Cash flow volatility	-0.0005	0.0066***	0.0061	0.0068**
	(-0.03)	(2.86)	(0.53)	(2.08)
Dividend	-0.0112*	-0.0099**	-0.0107	0.0025
	(-1.80)	(-1.98)	(-1.40)	(0.39)
R&D	-0.0800	-0.0013	-0.0880	0.0260
	(-0.61)	(-0.06)	(-0.68)	(0.72)
Tangibility	0.2200***	0.1752***	0.4396***	0.3153***
	(4.63)	(4.97)	(8.30)	(9.73)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51187	51187	51187	51187
Adj.R^2	0.650	0.708	0.703	0.740

Panel B: APR_EURO6 and leverage

	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)
APR_EURO6	**0.0005*****	**0.0004*****	**0.0003****	**0.0003***
	(3.94)	**(3.92)**	**(2.08)**	**(1.92)**
Size	0.0084	0.0357***	0.0289***	0.0372***
	(1.40)	(8.61)	(3.77)	(4.73)
M/B ratio	0.0017	-0.0038***	-0.0015	0.0013*
	(0.70)	(-5.58)	(-0.61)	(1.73)
ROA	-0.1554*	-0.0346***	-0.1683**	-0.0269***
	(-1.78)	(-3.36)	(-2.07)	(-3.69)
Cash flow volatility	-0.0004	0.0066***	0.0062	0.0069**
	(-0.02)	(2.87)	(0.54)	(2.10)
Dividend	-0.0112*	-0.0099**	-0.0107	0.0025
	(-1.80)	(-1.98)	(-1.40)	(0.38)
R&D	-0.0800	-0.0013	-0.0879	0.0260
	(-0.61)	(-0.06)	(-0.68)	(0.72)
Tangibility	0.2204***	0.1755***	0.4401***	0.3156***
	(4.64)	(4.98)	(8.32)	(9.75)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51187	51187	51187	51187
Adj.R^2	0.650	0.708	0.703	0.740

Panel C: APR_EURO8 and leverage

	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)
APR_EURO8	**0.0005*****	**0.0005*****	**0.0003****	**0.0003****
	(3.82)	**(4.33)**	**(2.02)**	**(2.02)**
Size	0.0084	0.0357***	0.0289***	0.0371***
	(1.40)	(8.63)	(3.77)	(4.73)
M/B ratio	0.0017	-0.0038***	-0.0015	0.0013*
	(0.70)	(-5.58)	(-0.61)	(1.73)
ROA	-0.1554*	-0.0346***	-0.1683**	-0.0269***
	(-1.78)	(-3.36)	(-2.07)	(-3.69)
Cash flow volatility	-0.0004	0.0066***	0.0062	0.0069**
	(-0.02)	(2.87)	(0.54)	(2.09)
Dividend	-0.0112*	-0.0099**	-0.0107	0.0025
	(-1.80)	(-1.98)	(-1.40)	(0.39)
R&D	-0.0799	-0.0013	-0.0879	0.0260
	(-0.61)	(-0.06)	(-0.68)	(0.72)
Tangibility	0.2204***	0.1754***	0.4401***	0.3155***
	(4.64)	(4.98)	(8.31)	(9.74)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51187	51187	51187	51187
Adj.R^2	0.650	0.708	0.703	0.740

Table 7. Penetration of robots and capital structure: instrumental variable estimation

This table presents IV two-stage least squares regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables using an alternative measure of automation exposure as in Acemoglu and Restrepo (2020). Panel A reports the IV estimation results by instrumenting U.S. exposure to robots using exposure to robots from five European countries. Panel B reports the IV estimation results by instrumenting U.S. exposure to robots using exposure to robots from six European countries. Panel C reports the IV estimation results by instrumenting U.S. exposure to robots using exposure to robots from eight European countries.

The industry-level US adjusted penetration of robots ($APR\_US_{j,(t-5,t-1)}$) is computed in a five-year window as in Acemoglu and Restrepo (2020). The firm-level automation exposure variable ($APR\_US_{i,t-1}$) is aggregated as the segment-sales-weighted sum of industry-level US adjusted penetration of robots across N industries in which a firm operates in a given year,

$$APR\_US_{j,(t-5,t-1)} = \frac{M_{j,t-1}^{US} - M_{j,t-5}^{US}}{L_{j,1995}^{US}} - g_{j,(t-5,t-1)}^{US} \frac{M_{j,t-5}^{US}}{L_{j,1995}^{US}},$$

$$APR\_US_{i,t-1} = \sum_{j=1}^{N} s_{i,j,t-1} APR\_US_{j,(t-5,t-1)},$$

where $M_{j,t}^{US}$ is the number of robots in industry j in U.S. at time t from the IFR, $g_{j,(t-5,t-1)}^{US}$ is the growth rate of output of industry j in U.S. between $t-5$ and $t-1$, $L_{j,1995}^{US}$ is the baseline employment level in industry j in U.S. in 1995, and $s_{i,j,t-1}$ is the proportion of segment sales of a firm i in industry j. Since IFR data for U.S. industries only goes back to 2004, *APR_US* is constructed using the U.S. robotics data from 2004 to 2015.

