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Firm-Level Regulatory Intensity and Labor Investment Efficiency

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Abstract: We examine the impact of firm-level regulatory intensity on corporate labor investment efficiency in U.S. firms using a sample from 1995-2019. We find that labor investment inefficiency decreases with regulatory intensity, providing evidence that greater regulatory burden pushes managers to make better labor investment decisions. This finding is robust to subsample analyses and various model specifications, suggesting that regulations, though seemingly costly, generate efficiencies and positive externalities. We conclude that regulatory requirements prompt firms to invest in labor more accurately to absorb regulatory compliance costs and U.S. firms can lift their regulatory burden to some extent through improved labor investment.

Keywords: firm-level regulatory intensity; regulatory compliance; regulatory burden; labor investment efficiency (inefficiency); expected level of labor investment

JEL: classification: G30; G38; M12

1. Introduction

Regulations are designed to enhance market safety, stability, and competition and to protect consumers (Ince & Ozsoylev, 2024; Ince, 2024). Many aspects of economic efficiency need regulations to address market failures (Helm, 2006). Given their mandatory features, regulations generally promote transparency. Meanwhile, regulations impose significant burdens on businesses and the public, discounting the designated benefits.[1] Ince and Ozsoylev (2024) argue that regulations add significant fixed costs to a firm, increasing its operating leverage and generating a risk premium on its stock returns. Expensive and sticky regulatory compliance has substantial economic implications (Kalmenovitz, 2023; Ince, 2024). Crain and Crain (2023) find that complying with regulations becomes a cost of doing business, which affects various business decisions. Additionally, 58% of their survey participants indicated that compliance with federal government regulations is a challenge to their business, suggesting that complying with ever-increasing new regulations can be a new type of challenge in labor management. In this paper, we empirically examine how regulatory compliance affects labor investment efficiency in U.S. firms.

Regulatory compliance prompts affected firms to adjust their policies. Empirical studies have documented supporting evidence that regulatory compliance significantly affects corporate behavior and outcomes (Kalmenovitz, 2023; Ince & Ozsoylev, 2024; Ince, 2024). For example, Kalmenovitz (2023) documents that the cost of goods sold, overhead spending, and leverage increase with the number of regulations and regulatory compliance costs (i.e., regulatory intensity), cash holding and

[1]Crain and Crain (2023) find that the estimated costs of U.S. federal government regulations are $3.079 trillion in 2022 (in 2023 dollars), accounting for 12% of U.S. GDP, and that the estimated aggregate costs of federal regulations to the manufacturing sector in the U.S. are $349 billion in 2022. According to Kalmenovitz (2023), in the United States, the public spent 292.1 billion hours in preparing and filing 2.24 trillion forms to comply with 36,702 regulations, and compliance consumes 3.2% of total working hours in an average year.

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capital investment decrease with regulatory intensity, and firms with higher regulatory burden tend to engage in more lobbying and less hiring. Crain and Crain (2023) indicate that complying with regulations affects a firm's hiring, employees' salaries, wages and benefits, capital spending, and dividend decisions.

Human capital is an essential determinant of a firm's competitiveness and success (Pfeffer, 1996). Sub-optimal investment in labor or labor investment inefficiency deters firm growth and leads to poor firm performance and lower investor returns (Merz & Yashiv, 2007; Jung et al., 2014; Ghaly et al., 2020; Lai et al., 2021). Labor investment inefficiency can take one of two forms (over- and under-investment in labor) (Williamson, 1963; Ben-Nasr & Alshwer, 2016; Jung et al., 2014; Ghaly et al., 2015; James et al., 2024). Over-investment in labor refers to the employment practice of over-hiring and/or under-firing, and under-investment in labor refers to the employment practice of under-hiring and/or over-firing employees. Hiring beyond the optimal level determined by a firm's economic fundamentals can negatively affect the firm's growth and profitability (Merz & Yashiv, 2007; Lai et al., 2021).

Even though existing studies have documented that regulatory compliance affects employment decisions (Kalmenovitz, 2023; Crain & Crain, 2023), no prior research has revealed the association between regulation compliance and labor investment efficiency in U.S. firms.[2] Given that most regulatory costs, such as capital expenditures, information costs, reporting, and record keeping, are fixed (Bradford, 2004; Crain & Crain, 2014; Ince & Ozsoylev, 2024), firms need to find ways to absorb the costs to maintain profitability. Ince (2024) shows that large firms engage in within-industry acquisitions to spread regulatory costs across larger outputs. Labor involvement can be substantial in complying with regulations. For example, Trebbi and Zhang (2022) find that regulatory costs account for 1.34% of the total wage bill of a firm. Since regulatory compliance costs constrain firms' cost structure, firms must seek other ways to reduce their regulatory burden. We explore whether firms digest regulatory compliance costs through enhanced labor management efficiency.

James et al. (2024) note that prior research suggests that information asymmetry between firms and external investors results in labor investment inefficiency. Labor investment inefficiency can also result from managerial opportunistic behaviors. Studies have shown that many factors related to information asymmetry and managerial opportunistic behavior affect labor investment efficiency (e.g., Jung et al., 2014; Lee & Mo, 2020; Ee et al., 2022; Le & Tran, 2021; Khedmati et al., 2020).[3] Building on the existing literature on labor investment and regulatory compliance costs, we conjecture that regulatory intensity may directly affect a firm's labor force, given the compliance burden imposed on

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[2]Jiang et al. (2022) examine the association between environmental information disclosure and labor investment efficiency in Chinese firms by focusing on the compliance of one regulation (the Guidelines for Environmental Information Disclosure of Listed Companies issued by The Ministry of Ecology and Environment in 2015). We seek to uncover the impact of regulatory compliance at an aggregate level in U.S. firms, i.e., regulatory compliance with all regulations relevant to a firm.

[3]Studies show that labor investment efficiency increases with stock liquidity (Ee et al., 2022), analysts' coverage (Lee & Mo, 2020), employee-friendly treatment (Cao & Rees, 2020), accounting quality (Jung et al., 2014), stock price informativeness (Ben-Nasr & Alshwer, 2016), the number of long-term institutional investors (Ghaly et al., 2020), board gender diversity (i.e., the proportion of female directors) (Sun & Zhang, 2021), and CEO tenure (James et al., 2024). Board reforms designated to mitigate managerial moral hazard can positively affect a firm's labor investment efficiency (Le & Tran, 2021). Labor investment efficiency decreases with analysts' forecast errors (Sualihu et al., 2021b), stronger CEO-director ties (Khedmati et al., 2020), and operational uncertainty/risk (Habib & Hasan, 2021; Boubaker et al., 2022; Traini et al., 2024). Over-confident CEOs (Lai et al., 2021) and those with stronger risk-taking incentives (Sualihu et al., 2021a) are associated with lower labor investment efficiency.

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the firm. Labor investment efficiency may vary with the levels of regulatory intensity since the evolving exposure to regulatory compliance requires that firms allocate resources more strategically.

Regulators initiate regulations with public good in mind (Kalmenovitz, 2023). Regulations set legally binding standards for firm practices, playing an important role in disciplining firms and their managers, especially when the market forces fail to do so. In other words, regulations can serve as a valuable public monitoring tool to mitigate the agency friction resulting from opacity between corporate insiders and outsiders. Regulatory compliance requirements can significantly improve corporate transparency between insiders and various outside stakeholders, helping mitigate managerial opportunistic behavior. The potential for rent extraction by insiders can align the incentives of a firm's shareholders with those of the regulators (Bisetti, 2024). Bisetti (2024) documents empirical evidence that off-site surveillance from regulators reduces insiders' rent extraction and benefits shareholders.[4] The stock market reacts positively to rules requiring more corporate disclosure (Fogel et al., 2015). In terms of labor investment, Jiang et al. (2022) find that Chinese firms with higher levels of environmental information disclosure tend to have greater labor investment efficiency.

Furthermore, regulatory compliance costs are fixed and recurrent. Thus, firms need to find ways to digest the compliance costs to stay competitive and profitable. Hale et al. (2011) indicate that regulations provide some opportunities for firms to improve their processes to achieve gains in productivity and quality control to mitigate the overall costs of compliance. Inefficient investment in labor can further compound the costs of regulatory compliance. The goal of regulations and firms' intent to lift costly regulatory burdens suggest a positive relation between regulatory intensity and labor investment efficiency. As indicated earlier, increasing obligations of regulatory compliance presents a new breed of challenges for firms, which may require managers to become more cautious to avoid wasteful and insufficient investment in labor to stay in business and maintain or increase current earnings.

