

# The impact of labor-saving innovations on corporate dividend policy

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## Abstract

This study investigates the effect of labor-saving innovations on corporate dividend payouts. Using 170,167 firm-year observations for 17,645 U.S. public firms from 1974 to 2019, we find a positive association between labor-saving innovations and dividend payouts. Our results further indicate that labor-saving innovations reduce labor costs and labor-cost rigidity, thereby improving the sufficiency and stability of operating cash flows and strengthening firms' capacity to pay dividends. In particular, the cross-sectional tests show that the effect of labor-saving is more pronounced for more mature firms and firms with tighter employment protection. Finally, and more importantly, we also prove that labor-saving innovations increase both share repurchases and total payouts. This implies that labor-saving innovations increase dividend payments by improving the adequacy and stability of firms' cash flows, rather than merely reallocating cash contributions between dividend payments and share repurchases.

**JEL classification:** G35; J30; O31

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## 1. Introduction

Labor-saving technologies, including robotics and AI-enabled process automation, have become widespread in modern firms. Empirical evidence links their adoption to lower routine employment, higher productivity and TFP, and lower output prices (Graetz & Michaels, 2018; Koch et al., 2021). Related corporate-finance studies show that firms exposed to labor-saving innovation use more financial leverage and hold less precautionary cash, consistent with lower operating risk and greater cost flexibility (Simintzi et al., 2015; Qiu et al., 2024; Liu, 2024). These changes raise a natural question of whether labor-saving innovation also affects firms' ability and willingness to commit to dividend payouts.

Labor-saving innovations may increase dividend payouts by improving both the level and stability of firms' cash flows. A substantial body of evidence shows that technologies such as automation, robotics, and AI enhance productivity, reduce operating and labor costs, and strengthen profitability, thereby expanding firms' free cash flows (Bartel et al., 2007; Graetz & Michaels, 2018; Damioli et al., 2021; Czarnitzki et al., 2023). Beyond efficiency gains, labor-saving innovations can reduce labor rigidity and cost stickiness by lowering firms' dependence on labor, particularly in routine and low-skilled tasks, which improves cost flexibility and dampens cash-flow volatility (Acemoglu & Restrepo, 2018; Jia et al., 2023; Qiu et al., 2024). Because dividend payments represent a long-term commitment and dividend cuts convey negative signals to the market, greater cash-flow sufficiency and stability increase firms' willingness and capacity to sustain dividend payouts. This channel predicts a positive relation between labor-saving innovation and corporate dividend policy.

Alternatively, labor-saving innovations may reduce dividend payouts by locking in capital and constraining financial flexibility. The adoption of robotics, automation, and AI systems typically requires substantial upfront investments in fixed assets, software, and R&D, as well as ongoing expenditures on system upgrades, maintenance, and employee retraining (Acemoglu & Restrepo, 2018; Bughin et al., 2018). Moreover, automation tends to shift firms' labor demand toward higher-skilled workers, whose recruitment, training, and retention entail higher and less predictable costs (Acemoglu & Restrepo, 2018; Liu, 2022; Chen et al., 2024). These capital and

skill-related commitments can absorb internal funds and increase cash-flow uncertainty. Under the residual dividend view, firms prioritize investment needs over shareholder payouts, implying that labor-saving innovation may crowd out dividend payments despite potential long-run efficiency gains. This channel predicts a negative relation between labor-saving innovation and dividend payout policy.

Using a sample of 170,167 firm-year observations for 17,645 U.S. public firms from 1974 to 2019, we examine the effects of labor-saving innovations corporate dividend payout policy. We employ the process innovation dataset of Bena et al. (2022) to measure labor-saving innovation (LSI). Process innovations refer to the improvement of production methods or technologies employed by a firm in the manufacture of existing products or the development of new products, with the aim of enhancing efficiency, productivity, and cost savings (Bena et al., 2022). We proxy dividend payouts by the Dividends-to-Assets (DVA) ratio. We find a significant and positive relationship between labor-saving innovations and dividend payouts. In a specification with industry and year fixed effects, a one-unit increase in LSI is associated with a 0.056 increase in DVA. Adding firm fixed effects yields a coefficient of 0.037, and both estimates are significant at the 1% level. These results are consistent with our expectation that labor-saving innovations can increase firms' dividend payouts.

To further understand how the impact of labor-saving innovations transfers to firms' dividend payouts, we also examine cross-sectional heterogeneity along two dimensions. According to our aforementioned argument, labor-saving innovations may facilitate firms reduce labor costs and labor rigidity, thereby improving the adequacy and stability of profits, which ultimately contributes higher dividend payouts. If this argument holds, the positive impact of labor-saving technology on dividend payments would be more pronounced in corporate environments with stronger employment protection, as the labor cost-reducing and labor cost flexibility-enhancing effects of such innovations become more valuable. For our empirical investigation, we adopt two proxies to represent employment protection, including annual state-level rates of union membership and collective-bargaining coverage (Hirsch & Macpherson, 2003). Consistent with our conjecture, our results show that the positive relationship between labor-saving innovations

and dividend payouts is more pronounced for firms operating in contexts with higher levels of employee protection. This finding supports our proposed mechanism by showing that employment protection amplifies the impact of labor-saving innovations on firms' dividend policies.

Beyond labor protection, we also conduct a cross-sectional analysis by looking at firms' life-cycle stage. According to life-cycle theory, firms in the maturity stage face fewer reinvestment opportunities and therefore choose to return earnings to shareholders. If labor-saving innovations improve efficiency and reduce costs, thereby generating more free cash flows, then for mature firms with reduced reinvestment opportunities, the impact of labor-saving technology on dividend payouts would be expected to be greater. To investigate this life-cycle argument, we employ the life-cycle classification of Dickinson (2011) and the ratio of retained earnings to total assets (DeAngelo et al., 2006) to measure firms' maturity stage. We interact firm maturity with labor-saving innovations and find that when firms are in the maturity stage, the effect of labor-saving technology on dividend payouts is stronger as expected.

We also perform a series of robustness checks to validate our baseline findings. First, we replace the original labor-saving innovation (LSI) measure with two alternatives including (i) an inverse hyperbolic sine transformation of the count of labor-saving patents to address the right-skew of the distribution of labor-saving patents, and (ii) automation penetration (Auto) from the International Federation of Robotics (IFR) as a proxy for technology adoption, which captures the intensity of firms' exposure to labor-saving technologies after mapping the industry-level series to firms. Using either alternative measure, our results remain positive and statistically significant. Second, we consider alternative measures of dividend payouts by scaling dividends by market capitalization (DVM) and by estimating a dividend-payer indicator in a logit model. Both approaches yield evidence consistent with our main findings. Finally, we incorporate more controls with additional determinants of dividend payouts documented in the literature including board size, board independence, income tax, investment and retained earnings and further include the count of non-labor-saving patents (NLSI) to isolate LSI from general technological

innovations. Across these specifications, the positive association between LSI and dividend payouts remains consistent.

To mitigate endogeneity concerns such as omitted variables and reverse causality, we implement a layered identification and endogeneity checks. First, we include region-by-year fixed effects to absorb contemporaneous region-level policy shocks. Second, we regress DVA on LSI lagged by three periods to address potential reverse causality. Third, we employ European robot penetration as an instrument and estimate the effect of LSI on DVA with a two stage least squares specification to address the potential concerns about omitted variables and reverse causality. We consider European robot penetration as the instrumental variable because European and U.S. automation trends are correlated, while U.S. dividend policies are unlikely to be directly affected by European automation trends (Acemoglu & Restrepo, 2020). Finally, we utilize the double machine learning approach by using flexible learners to model and remove the components of both the treatment and the outcome that are explained by observed firm characteristics, and then estimating the net effect of LSI on the remaining variation. Taken together, our findings are consistent across various specifications with firm and spatiotemporal fixed effects, the lagged independent variable, an instrumental variable, and the double machine learning model.

In addition, we conduct a subperiod analysis. Fama & French (2001) document a decline in U.S. cash dividends in the late twentieth century, whereas our measure of labor-saving innovations rises over time, which could appear at odds with a positive relation between LSI and dividends. To address this concern, we split the sample into 1974–1999 and 2000–2019 and find that the relation remains positive in both periods. Comparing the magnitude of effects across periods, the positive effect of labor-saving innovations on dividend payout is stronger in 2000–2019. These results indicate that the within-period firm-level mechanism is not inconsistent with aggregate time trends and that the effect exhibits heterogeneity across periods.

Finally, our additional analyses show that labor-saving innovations increase not only dividend payouts but also share repurchases and total payouts. Compared with cash dividends, share repurchases are more flexible and carry lower signaling costs, making them particularly

attractive under heightened uncertainty as argued by previous studies (Jagannathan et al., 2000; Brav et al., 2005). Consequently, our finding reinforces the view that labor-saving innovations improve operating efficiency and boosts free cash flows, ultimately enabling firms to return more capital to shareholders.

This paper makes three related contributions. First, we use dividend policy, a particularly sticky and commitment-heavy corporate decision, to reveal how labor-saving innovation changes firms' ability and willingness to commit to payouts (Lintner, 1956; Fama & Babiak, 1968). This extends the small corporate-finance literature on labor-saving technologies, which has begun to link such innovations to capital structure (Qiu et al., 2024) and to firms' information environment reporting quality (Oesch & Walser, 2025).

Second, we show that labor-saving innovation expands payout capacity rather than simply shifting cash across payout channels. Prior work emphasizes that repurchases often substitute for dividends (Grullon & Michaely, 2002). In contrast, we find that labor-saving innovation is associated with higher dividends and higher repurchases, consistent with an increase in overall distributable resources.

Third, we identify cash-flow stability and labor rigidity as the underlying mechanism. We connect labor-saving innovation to lower labor-related adjustment frictions and cost asymmetry, drawing on evidence that labor adjustment costs contribute to sticky costs (Anderson et al., 2003) and that labor protection affects firms' financial policies through operating leverage and rigidity (Simintzi et al., 2015). This mechanism links technological change directly to classic dividend theories that emphasize stable, sustainable cash flows as a prerequisite for dividend commitments (Lintner, 1956; Fama & Babiak, 1968).

The remainder of this paper is structured as follows. Section 2 presents the literature review and develops our research hypotheses. Section 3 outlines the methodology, including the sample construction and empirical model. Section 4 reports the main empirical findings, while Section 5 addresses endogeneity concerns through a series of tests. Section 6 proves the influence of

labor-saving innovations on share repurchases and the total payout policy of firms. Section 7 concludes the study.

## **2. Literature Review**

### **2.1. Labor-Saving Innovation**

Labor-saving innovations refer to innovations in production and operation that reduce reliance on human labor, including mechanization, automation, digitalization, artificial intelligence, and robotics (Qiu et al., 2024). The historical roots of labor-saving innovations can be traced back to the Industrial Revolution of the 18th and 19th centuries. The widespread adoption of steam engines and mechanized production lines significantly boosted productivity by replacing manual labor, marking the first large-scale wave of labor displacement (Mokyr, 1992). In the 20th century, the development of assembly line production and the emergence of automated machinery enabled firms to reduce labor costs and increase output through standardized and large-scale production processes. Since the late 20th century, the proliferation of information technology has automated a wide range of white-collar tasks, such as data processing and office administration (Autor et al., 2003). More recently, emerging technologies, including the internet, big data, cloud computing, and artificial intelligence, have continued to reshape the structure of labor markets. The development of labor-saving innovations in the United States is evident in the number of patents held by U.S. firms. Figure 1 reports the annual counts of labor-saving innovation patents for U.S. firms from 1974 to 2019 and shows an upward trend.

In academia, prior studies on the impact of labor-saving innovations have predominantly concentrated on its implications for labor market and labor management. For example, as labor-saving innovations, routine and low-skilled occupations are increasingly susceptible to displacement, while new roles, particularly in the service and creative sectors, are emerging in response to changing technological demands (Acemoglu & Restrepo, 2018; Autor et al., 2003; Autor, 2015). Concurrently, labor-saving innovations tend to heighten the demand for high-skilled labor, while reducing reliance on human input for programmable or codifiable tasks (Bresnahan et al., 2002).