The automation exposure variables *APR_EURO5*, *APR_EURO6* and *APR_EURO8* are as described in Table 5. The dependent variable in the first column of each panel is the firm-level US adjusted penetration of robots as defined above. All control variables are as described in Table 1 and are lagged one year. All regressions include the firm fixed effect and year fixed effect. Standard errors cluster at industry level. F-stats from first stage IV regression are reported at the end of column 1. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: APR_EURO5 and IV estimation

	First-stage	Book	Market	Net book	Net market
APR_EURO5	**0.1705*****				
	(10.30)				
APR_US		**0.0096*****	**0.0107*****	**0.0081*****	**0.0027**
		(7.74)	**(5.62)**	**(4.67)**	**(1.33)**
Size	-0.0245	0.0110*	0.0352***	0.0332***	0.0296***
	(-0.40)	(1.92)	(7.12)	(4.20)	(3.34)
M/B ratio	0.0168***	0.0036	-0.0027***	0.0013	0.0018**
	(3.03)	(1.21)	(-4.07)	(0.46)	(1.97)
ROA	0.0356	-0.1665	-0.0286**	-0.1910	-0.0317***
	(1.64)	(-1.25)	(-2.24)	(-1.46)	(-4.38)
Cash flow volatility	-0.0159	-0.0090	0.0054***	-0.0028	0.0048*
	(-0.79)	(-0.43)	(2.83)	(-0.19)	(1.67)
Dividend	0.0481*	0.0023	-0.0052	0.0048	0.0081
	(1.84)	(0.24)	(-0.71)	(0.47)	(0.88)
R&D	-0.0683	-0.1568	0.0094	-0.1490	0.0059
	(-0.82)	(-0.83)	(0.35)	(-0.78)	(0.13)
Tangibility	-0.3723***	0.2070***	0.1757***	0.4119***	0.2888***
	(-3.00)	(3.93)	(3.70)	(7.00)	(5.41)
F-stats	105.99				
p-value	[0.000]				
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	32361	32361	32361	32361	32361
Adj.R^2	0.905	0.023	0.050	0.033	0.041

Panel B: APR_EURO6 and IV estimation

	First-stage	Book	Market	Net book	Net market
APR_EURO6	**0.1803*****				
	(9.65)				
APR_US		**0.0096*****	**0.0109*****	**0.0082*****	**0.0029**
		(7.65)	**(5.63)**	**(4.74)**	**(1.30)**
Size	-0.0220	0.0109*	0.0351***	0.0331***	0.0296***
	(-0.38)	(1.90)	(7.14)	(4.19)	(3.36)
M/B ratio	0.0160***	0.0036	-0.0027***	0.0013	0.0018**
	(3.17)	(1.21)	(-4.07)	(0.46)	(1.97)
ROA	0.0309	-0.1665	-0.0285**	-0.1910	-0.0317***
	(1.55)	(-1.25)	(-2.24)	(-1.46)	(-4.37)
Cash flow volatility	-0.0105	-0.0090	0.0054***	-0.0028	0.0048*
	(-0.58)	(-0.43)	(2.83)	(-0.19)	(1.67)
Dividend	0.0465*	0.0023	-0.0052	0.0048	0.0081
	(1.78)	(0.24)	(-0.71)	(0.47)	(0.88)
R&D	-0.0760	-0.1568	0.0093	-0.1491	0.0058
	(-0.90)	(-0.83)	(0.35)	(-0.78)	(0.13)
Tangibility	-0.3340***	0.2070***	0.1757***	0.4119***	0.2888***
	(-2.85)	(3.93)	(3.70)	(7.00)	(5.41)
F-stats	93.22				
p-value	[0.000]				
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	32361	32361	32361	32361	32361
Adj.R^2	0.902	0.023	0.049	0.033	0.041

Panel C: APR_EURO8 and IV estimation

	First-stage	Book	Market	Net book	Net market
APR_EURO8	**0.2019*****				
	(11.10)				
APR_US		**0.0103*** **	**0.0117*****	**0.0090*****	**0.0034**
		(8.02)	**(6.08)**	**(5.14)**	**(1.46)**
Size	-0.0150	0.0107*	0.0348***	0.0329***	0.0294***
	(-0.32)	(1.87)	(7.23)	(4.17)	(3.37)
M/B ratio	0.0156***	0.0036	-0.0027***	0.0013	0.0018**
	(3.24)	(1.21)	(-4.07)	(0.46)	(1.97)
ROA	0.0298	-0.1664	-0.0285**	-0.1909	-0.0317***
	(1.59)	(-1.25)	(-2.23)	(-1.46)	(-4.35)
Cash flow volatility	-0.0113	-0.0091	0.0053***	-0.0028	0.0048*
	(-0.65)	(-0.43)	(2.81)	(-0.19)	(1.65)
Dividend	0.0442*	0.0022	-0.0053	0.0048	0.0081
	(1.67)	(0.23)	(-0.72)	(0.46)	(0.88)
R&D	-0.0633	-0.1570	0.0091	-0.1493	0.0057
	(-0.86)	(-0.84)	(0.34)	(-0.78)	(0.13)
Tangibility	-0.3422***	0.2070***	0.1757***	0.4120***	0.2888***
	(-2.83)	(3.93)	(3.70)	(7.00)	(5.41)
F-state	123.16				
p-value	[0.000]				
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	32361	32361	32361	32361	32361
Adj.R^2	0.905	0.023	0.047	0.033	0.041