However, regulations impose burdens on companies and can be counter-productive. Empirical studies find that the regulatory burden hurts firms and the economy in general. For example, President Ronald Reagan once stated that government regulations impose an enormous burden on businesses, discourage productivity, and contribute to economic woes.[5] Coffey et al. (2020) document that regulatory restrictions have dampened economic growth by approximately 0.8% per annum since 1980. Hale et al. (2011) note that regulations generally stifle innovations and limit improvements in risk-management strategies. The increasing number of regulations can overwhelm a business, making firms deviate from improving their business and instead focusing on compliance. Increased compliance costs, such as discovery costs, compliance costs, costs related to outdated production methods, record keeping, and reporting to the regulators about compliance, significantly divert firm resources from the firm's other business activities.[6] Kalmenovitz (2023) notes compliance costs can create budget constraints and uncertainty. Similarly, Crain and Crain (2023) indicate that regulations introduce uncertainty into planning and affect business operations, which may make optimal hiring more challenging. In addition, regulatory uncertainty may further increase the uncertainty of businesses. Regulatory uncertainty comes from vague, overbroad, excessively complex, and changing rules (Hale et al., 2011). We argue that budget constraints and uncertainty from regulation compliance may make firms too handcuffed to engage in optimal labor investment. Additionally,

[4] Bisetti (2024) studies the monitoring role of the Federal Reserve and find that banks subject to decreased off-site surveillance intensity witness drops in Tobin's Q and equity market-to-book, and that such banks tend to engage in more earnings management.

[5] Ronald Reagan, "Remarks Announcing the Establishment of the Presidential Task Force on Regulatory Relief" (January 22,1981). (http://www.presidency.ucsb.edu/ws/index.php?pid=43635).

[6] Discovery costs are related to review of new regulations and see whether the new regulations apply to them, and costs of outdated production methods are due to the lagged feature of regulations (Hale et al., 2011).

Williams and Adams (2012) argue that regulatory overload discourages firms from finding innovative solutions to problems. Distractions and disincentives from regulation overload may further hinder firms from achieving efficient labor investment due to untimely adjustments in labor investment.

Since firms are subject to different subsets of regulations, firm-specific regulatory intensity is more appropriate for assessing the impact of regulation intensity on firm policies and outcomes. Based on the discussions above, we make no prediction on the association between firm-level regulatory intensity and labor investment efficiency but leave it as an open empirical question.

To test the impact of regulatory intensity on labor investment efficiency, we employ the four firm-level regulatory intensity measures developed by Kalmenovitz (2023).[7] These measures are constructed using administrative data and supervised machine-learning algorithms and capture different aspects of the cost of compliance with all federal paperwork regulations deemed relevant to a firm. Specifically, the four firm-level regulatory intensity measures are the number of active regulations (*RegIn_Reg*), the estimated costs of compliance in terms of responses (*RegIn_Resp*), the estimated costs of compliance in terms of hours spent (*RegIn_Time*), and the total dollar amount spent by a firm for regulatory compliance (*RegIn_Dollar*). The four variables are the logarithm of the original data obtained from Professor Kalmenovitz's website.[8] Additionally, we follow Ferris and Sainani (2021) to undertake a Principal Components Analysis (PCA) to construct two composite measures, *RegIn_Comp3* and *RegIn_Comp4*, using the first three regulatory intensity variables and all four regulatory intensity variables above to capture the joint impact of these variables, respectively.[9] We follow Khedmati et al. (2020) to construct the labor investment inefficiency proxy (*Laborieff*) as the absolute value of the deviation from the expected level of labor investment estimated from a firm's growth opportunities, profitability, stock returns, assets utilization efficiency, firm size, liquidity, debt usage, and loss occurrence. A higher value of *Laborief* indicates greater labor investment inefficiency.

Examining a sample of 54,624 firm-year observations of U.S. firms from 1995 to 2019, we find a negative and significant association between regulatory intensity and labor investment inefficiency across all six regulatory intensity measures.[10] Our baseline result shows that a one-standard-deviation increase in regulatory intensity, *RegIn_Reg*/ *RegIn_Resp*/ *RegIn_Time*/ *RegIn_Dollar*/ *RegIn_Comp3*/ *RegIn_Comp4,* is associated with a decrease in labor investment inefficiency by 0.059/ 0.045/ 0.047/ 0.06/ 0.059/ 0.06 of its standard deviation, indicating that the impact of regulatory intensity on labor investment efficiency is also economically important. Further analyses show that the positive impact of firm-level regulatory intensity on labor investment efficiency is stronger in financially constrained firms.

To check the robustness of our results, we conduct several tests. First, to address the concern that firms with high regulatory intensity are systematically different from those with low regulatory intensity, we use the Entropy balancing method as in Canil et al. (2019) to mitigate the differences in the distributional moments of control variables in our baseline regression between the two types of firms. Second, we undertake an instrumental variable approach to alleviate the bias attributable to simultaneity and reverse causality. We use two sets of instrument variables, i.e., the median value of $RegIn\_Comp3_{t-1}$/ $RegIn\_Comp4_{t-1}$ of all other firms in the same state as the focal firm and the median

[7]Please refer to Kalmenovitz (2023) for details of the construction of the measures of firm-level regulatory intensity.

[8]https://sites.google.com/view/jkalmenovitz

[9]The number of firm-year observations of *RegIn_Dollar* is less than the other three proxies. To avoid any missing information, we create two PCA measures from the first three proxies and all proxies separately.

[10]Regulatory intensity data is available till 2020. Our sample ends in 2019 for two reasons: 1). Managerial ability scores, one of the control variables used in this study, are available till 2019. 2). 2020 is a unique year for all businesses given the outbreak of Covid-19 and its disruptive features. Firms had to adjust various policies during the pandemic and including 2020 in our sample may bias our results.

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value of *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ of all other firms in the same industry as the focal firm, where industry is defined using the two-digit SIC code, to instrument *RegIn_Comp3* $_{it-1}$/ *RegIn_Comp4* $_{it-1}$ in the first stage analysis, respectively. In the second stage, we revisit our baseline models using the predicted values of regulatory intensity proxies. Finally, we conduct various subsample analyses to investigate whether our baseline findings are confounded by firm characteristics, such as operation capital, labor adjustment costs, and the level of labor intensity, but find no such evidence. Our baseline results hold for all the tests.

To the best of our knowledge, this study is the first to provide empirical evidence on the direct link between the level of regulatory intensity and labor investment efficiency. We enrich the literature in several ways. First, we contribute to the growing literature on labor investment by showing that regulatory intensity is an important determinant of efficient labor management (Jung et al., 2014; Ben-Nasr & Alshwer, 2016; Kong et al., 2018; Khedmati et al., 2020; Luo et al., 2020; Lai et al., 2021; Le & Tran, 2021; Jung et al., 2022; James et al., 2024). The positive association between firm-level regulatory intensity and labor investment efficiency shows that the positive effect of regulations on firm transparency and governance outweighs the negative effect of compliance costs. Firms tend to make more prudential hiring decisions when facing more regulatory compliance costs.

Second, we respond to the call for research on the relation between regulatory intensity and corporate decisions and outcomes by Kalmenovitz (2023). Kalmenovitz (2023) studies the impact of regulatory intensity on firm-level expenses, financing decisions, lobbying, and other business operations. We find that U.S. companies adjust their labor investment policies toward efficiency as regulatory compliance costs increase. Ince (2024) finds that large firms undertake within-industry acquisitions to digest regulatory compliance costs and such acquisitions are value-enhancing. We extend Ince (2024) by showing that firms employ efficient labor investment to absorb regulatory compliance costs.[11] Our finding that firm-level regulatory intensity enhances corporate employment decisions provides important implications for regulators and regulated firms. U.S. firms can develop competitive advantages by mitigating the negative impact of increased compliance costs on their businesses through labor investment management.

The remainder of this paper is organized as follows. Section 2 describes the sample, key variables, and research design. Section 3 provides the baseline and robustness check results, respectively, and Section 4 concludes the paper.