Beyond their effects on labor dynamics, labor-saving innovations have been shown to influence firm-level productivity and operational performance significantly. For example, Graetz & Michaels (2018) provide cross-country evidence indicating that the adoption of industrial robots leads to substantial gains in productivity and contributes positively to aggregate economic output. Aral et al. (2012) underscore the complementarities between information systems, viewed as a form of labor-saving technology, and performance management mechanisms, suggesting that such synergies can drive performance enhancements. Similarly, Tambe (2014) demonstrates that automation and related analytics capabilities can generate considerable improvements in firm value and efficiency. Moreover, Huang & Rust (2018) find that artificial intelligence enhances customer communication and relationship management, thereby fostering superior firm performance. Accordingly, existing studies show that automation increases production efficiency and resource allocation efficiency.

In recent years, an emerging strand of corporate finance literature has begun to examine the implications of labor-saving innovation. Liu (2024) shows that the adoption of robots is associated with higher leverage and lower cash holdings. Liu (2024) and Zhang & Wang (2023) explore the effects of industrial robot adoption on labor cost stickiness and labor investment efficiency in Chinese firms, arguing that the use of robots increases labor adjustment costs by expanding employment scale and upgrading employment structure. Qiu et al. (2024) further confirm that labor-saving innovations reduce wage rigidity and operating leverage, thereby enabling firms to increase their financial leverage.

Overall, while research in corporate finance has increasingly recognized the importance of labor-saving innovation, systematic studies on how labor-saving innovations influence dividend policy remain scarce. Existing literature primarily focuses on investment, capital structure, and labor cost stickiness, leaving room for further exploration of the relationship between labor-saving innovations and dividend policy.

## **2.2. The influence of labor-saving innovations on corporate dividend policy**

Although direct evidence on the relation between labor-saving innovation and corporate dividend policy remains scarce, a large literature documents how labor-saving technologies shape firm operations, cost structures, and managerial decision-making (Ajiga et al., 2024; Chen et al., 2024; Haenlein et al., 2019). This literature implies that labor-saving innovation can affect firms' dividend policies through its impact on the level and stability of operating cash flows, which are central determinants of dividend commitments.

First, labor-saving innovation can increase firms' capacity to pay dividends by improving long-run profitability and free cash flow. A substantial body of evidence shows that investments in automation, robotics, artificial intelligence, and data-driven management raise productivity, reduce operating and labor costs, and enhance output efficiency (Bartel et al., 2007; Graetz & Michaels, 2018; Damioli et al., 2021; Czarnitzki et al., 2023). By lowering reliance on labor, particularly in low-skill and routine tasks, labor-saving innovation further mitigates rising labor costs and strengthens firms' cash-flow generating ability over time (Acemoglu & Restrepo, 2018, 2019, 2020; Dechezleprêtre et al., 2021; Xiang et al., 2025). When firms generate more abundant free cash flows, dividend payouts become more feasible and desirable, both as a means of returning excess cash to shareholders and of mitigating agency problems associated with managerial discretion (Jensen, 1986).

Second, labor-saving innovation can increase firms' willingness to pay dividends by stabilizing earnings and cash flows. Prior studies show that labor adjustment costs are a major source of cost stickiness, which amplifies earnings volatility during downturns and undermines firms' ability to sustain dividend commitments (Anderson et al., 2003; Abowd & Kramarz, 2003; Banker et al., 2016; Weiss, 2010). By substituting capital, machines, and digital processes for labor, labor-saving innovation reduces labor rigidity and cost stickiness, enhances cost flexibility, and dampens cash-flow volatility (Liu & Liu, 2022; Jia et al., 2023; Du et al., 2024; Qiu et al., 2024). Because dividend reductions are typically interpreted as negative signals by the market and are associated with adverse stock-price reactions (Spence, 1973; DeAngelo et al., 2006), managers are more inclined to maintain or increase dividends when cash flows are stable and predictable.

Taken together, the literature suggests that labor-saving innovation improves both the sufficiency and stability of firms' cash flows, thereby increasing their capacity and willingness to distribute dividends. We therefore propose the following hypothesis:

**H1(a):** *Labor-saving innovations have a positive effect on corporate dividend payout policy.*

Despite the potential efficiency gains from labor-saving innovation, such technologies may also constrain firms' ability to distribute cash to shareholders by increasing capital commitment and reducing financial flexibility. Implementing automation, robotics, and AI systems typically requires substantial upfront investments in fixed assets, software, and R&D, often accompanied by long payback periods (Acemoglu & Restrepo, 2018). Moreover, rapid technological progress necessitates continuous follow-on expenditures for system upgrades, maintenance, integration, and employee retraining, further tying up internal funds (Bughin et al., 2018).

In addition, labor-saving innovation tends to restructure the workforce toward higher-skilled labor, even as it displaces routine and low-skilled tasks. Automation increases demand for complex roles such as data analytics, programming, system calibration, and human-machine interaction, which require specialized skills and command higher wages (Acemoglu & Restrepo, 2018). Prior evidence shows that recruiting, training, and retaining high-skilled workers involve significantly higher and less predictable costs than low-skilled labor, increasing operating commitments and cash-flow uncertainty (Liu, 2022; Chen et al., 2024). Together, these capital and skill-related investments can create capital lock-in, limiting firms' ability to redeploy resources or return cash to shareholders.

According to the residual dividend theory, firms fund investment opportunities first and distribute dividends only from remaining cash flows. When labor-saving innovation absorbs substantial financial resources through fixed investment and ongoing operating commitments, fewer funds may remain available for payout, even if long-run profitability improves. Under this view, labor-saving innovation crowds out dividend payments by tightening financial constraints and reducing payout flexibility. We therefore propose the following competing hypothesis:

**H1(b):** *Labor-saving innovations have a negative effect on corporate dividend payout policy.*

### **2.3. The role of employment protection on the influence of labor-saving innovations on dividend payout policy**

Labor-saving innovations affect corporate dividend policy differently across companies. The strength of employment protection plays a crucial role in shaping how labor-saving innovations affect dividend payouts. Employment protection refers to legal constraints on employee dismissals, wage adjustments, and working conditions, arising either from labor unions or from legislation enacted by individual states. The higher the level of employment protection, the higher labor costs and adjusting costs firms face (Lazear, 1990; Bentolila & Bertola, 1990; Banker et al., 2013). Prior research has shown that stronger employment protection significantly increases the proportion of fixed costs and amplifies profit volatility for firms (Simintzi et al., 2015; Serfling, 2016).

If the impact of labor-saving innovations on dividend payments is positive, which means that its implementation reduces labor costs and labor rigidity, thereby improving the adequacy and stability of corporate cash flows, then firms operating in environments with stronger employment protection are likely to benefit more from cost reductions and decreased earnings volatility. Under the influence of the dividend signal motive and the agency problem reduction motive, such firms are more inclined to use the additional cash flows to increase dividend payouts, thereby sending a positive signal of more stable earnings and stronger corporate governance to capital markets.

Conversely, when labor-saving innovations are accompanied by substantial capital expenditures or increased reliance on high-skilled employees, firms in high employment protection environments find it difficult to alleviate financial pressure through layoffs or flexible working arrangements (Acemoglu & Restrepo, 2018). As a result, they would resort to reducing dividend payouts to reallocate internal funds and cover the shortfall (Hoberg & Prabhala, 2008). Therefore, regardless of whether automation generates a positive or negative cash flow shock, its impact on

dividend policy is likely to be more pronounced and sensitive in contexts with stronger employment protection.

By contrast, firms operating in environments with weaker employment protection enjoy greater external and internal labor adjustment flexibility. As a result, they are less dependent on dividend adjustments in response to automation-induced financial fluctuations, and the marginal effect of automation on their dividend policy is thus attenuated. Following the discussion, we propose the following hypothesis:

**H2:** *Employment protection strengthens the impact of labor-saving innovations on dividend payouts.*

#### **2.4. The influence of labor-saving innovations on dividend payment in different life-cycle stages**

In addition, according to the life-cycle theory, firms' development stages condition the relationship between automation and dividend payouts. Life-cycle theory means that as firms evolve from startup to growth, maturity, and eventual decline, their profitability, investment opportunities, financing constraints, and internal funding structures change systematically, thereby shaping dividend policy. Firms in the maturity stage typically have accumulated high and sustainable retained earnings, face relatively scarce marginal investment opportunities, and encounter weaker external financing constraints; consequently, they are more inclined to initiate or raise cash dividends and to maintain higher, more stable payout ratios. By contrast, firms in the early or high-growth stage, which are characterized by abundant investment opportunities, substantial capital expenditure and R&D needs, and relatively scarce internal funds, tend not to pay cash dividends or pay only modest amounts (Fama & French, 2001; DeAngelo et al., 2006; Denis & Osobov, 2008).

Consequently, the effect of labor-saving innovations on dividend payouts is expected to vary across life-cycle stages. If the effect is positive, meaning that labor-saving innovations raise profits and increase retained earnings available for distribution, then growth firms, which have

more investment opportunities, are inclined to channel incremental cash flows into reinvestment, thereby attenuating the impact of labor-saving innovations on dividends. In contrast, mature firms, with fewer reinvestment opportunities, are more likely to return the gains from labor-saving innovations to shareholders.

Conversely, if the effect of labor-saving innovations on dividends is negative because substantial upfront investment and ongoing maintenance crowd out corporate cash flows, the implications also differ by life-cycle stage. Growth firms are more inclined to reinvest rather than distribute dividends; additional commitments to labor-saving innovations during this stage would further compress dividend payouts. Therefore, the negative effect of labor-saving innovations on dividends should be stronger among growth firms. For mature firms, even after undertaking labor-saving innovations and covering the initial outlays, residual cash flow is more likely to remain; given the scarcity of high-return projects, mature firms tend to distribute these surpluses to shareholders. Hence, the negative effect of labor-saving innovations on dividends should be weaker among mature firms. Based on the foregoing, we propose the following hypotheses:

**H3(a):** *Among mature firms, the impact of labor-saving innovations on dividend payouts is greater than among firms in the non-mature period.*

**H3(b):** *Among mature firms, the impact of labor-saving innovations on dividend payouts is smaller than among firms in the non-mature period.*

### **3. Research Methodology**

#### **3.1. Measurement of labor-saving innovations**

We measure labor-saving innovations using the number of labor-saving patents at the firm-year level. We do not use direct measures of labor-saving technology adoption for two reasons. First, there is no accurate firm-level measurement for the true adoption rate of labor-saving technologies. Although Acemoglu & Restrepo (2018) developed an industry-level robot penetration measure, mapping industry-level adoption directly to the firm level would introduce measurement error. Qiu et al. (2024) propose a firm-level measure of labor-saving technology

adoption, which has not yet been widely cited, we therefore use it only as a robustness check. Second, while patents capture invention rather than adoption, they are widely used as proxies for the technology supply and for directed innovation. Prior studies show that firms' in-house innovations affect absorptive and learning capacity, and that patenting activity shapes firms' expectations, cash flows, and financial policies (Griffith et al., 2004; Babina et al., 2024). In addition, internal implementation accounts for the largest share of post-application patent utilization. Specifically, more than 50% of patent applications are ultimately used in-house, and this proportion exceeds 60% for labor-saving technologies (Giuri et al., 2007; Torrisi et al., 2016). Accordingly, the firm-year count of a firm's labor-saving patent applications is an effective proxy for its actual adoption of such technologies.