Table 8. Penetration of robots, Chinese import competition and capital structure

This table presents regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables using an alternative measure of automation exposure as in Acemoglu and Restrepo (2020) by controlling for the effect of Chinese import competition.

Panel A (Panel B or Panel C) shows the results by controlling for Chinese import competition using *APR_EURO5* (*APR_EURO6* or *APR_EURO8*). *China* is defined as the changes in industry share of U.S. imports from Autor et al. (2013). The leverage ratios and control variables are as described in Table 1.

All control variables are as described in Table 1 and are lagged one year. All regressions include control variables, the firm and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: APR_EURO5 and Chinese import competition

	Book (1)	Market (2)	Net book (3)	Net market (4)
APR_EURO5	**0.0006*****	**0.0004*****	**0.0004*****	**0.0003*****
	(4.91)	**(5.01)**	**(3.24)**	**(2.79)**
China	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.97)	(-0.93)	(-1.04)	(-0.85)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51187	51187	51187	51187
Adj.R^2	0.650	0.708	0.703	0.740

Panel B: APR_EURO6 and Chinese import competition

	Book (1)	Market (2)	Net book (3)	Net market (4)
APR_EURO6	**0.0005*****	**0.0004*****	**0.0003****	**0.0003***
	(3.98)	**(3.92)**	**(2.08)**	**(1.91)**
China	-0.0001	-0.0001	-0.0001	-0.0000
	(-0.98)	(-0.92)	(-1.05)	(-0.81)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51187	51187	51187	51187
Adj.R^2	0.650	0.708	0.703	0.740

Panel C: APR_EURO8 and Chinese import competition

	Book	Market	Net book	Net market
	(1)	(2)	(3)	(4)
APR_EURO8	**0.0005*****	**0.0005*****	**0.0003****	**0.0003****
	(3.85)	**(4.33)**	**(2.02)**	**(2.01)**
China	-0.0001	-0.0001	-0.0001	-0.0000
	(-0.96)	(-0.91)	(-1.04)	(-0.80)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51187	51187	51187	51187
Adj.R^2	0.650	0.708	0.703	0.740

Table 9. Penetration of robots, capital deepening and capital structure

This table presents regression results of leverage ratios on a firm's measure of automation exposure and relevant control variables using an alternative measure of automation exposure as in Acemoglu and Restrepo (2020) by controlling for the effect of capital deepening.

Panel A (Panel B or Panel C) shows the results by controlling for industry capital (industry IT capital or industry value added). The three measures of capital deepening are constructed using the industry-level data from Integrated Industry-Level Production Account (KLEMS). The industry capital is constructed as the logarithm of total industry capital from KLEMS. The IT capital is constructed as the logarithm of industry IT capital expenditure from KLEMS. The industry value added is constructed as the logarithm of the total industry value added from KLEMS.

All control variables are as described in Table 1 and are lagged one year. All regressions include control variables, the firm and year fixed effect. Standard errors cluster at industry level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: APR and industry capital

	Book (1)	Market (2)	Net book (3)	Net market (4)
APR_EURO5	**0.0006*** **	**0.0005*** **	**0.0005*** **	**0.0003** **
	(7.22)	**(6.26)**	**(3.39)**	**(2.52)**
Industry capital	-0.0002*	-0.0002**	-0.0002	0.0000
	(-1.71)	(-2.04)	(-1.03)	(0.07)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51064	51064	51064	51064
Adj.R^2	0.650	0.708	0.702	0.740

Panel B: APR and IT capital

	Book (1)	Market (2)	Net book (3)	Net market (4)
APR_EURO5	**0.0006*** **	**0.0005*** **	**0.0004*** **	**0.0003*** **
	(5.04)	**(5.04)**	**(3.34)**	**(2.75)**
IT capital	0.0028*	0.0031**	0.0059**	0.0048***
	(1.87)	(2.25)	(2.41)	(2.95)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51064	51064	51064	51064
Adj.R^2	0.650	0.708	0.703	0.740

Panel C: APR and industry value added

	Book (1)	Market (2)	Net book (3)	Net market (4)
APR_EURO5	**0.0006***** **(5.64)**	**0.0005***** **(5.24)**	**0.0004***** **(3.22)**	**0.0003***** **(2.69)**
Industry value added	-0.0000 (-0.84)	-0.0000 (-0.78)	-0.0000 (-0.50)	0.0000 (0.52)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	51064	51064	51064	51064
Adj.R^2	0.650	0.708	0.702	0.740