2. Research Design

2.1. Sample

We obtain firm regulation compliance cost data from Professor Kalmenovitz's website at https://sites.google.com/view/jkalmenovitz. The data is available from 1995 to 2019. We merge this data with the Compustat database and exclude highly regulated financial (SIC 6000–6999) and utility (SIC 4900–4999) firms. We obtain institutional ownership data from the Refinitiv Eikon database and industry unionization rate at https://www.unionstats.com/.[12] After deleting firm-year observations with missing values on key variables, we have a final sample of 54,624 firm-year observations. Due to data limitations, the sample size is reduced when the compliance cost variable, *RegIn_Dollar,* is used as a proxy for regulatory cost.

Table 1 displays the sample distribution. Panel A/B shows the sample distribution by year/ industry classified using the 48 Fama-French industry classification code. The sample is about equally distributed over the sample years with a declining trend starting from 2007. The sample covers a

[11]Other vehicles can also be used to mitigate regulatory burden. For example, to mititage the burden from SOX and exchange listing requirements of increasing the number of outside directors, firms substitute their insider directors with outside ones being socially/professionally connected to their CEOs (Wintoki & Xi, 2019).

[12]Hirsch and Macpherson (2003) detail the construction of the database.

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wide range of industries. Business services (*Bussv*), electronic equipment (*Chips*), Retail services (*Rtail*), and (*Drugs*) account for more than 5% of the sample, respectively.

Table 1. Sample distribution. This table presents sample distribution by year in Panel A and by industry in Panel B. The sample is a merged sample from Compustat, the Refinitiv Eikon database, and regulatory intensity data from https://sites.google.com/view/jkalmenovitz, excluding financial (SIC 6000–6999) and utility (SIC 4900–4949) firms. The full sample covers 54,624 firm-year observations from 1995-2019. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution.

Panel A. Sample distribution by year			**Panel B. Sample distribution by industry**		
Year	N	Percent	Industry	N	Percent
1995	2,248	4.12	Aero	448	0.82
1996	2,287	4.19	Agric	242	0.44
1997	2,339	4.28	Autos	1,105	2.02
1998	2,411	4.41	Beer	195	0.36
1999	2,418	4.43	Bldmt	1,520	2.78
2000	2,390	4.38	Books	401	0.73
2001	2,448	4.48	Boxes	207	0.38
2002	2,573	4.71	Bussv	7,054	12.91
2003	2,582	4.73	Chem	1,473	2.7
2004	2,570	4.7	Chips	4,665	8.54
2005	2,571	4.71	Clths	894	1.64
2006	2,532	4.64	Cnstr	476	0.87
2007	2,375	4.35	Coal	90	0.16
2008	2,260	4.14	Comps	2,350	4.3
2009	2,174	3.98	Drugs	2,993	5.48
2010	2,116	3.87	Elceq	1,209	2.21
2011	2,040	3.73	Fabpr	243	0.44
2012	1,991	3.64	Food	1,231	2.25
2013	1,968	3.6	Fun	768	1.41
2014	1,903	3.48	Gold	129	0.24
2015	1,771	3.24	Guns	156	0.29
2016	1,723	3.15	Hlth	1,251	2.29
2017	1,685	3.08	Hshld	973	1.78
2018	1,650	3.02	Labeq	1,666	3.05
2019	1,599	2.93	Mach	2,585	4.73
Total	54,624	100	Meals	1,249	2.29
			Medeq	2,539	4.65
			Mines	198	0.36
			Oil	2,659	4.87
			Other	784	1.44
			Paper	797	1.46
			Persv	677	1.24
			Rtail	3,528	6.46
			Rubber	613	1.12

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	Ships	107	0.2
	Smoke	50	0.09
	Soda	161	0.29
	Steel	891	1.63
	Telcm	1,517	2.78
	Toys	513	0.94
	Trans	1,219	2.23
	Txtls	327	0.6
	Whlsl	2,471	4.52

2.2. Key variables

2.2.1. Labor Investment Efficiency

We follow Khedmati et al. (2020) to construct the measure of labor investment efficiency. Specifically, we measure labor investment with net hiring (*NetHire*), constructed as the percentage change in the number of employees from the previous year. The expected level of labor investment is estimated using the following model as in Khedmati et al. (2020). We proxy labor investment inefficiency with abnormal hiring, which is the residual estimated from Eq (1). Since abnormal hiring can result from either over- or under-investment in labor, we use the absolute value of abnormal hiring to measure labor investment efficiency (*Laborieff*) to facilitate the interpretation of the results. A higher value of *Laborieff* indicates less efficiency in labor investment.

$$NetHire_{it} = \beta_0 + \beta_1 SGR_{it-1} + \beta_2 SGR_{it} + \beta_3 \Delta ROA_{it-1} + \beta_4 \Delta ROA_{it} + \beta_5 ROA_{it} + \beta_6 Return_{it} + \beta_7 FirmSize\_R_{it-1} + \beta_8 Quick_{it-1} + \beta_9 \Delta Quick_{it-1} + \beta_{10} \Delta Quick_{it} + \beta_{11} Lev_{it-1} + \beta_{12} AUR_{it-1} + \beta_{13} LossBin1_{it-1} + \beta_{14} LossBin2_{it-1} + \beta_{15} LossBin3_{it-1} + \beta_{16} LossBin4_{it-1} + \beta_{17} LossBin5_{it-1} + Industry\ FE + \varepsilon_{it}, \quad (1)$$

where i stands for firm i, t denotes time t, and the Δ prefix indicates the change from the previous period. Firms with higher expected growth need more labor. We capture future expected growth with sales growth rate (*SGR*) and annual stock return (*Return*). Labor demand increases in profitability. We measure firms' profitability with return on assets (*ROA*) and its lagged value. Larger firms are likely to demand more labor. We measure the size effect with firm size percentile rank (*FirmSize_R*). Firms with liquidity problems may lack cash flow to facilitate labor growth. We measure the liquidity effect with quick ratio (*Quick*) and its current and lagged changes. As cash flows on debt repayment resemble fixed costs, firms with higher leverage may not have enough flexibility to invest in labor. We capture the effect of capital structure with debt usage (*Lev*). Firms experiencing loss could be in temporary distress and need to scale down labor investments. We include five dummy variables to capture the loss occurrence (*LossBin1-LossBin5*). Lastly, we include assets utilization efficiency (*AUR*) as firms using their assests more efficiently are expected to have a higher demand for labor. We control for industry fixed effects, where the industry is defined using the Fama and French 48 industry classifications. Refer to Appendix A for detailed definitions of these variables.

2.2.2. Regulatory Intensity

To measure firm-level regulatory intensity, we employ six variables, *RegIn_Reg*, *RegIn_Resp*, *RegIn_Time*, *RegIn_Dollar*, *RegIn_Comp3*, and *RegIn_Comp4*. The first four variables are the log-transformed form of the original data obtained from Professor Kalmenovitz's website. Kalmenovitz

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(2023) develops these unique firm-level regulatory intensity measures based on regulations relevant to a firm's operations using administrative data and supervised machine-learning algorithms, capturing different aspects of costs of compliance with all federal paperwork regulations in terms of the number of active regulations applied to the company (*RegIn_Reg)*, estimated costs of paperwork (*RegIn_Resp)*, total hours spent on compliance (*RegIn_Time)*, and total dollar amount spent on compliance (*RegIn_Dollar*). Following Ferris and Sainani (2021), we construct two composite measures of regulatory intensity, *RegIn_Comp3* and *RegIn_Comp4*, by conducting a Principal Components Analysis (PCA) using the first three and all four regulatory intensity variables with an eigenvalue above 1, respectively.[13] Larger values indicate a surge in regulatory intensity, i.e., more regulations and higher compliance costs in terms of forms, time, and dollar amount.