Specifically, we adopt the process innovations measure developed by Bena et al. (2022) to capture firms' engagement with labor-saving technologies. Process innovations are the introduction of significantly improved methods, techniques, or operating procedures in the goods production, services delivery, and internal business processes, to increase efficiency, reduce costs, enhance quality, or improve flexibility (Bena et al., 2022). Typical examples include improvements in manufacturing processes (e.g., automated production lines, robotic operating systems, or advanced manufacturing such as 3D printing), enhancements in service delivery (e.g., online processing systems, self-service kiosks, or digital customer-support platforms), and innovations in logistics and supply chains (e.g., using Internet-of-Things technologies for inventory tracking, optimizing delivery routes, or applying blockchain for supply-chain record-keeping). Compared with conventional automation patents, process patents more explicitly capture labor-saving features (Qiu et al., 2024). Traditional forms of automation often involve localized task substitution, such as deploying robotic arms to replace assembly-line workers or using accounting software to automate report generation. By contrast, process innovations typically require task reconfiguration, information flows optimization, and reorganization of decision-making mechanisms, thereby fundamentally altering how work is organized (Bena et al., 2022). Consequently, process innovations are more systemic and holistic, and their labor-saving effects are often more pronounced than those of traditional automation. In this study, we use process innovations as a proxy for firms' adoption of labor-saving technologies.

Using process innovation patents as a proxy for labor-saving technology has precedent in the literature. Qiu et al. (2024) employ process innovation patents as a proxy for labor-saving technology and document that labor-saving innovations increase firms' financial leverage. In their framework, labor-saving innovations enable firms to replace manual labor with automation, thereby reducing labor cost rigidity, lowering the rigid component of operating leverage, and dampening cash flow volatility. These improvements raise firms' debt capacity and increase optimal leverage. Following Qiu et al. (2024), we use process innovation patents as a proxy for labor-saving innovations and examine their impact on corporate dividend payouts.

### 3.2. Sample Selection

We focus on firms listed in the U.S. market. The sample includes domestic common stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ, as identified by CRSP exchange codes 1, 2, and 3, respectively. We further limit the sample to CRSP share codes 10 and 11, which denote ordinary common shares. Firms in the financial services industry (SIC codes 6000 to 6999) and the utilities sector (SIC codes 4900 to 4999) are excluded due to their distinct regulatory and capital structure characteristics.

The study period spans from 1974 to 2019. We choose this period because the process patent dataset compiled by Bena et al. (2022) covers all U.S. process patents from 1974 to 2020. The starting year corresponds to the beginning of the database provided by Bena et al. (2022). We exclude 2020 to minimize pandemic-related confounding, as COVID-19 disrupted firm operations and patenting activity, and the number of process patents dropped sharply in 2020. We therefore retain observations through 2019.

### 3.3. Baseline Regression Model

In this section, we construct the baseline regression model as follows:

$$DVA_{i,t} = \beta_0 + \beta_1 LSI_{i,t} + \gamma X_{i,t} + \mu_{i,t} \quad (1)$$

In this specification,  $DVA_{i,t}$  represents the dividend payout policy of firm  $i$  in year  $t$ , defined as cash dividends scaled by total assets and expressed as a percentage.  $LSI_{i,t}$  captures the firm's level of labor-saving innovation. The vector  $X_{i,t}$  includes a set of firm-level control variables: return on assets (ROA), firm size (Size), cash holdings (Cash), leverage (Leverage), asset tangibility (Tangibility), growth (Growth), and Tobin's Q (TobinQ). We also include year fixed effects and four-digit SIC industry fixed effects to control for unobservable factors at the time and industry levels. Standard errors are clustered at the firm level to account for within-firm correlation over time.

To measure LSI, we follow Bena et al. (2022) and Kogan et al. (2017), who provide a dataset linking process innovation patents to publicly listed U.S. firms. We calculate the annual number of process innovation patents held by each firm and then take the natural logarithm of one plus this count to construct a firm-year-level proxy for labor-saving innovation.

The control variables included in our model capture firm characteristics known to influence dividend payout policies. In selecting control variables, we follow Jagannathan et al. (2000), Kumar & Vergara-Alert (2020), and Chang et al. (2024). Firm size (Size) is positively associated with dividend payments, as larger firms typically face lower information asymmetry and have greater access to external financing, making them more likely to pay stable dividends. Profitability (ROA) reflects a firm's ability to pay dividends, with more profitable firms often distributing dividends to signal financial strength. Cash holdings (Cash) indicate the firm's liquidity position, where firms with higher reserves are better positioned to pay dividends. Leverage (Leverage) captures financial constraints, as highly leveraged firms prefer to retain earnings for debt servicing rather than dividend distribution. Tangibility (Tangibility) reflects the proportion of tangible assets, and a higher ratio suggests stronger collateral value but fewer growth opportunities, which tends to increase the likelihood of dividend payments. Growth (Growth) measures the firm's growth rate, where fast-growing firms are more likely to retain earnings for reinvestment. Finally, Tobin's Q (TobinQ) captures investment opportunities, with higher values indicating that firms are more likely to retain earnings for future investments rather than pay dividends.

Panel A of table 1 reports the descriptive statistics for the key variables used in the regression analyses. The sample comprises 170,167 firm-year observations. The mean value of LSI is 0.591, with a standard deviation of 1.196, indicating substantial variation across firms in their exposure to labor-saving technologies. For dividend payouts, the mean of DVA, defined as cash dividends scaled by total assets and reported in percent, is 0.911, with a standard deviation of 1.906. These figures suggest considerable heterogeneity in firms' dividend payout intensity.

[Insert Table 1 around here]

For control variables, the mean ROA is -0.050, with the minimum of -1.617, reflecting the presence of loss-making firms in the sample. The Tangibility average is 0.293, suggesting a moderate proportion of tangible assets, while the Cash average is 0.172. Tobin's Q has a mean value of 1.891, indicating there are some growth opportunities. The average Leverage is 0.182, and the average Size is 5.110, which are both consistent with typical values reported in the literature. The Growth has a mean of 0.141, and the wide range between its minimum and maximum values suggests substantial variation in growth across firms. To mitigate the influence of outliers on the regression results, all continuous firm-level characteristics are winsorized at the 1st and 99th percentiles.

Panel B of table 1 presents the results of a univariate mean comparison test for the dividend payout measure DVA based on whether firms hold labor-saving innovation patents. Specifically, we divide the firm-year observations into two groups: one group comprises firms that hold at least one labor-saving innovation patent ("Have LSI"), and the other consists of firms without any such patents ("No LSI").

The results indicate that firms with labor-saving innovation patents have significantly higher average dividend payout measures than those without such patents. Specifically, for DVA, the mean value in the "Have LSI" group is 1.081, which is higher than the 0.839 observed in the "No LSI" group, with a corresponding t-statistic of -24.06.

In addition, this panel separately reports other firm characteristics for firms with and without labor-saving innovations. Overall, firms engaging in labor-saving innovation have, on average, lower ROA, tangibility, leverage, and growth, while holding more cash, exhibiting higher Tobin's Q, and being larger in size.

Overall, these findings suggest that firms that have labor-saving innovation patents are significantly more likely to pay dividends and tend to pay them at a higher intensity. This provides strong evidence in support of a potential causal link between labor-saving innovations and corporate dividend policy, laying the groundwork for the subsequent multivariate analysis.

Table 2 presents the Pearson correlation coefficients among the main variables to examine their linear relationships. LSI is positively correlated with dividend measures DVA, with a correlation coefficient of 0.128. This correlation is statistically significant at the 1% level, providing preliminary evidence that firms with higher levels of labor-saving innovations tend to exhibit stronger dividend payout tendencies.

[Insert Table 2 around here]

Among the control variables, ROA shows a significantly positive correlation with the dividend variables, which is consistent with the expectation that more profitable firms are more likely to pay dividends. Size is also highly positively correlated with DVA, suggesting that larger firms are more inclined to distribute dividends. Notably, Cash are negatively correlated with the DVA, which indicate a tendency for firms to retain cash rather than distribute it as dividends. Furthermore, Tobin's Q is negatively and significantly correlated with DVA, consistent with the view that high-growth firms are more likely to retain earnings to fund future investments.

Overall, none of the correlation coefficients exceeds 0.7, suggesting that multicollinearity is not a serious concern, thereby providing a sound basis for the subsequent regression analysis.

## 4. Regression Results

### 4.1. The influence of labor-saving innovation on dividend policy

Table 3 reports OLS estimates of the association between labor-saving innovation and corporate dividend payouts. The regression includes year fixed effects and four-digit SIC industry fixed effects. Standard errors are clustered at the firm level to account for within-firm serial correlation over time.

[Insert Table 3 around here]

The regression results indicate that labor-saving innovation is positively and significantly associated with the dividend payout, with statistical significance at the 1% level. Specifically, a one-unit increase in LSI is associated with an increase of approximately 0.056 percentage points in DVA. This finding suggests that the implementation of labor-saving innovations can enhance firms' operational efficiency, expand free cash flows, and reduce labor costs, thereby improving both capacity and incentive to distribute profits to shareholders. This evidence provides direct support to the core hypothesis of this study, indicating that labor-saving innovations are positively associated with firms' willingness and ability to pay more dividends.

The estimated coefficients on control variables are generally consistent with prior literature. ROA is positively and significantly associated with dividend payouts in all models, implying that more profitable firms are more likely to pay dividends. Tangibility and Size also exhibit significantly positive coefficients, likely reflecting the fact that larger firms with more stable asset structures tend to have stronger financial positions and a greater propensity to distribute dividends. Cash is positively associated with DVA, which suggests that firms with abundant cash prefer immediate distribution rather than retain funds for reinvestment. Tobin's Q shows a positive association with DVA, which relates to how asset size influences scaling. Leverage exhibits a strong and significantly negative relationship with dividend payouts, indicating that firms with higher debt burdens are less likely to distribute dividends. Growth is also negatively and significantly associated with dividend payout, further supporting the idea that high-growth firms tend to reinvest earnings rather than distribute them.

Taken together, the empirical findings in Table 3 demonstrate that labor-saving innovations are significantly associated with stronger dividend payout behavior and have meaningful economic implications. This evidence offers new insights into corporate financial decision-making in the context of technological transformation and lays a foundation for further analysis of underlying mechanisms and heterogeneity across firms.

## **4.2. Firm Fixed Effects Regression Results**

To address potential bias from unobserved firm characteristics and to ensure robustness, we estimate a firm fixed effects model. Including firm fixed effects allows us to control for firm-specific characteristics, such as corporate culture or governance structures that might simultaneously influence both labor-saving innovations and dividend behavior.

[Insert Table 4 around here]

As shown in Table 4, the coefficient on LSI remains positive and statistically significant at 0.037. This finding indicates that the positive association between labor-saving innovations and dividend payouts persists even after accounting for unobserved firm-level heterogeneity. In addition, the magnitudes and signs of the other control variables are similar to those in the baseline model that includes only industry fixed effects, which further strengthens the robustness of the baseline results.

## **4.3. Additional Robustness Checks**

We perform several additional checks to verify that our results are not sensitive to alternative choices. Specifically, we use alternative measures of the key independent variable, redefine the dependent variable, and include additional control variables.

### **4.3.1. Alternative independent variable**

We construct two alternative measures of labor-saving innovation. Our first concern is the highly skewed distribution of patent counts across firms, that a small number of firms account for most

labor-saving patents, while many firms hold few. This right-skewness may bias regression estimates. To solve this problem, we normalize the LSI variable (Jaffe & Trajtenberg, 2002; Qiu et al., 2024). Specifically, we construct an adjusted LSI measure (Adjusted LSI) by dividing each firm's annual number of labor-saving patents by the total number of such patents granted to all firms in the same year:

$$Adj.LSI_{i,t} = \frac{\text{number of automation patents}_{i,t}}{\sum_{i=1}^F \text{number of automation patents}_{i,t}} \quad (2)$$

To further address the influence of extreme values and improve model linearity, we apply the inverse hyperbolic sine (IHS) transformation to the Adjusted LSI, resulting in a smoothed measure denoted as LSI2. We then re-estimate the model using LSI2 as the key explanatory variable. Column (1) of Table 5 reports the results. Empirical findings show that LSI2 remains positively and significantly associated with the dividend payout measure. This result confirms that after normalizing and nonlinearly transforming the labor-saving technology measure, the positive relationship between labor-saving innovations and firms' dividend payout behavior remains robust.