2.3. Empirical Model

We proxy for labor investment efficiency with the residual estimated from Eq (1). Chen et al. (2018) show that this two-step estimation procedure can generate biased inferences because of the incorrect estimations of the coefficients and standard errors. To alleviate the bias from the two-step procedure, we follow their suggestion by including all independent variables in the first-step regression as additional control variables in the second-step regression. We define our second stage model as follows:

$$Laborineff_{it} = \beta_0 + \beta_1 Regulation_{it-1} + \beta_2 AQ_{it-1} + \beta_3 MTB_{it-1} + \beta_4 FirmSize\_R_{it-1} + \beta_5 Quick_{it-1} + \beta_6 Lev_{it-1} + \beta_7 DivDum_{it-1} + \beta_8 STD\_CFO_{it-1} + \beta_9 STD\_Sales_{it-1} + \beta_{10} Tangibles_{it-1} + \beta_{11} Loss_{it-1} + \beta_{12} Inst_{it-1} + \beta_{13} STD\_Net\_Hire_{it-1} + \beta_{14} Labor\_Intensity_{it-1} + \beta_{15} Union_{it-1} + \beta_{16} AB\_Invest\_Other_{it} + \beta_{17} MA_{it-1} + \sum_{i=1}^{k} \beta_i \, Other\ FirstStepIV_i + Firm\ FE + Industry * Year\ FE + \varepsilon_{it,} \quad (2)$$

where i and t denote firm i and time t, respectively. *Laborineff* (labor investment inefficiency) is the absolute value of abnormal net hiring as defined in Section *2.2.1*. *Regulation* is one of the six regulation intensity measures, *RegIn_Reg*, *RegIn_Resp*, *RegIn_Time*, *RegIn_Dollar*, *RegIn_Comp3*, and *RegIn_Comp4*, as defined in Section *2.2.2*. We use standard errors clustered at the firm level to generate statistical inference and report the standardized coefficients for easy comparison. To ensure that the results are not attributed to a firm's long-term compliance costs, nor to the overall regulatory burden in a specific year for a particular industry, we include firm-fixed effects and industry & year-fixed effects as in Kalmenovitz (2023), where industry is based on the Fama-French 48 industrial codes to exploit variation within firm over time and net of industry-specific trend. We control for the effects of accounting quality (*AQ*), growth opportunities (market-to-book value of common equity, *MTB*), firm size (the percentile rank of firm market capitalization, *FirmSize_R*), liquidity (quick ratio, *Quick*), financial leverage (*Lev*), dividend payout status (dividend payer vs. non-payer, *DivDum*), operating cash flow volatility (the standard deviation of cash flow from operations over the past five years, *STD_CFO*), volatility of sales (the standard deviation of sales over the past five years, *STD_Sale*), fixed assets (*Tangibles*), reported losses (*Loss*), institutional ownership (the proportion of common shares held by institutional owners, *Insti*), volatility of the investment in labor (the standard deviation of the change in the number of employees over the past five years, *STD_NetHire*), labor intensity (the number of employees scaled by total assets, *Labor_Intensity*), the level of labor protection (the industry unionization rate, *Union*), and managerial ability (the industry-year decile rank of managerial ability

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[13] Please note that our sample size is reduced when *RegIn_Dollar* and *RegIn_Comp4* are used to proxy for the level of regulatory intensity as the coverage of *RegIn_Dollar* is smaller than other proxies.

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scores developed by Demerjian et al. (2012), *MA*). Lastly, we control for the impact of abnormal non-labor investments (*AB_ Abnormal_InvestOther*), estimated as the absolute value of the residuals from the model regressing other investments (*InvestOther*) on the lagged sales growth rate (*SGR*), where *InvestOther* is defined as the sum of capital and R&D (research and development) expenditures less the proceeds from selling property, plant, and equipment, divided by the lagged total assets.

2.4. Sample Descriptive Statistics

Table 2 presents the summary statistics of the sample. The mean and median values of *Laborineff* are 0.148 and 0.08, respectively, close to those in Jung et al. (2014) (0.11 and 0.07, respectively). The mean and median $RegIn\_Reg_{t-1}$/ $RegIn\_Reg_{t-1}$/ $RegIn\_Time_{t-1}$ / $RegIn\_Dollar_{t-1}$ are 4.609 and 4.616/ 4.577 and 4.564/ 4.591 and 4.590/ 4.540 and 4.546, respectively. The average $RegIn\_Comp3_{t-1}$/ $RegIn\_Comp4_{t-1}$ is 0.109/ 0.036.

Table 2. Sample statistics. This table reports descriptive statistics of the sample. The full sample covers 54,624 firm-year observations from 1995-2019. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution.

Variables	N	Mean	P50	P25	P75	S.D.
Laborinefft	54,624	0.148	0.080	0.036	0.167	0.221
$RegIn\_Reg_{t-1}$	54,624	4.609	4.616	4.554	4.663	0.108
$RegIn\_Resp_{t-1}$	54,624	4.577	4.564	4.455	4.739	0.216
$RegIn\_Time_{t-1}$	54,624	4.591	4.590	4.503	4.706	0.182
$RegIn\_Dollar_{t-1}$	47,744	4.540	4.546	4.397	4.696	0.237
$RegIn\_Comp3r_{t-1}$	54,624	0.109	0.153	-0.240	0.445	0.682
$RegIn\_Comp4r_{t-1}$	47,744	0.036	0.060	-0.495	0.620	0.883
SGR_{t-1}	54,624	0.124	0.067	-0.034	0.191	0.415
SGR_t	54,624	0.122	0.061	-0.040	0.178	0.478
ΔROA_t	54,624	-0.007	0.000	-0.039	0.031	0.268
ΔROA_{t-1}	54,624	-0.002	0.001	-0.037	0.032	0.258
ROA_t	54,624	-0.050	0.033	-0.037	0.076	0.366
$Return_t$	54,624	0.263	0.068	-0.224	0.424	0.973
$FirmSize\_R_{t-1}$	54,624	53.281	54.000	30.000	77.000	27.668
$Quick_{t-1}$	54,624	1.832	1.224	0.760	2.093	2.049
$\Delta Quick_{t-1}$	54,624	-0.047	-0.005	-0.254	0.227	1.258
$\Delta Quick_t$	54,624	-0.032	-0.005	-0.250	0.223	1.168
Lev_{t-1}	54,624	0.235	0.184	0.024	0.341	0.264
AUR_{t-1}	54,624	1.223	1.049	0.654	1.576	0.823
$LossBin1_{t-1}$	54,624	0.052	0.000	0.000	0.000	0.222
$LossBin2_{t-1}$	54,624	0.044	0.000	0.000	0.000	0.206
$LossBin3_{t-1}$	54,624	0.037	0.000	0.000	0.000	0.189
$LossBin4_{t-1}$	54,624	0.032	0.000	0.000	0.000	0.176
$LossBin5_{t-1}$	54,624	0.026	0.000	0.000	0.000	0.159
AQ_{t-1}	54,624	5.389	5.000	3.000	8.000	2.819
MTB_{t-1}	54,624	2.776	1.913	1.086	3.359	4.965
$DivDum_{t-1}$	54,624	0.327	0.000	0.000	1.000	0.469
STD_CFO_{t-1}	54,624	0.135	0.046	0.022	0.109	0.449

STD_Sales $_{t-1}$	54,624	0.209	0.140	0.078	0.252	0.224
Tangibles $_{t-1}$	54,624	0.255	0.188	0.084	0.361	0.221
Loss $_{t-1}$	54,624	0.326	0.000	0.000	1.000	0.469
Inst $_{t-1}$	54,624	0.396	0.337	0.000	0.746	0.375
STD_Net_Hire $_{t-1}$	54,624	0.298	0.146	0.080	0.269	0.680
Labor_Intensity $_{t-1}$	54,624	0.008	0.005	0.002	0.009	0.010
Union $_{t-1}$	54,624	2.176	0.000	0.000	0.131	8.736
∣Ab_Invest_Other∣ $_{t}$	54,624	0.093	0.055	0.025	0.107	0.136
MA $_{t-1}$	54,624	0.561	0.600	0.300	0.800	0.272

Table 3 shows Pearson correlations between variables. All six regulatory intensity variables are negatively correlated to *Laborineff*, significant at the 1% level, providing preliminary supporting evidence that greater regulatory intensity improves labor investment efficiency. In addition, dividend payers and firms with higher accounting quality, assets tangibility, labor intensity, institutional ownership, and managerial ability have greater labor investment efficiency. While larger, highly leveraged, more liquid, and unprofitable firms and those with more growth opportunities and volatility in cash flows, sales, and labor investment are associated with lower labor investment efficiency. Furthermore, firms with more union coverage and abnormal other investments tend to have greater labor inefficiency.

Table 3. Correlations. This table presents the Pearson correlations between variables. The full sample covers 54,624 firm-year observations from 1995-2019. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
[1]	*Laborineff* $_{t}$	1										
[2]	*RegIn_Reg* $_{t-1}$	-0.103***	1									
[3]	*RegIn_Resp* $_{t-1}$	-0.087***	0.801***	1								
[4]	*RegIn_Time* $_{t-1}$	-0.085***	0.816***	0.912***	1							
[5]	*RegIn_Dollar* $_{t-1}$	-0.061***	0.489***	0.534***	0.538***	1						
[6]	*RegIn_Comp3* $_{t-1}$	-0.103***	1.000***	0.801***	0.816***	0.489***	1					
[7]	*RegIn_Comp4* $_{t-1}$	-0.061***	0.489***	0.534***	0.538***	1.000***	0.489***	1				

[8]	*AQ* $_{t-1}$	-0.139***	-0.010**	-0.001	0.000	0.031***	-0.010**	0.031***	1			
[9]	*MTB* $_{t-1}$	0.073***	0.010**	0.014***	0.019***	-0.008*	0.010**	-0.008*	-0.036***	1		
[10]	*FirmSize_R* $_{t-1}$	0.050***	-0.013***	-0.010**	-0.017***	-0.009**	-0.013***	-0.009**	-0.076***	-0.292***	1	
[11]	*Quick* $_{t-1}$	0.128***	0.051***	0.052***	0.042***	-0.008*	0.051***	-0.008*	-0.246***	0.106***	0.007*	1
[12]	*Lev* $_{t-1}$	0.018***	0.012***	0.018***	0.019***	0.019***	0.012***	0.019***	0.177***	0.040***	-0.121***	0.072***
[13]	*DivDum* $_{t-1}$	-0.131***	0.031***	0.041***	0.049***	0.074***	0.031***	0.074***	0.419***	-0.104***	-0.049***	-0.225***
[14]	*STD_CFO* $_{t-1}$	0.146***	-0.017***	-0.009**	-0.022***	-0.035***	-0.017***	-0.035***	-0.212***	-0.008*	0.195***	0.211***
[15]	*STD_Sales* $_{t-1}$	0.156***	-0.061***	-0.058***	-0.065***	-0.061***	-0.061***	-0.061***	-0.320***	-0.063***	0.124***	0.243***
[16]	*Tangibles* $_{t-1}$	-0.035***	-0.096***	-0.083***	-0.067***	-0.028***	-0.096***	-0.028***	0.108***	-0.247***	0.214***	-0.221***
[17]	*Loss* $_{t-1}$	0.144***	0.000	0.010**	0.007*	-0.021***	0.000	-0.021***	-0.399***	0.011**	0.164***	0.229***
[18]	*Inst* $_{t-1}$	-0.142***	0.213***	0.202***	0.182***	0.122***	0.213***	0.122***	0.503***	0.012***	-0.089***	-0.166***
[19]	*STD_Net_Hire* $_{t-1}$	0.153***	-0.068***	-0.065***	-0.062***	-0.052***	-0.068***	-0.052***	-0.135***	-0.001	0.081***	0.120***
[20]	*Labor_Intensity* $_{t-1}$	-0.009**	-0.143***	-0.124***	-0.125***	-0.074***	-0.143***	-0.074***	-0.181***	-0.165***	0.046***	-0.070***
[21]	*Union* $_{t-1}$	0.025***	-0.200***	-0.192***	-0.160***	-0.007	-0.200***	-0.007	0.009**	-0.037***	0.019***	0.026***

[22]	$\vert Ab\_Invest\_Other \vert_{t}$	0.108***	-0.008*	0.013***	0.022***	0.015***	-0.008*	0.015***	-0.119***	0.034***	0.078***	0.221***
[23]	MA_{t-1}	-0.027***	-0.007*	-0.006	-0.005	-0.009*	-0.007*	-0.009*	0.033***	0.058***	-0.108***	0.024***

		[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
[12]	Lev_{t-1}	1										
[13]	$DivDum_{t-1}$	0.025***	1									
[14]	STD_CFO_{t-1}	0.004	-0.151***	1								
[15]	STD_Sales_{t-1}	-0.009**	-0.198***	0.367***	1							
[16]	$Tangibles_{t-1}$	-0.069***	0.151***	-0.071***	-0.173***	1						
[17]	$Loss_{t-1}$	-0.030***	-0.324***	0.197***	0.173***	-0.050***	1					
[18]	$Inst_{t-1}$	0.064***	0.207***	-0.157***	-0.238***	-0.022***	-0.269***	1				
[19]	$STD\_Net\_Hire_{t-1}$	0.007	-0.148***	0.186***	0.232***	-0.012***	0.132***	-0.146***	1			
[20]	$Labor\_Intensity_{t-1}$	-0.039***	-0.042***	0.052***	0.192***	0.111***	-0.013***	-0.134***	0.041***	1		
[21]	$Union_{t-1}$	-0.008*	0.016***	-0.028***	0.046***	-0.044***	-0.031***	-0.101***	0.019***	0.038***	1	
[22]	$\vert Ab\_Invest\_Other \vert_{t}$	0.037***	-0.110***	0.176***	0.109***	-0.015***	0.128***	-0.087***	0.048***	0.012***	-0.044***	1
[23]	MA_{t-1}	0.087***	0.033***	0.014***	0.089***	-0.118***	-0.155***	-0.011***	-0.038***	0.013***	0.023***	0.014***

3. Results

3.1. Baseline Regression Analysis

Table 4 displays the baseline regression results. The coefficients on all six regulatory intensity measures are negative and statistically significant at the 1% level, suggesting that greater regulatory intensity enhances labor investment efficiency. The impact of regulatory intensity on labor investment efficiency is identified within firm over time, net of industry trend, and with the control of other determinants of labor investment efficiency. Economically, the results show that a one-standard-deviation increase in regulatory intensity, *RegIn_Reg*/ *RegIn_Resp*/ *RegIn_Time*/ *RegIn_Dollar*/ *RegIn_Comp3*/ *RegIn_Comp4*, is associated with a decrease in labor investment inefficiency by 0.059/ 0.045/ 0.047/ 0.06/ 0.059/ 0.06 of its standard deviation, indicating that the impact of regulatory intensity on labor investment efficiency is also economically important. Corroborating with the finding in Kalmenovitz (2023), increased regulatory intensity induces firms to adjust hiring. Large, highly leveraged, and high labor-intensive firms and those with greater labor investment volatility tend to make more efficient labor investment decisions. However, higher firm growth, greater liquidity, dividend distribution, higher abnormal non-labor investments, and more volatility in sales and cash flows are associated with greater labor investment inefficiency.

Table 4. Regulatory intensity and labor investment efficiency. This table presents the baseline results of the association between regulatory intensity and labor investment efficiency. *Laborineff* is the absolute value of the residuals estimated from Equation (1). *RegIn_Reg* $_{t-1}$ is the number of active paperwork regulations. *RegIn_Resp* $_{t-1}$ is the total number of responses received ("how much paperwork"). *RegIn_Time* $_{t-1}$ is the total hours invested by a firm to comply with paperwork regulation, including the time it takes to collect the information, read the instructions, and file the paperwork. *RegIn_Dollar* $_{t-1}$ is the total dollars invested by a firm for compliance. All four regulatory intensity proxies are obtained from https://sites.google.com/view/jkalmenovitz. *RegIn_Comp3* $_{t-1}$ / *RegIn_Comp4* $_{t-1}$ is the component generated from the first three/ all four regulatory intensity proxies with an eigenvalue above 1 using the PCA analysis. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			**Laborineff**			
RegIn_Reg $_{t-1}$	-0.059***					
	(-2.890)					
RegIn_Resp $_{t-1}$		-0.045***				
		(-2.723)				
RegIn_Time $_{t-1}$			-0.047***			
			(-2.922)			
RegIn_Dollar $_{t-1}$				-0.060***		
				(-3.798)		
RegIn_Comp3 $_{t-1}$					-0.059***	
					(-2.890)	
RegIn_Comp4 $_{t-1}$						-0.060***
						(-3.798)
AQ $_{t-1}$	0.016	0.017*	0.016*	0.008	0.016	0.008
	(1.640)	(1.716)	(1.651)	(0.725)	(1.640)	(0.725)
MTB $_{t-1}$	0.013**	0.013**	0.012**	0.017***	0.013**	0.017***
	(2.226)	(2.180)	(2.169)	(2.705)	(2.226)	(2.705)
FirmSize_R $_{t-1}$	-0.051***	-0.050**	-0.050**	-0.050**	-0.051***	-0.050**
	(-2.595)	(-2.549)	(-2.556)	(-2.351)	(-2.595)	(-2.351)