[Insert Table 5 around here]

Our second concern regarding the independent variable is whether patent-based LSI measurement accurately captures a firm's level of labor-saving innovation. To address this concern, we construct an alternative measure of labor-saving innovations that relies on an independent data source not based on patents. Specifically, following Acemoglu & Restrepo (2020) and Qiu et al. (2024), we use the Auto variable as a proxy for firms' exposure to automation technologies. This variable is based on the International Federation of Robotics (IFR) database, which reports global data on robot installations by country and industry since 1993<sup>1</sup>. We extract data for North America and match it with firms' industries to construct firm-level

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<sup>1</sup> Our robot-penetration measure is constructed from International Federation of Robotics (IFR) data. Because the IFR series for the United States begins in 2004 and computing robot penetration results in the loss of five years of observations (see Appendix 2), the estimation window for Table 5 column (2) is 2009–2019.

measures of robot penetration. The construction of Auto is detailed in Appendix 2. Auto captures the degree of automation penetration at the firm level and thus serves as an alternative proxy for labor-saving innovation. Column (2) of Table 5 reports the results. Auto is positively and significantly associated with firms' dividend payout behavior in the model, with coefficient of 4.352 and significant at the 1% level. This evidence further supports the conclusion that firms operating in more automated environments exhibit stronger tendencies and capacities to pay dividends.

#### **4.3.2. Alternative dependent variable**

To ensure robustness, we construct two alternative definitions of dividend payout. First, we construct a new continuous dependent variable DVM, which is the dividend divided by the market value. The result in column (3) shows that the coefficient of LSI is 0.034 and significant at 1%. Additionally, we construct a dummy variable D that equals 1 if a firm pays dividends and 0 otherwise. We then estimate a logit model to examine the relationship between labor-saving innovations and the likelihood of dividend payment. The regression result is presented in Column (4) of Table 5. As shown in the table, using the dummy variable as the dependent variable, the coefficient on LSI is positive and statistically significant, indicating that higher levels of labor-saving innovations are associated with a higher probability of dividend payment.

#### **4.3.3. Alternative control variables**

Finally, to avoid omitting other relevant controls, we incorporate additional control variables that may influence corporate dividend payouts to further mitigate concerns about omitted variable bias (Bodnaruk & Östberg, 2013; Fama & French, 2001; Hoberg & Prabhala, 2008). These controls include corporate board size (Board Size), independent board ratio (Independent Board Ratio), income tax (Tax), investment (Investment), the market-to-book (MtB) ratio and retained earnings (RE)<sup>2</sup>. Additionally, to account for the broader impact of technological adoption trends and to avoid conflating all forms of technological progress with labor-saving innovations, we include a control variable for non-labor-saving innovation (NLSI). This variable is constructed

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<sup>2</sup> The data of board size and board independence are from LSEG, thus the sample period of Table 5 column (5) is 2002-2019 due to database restriction.

based on the number of patents held by a firm during the same period that do not fall under the labor-saving category, with a logarithmic transformation applied (Qiu et al., 2024). As shown in Column (5) of Table 5, the coefficient on LSI remains significantly positive after including these additional controls. The coefficient of NLSI is insignificant, which means that the increase in dividend payouts is not due to the traditional innovation. Moreover, the estimated magnitudes are largely consistent with the baseline regression results, underscoring the robustness of our findings. These results provide further evidence of the distinctive role played by labor-saving technology in shaping corporate dividend policy and confirm that this effect is not merely a reflection of a firm's overall technological innovation intensity.

#### **4.4. Subperiod Regression**

In the baseline regressions, we find that firms' labor-saving innovations significantly increase dividend payouts. However, Fama & French (2001) document a declining propensity to pay dividends from 1978 to 1999, whereas Figure 1 shows a pronounced upward trend in U.S. labor-saving innovations over the same period. This divergence appears at odds with our baseline result that labor-saving innovations are associated with higher dividend payments. To reconcile these patterns, we estimate subperiod regressions to test whether the effect of labor-saving innovations on dividends exhibits temporal heterogeneity.

Using U.S. listed firms, Fama & French (2001) report a marked decline in the propensity to pay dividends from 1978 to 1999. In contrast, Michaely & Moin (2022) document a resurgence in dividend payments from 2000 to 2018. Accordingly, we divide the sample into two subperiods: 1974 to 1999 and 2000 to 2019. The first subperiod spans the structural decline in dividends identified by Fama & French (2001). The second subperiod corresponds to the period after 2000, during which automation technologies matured and firms adjusted their dividend policies. For each subperiod, we replicate the baseline specification with the same set of controls and industry fixed effects.

As reported in Table 6, the estimated effect of labor-saving innovations on dividend payouts is larger from 2000 to 2019 than from 1974 to 1999. This finding indicates that, relative to the

twentieth century period when dividends trended downward, the impact of labor-saving technologies on dividends is comparatively weaker. From 2000 onward, as automation technologies matured and became more widely adopted, their positive effects on operating efficiency, profitability, and cash flow stability intensified, providing a firmer basis for higher dividend distributions. These results are consistent with the structural patterns documented by Fama & French (2001), who report a decline in the propensity to pay dividends from 1978 to 1999, and by Michaely & Moin (2022), who document a resurgence from 2000 to 2018. They also show that the influence of automation on dividend policy exhibits pronounced temporal heterogeneity across historical periods.

[Insert Table 6 around here]

## **4.5. Cross-sectional Tests**

### **4.5.1. Labor cost and labor rigidity reduction**

To further examine the underlying mechanism by which labor-saving innovations affect firms' dividend policies, we test Hypothesis 2: whether the effect of labor-saving innovations on dividend payouts varies with the degree of employment protection faced by the firm.

To test the mechanism that labor-saving innovations reduce labor costs and labor rigidity, we conduct a cross-sectional moderation analysis based on the labor protection firms face. Under the hypothesis, labor-saving innovations lower labor costs and rigidity, which increases profitability and reduces earnings volatility, thereby improving firms' capacity to make payouts. If this mechanism holds, the positive effect of labor-saving innovations on dividend payouts should be more pronounced in firms operating in environments with stronger employment protection, where the benefits from reduced labor costs and rigidity are greater. By contrast, for firms facing lower employment protection, the impact of labor-saving innovations on dividend policy is expected to be weaker. Therefore, employment protection serves as a moderator that helps identify whether labor-saving innovations affect dividend policy through improvements in firms' labor flexibility and labor costs.

To measure employment protection, we proxy the degree of employment protection with two state-level indicators: (i) the share of employees who are union members and (ii) the share of employees covered by collective bargaining agreements. Both measures are sourced from Hirsch & Macpherson (2003), with higher values indicating stronger union presence and greater worker protection.

We then estimate the following extended regression model:

$$Dividend_{i,t} = \beta_0 + \beta_1 LSI_{i,t} + \beta_2 LaborPower_{i,t} + \beta_3 LSI_{i,t} LaborPower_{i,t} + \gamma control_{i,t} + \mu_{i,t} \quad (3)$$

where  $LSI_{i,t}$  denotes the level of labor-saving innovations for firm  $i$  in year  $t$ .  $LaborPower_{i,t}$  captures the degree of employment protection faced by the firm, we use two proxies to measure it, which are the proportion of employees covered by collective bargaining agreements (Covered) and the proportion of employees who are union members (Member).  $control_{i,t}$  represents a set of control variables. Industry and year fixed effects are included in all specifications. A significantly positive coefficient on the interaction term  $\beta_3$  indicates that the effect of labor-saving innovations on dividend payouts is stronger for firms with higher employment protection, thereby providing further support for Hypothesis 2.

Table 7 column (1) and (2) present the regression results testing Hypothesis 2, which examines whether employment protection faced by firms moderates the effect of labor-saving innovations on dividend policy<sup>3</sup>. Column (1) uses the proportion of employees covered by collective bargaining agreements (Covered) as the proxy for employment protection, while Column (2) uses the proportion of employees who are union members (Member) as an alternative measure.

[Insert Table 7 around here]

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<sup>3</sup> Hirsch & Macpherson (2003) provide a dataset with U.S. state-level union membership and coverage for 1983–2015. Accordingly, the sample period in Table 7, columns (1) and (2), is 1983–2015.

The regression results show that, after including the interaction terms, the coefficients on the interaction between LSI and employment protection are consistently positive and highly significant across all models ( $p < 0.001$ ). This indicates that the positive effect of LSI on dividend policy is stronger in environments with higher employment protection. This finding supports the proposed mechanism that labor-saving innovations reduce labor costs and rigidity, improve profit stability and financial flexibility, and thereby enhance dividend-paying capacity, with a stronger effect when employment protection is higher.

Meanwhile, the employment protection variables Covered and Member themselves are not statistically significant in any of the models, suggesting no direct association between employment protection and dividend policy. Instead, its impact operates primarily through interaction with labor-saving innovations. Overall, these results confirm Hypothesis 2: the effect of labor-saving innovations on dividend payouts is strengthened by the employment protection firms face.

Moreover, once the interaction with employment protection is introduced, the coefficient on LSI turns insignificant. It should be emphasized that in the interaction specification, the LSI coefficient no longer captures the overall average effect but represents the marginal effect when employment protection is set to zero. Because employment protection in our sample is rarely near zero, that coefficient has limited economic relevance.

#### **4.5.2. The influence of labor-saving innovations on different life-cycle periods**

In the preceding section, we showed that labor-saving innovations are positively associated with dividend payouts, consistent with higher profitability and more stable earnings. In this subsection, we examine Hypothesis 3: the strength of this effect varies across stages of the corporate life-cycle.

During the maturity stage, firms face fewer marginal expansion opportunities and exhibit slower growth, resulting in more stable cash flows available for distribution. In this context, when labor-

saving innovations raise profits, firms are more likely to allocate additional cash to dividends. By contrast, at other life-cycle stages, firms expand rapidly and encounter abundant investment opportunities. Even if labor-saving innovations increase cash flows, firms tend to reinvest in new projects rather than distribute cash to shareholders. Therefore, we expect the positive impact of labor-saving innovations on dividend payouts should be stronger when firms are in the maturity stage.

To test this prediction, we augment the baseline regression with an interaction between firm maturity and labor-saving innovations. First, following Dickinson (2011), we classify firms as mature if operating cash flows are positive while investing and financing cash flows are non-positive, while firms not meeting these criteria are classified as non-mature. In addition, to ensure robustness, we also follow DeAngelo et al. (2006) and use the ratio of retained earnings to total assets (RETA) as a continuous measure of maturity. Higher RETA indicates greater maturity. We then estimate the following regression specification.

$$Dividend_{i,t} = \beta_0 + \beta_1 LSI_{i,t} + \beta_2 Maturity_{i,t} + \beta_3 LSI_{i,t} Maturity_{i,t} + \gamma control_{i,t} + \mu_{i,t} \quad (4)$$

where  $LSI_{i,t}$  denotes the level of labor-saving innovations for firm  $i$  in year  $t$ .  $Maturity_{i,t}$  captures the degree of mature level of firms, we employ two proxies to measure firm maturity: (i) a binary indicator for whether a firm is in the maturity stage (Maturity), following Dickinson (2011), and (ii) the firm's level of retained earnings (RETA).  $Control_{i,t}$  represent a vector of control variables. Industry and year fixed effects are included in all specifications. A significantly positive coefficient on the interaction term  $\beta_3$  indicates that if the firm is in the maturity stage of its life-cycle, the positive effect of labor-saving innovations on dividend payouts is stronger, thereby supporting Hypothesis 3a.

Drawing on the cross-sectional regressions reported in Table 7 column (3) and column (4), we examine whether corporate life-cycle maturity moderates the dividend effect of labor-saving innovations. Using the Dickinson (2011) cash-flow pattern to construct a maturity indicator (column 3), the coefficient on LSI is 0.036 and significant at 1%. The maturity indicator is

positive, consistent with higher dividends among mature firms. More importantly, the interaction term  $LSI \times \text{Maturity}$  is 0.042 and is statistically significant, implying a stronger dividend response to LSI in the mature stage. This pattern is consistent with the mechanism that mature firms, which face fewer incremental growth opportunities and have more stable cash flows, are more likely to distribute the incremental cash generated by LSI.