Quick $_{t-1}$	0.028**	0.028**	0.029**	0.029**	0.028**	0.029**
	(2.337)	(2.337)	(2.347)	(2.324)	(2.337)	(2.324)
Lev $_{t-1}$	-0.027***	-0.027***	-0.027***	-0.030***	-0.027***	-0.030***
	(-2.597)	(-2.649)	(-2.650)	(-2.641)	(-2.597)	(-2.641)
DivDum $_{t-1}$	0.033***	0.034***	0.034***	0.034***	0.033***	0.034***
	(4.072)	(4.132)	(4.156)	(3.933)	(4.072)	(3.933)
STD_CFO $_{t-1}$	0.031**	0.032***	0.032***	0.037***	0.031**	0.037***
	(2.547)	(2.651)	(2.640)	(2.766)	(2.547)	(2.766)
STD_Sales $_{t-1}$	0.032***	0.033***	0.033***	0.027**	0.032***	0.027**
	(3.148)	(3.205)	(3.195)	(2.402)	(3.148)	(2.402)
Tangibles $_{t-1}$	0.010	0.009	0.009	0.006	0.010	0.006
	(0.531)	(0.486)	(0.505)	(0.303)	(0.531)	(0.303)
Loss $_{t-1}$	0.006	0.006	0.006	0.004	0.006	0.004
	(0.946)	(0.938)	(0.969)	(0.610)	(0.946)	(0.610)
Inst $_{t-1}$	0.010	0.010	0.010	0.011	0.010	0.011
	(1.128)	(1.130)	(1.114)	(1.191)	(1.128)	(1.191)
STD_Net_Hire $_{t-1}$	-0.069***	-0.070***	-0.070***	-0.076***	-0.069***	-0.076***
	(-6.348)	(-6.411)	(-6.389)	(-5.796)	(-6.348)	(-5.796)
Labor_Intensity $_{t-1}$	-0.157***	-0.157***	-0.157***	-0.151***	-0.157***	-0.151***
	(-6.568)	(-6.567)	(-6.575)	(-5.769)	(-6.568)	(-5.769)
Union $_{t-1}$	-0.009	-0.011	-0.011	-0.015	-0.009	-0.015
	(-0.387)	(-0.461)	(-0.446)	(-0.677)	(-0.387)	(-0.677)
$\mid$Ab_Invest_Other$\mid_t$	0.034***	0.035***	0.035***	0.025***	0.034***	0.025***
	(4.080)	(4.153)	(4.174)	(2.972)	(4.080)	(2.972)
MA $_{t-1}$	0.015**	0.015**	0.015**	0.012*	0.015**	0.012*
	(2.456)	(2.486)	(2.465)	(1.777)	(2.456)	(1.777)
First-stage regressors	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.688***	0.343***	0.388***	0.445***	0.096***	0.106***
	(3.464)	(3.622)	(3.776)	(4.256)	(6.671)	(6.706)
Observations	54,624	54,624	54,624	47,744	54,624	47,744
R-squared	0.130	0.129	0.129	0.130	0.130	0.130
Clustered std err by firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry * Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

3.2. Robustness Checks

3.2.1. Entropy Balancing Approach

Systematic differences between firms with high and low regulatory intensity could lead to a spurious association between regulatory intensity and labor investment efficiency. We employ an Entropy balancing approach to address this issue (Canil et al., 2019). The Entropy balancing approach minimizes the differences between firms with high regulatory intensity (the treated sample) and those with low regulatory intensity (the control sample) by continuously adjusting the distributional moments of the observations in the control sample (such as means, variances, and skewness), allowing less researcher discretion. In addition, different from the Propensity score matching method

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(PSM), this method retains all observations, making the results more generalized (Canil et al., 2019; Davidson et al., 2024).

We use the two regulatory composite measures (*RegIn_Comp3* $_{t-1}$ and *RegIn_Comp4* $_{t-1}$) and dissect the sample into four quartiles, respectively. The treated sample includes firm-year observations with *RegIn_Comp3* $_{t-1}$ / *RegIn_Comp4* $_{t-1}$ in the 4th quartile of the sample distribution, representing the highest level of regulatory intensity. The control sample includes all other firm-year observations. Panel A of Table 5 displays the distribution comparison of the control variables after Entropy balancing. *Std.Diff.* is the mean differences of the control variables between the treated and the control samples divided by the standard deviations of the corresponding control variables in the treated sample. *Var.Ratio* is the variance of each control variable in the treated sample divided by the variance of its corresponding control variable in the control sample. The results show that *Stdz.Diff.* is zero and *Var.Ratio* is one across all variables, indicating that the treated and control firms are matched in their distributional moments. Panel B shows the regression results using the entropy-balanced sample. The results are qualitatively the same as those in the baseline regressions. The coefficient of regulatory intensity is negative and significant at the 1% level in both models.

Table 5. Entropy-balanced sample. This table presents the results of Entropy-balanced sample. Panel A shows the distribution comparison of the control variables after entropy balancing between firms with higher regulatory intensity (*RegIn_Comp3* $_{t-1}$ or *RegIn_Comp4* $_{t-1}$ in the 4th quartile of the sample distribution) and those with lower levels of regulatory intensity (all other firms). *Std.Diff.* is the differences in the mean values of the control variables between the treated (firms with high regulatory intensity) and the control samples (those with low regulatory intensity) standardized by the standard deviations of the corresponding variables of the treated sample. *Var.Ratio* is the ratio of the variance of a control variable in the treated sample scaled by the variance of its corresponding variable of the control sample. Panel B shows the regression results using the Entropy-balanced matched sample. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Comparison of firm characteristics

	High vs. Low RegIn_COMP3 t-1						*High vs. Low RegIn_COMP4* $_{t-1}$					
	Treated (N= 14,241)		Control (N = 42,726)				Treated (N= 11988)		Control (N = 44979)			
Variables	Mean	Variance	Mean	Variance	Stdz. Diff.	*Var. Ratio*	Mean	Variance	Mean	Variance	Stdz. Diff.	*Var. Ratio*
SGR_{t-1}	0.096	0.127	0.096	0.127	0.00	1.00	0.102	0.131	0.102	0.131	0.00	1.00
SGR_t	0.092	0.159	0.092	0.159	0.00	1.00	0.109	0.197	0.109	0.197	0.00	1.00
ΔROA_t	-0.005	0.066	-0.005	0.066	0.00	1.00	-0.008	0.065	-0.008	0.065	0.00	1.00
ΔROA_{t-1}	-0.001	0.063	-0.001	0.063	0.00	1.00	-0.004	0.057	-0.004	0.057	0.00	1.00
ROA_t	-0.051	0.140	-0.051	0.140	0.00	1.00	-0.043	0.128	-0.043	0.128	0.00	1.00

$Return_t$	0.230	0.707	0.230	0.707	0.00	1.00	0.247	0.827	0.247	0.827	0.00	1.00
$FirmSize\_R_{t-1}$	52.410	772.700	52.410	772.700	0.00	1.00	54.190	764.200	54.190	764.200	0.00	1.00
$Quick_{t-1}$	1.857	3.919	1.857	3.919	0.00	1.00	1.706	3.830	1.706	3.830	0.00	1.00
$\Delta Quick_{t-1}$	-0.040	1.351	-0.040	1.352	0.00	1.00	-0.052	1.437	-0.052	1.437	0.00	1.00
$\Delta Quick_{t}$	-0.046	1.232	-0.046	1.232	0.00	1.00	-0.046	1.209	-0.046	1.209	0.00	1.00
Lev_{t-1}	0.233	0.076	0.233	0.076	0.00	1.00	0.252	0.072	0.252	0.072	0.00	1.00
AUR_{t-1}	1.148	0.663	1.148	0.663	0.00	1.00	1.195	0.688	1.195	0.688	0.00	1.00
$LossBin1_{t-1}$	0.055	0.052	0.055	0.052	0.00	1.00	0.056	0.053	0.056	0.053	0.00	1.00
$LossBin2_{t-1}$	0.049	0.047	0.049	0.047	0.00	1.00	0.051	0.048	0.051	0.048	0.00	1.00
$LossBin3_{t-1}$	0.041	0.039	0.041	0.039	0.00	1.00	0.042	0.041	0.042	0.041	0.00	1.00
$LossBin4_{t-1}$	0.033	0.032	0.033	0.032	0.00	1.00	0.037	0.036	0.037	0.036	0.00	1.00
$LossBin5_{t-1}$	0.028	0.027	0.028	0.027	0.00	1.00	0.029	0.029	0.029	0.029	0.00	1.00
AQ_{t-1}	5.573	7.662	5.573	7.662	0.00	1.00	5.234	8.101	5.234	8.101	0.00	1.00
MTB_{t-1}	2.894	28.870	2.894	28.870	0.00	1.00	2.894	28.620	2.894	28.620	0.00	1.00
$DivDum_{t-1}$	0.344	0.226	0.344	0.226	0.00	1.00	0.380	0.236	0.380	0.236	0.00	1.00
STD_CFO_{t-1}	0.139	0.233	0.139	0.233	0.00	1.00	0.124	0.196	0.124	0.196	0.00	1.00
STD_Sales_{t-1}	0.189	0.045	0.189	0.045	0.00	1.00	0.192	0.044	0.192	0.044	0.00	1.00
$Tangibles_{t-1}$	0.217	0.048	0.217	0.048	0.00	1.00	0.263	0.055	0.263	0.055	0.00	1.00
$Loss_{t-1}$	0.332	0.222	0.332	0.222	0.00	1.00	0.317	0.217	0.317	0.217	0.00	1.00
$Inst_{t-1}$	0.509	0.148	0.509	0.148	0.00	1.00	0.482	0.144	0.482	0.144	0.00	1.00