When maturity is measured continuously using the ratio of retained earnings to assets (RETA) following DeAngelo et al. (2006) in Column (4), LSI remains positive and statistically significant, whereas the RETA main effect is small and statistically insignificant. Crucially, the interaction  $LSI \times \text{RETA}$  is positive and significant (0.041,  $p < 0.001$ ). Therefore, the marginal effect of LSI on dividends increases monotonically with maturity. Taken together, the two maturity proxies yield consistent evidence. The dividend-enhancing effect of labor-saving innovations is significantly stronger for more mature firms, providing robust support for our life-cycle heterogeneity hypothesis.

## **5. Endogeneity concerns**

Although the preceding sections show a robust and significant positive relationship between labor-saving innovations and firms' dividend payouts through a series of robustness tests, the baseline regression may still be exposed to potential endogeneity concerns. Therefore, in this section, we further address endogeneity concerns by using alternative models.

### **5.1. Policy influence: Region-year fixed effects**

First, we address potential confounding effects of local government policies. Regional labor regulations, such as minimum wage laws, may simultaneously encourage firms to adopt labor-saving technologies and influence corporate profit distribution decisions, including dividend payouts. Without proper controls, changes in regional policies could bias the regression results. To mitigate this concern, we replace year fixed effects with region-year fixed effects, thereby effectively controlling for local policy interventions over time. Column (1) of Table 8 reports the results. The coefficient on LSI remains positive and statistically significant, suggesting that policy interventions do not materially affect our core findings.

[Insert Table 8 around here]

### **5.2. Reverse causality: Lagged LSI term**

Another potential endogeneity concern is reverse causality. Specifically, it is important to ensure that the observed positive relationship between labor-saving innovations and dividend payouts reflects a causal effect of LSI on dividend policy rather than the reverse. To address this concern, we use a three year lag of LSI as the key independent variable, which focuses inference on innovations already adopted and implemented by the firm. The regression results are reported in Column (2) of Table 8. As shown, the coefficient on the lagged LSI remains positive and statistically significant, which suggests that the effect of labor-saving innovations on dividend payouts persists after accounting for the timing of innovation adoption. This result strengthens the credibility of the identification strategy and further supports a causal interpretation of the relationship between LSI and dividend policy.

### **5.3. Omitted variable and reverse causality: Instrumental variable in 2SLS.**

To strengthen the causal interpretation of our results and further mitigate endogeneity concerns, we also employ an instrumental variable (IV) approach using two-stage least squares (2SLS) estimation. Following the methodology of Acemoglu & Restrepo (2020) and Qiu et al. (2024), we use the robot penetration rate in European countries as an instrument for U.S. firms' labor-saving innovations, denoted as `wARP_EURO`. This instrument is based on the premise that labor shortages led to earlier automation adoption in Europe, and that technological diffusion influenced subsequent developments in U.S. automation (Acemoglu & Restrepo, 2020). Therefore, European and U.S. trends in labor-saving innovations are correlated. At the same time, U.S. firms' dividend policies are primarily influenced by domestic institutions, capital market regulations, and investor structures, which are unlikely to be directly affected by European automation trends. This satisfies the exclusion restriction required for a valid instrument. The robot data are sourced from the International Federation of Robotics (IFR). Details on the construction of the instrument are provided in Appendix B.

Column (3) of Table 8 reports the 2SLS estimation results<sup>4</sup>. The coefficient on LSI remains positive and statistically significant in the models. The finding suggests that even after addressing potential endogeneity, the positive impact of labor-saving innovations on firms' dividend payout behavior remains robust, thereby further strengthening the causal interpretation of our empirical results<sup>5</sup>. Additionally, the first stage Kleibergen–Paap rk Wald F-statistic exceeds 10, suggesting that instrument strength is sufficient. Moreover, weak instrument robust inference Anderson and Rubin test and weak IV robust Wald test yields 95 percent confidence intervals that exclude zero, confirming that our IV estimates are not sensitive to concerns about weak instruments.

#### **5.4. Double machine learning**

Beyond biases arising from omitted variables and causal identification, observational data may also suffer from selection bias that is driven by observable firm characteristics. For example, larger and more profitable firms or firms that differ in asset structure may be more likely to undertake LSI and more inclined to pay dividends. To mitigate this concern, researchers often employ propensity score matching (PSM) to construct comparable treatment and control groups. However, because our treatment variable LSI is continuous, we instead adopt the double machine learning (DML) approach.

Proposed by Chernozhukov et al. (2018), DML effectively alleviates model dependence and selection bias induced by high-dimensional and nonlinear covariates in observational studies. Specifically, it uses flexible prediction models to capture the components of both the outcome and the treatment that are explainable by observed characteristics, removes these systematic components from the data, and then estimates the net treatment effect using the residuals. Relative to simply including linear controls in a regression, DML partials out nonlinear and potentially interacting relationships between observables and the outcome, and then estimates the treatment effect on this purified variation, yielding more robust conclusions.

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<sup>4</sup> Following Qiu et al. (2024), we set 1995 as the base year when computing European robot penetration. Because constructing the penetration measure entails a five year data loss (see Appendix 2), the sample period for Table 7, column (3), is 2000–2019.

<sup>5</sup> The complete TSLS form is in appendix 3.

The robustness of DML has been substantiated in prior work. Xiang et al. (2025) show that, in common high-dimensional and nonlinear settings, DML is typically more robust and exhibits better controlled variance than PSM. Xiong et al. (2025) examine the impact of corporate data security on audit fees and use a DML framework to address potential omitted-variable and model-specification concerns. Hansen & Siggaard (2024) also employ DML to mitigate omitted-variable bias. Using machine-learning methods, Yang et al. (2020) study audit quality effects in large-N settings and obtain results that are more robust than earlier studies.

In our research, we consider the following linear model:

$$y_{i,t} = \theta d_{i,t} + g(X_{i,t}) + \varepsilon_{i,t} \quad (5)$$

where  $y_{i,t}$  denotes the dividend outcome,  $d_{i,t}$  is the treatment variable (LSI), and  $X_{i,t}$  is the vector of controls; industry and year dummies are included. We apply 5-fold cross-fitting with two random repetitions, and report firm-clustered standard errors, which match the baseline specification. Within each training set, we estimate the conditional expectations  $E[Y|X]$  and  $E[D|X]$  via cross-validated Lasso regressions to obtain the prediction functions  $\hat{g}(X)$  and  $\hat{d}(X)$ . We then residualize the outcome and treatment by removing the components explained by  $X$ , rendering the estimator orthogonal to first-order estimation errors arising from high-dimensional or nonlinear nuisance learning.

Through these steps, we mitigate selection bias arising from observable firm attributes. DML first absorbs and removes the portions of both LSI and dividends that are explained by observed characteristics, so we do not confound interaction effects between control variables with the effect of LSI. This yields an estimate that is closer to the net impact of LSI. In addition, if dividends relate to size, profitability, leverage, and other control variables in a nonlinear way, or if interaction patterns exist, such as firms that are both large and highly profitable, the DML framework can effectively reduce bias that would otherwise result from omitting curvature terms and interactions.

## **6. Share repurchases and total payout policy**

Share repurchases refer to the practice by which companies buy back their outstanding shares from the market, representing one of the primary mechanisms for returning capital to shareholders, alongside traditional dividend payments. Since the 1980s, with the development of the U.S. capital markets, share repurchases have increasingly become an important complement to dividends (Grullon & Michaely, 2002). Compared to dividend payments, share repurchases offer greater flexibility (Grullon & Michaely, 2002; Jagannathan et al., 2000). Dividends are generally viewed as a long-term commitment, and any reduction is often interpreted by the market as a negative signal regarding a firm's prospects, potentially leading to a decline in stock prices. In contrast, share repurchases are less binding and adjustments to repurchase programs are less likely to trigger negative market reactions. Therefore, when uncertainty is high or when firms seek to preserve operating flexibility, managers often prefer share repurchases as the vehicle for distributing cash. In recent years, the proportion of share repurchases in firms' payout policies has steadily increased. In many cases, repurchases have surpassed dividends to become the dominant form of capital return in the U.S. market (Fama & French, 2001).

Labor-saving innovations enhance firms' profitability and free cash flows by reducing reliance on manual labor and improving production efficiency. This financial improvement enables firms to distribute greater amounts of profits, as reflected in increased dividend payouts. However, in modern corporate practice, share repurchases have become a major channel for returning surplus capital to shareholders, offering greater flexibility and avoiding the signaling risks associated with dividend cuts. Therefore, in addition to promoting dividend growth, the rise in free cash flows driven by labor-saving innovations may also incentivize firms to engage more actively in share repurchases. This trend has become more prominent in recent years as share repurchases have taken a larger role in firms' capital allocation and have often exceeded traditional dividends. If automation improves firms' financial conditions, companies are likely to increase dividend payments and to pursue more aggressive share repurchase programs so that they can return capital to shareholders in a more flexible and controllable way. Moreover, if a firm's long-term profitability and cash flows improve, its total payouts including cash dividends and share

repurchases are likely to increase. Therefore, we examine whether labor-saving innovations have a positive impact on firms' total payout policies. This analysis provides additional support for the view that labor-saving innovations contribute to enhancing firms' long-term profitability.

To test whether labor-saving innovations increase share repurchases and total payouts, we replace the dependent variable in the baseline specification with measures for share repurchases and total payouts. RepA measures share repurchases, and PayoutA measures total payouts, defined as cash dividends plus share repurchases. The results are reported in Table 9. As shown, LSI exhibits significantly positive coefficients across all models, with statistical significance at the 1% level ( $p < 0.01$ ). Specifically, the regression coefficient of LSI on RepA is 0.194 ( $p < 0.01$ ). The coefficient of LSI on PayoutA is 0.264 ( $p < 0.01$ ). These results indicate that higher levels of labor-saving innovations significantly increase both share repurchases and total payout.

[Insert Table 9 around here]

Overall, the regression results further validate the impact of labor-saving innovations on corporate capital allocation behavior. Specifically, higher levels of labor-saving innovations are associated with increases in both the scale and likelihood of share repurchases. Combined with our earlier empirical findings regarding increased dividend payouts, these results are consistent with the existing literature suggesting that labor-saving innovations enhance firms' profitability and free cash flows.

Given that both dividend payments and share repurchases depend on the availability of sufficient free cash flows, the evidence in this study also indirectly indicates that labor-saving innovations are associated with higher corporate free cash flows. Furthermore, advances in automation improve operational stability. They also influence firms' decisions on how to return capital to shareholders and how to adjust payout policies by expanding the pool of surplus resources available for distribution.

## 7. Conclusion

In sum, using U.S. listed firms, we provide empirical evidence that labor-saving innovations have a significant positive effect on corporate dividend payments. In particular, labor-saving innovations reduce labor costs, mitigate labor cost stickiness, and enhance the sufficiency and stability of cash flows, thereby improving firms' capacity to distribute dividends to shareholders. We also show that labor-saving innovations increase not only dividend payments but also share repurchases, leading to higher total payouts.

Naturally, these results could be subject to bias arising from variable selection, omitted variables, or model misspecification. To address these concerns, we conduct a comprehensive set of robustness checks and identification exercises. Drawing on the related literature, we replace the key independent variable, the dependent variable, and supplement the specification with additional controls to mitigate variable-selection bias. We further employ lagged values of the independent variable, and the instrumental-variables approach to address potential omitted-variable concerns and causal confounding. Finally, we implement the double machine learning procedure to reduce sample-selection bias and model specification errors due to nonlinearities and interactions. Collectively, these strategies support the conclusion that the effect of labor-saving innovations on dividend payments is positive and highly robust.