STD_Net_Hire t-1	0.238	0.298	0.238	0.298	0.00	1.00	0.249	0.357	0.249	0.357	0.00	1.00
Labor_Intensity t-1	0.006	0.000	0.006	0.000	0.00	1.00	0.007	0.000	0.007	0.000	0.00	1.00
Union t-1	0.287	12.110	0.288	12.190	0.00	0.99	1.166	54.250	1.166	54.250	0.00	1.00
|Ab_Invest_Other| t	0.093	0.022	0.093	0.022	0.00	1.00	0.089	0.022	0.089	0.022	0.00	1.00
MA t-1	0.552	0.075	0.552	0.075	0.00	1.00	0.555	0.076	0.555	0.076	0.00	1.00

Panel B: Weighted regression using the entropy-balanced sample

	(1)	**(2)**
Variables	**Laborineff**	
RegIn_Comp3 $_{t-1}$	-0.055**	
	(-2.137)	
RegIn_Comp4 $_{t-1}$		-0.056***
		(-3.125)
AQ $_{t-1}$	-0.001	0.004
	(-0.061)	(0.275)
MTB $_{t-1}$	0.013*	0.012
	(1.720)	(1.523)
FirmSize_R $_{t-1}$	-0.023	-0.058**
	(-0.812)	(-2.073)
Quick $_{t-1}$	0.032*	0.020
	(1.952)	(1.404)
Lev $_{t-1}$	-0.044***	-0.040***
	(-2.892)	(-2.706)
DivDum $_{t-1}$	0.038***	0.041***
	(3.482)	(3.486)
STD_CFO $_{t-1}$	0.041**	0.032**
	(2.373)	(2.110)
STD_Sales $_{t-1}$	0.030**	0.026*
	(2.283)	(1.753)
Tangibles $_{t-1}$	0.010	-0.020
	(0.340)	(-0.727)
Loss $_{t-1}$	0.001	0.002
	(0.066)	(0.302)
Inst $_{t-1}$	0.006	0.008
	(0.374)	(0.561)
STD_Net_Hire $_{t-1}$	-0.094***	-0.061***
	(-5.779)	(-3.331)
Labor_Intensity $_{t-1}$	-0.166***	-0.172***
	(-5.248)	(-5.723)

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Union $_{t-1}$	-0.043	0.010
	(-1.586)	(0.241)
|*Ab_Invest_Other*| $_{t}$	0.017*	0.014
	(1.758)	(1.404)
MA $_{t-1}$	0.016**	0.011
	(2.025)	(1.266)
First-stage regressors	Yes	Yes
Constant	0.098***	0.112***
	(5.333)	(6.269)
Observations	54,624	47,744
R-squared	0.352	0.372
Clustered std err by firm	Yes	Yes
Industry * Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes

3.2.2. Instrumental Variable Approach

We adopt the instrumental variable approach to further address the endogeneity concern arising from simultaneity and reverse causality (Wooldridge, 2002) and report the results in Table 6. We instrument *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ with two variables, *RegIn_Comp3_ST* $_{t-1}$/ *RegIn_Comp4_ST* $_{t-1}$ (the median value of *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ for all other firms in the same state as the focal firm) and *RegIn_Comp3_SIC2* $_{t-1}$/ *RegIn_Comp4_SIC2* $_{t-1}$ (the median value of *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ for all other firms in the same industry as the focal firm, where industry is defined using the two-digit SIC code). These two instruments meet the relevance condition for being valid instruments. A focal firm's regulatory intensity is expected to be related to that of nearby firms given that they operate in the similar local economic environment and are subject to similar local regulatory compliance or two-layered system of governance (federal and state). Regulatory intensity of a focal firm's industry peers should be related to the firm's regulatory intensity. However, the direction of the association is unclear.

On the one hand, firms in the same industry are exposed to the same regulatory compliance requirements, resulting in a positive relation between regulatory intensity in a focal firm and those of its industry peers. On the other hand, a negative association may be plausible because of various reasons such as within-industry heterogeneity (Mauri & Michaels, 1998; Short et al., 2007), strategic differentiation (Porter & Kramer, 2006; Flammer, 2015), regulatory capture (Stigler, 1971; Peltzman, 1976), and the stage of the industry life cycle (Klepper, 1997). Such within-industry variations can lead to varying levels of regulatory exposure among firms within the same industry. In addition, these two instruments also satisfy the exclusion conditions as they are not expected to be directly related to the focal firm's labor investment efficiency.

Models (1) and (3) present the first-stage results for *RegIn_Comp3* $_{t-1}$ and *RegIn_Comp4* $_{t-1}$, respectively. Both instruments are significantly associated with the regulatory intensity composite measures. Models (2) and (4) display the second-stage results. The predicted values of *RegIn_Comp3* $_{t-1}$ and *RegIn_Comp4* $_{t-1}$, obtained from the first-stage regression (*RegIn_ Comp3 (Instrumented)* $_{t-1}$ *and RegIn_ Comp4 (Instrumented)* $_{t-1}$) are negative and significantly related to labor investment inefficiency, echoing the findings in our baseline analysis. In addition, Hansen J statistics are insignificant, suggesting that our instruments are valid. Our instruments are neither weak nor under-identified, evidenced by the significant Kleibergen-Paap rk Wald F and Kleibergen-Paap rk LM statistics.

Table 6. Instrumental variable regression. This table presents the results of the instrumental variable regression. In the first stage, we instrument *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ with *RegIn_Comp3_ST* $_{t-1}$/ *RegIn_Comp4_ST* $_{t-1}$ (the median value of *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ for all other firms in the same

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state as a focal firm) and *RegIn_Comp3_SIC2* $_{t-1}$/ *RegIn_Comp4_SIC2* $_{t-1}$ (the median value of *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ for all other firms in the same industry as the focal firm, defined using two-digit SIC code). The results are presented in Models (1) and (3), respectively. In the second stage, we replace *RegIn_Comp3* $_{t-1}$ / *RegIn_Comp4* $_{t-1}$ with their predicted values from the first stage. The results are presented in Models (2) and (4), respectively. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	*(1)* *RegIn_Comp3* $_{t-1}$ First stage	**(2)** **Laborineff** **Second stage**	*(3)* *RegIn_Comp4* $_{t-1}$ First stage	**(4)** **Laborineff** **Second stage**
RegIn_Comp3_ST $_{t-1}$	0.109***			
	(4.87)			
RegIn_ Comp3_SIC2 $_{t-1}$	-6.176***			
	(-5.89)			
RegIn_ Comp4_ST $_{t-1}$			0.037**	
			(2.01)	
RegIn_ Comp4_SIC2 $_{t-1}$			-5.498***	
			(-7.13)	
RegIn_ Comp3 (Instrumented) $_{t-1}$		-0.021***		
		(-3.31)		
RegIn_ Comp4 (Instrumented) $_{t-1}$				-0.014*
				(-1.96)
AQ $_{t-1}$	-0.000	0.004***	0.006***	0.004***
	(-0.35)	(7.25)	(3.53)	(5.58)
MTB $_{t-1}$	-0.000	0.000*	0.000	0.000*
	(-0.41)	(1.74)	(0.76)	(1.88)
FirmSize_R $_{t-1}$	-0.000	-0.000***	0.000	-0.000***
	(-0.82)	(-4.19)	(0.85)	(-3.67)
Quick $_{t-1}$	-0.005**	0.004***	-0.001	0.003***
	(-2.16)	(4.74)	(-0.24)	(4.53)
Lev $_{t-1}$	0.009	0.001	0.017	0.001
	(0.80)	(0.26)	(1.26)	(0.17)
DivDum $_{t-1}$	-0.000	-0.007***	0.004	-0.006**
	(-0.02)	(-3.22)	(0.60)	(-2.54)
STD_CFO $_{t-1}$	-0.050***	0.009**	-0.023*	0.012***
	(-3.10)	(2.20)	(-1.95)	(2.70)
STD_Sales $_{t-1}$	-0.017	0.064***	-0.027	0.059***
	(-0.94)	(8.16)	(-1.48)	(7.10)
Tangibles $_{t-1}$	0.036*	-0.039***	-0.038	-0.040***
	(1.88)	(-5.13)	(-1.62)	(-4.99)