Our findings add an important nuance to the existing literature. We document that labor-saving innovations can tangibly expand firms' cash flows and, as a result, raise both dividends and repurchases. Prior studies often emphasize substitutability between repurchases and dividends under heightened risk or tighter constraints, portraying a reallocation across payout channels. By contrast, our evidence indicates that labor-saving innovations do not merely reallocate cash between dividends and repurchases. Instead, it enlarges the pool of distributable cash and improves its stability. In years with higher labor-saving innovations, total cash distributions rise, dividends and repurchases increase together, operating cash flows become more predictable with higher coverage ratios, cost stickiness weakens, and efficiency metrics improve. These patterns are more pronounced where employment protection is stronger and among more mature firms, suggesting that when labor adjustment costs and the need for persistence are greater, labor-saving

innovations more readily translates into both dividend commitment capacity and repurchase flexibility.

Our research also carries practical implications for managers and policymakers. For managers, advancing labor-saving innovations can lower costs, stabilize and grow profits, and support sustainable payout policies through stronger and more reliable cash flows. For policymakers, labor-saving technologies influence corporate capital allocation through cash-flow sufficiency and stability. Policies that encourage firms to invest in labor-saving innovation, coupled with stronger institutional protections for workers, can facilitate healthier corporate payout policies without sacrificing resilience.

We acknowledge several limitations. First, although we employ multiple measures of firms' labor-saving innovations and obtain consistent results, these proxies may still imperfectly capture the true, and often hard-to-quantify, adoption of labor-saving technologies such as GPT-type systems. Second, due to data availability, our sample spans 1974–2019. The rapid diffusion of AI and related labor-saving technologies in recent years may affect the external validity of our findings. Building on this study, future research could incorporate firm-level usage data for AI software, such as GPT-based applications, to refine measurement of labor-saving technology. Future work could also differentiate more precisely between categories of labor-saving innovation, for example, comparing the effects of hardware-based automation and software-based AI on dividend policy.

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**Table 1. Summary statistics**

This table presents the summary statistics for the key variables used in this research. The sample period spans from 1974 to 2019 and includes 170,167 firm-year observations from 17,645 unique firms. Detailed definitions and constructions of these variables are provided in Appendix Table A1.

**Panel A Descriptive statistics**

| Variable    | Mean   | SD    | Min    | p25    | p50   | p75   | Max    |
|-------------|--------|-------|--------|--------|-------|-------|--------|
| DVA         | 0.911  | 1.906 | 0.000  | 0.000  | 0.000 | 1.150 | 12.183 |
| LSI         | 0.591  | 1.196 | 0.000  | 0.000  | 0.000 | 0.693 | 9.098  |
| ROA         | -0.050 | 0.282 | -1.617 | -0.046 | 0.033 | 0.075 | 0.273  |
| Tangibility | 0.293  | 0.233 | 0.001  | 0.106  | 0.233 | 0.426 | 0.903  |
| Cash        | 0.173  | 0.210 | 0.000  | 0.028  | 0.086 | 0.235 | 0.929  |
| TobinQ      | 1.891  | 1.673 | 0.529  | 0.998  | 1.340 | 2.062 | 11.689 |
| Leverage    | 0.182  | 0.190 | 0.000  | 0.009  | 0.135 | 0.287 | 0.847  |
| Size        | 5.110  | 2.271 | 0.417  | 3.445  | 4.933 | 6.650 | 10.782 |
| Growth      | 0.141  | 0.426 | -0.588 | -0.044 | 0.061 | 0.201 | 2.511  |

**Panel B Univariate analysis**

|              | No LSI<br>Mean | Have LSI<br>Mean | Difference | Test of Difference<br>t-stat |
|--------------|----------------|------------------|------------|------------------------------|
| DVA          | 0.839          | 1.082            | -0.243     | -24.059                      |
| ROA          | -0.047         | -0.059           | 0.012      | 8.237                        |
| Tangibility  | 0.316          | 0.241            | 0.075      | 61.618                       |
| Cash         | 0.152          | 0.220            | -0.086     | -61.890                      |
| TobinQ       | 1.788          | 2.133            | -0.345     | -39.127                      |
| Leverage     | 0.192          | 0.158            | 0.033      | 33.689                       |
| Size         | 4.774          | 5.903            | -1.129     | -96.330                      |
| Growth       | 0.147          | 0.126            | 0.021      | 9.325                        |
| Observations | 119,433        | 50,729           |            |                              |

**Table 2. Correlation matrix**

This table reports the Pearson correlation coefficients among the variables used in the baseline regression. p-values are reported in parentheses.

|             | DVA               | LSI               | ROA               | Tang              | Cash              | TobinQ            | Leverage         | Size             | Growth |
|-------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|------------------|------------------|--------|
| DVA         | 1.000             |                   |                   |                   |                   |                   |                  |                  |        |
| LSI         | 0.128<br>(0.000)  | 1.000             |                   |                   |                   |                   |                  |                  |        |
| ROA         | 0.225<br>(0.000)  | 0.046<br>(0.000)  | 1.000             |                   |                   |                   |                  |                  |        |
| Tangibility | 0.096<br>(0.000)  | -0.096<br>(0.000) | 0.105<br>(0.000)  | 1.000             |                   |                   |                  |                  |        |
| Cash        | -0.072<br>(0.000) | 0.073<br>(0.000)  | -0.280<br>(0.000) | -0.399<br>(0.000) | 1.000             |                   |                  |                  |        |
| TobinQ      | 0.024<br>(0.000)  | 0.055<br>(0.000)  | -0.299<br>(0.000) | -0.180<br>(0.000) | 0.371<br>(0.000)  | 1.000             |                  |                  |        |
| Leverage    | -0.031<br>(0.000) | -0.045<br>(0.000) | 0.025<br>(0.000)  | 0.324<br>(0.000)  | -0.331<br>(0.000) | -0.139<br>(0.000) | 1.000            |                  |        |
| Size        | 0.247<br>(0.000)  | 0.401<br>(0.000)  | 0.329<br>(0.000)  | 0.157<br>(0.000)  | -0.193<br>(0.000) | -0.153<br>(0.000) | 0.258<br>(0.000) | 1.000            |        |
| Growth      | -0.058<br>(0.000) | -0.032<br>(0.000) | 0.221<br>(0.000)  | -0.044<br>(0.000) | 0.070<br>(0.000)  | 0.139<br>(0.000)  | 0.028<br>(0.000) | 0.047<br>(0.000) | 1.000  |

**Table 3. The influence of labor-saving innovations on corporate dividend policy**

This table reports the main regression results on the effect of labor-saving innovations on corporate dividend policy. The dependent variable is the ratio of dividends to total assets (DVA). The key explanatory variable is the logarithm of 1 plus the firm's labor-saving innovation (LSI). Variable definitions are provided in Appendix Table A1. The sample consists of 170,167 firm-year observations from 17,645 firms over the period 1974–2019. The model includes control variables, four-digit SIC industry fixed effects and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                       | (1)<br>DVA           |
|-----------------------|----------------------|
| LSI                   | 0.056***<br>(0.000)  |
| ROA                   | 1.110***<br>(0.000)  |
| Tangibility           | 0.571***<br>(0.000)  |
| Cash                  | 0.355***<br>(0.000)  |
| TobinQ                | 0.172***<br>(0.000)  |
| Leverage              | -1.168***<br>(0.000) |
| Size                  | 0.190***<br>(0.000)  |
| Growth                | -0.497***<br>(0.000) |
| Constant              | 0.614<br>(1.027)     |
| Industry fixed effect | Yes                  |
| Year fixed effect     | Yes                  |
| Adj. R <sup>2</sup>   | 0.235                |
| Observations          | 170167               |

**Table 4. The influence of LSI on dividend policy with firm fixed effects**

This table reports the main regression results on the effect of labor-saving innovations on corporate dividend policy. The dependent variable is the ratio of dividends to total assets (DVA). The key explanatory variable is the logarithm of 1 plus the firm's labor-saving innovation (LSI). Variable definitions are provided in Appendix Table A1. The model includes control variables, firm fixed effects and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                     | (1)<br>DVA           |
|---------------------|----------------------|
| LSI                 | 0.037***<br>(0.005)  |
| ROA                 | 0.566***<br>(0.000)  |
| Tangibility         | 0.111<br>(0.155)     |
| Cash                | 0.503***<br>(0.000)  |
| TobinQ              | 0.094***<br>(0.000)  |
| Leverage            | -0.610***<br>(0.000) |
| Size                | 0.050***<br>(0.000)  |
| Growth              | -0.235***<br>(0.000) |
| Constant            | 0.513***<br>(0.000)  |
| Firm fixed effect   | Yes                  |
| Year fixed effect   | Yes                  |
| Adj. R <sup>2</sup> | 0.615                |
| Observations        | 168189               |

**Table 5. Robustness tests**

This table presents the results of robustness checks on the effect of labor-saving innovations on corporate dividend policy. In Column (1), the independent variable LSI is normalized and transformed using the Inverse Hyperbolic Sine (IHS) function to construct a smoothed variable, LSI2. Column (2) uses an alternative measure of labor-saving innovation, Auto, as the key independent variable. Column (3) replaces the dependent variable with DVM, which is the dividend divided by market value. Column (4) replaces the dependent variable with a dividend dummy (D), indicating whether the firm pays dividends, and employs a logit model for estimation. Column (5) adds additional control variables in the baseline regression. Variable definitions are provided in Appendix Table A1. All models include control variables, four-digit SIC industry fixed effects and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                                            | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  |
|--------------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                                            | DVA                  | DVA                  | DVM                  | D                    | DVA                  |
| LSI2                                       | 17.891**<br>(0.049)  |                      |                      |                      |                      |
| Auto                                       |                      | 4.352***<br>(0.000)  |                      |                      |                      |
| LSI                                        |                      |                      | 0.034***<br>(0.003)  | 0.066***<br>(0.002)  | 0.105***<br>(0.001)  |
| NLSI                                       |                      |                      |                      |                      | 0.114<br>(0.66)      |
| Board Size                                 |                      |                      |                      |                      | 0.044***<br>(0.009)  |
| Independent Board                          |                      |                      |                      |                      | -0.002<br>(0.513)    |
| Income Tax                                 |                      |                      |                      |                      | 16.641***<br>(0.000) |
| Investment                                 |                      |                      |                      |                      | -5.631***<br>(0.000) |
| Retained Earning                           |                      |                      |                      |                      | 0.028<br>0.420       |
| MtB Ratio                                  |                      |                      |                      |                      | 0.005<br>(0.502)     |
| ROA                                        | 1.099***<br>(0.000)  | 1.920***<br>(0.000)  | 0.257***<br>(0.000)  | 6.478***<br>(0.000)  | 1.852***<br>(0.000)  |
| Tangibility                                | 0.564***<br>(0.000)  | 0.205<br>(0.342)     | 0.598***<br>(0.000)  | 1.190***<br>(0.000)  | 1.038***<br>(0.003)  |
| Cash                                       | 0.369***<br>(0.000)  | 0.435***<br>(0.006)  | 0.391***<br>(0.000)  | -0.235*<br>(0.098)   | 0.714**<br>(0.022)   |
| TobinQ                                     | 0.174***<br>(0.000)  | 0.306***<br>(0.000)  | -0.035***<br>(0.000) | -0.070***<br>(0.000) | 0.216***<br>(0.000)  |
| Leverage                                   | -1.181***<br>(0.000) | -0.108<br>(0.463)    | -0.731***<br>(0.000) | -2.108***<br>(0.000) | -1.166***<br>(0.000) |
| Size                                       | 0.203***<br>(0.000)  | 0.077***<br>(0.000)  | 0.243***<br>(0.000)  | 0.661***<br>(0.000)  | 0.114***<br>(0.006)  |
| Growth                                     | -0.504***<br>(0.000) | -0.676***<br>(0.000) | -0.382<br>(0.000)    | -0.762***<br>(0.000) | -0.685***<br>(0.000) |
| Constant                                   | 0.358<br>(0.191)     | -0.307<br>(0.331)    | 1.734***<br>(0.000)  | -1.498***<br>(0.000) | -1.422***<br>(0.025) |
| Industry fixed effect                      | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Year fixed effect                          | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Adj. R <sup>2</sup> /Pseudo R <sup>2</sup> | 0.235                | 0.240                | 0.111                | 0.409                | 0.419                |
| Observations                               | 170,167              | 35,063               | 170,162              | 169,865              | 12,201               |

**Table 6. The influence of labor-saving innovations on corporate dividend policy in different time periods**

This table reports the regression results on the effect of labor-saving innovations on corporate dividend policy in different time periods. The dependent variable is the ratio of dividends to total assets (DVA). The key explanatory variable is the logarithm of 1 plus the firm's labor-saving innovation (LSI). Column (1) is the regression results of the observations from 1974 to 1999. Column (2) is the regression results of the observations from 2000 to 2019. Variable definitions are provided in Appendix Table A1. All models include control variables, four-digit SIC industry fixed effects and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                       | (1)<br>1974-1999<br>DVA | (2)<br>2000-2019<br>DVA |
|-----------------------|-------------------------|-------------------------|
| LSI                   | 0.044**<br>(0.025)      | 0.065***<br>(0.000)     |
| ROA                   | 0.901***<br>(0.000)     | 1.251***<br>(0.000)     |
| Tangibility           | 0.666***<br>(0.000)     | 0.399***<br>(0.005)     |
| Cash                  | 0.409***<br>(0.000)     | 0.240**<br>(0.015)      |
| TobinQ                | 0.122***<br>(0.000)     | 0.225***<br>(0.000)     |
| Leverage              | -1.764***<br>(0.000)    | -0.450***<br>(0.000)    |
| Size                  | 0.250***<br>(0.000)     | 0.108***<br>(0.000)     |
| Growth                | 0.424***<br>(0.000)     | 0.543***<br>(0.000)     |
| Constant              | 0.517<br>(0.131)        | -0.387<br>(0.125)       |
| Industry fixed effect | Yes                     | Yes                     |
| Year fixed effect     | Yes                     | Yes                     |
| Adj. R <sup>2</sup>   | 0.296                   | 0.227                   |
| Observations          | 98,467                  | 71,700                  |

**Table 7. Cross-sectional analysis**

This table reports the cross-sectional results on the effect of labor-saving innovations on corporate dividend policy. In Column (1), Covered and the interaction term of Covered and LSI are added. In Column(2), Member and the interaction term of Member and LSI are added. In Column (3), Maturity and the interaction term of Maturity and LSI are added. In Column (4), RETA and the interaction term of RETA and LSI are added. Variable definitions are provided in Appendix Table A1. The sample is over the period 1986–2019. All models include control variables, four-digit SIC industry fixed effects and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

|                       | (1)<br>DVA           | (2)<br>DVA           | (3)<br>DVA           | (4)<br>DVA           |
|-----------------------|----------------------|----------------------|----------------------|----------------------|
| LSI                   | -0.096**<br>(0.013)  | -0.085**<br>(0.021)  | 0.036***<br>(0.006)  | 0.070***<br>(0.000)  |
| Covered               | -0.335<br>(0.132)    |                      |                      |                      |
| LSI*Covered           | 0.990***<br>(0.000)  |                      |                      |                      |
| Member                |                      | -0.284<br>(0.207)    |                      |                      |
| LSI*Member            |                      | 1.014***<br>(0.000)  |                      |                      |
| Maturity              |                      |                      | 0.484***<br>(0.000)  |                      |
| LSI*Maturity          |                      |                      | 0.042**<br>(0.012)   |                      |
| RETA                  |                      |                      |                      | -0.003<br>(0.634)    |
| LSI*RETA              |                      |                      |                      | 0.041***<br>(0.000)  |
| ROA                   | 0.901***<br>(0.000)  | 0.900***<br>(0.000)  | 0.927***<br>(0.000)  | 0.979***<br>(0.000)  |
| Tangibility           | 0.482***<br>(0.000)  | 0.484***<br>(0.000)  | 0.538***<br>(0.000)  | 0.423***<br>(0.000)  |
| Cash                  | 0.253***<br>(0.000)  | 0.252***<br>(0.000)  | 0.461***<br>(0.000)  | 0.401***<br>(0.000)  |
| TobinQ                | 0.140***<br>(0.000)  | 0.140***<br>(0.000)  | 0.163***<br>(0.000)  | 0.163***<br>(0.000)  |
| Leverage              | -0.947***<br>(0.000) | -0.948***<br>(0.000) | -1.095***<br>(0.000) | -1.249***<br>(0.000) |
| Size                  | 0.174***<br>(0.000)  | 0.174***<br>(0.000)  | 0.180***<br>(0.000)  | 0.186***<br>(0.000)  |
| Growth                | -0.442***<br>(0.000) | -0.442***<br>(0.000) | -0.396***<br>(0.000) | -0.480***<br>(0.000) |
| Constant              | 0.356<br>(0.309)     | 0.340<br>(0.331)     | 0.494*<br>(0.065)    | 0.397*<br>(0.077)    |
| Industry fixed effect | Yes                  | Yes                  | Yes                  | Yes                  |
| Year fixed effect     | Yes                  | Yes                  | Yes                  | Yes                  |
| Adj. R <sup>2</sup>   | 0.231                | 0.231                | 0.246                | 0.239                |
| Observations          | 119,279              | 119,279              | 170,167              | 168,400              |

**Table 8. Endogeneity concerns**

This table reports the tests addressing endogeneity concerns based on the baseline results. Column (1) presents regression results with firm fixed effects. Column (2) includes interaction terms of geographic fixed effects and year fixed effects. Column (3) reports results from a two-stage least squares (TSLS) model, where the first-stage instrument is the level of automation in European industries. Column (4) displays results from a double machine learning (DML) model which is Lasso regression and apply 5-fold cross-fitting with two random repetitions. Variable definitions are provided in Appendix Table A1. All models include control variables, four-digit SIC industry fixed effects, and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

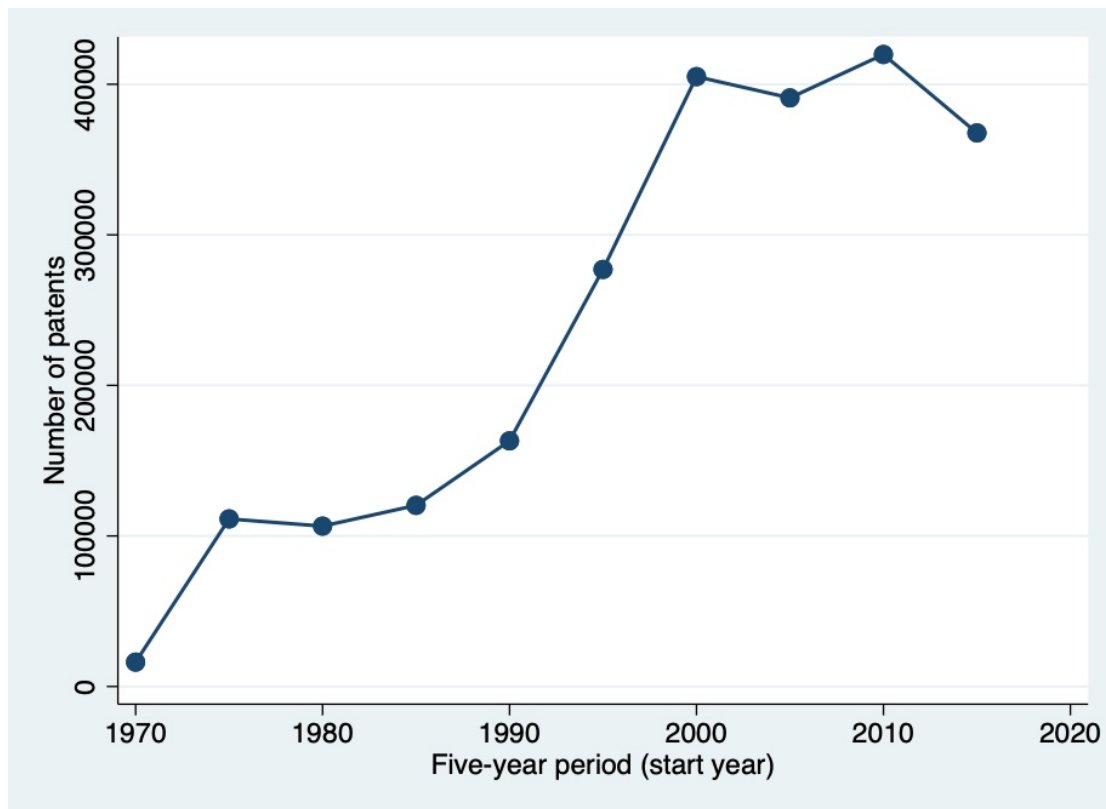
|                           | (1)                  | (2)                  | (3)                  | (4)                 |
|---------------------------|----------------------|----------------------|----------------------|---------------------|
|                           | DVA                  | DVA                  | DVA                  | DVA                 |
| LSI                       | 0.073***<br>(0.000)  |                      | 0.346**<br>(0.036)   | 0.056***<br>(0.000) |
| L3.LSI                    |                      | 0.082***<br>(0.000)  |                      |                     |
| ROA                       | 0.926***<br>(0.000)  | 1.358***<br>(0.000)  | 1.183***<br>(0.000)  |                     |
| Tangibility               | 0.511***<br>(0.000)  | 0.589***<br>(0.000)  | -0.005<br>(0.978)    |                     |
| Cash                      | 0.429***<br>(0.000)  | 0.472***<br>(0.000)  | -0.082<br>(0.565)    |                     |
| TobinQ                    | 0.140***<br>(0.000)  | 0.217***<br>(0.000)  | 0.162***<br>(0.000)  |                     |
| Leverage                  | -1.242***<br>(0.000) | -1.227***<br>(0.000) | -0.405***<br>(0.005) |                     |
| Size                      | 0.230***<br>(0.000)  | 0.181***<br>(0.000)  | 0.026<br>(0.719)     |                     |
| Growth                    | -0.409***<br>(0.000) | -0.568***<br>(0.000) | -0.430***<br>(0.000) |                     |
| Constant                  | 0.304<br>(0.628)     | 0.530*<br>(0.063)    | 1.449*<br>(0.083)    | -0.000<br>(0.997)   |
| Industry fixed effect     | Yes                  | Yes                  | Yes                  | Yes                 |
| Region*Year fixed effect  | Yes                  | No                   | No                   | No                  |
| Year fixed effect         | Yes                  | Yes                  | Yes                  | Yes                 |
| Kleibergen–Paap rk Wald F |                      |                      | 46.879               |                     |
| Wald statistics           |                      |                      | 4.39                 |                     |
| Adj. R <sup>2</sup>       | 0.252                | 0.252                | 0.212                |                     |
| Observations              | 145,117              | 137,765              | 41,949               | 170,167             |

**Table 9. The influence of labor-saving innovations on corporate share repurchases and total payout policy**

This table reports the main regression results on the effect of labor-saving innovations on corporate share repurchase policy. The dependent variable in Column (1) is the ratio of share repurchase to total assets (RepA). The dependent variable in column (2) is the ratio of total payout to total assets (PayoutA). Variable definitions are provided in Appendix Table A1. The sample consists of 160,411 firm-year observations from 17,645 firms over the period 1974–2019. Variable definitions are provided in Appendix Table A1. All models include control variables, four-digit SIC industry fixed effects and year fixed effects. p-values in parentheses are based on robust standard errors clustered at the firm level.

|                       | (1)<br>RepA           | (2)<br>PayoutA       |
|-----------------------|-----------------------|----------------------|
| LSI                   | 0.194***<br>(0.000)   | 0.264***<br>(0.000)  |
| ROA                   | 2.001***<br>(0.000)   | 3.623***<br>(0.000)  |
| Tangibility           | -0.453***<br>(0.000)  | 0.097<br>(0.481)     |
| Cash                  | 0.502***<br>(0.000)   | 1.152***<br>(0.000)  |
| TobinQ                | 0.304***<br>(0.000)   | 0.053***<br>(0.000)  |
| Leverage              | -0.060<br>(0.502)     | -1.107***<br>(0.000) |
| Size                  | 0.140***<br>(0.000)   | 0.313***<br>(0.000)  |
| Growth                | -1.014***<br>(0.000)  | -1.713***<br>(0.000) |
| Constant              | -0.820***<br>(0.0000) | -0.460<br>(0.312)    |
| Industry fixed effect | Yes                   | Yes                  |
| Year fixed effect     | Yes                   | Yes                  |
| Adj. R <sup>2</sup>   | 0.111                 | 0.174                |
| Observations          | 160,411               | 160,411              |

**Figure 1. The number of labor-saving patents of U.S. listed companies**



## Appendix 1. Variables and data sources

| Variable                | Definition                                                                                                                                                                                                                                                                                                                                                     |
|-------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| DVA                     | Dividend divided by total assets times 100 percent                                                                                                                                                                                                                                                                                                             |
| LSI                     | The log of number of labor-saving patents plus one                                                                                                                                                                                                                                                                                                             |
| ROA                     | The net income divided by total assets                                                                                                                                                                                                                                                                                                                         |
| Tangibility             | The net PPE divided by total assets                                                                                                                                                                                                                                                                                                                            |
| Cash                    | Cash and short-term investment divided by total assets                                                                                                                                                                                                                                                                                                         |
| TobinQ                  | The market value of firm divided by total assets                                                                                                                                                                                                                                                                                                               |
| Leverage                | Debt divided by total assets                                                                                                                                                                                                                                                                                                                                   |
| Size                    | The log of total assets                                                                                                                                                                                                                                                                                                                                        |
| Growth                  | The growth rate of assets                                                                                                                                                                                                                                                                                                                                      |
| DVM                     | Dividend divided by market value of firm times 100 percent                                                                                                                                                                                                                                                                                                     |
| D                       | The dummy variable that whether firm has dividend payout                                                                                                                                                                                                                                                                                                       |
| NLSI                    | The log of number of non-labor-saving patents plus one                                                                                                                                                                                                                                                                                                         |
| Board Size              | Total number of the board members.                                                                                                                                                                                                                                                                                                                             |
| Independent Board Ratio | Total number of independent directors divided by total number of board members.                                                                                                                                                                                                                                                                                |
| Income Tax              | Tax divided by total assets                                                                                                                                                                                                                                                                                                                                    |
| Investment              | Capital expenditure divided by total assets                                                                                                                                                                                                                                                                                                                    |
| Retained Earning        | Retained earnings divided by total assets                                                                                                                                                                                                                                                                                                                      |
| MtB Ratio               | Market value divided by book value of firm                                                                                                                                                                                                                                                                                                                     |
| LSI2                    | $Adj. LSI_{i,t} = \frac{\text{number of automation patents}_{i,t}}{\sum_{i=1}^F \text{number of automation patents}_{i,t}}$ <p>The inverse hyperbolic sine (IHS) transformation of the Adjusted LSI</p> $APR\_US_{j,(t-5,t-1)} = \frac{M_{j,t-1}^{US} - M_{j,t-5}^{US}}{L_{j,2004}^{US}} - g_{j,(t-5,t-1)}^{US} \times \frac{M_{j,t-5}^{US}}{L_{j,2004}^{US}}$ |
| Auto                    | $wAPR\_US_{i,t-1} = \sum_{j=1}^N S_{i,k,t-1} \times APR\_US_{j,(t-5,t-1)}$ $APR\_EURO_{j,(t-5,t-1)} = \frac{1}{5} \sum_{k \in EURO5} \left[ \frac{M_{j,t-1}^k - M_{j,t-5}^k}{L_{j,1995}^k} - g_{j,9t-5,t-1}^k \frac{M_{j,t-5}^k}{L_{j,1995}^k} \right]$                                                                                                        |
| wAPR_EURO               | $wAPR\_EURO_{i,t-1} = \sum_{j=1}^N S_{i,k,t-1} \times APR\_EURO_{j,(t-5,t-1)}$                                                                                                                                                                                                                                                                                 |
| Covered                 | The percentage of employees covered by collective bargaining agreements                                                                                                                                                                                                                                                                                        |
| Member                  | The percentage of employees who are union members                                                                                                                                                                                                                                                                                                              |
| Maturity                | OCF>0, ICF<=0, FCF<=0                                                                                                                                                                                                                                                                                                                                          |
| RETA                    | Retained earnings divided by total assets                                                                                                                                                                                                                                                                                                                      |
| RepA                    | Share repurchase divided by total assets times 100 percent                                                                                                                                                                                                                                                                                                     |
| PayoutA                 | Total payout divided by total assets times 100 percent                                                                                                                                                                                                                                                                                                         |

## Appendix 2. Calculation of the Alternative Independent variable and Instrumental Variable

Our primary data source is the industrial robot dataset provided by the International Federation of Robotics (IFR). The IFR dataset offers information on the stock of industrial robots across countries, allocating robots to industries based on ISIC Rev. 4 classifications. Following Acemoglu & Restrepo (2020), we classify industries into 19 categories (denoted by  $j$ ): agriculture, forestry, and fishing; mining; utilities; construction; education, research, and development; services; food and beverages; textiles (including apparel); wood and fur products; paper and printing; plastics and chemicals; minerals; basic metals; fabricated metal products; industrial machinery; electronics; automobiles; shipbuilding and aerospace; and miscellaneous manufacturing (such as jewelry and toys production).

We then calculate the industry-level robot penetration rates for the 19 industries in Europe ( $APR\_EURO$ ) based on the following formula:

$$APR\_EURO_{j,(t-5,t-1)} = \frac{1}{5} \sum_{k \in EURO5} \left[ \frac{M_{j,t-1}^k - M_{j,t-5}^k}{L_{j,1995}^k} - g_{j,9t-5,t-1}^k \frac{M_{j,t-5}^k}{L_{j,1995}^k} \right] \quad (A.1)$$

where  $k$  denotes the country (Denmark, Finland, France, Italy, Sweden, Spain)<sup>6</sup>,  $M$  represents the number of industrial robots installed in country  $k$ , industry  $j$ , and year  $t$ , and  $L$  is the employment level of country  $k$ , industry  $j$  in 1995<sup>7</sup>. The term  $g$  denotes the industry output growth rate over the previous five years, with employment and output growth rate data sourced from the EU KLEMS 2017 release<sup>8</sup>.

<sup>6</sup> Regarding the selection of European countries, we follow Acemoglu & Restrepo (2020) and Qiu et al. (2024) by using Denmark, Finland, France, Italy, and Sweden to represent Europe.

<sup>7</sup> Consistent with Qiu et al. (2024), we set 1995 as the baseline year.

<sup>8</sup> Following Acemoglu & Restrepo (2020) and Oesch & Walser (2025), we use employment and output growth data from the EU KLEMS database. However, the EU KLEMS database presents certain limitations, as its industry classifications do not perfectly align with the IFR industry categories proposed by Acemoglu & Restrepo (2020). For instance, in the IFR classification, C16 (Wood Products) is treated as a separate industry category, whereas EU KLEMS aggregates C16-C18 (Wood and Paper Products) into a single category. To address this inconsistency, we utilize detailed industry data provided by Eurostat to calculate the proportional distribution within the broader EU KLEMS industry groupings. Based on these proportions, we reallocate the EU KLEMS data to match the IFR industry classification more accurately. Additionally, for the C31-C33 (Miscellaneous Manufacturing) category in EU KLEMS, we follow Acemoglu & Restrepo (2020) by allocating 40% of this category to C16 (Wood Products).

In this formula, the first term,  $\frac{M_{j,t-1}^k - M_{j,t-5}^k}{L_{j,1995}^k}$ , captures the net growth of industrial robot stock over the previous five years, normalized by 1995 baseline employment, thus reflecting robot growth per unit of baseline labor. The second term,  $g_{j,9t-5,t-1}^k \frac{M_{j,t-5}^k}{L_{j,1995}^k}$ , adjusts for industry output growth. Industries experiencing rapid output growth over the five-year period naturally tend to install more robots. To isolate pure technological adoption effects from size effects, we subtract this adjustment term, which reflects the expected robot increase attributable solely to output expansion given prior robot density.

After calculating the annual robot penetration rates for each industry in each of the five European countries, we take the average across countries to obtain a representative measure of Europe's robot penetration level for each industry.

Subsequently, following Qiu et al. (2024), we allocate the industry-level European robot penetration rates to U.S. firms according to each firm's sales share in the corresponding industries. The constructed firm-level instrumental variable is calculated as follows:

$$wAPR\_EURO_{i,t-1} = \sum_{j=1}^N S_{i,k,t-1} \times APR\_EURO_{j,(t-5,t-1)} \quad (A.2)$$

where  $S_{i,k,t-1}$  represents the share of firm  $i$ 's sales in industry  $j$  at time  $t-1$ .

Using a similar methodology, we also construct an alternative proxy for firms' labor-saving innovation intensity used in robustness tests, denoted as  $wAPR\_US$ . To build this measure, we first calculate the industry-level robot penetration rates in the United States based on IFR data, using the same calculation approach as described above.

$$APR\_US_{j,(t-5,t-1)} = \frac{M_{j,t-1}^{US} - M_{j,t-5}^{US}}{L_{j,2004}^{US}} - g_{j,(t-5,t-1)}^{US} \times \frac{M_{j,t-5}^{US}}{L_{j,2004}^{US}} \quad (A.3)$$

where US denotes the United States, M represents the number of industrial robots installed in U.S. industry  $j$  in year  $t$ ,  $L$  denotes the employment level of U.S. industry  $j$  in 2004, and  $g$

represents the five-year output growth rate for U.S. industry  $j$ . Data on employment levels and output growth rates are sourced from the EU KLEMS 2017 release<sup>9</sup>.

Subsequently, we compute the firm-level robot penetration rate for U.S. publicly listed companies by weighting the industry-level penetration rates according to each firm's sales share across IFR industries. The firm-level measure  $wAPR\_US$  calculated as:

$$wAPR\_US_{i,t-1} = \sum_{j=1}^N S_{i,j,t-1} \times APR\_US_{j,(t-5,t-1)} \quad (\text{A.4})$$

Thus, the resulting firm-level measure  $wAPR\_US_{i,t-1}$  captures the weighted average level of robot penetration across the industries in which firm  $i$  operates.

If a firm's revenue is concentrated in industries experiencing high robot adoption, its  $wAPR\_US_{i,t-1}$  value will be higher, indicating a greater exposure to labor-saving technology adoption. In our paper, we use *Auto* to represent  $wAPR\_US$ .

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<sup>9</sup> Following Acemoglu & Restrepo (2020) and Oesch & Walser (2025), we use the EU KLEMS database to obtain statistics on employment levels and output growth rates. To address the mismatch between the industry classifications in the EU KLEMS database and the IFR industry categories, we use detailed industry classification data provided by the Bureau of Economic Analysis (BEA). Based on the BEA data, we calculate the proportional distribution of detailed industries within broader EU KLEMS categories. We then use these proportions to reallocate the EU KLEMS data into classifications that align with the IFR industry structure.

### Appendix 3. Complete TSLS form

|                       | (1)<br>Stage 2<br>DVA | (2)<br>Stage 1<br>LSI |
|-----------------------|-----------------------|-----------------------|
| LSI                   | 0.346**<br>(0.036)    |                       |
| wARP EURO             |                       | 4.380***<br>(0.000)   |
| Size                  | 0.026<br>(0.719)      | 0.416***<br>(0.000)   |
| Leverage              | -0.405***<br>(0.005)  | -0.400***<br>(0.000)  |
| TobinQ                | 0.162***<br>(0.000)   | 0.068***<br>(0.000)   |
| Cash                  | -0.082<br>(0.565)     | 0.372***<br>(0.000)   |
| Tangibility           | -0.005<br>(0.978)     | -0.151***<br>(0.000)  |
| ROA                   | 1.183***<br>(0.000)   | -0.356***<br>(0.000)  |
| Growth                | -0.430***<br>(0.000)  | -0.204***<br>(0.000)  |
| Year fixed effect     | Yes                   | Yes                   |
| Industry fixed effect | Yes                   | Yes                   |
| Adj. R <sup>2</sup>   | 0.212                 | 0.499                 |
| Observations          | 41949                 | 41949                 |