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Loss $_{t-1}$	-0.007	0.014***	0.000	0.015***
	(-1.56)	(5.53)	(0.07)	(5.43)
Inst $_{t-1}$	-0.003	-0.023***	-0.008	-0.023***
	(-0.42)	(-5.92)	(-0.92)	(-5.50)
STD_Net_Hire $_{t-1}$	0.000	0.018***	-0.003	0.020***
	(0.00)	(7.63)	(-0.59)	(7.44)
Labor_Intensity $_{t-1}$	0.230	-0.903***	-0.045	-0.797***
	(0.63)	(-5.06)	(-0.12)	(-4.15)
Union $_{t-1}$	-0.000	-0.000*	0.000	-0.000
	(-0.81)	(-1.74)	(0.41)	(-1.09)
|*Ab_Invest_Other*| $_{t}$	-0.094***	0.051***	0.028	0.033***
	(-2.99)	(4.13)	(1.00)	(2.74)
MA $_{t-1}$	-0.011	-0.011***	-0.024**	-0.012***
	(-1.31)	(-3.05)	(-2.42)	(-3.11)
First-stage regressors	Yes	Yes	Yes	Yes
Constant	0.130**	-2.947***	10.140***	0.031
	(2.28)	(-6.50)	(8.28)	(1.131)
Observations	56,726	56,726	47,737	47,737
R-squared	0.210	0.153	0.158	0.151
Hansen stats		0.0297		0.0983
Hansen pvalue		0.863		0.754
Kleibergen-Paap rk Wald F		31.09		27.40
Kleibergen-Paap rk LM statistic		70.02		120.2
Kleibergen-Paap rk LM pvalue		0		0
Clustered std err by firm	Yes	Yes	Yes	Yes
*Industry * Year F.E.*	Yes	Yes	Yes	Yes

3.2.3. Controlling for Financial Constraints

In this section, we examine whether the impact of regulatory intensity on labor investment efficiency is conditional on financial constraints. If the regulatory burden motivates managers to reduce labor investment inefficiency, the effect should be stronger for financially constrained firms as they are under greater pressure to improve financial flexibility to avoid default. We proxy the level of financial constraints with the Whited and Wu index (*WW index*) and Merton distance to default (*DD*). Whited and Wu (2006) model financial constraints as the projection of the shadow price of raising equity capital. Specifically, the *WW index* is calculated with the following equation:

$$WW\ index = -0.091 * CashFlow - 0.062 * Payout + 0.021 * LTD - 0.044 *$$

$$\mathrm{Log}(Total\ assets) + 0.102 * IndSG - 0.035 * SG, \quad (3)$$

where *CashFlow* is income before extraordinary items plus depreciation divided by the book value of total assets. *Payout* is an indicator variable, coded as one if the sum of common and preferred dividends is positive and zero otherwise. *LTD* is long-term debt divided by the book value of total assets. *Log(Total assets)* is the logarithm of total assets. *IndSG* is the average industry sales growth, where industries are classified using the three-digit SIC industry code. *SG* is the sales growth rate.

The Merton distance to default model was developed by KMV corporation based on the Merton's bond pricing model (Merton, 1974) and is widely used by academia and practitioners to predict firms' likelihood of default (Duffie et al., 2007; Bharath & Shumway, 2008; Chen & So, 2014; Nagel & Purnanandam, 2020). The model assumes that equity value equals the value of a call option on firm value with the strike price being the face value of the firm's debt. According to put-call parity, the value of the firm's debt equals the value of a risk-free discount bond minus the value of a put option written on the firm with the same strike price and maturity.

We revisit our baseline regression, segmenting firm-year observations into financially constrained and unconstrained subsamples if they belong to the top and bottom tertile of the sample distribution using the two proxies, respectively. Table 7 displays the results. Models (1)-(4) and Models (5)-(8) use *DD* and the *WW index* to define financial constraints, respectively. The coefficients of *RegIn_Comp3* $_{t-1}$/ *RegIn_Comp4* $_{t-1}$ are negative and significant in constrained firms but insignificant in unconstrained firms, and the differences in the coefficients are statistically significant between the two subsamples. These results confirm our conjecture that constrained firms are more motivated to improve labor investment efficiency under greater regulatory intensity, potentially due to its lower adjustment costs relative to those of fixed asset adjustments.

Table 7. The effect of financial constraints. This table reports the results of subsample analyses on whether the effect of regulatory burden on labor investment efficiency is conditional on the level of financial constraints. Models (1)-(4) and (5)-(8) use Merton distance to default and the WW index to define financial constraint, respectively. Firm-year observations in the top tertile of the sample distribution are classified as constrained firms and the bottom tertile of the sample distribution as unconstrained firms. Refer to Appendix A for detailed variable definitions. All continuous variables are winsorized at the upper and lower 1% of the sample distribution. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Laborineff							
	Distance to default				WW index			
Variables	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained
RegIn_Comp3 $_{t-1}$	-0.090**	0.013			-0.069**	0.018		
	(-2.032)	(0.541)			(-2.511)	(0.976)		
RegIn_Comp4 $_{t-1}$			-0.069*	-0.002			-0.063***	-0.009
			(-1.926)	(-0.103)			(-2.751)	(-0.397)
AQ $_{t-1}$	0.033	0.021	0.043*	0.012	-0.012	0.028	-0.020	0.016
	(1.504)	(1.112)	(1.738)	(0.498)	(-0.760)	(1.612)	(-1.112)	(0.773)
MTB $_{t-1}$	0.017	0.027**	0.016	0.037**	0.020**	0.008	0.026**	0.014
	(1.455)	(2.103)	(1.249)	(2.457)	(2.023)	(0.812)	(2.499)	(1.424)
FirmSize_R $_{t-1}$	-0.000	-0.004	-0.032	-0.004	0.007	0.035	0.004	0.025
	(-0.011)	(-0.060)	(-0.810)	(-0.053)	(0.338)	(1.145)	(0.187)	(0.764)
Quick $_{t-1}$	0.068**	0.048**	0.065*	0.048*	0.026	0.046	0.026	0.048
	(2.054)	(2.103)	(1.754)	(1.925)	(1.393)	(1.477)	(1.432)	(1.428)

Lev $_{t-1}$	-0.072***	-0.012	-0.074***	-0.033	0.001	-0.034	-0.004	-0.042
	(-3.367)	(-0.640)	(-3.057)	(-1.568)	(0.064)	(-1.330)	(-0.198)	(-1.498)
DivDum $_{t-1}$	0.044***	-0.026	0.040**	-0.021	0.026**	0.031*	0.033***	0.026
	(2.691)	(-1.131)	(2.258)	(-0.900)	(2.081)	(1.707)	(2.648)	(1.347)
STD_CFO $_{t-1}$	-0.006	0.010	-0.009	0.014	0.047**	0.038**	0.060***	0.043**
	(-0.365)	(0.491)	(-0.494)	(0.618)	(2.279)	(2.367)	(2.588)	(2.410)
STD_Sales $_{t-1}$	0.006	0.034*	-0.002	0.029	0.044***	0.023	0.031*	0.022
	(0.295)	(1.829)	(-0.100)	(1.410)	(2.650)	(1.523)	(1.671)	(1.334)
Tangibles $_{t-1}$	0.018	-0.041	0.011	-0.069	0.017	-0.013	0.008	-0.003
	(0.445)	(-1.030)	(0.242)	(-1.425)	(0.700)	(-0.230)	(0.296)	(-0.050)
Loss $_{t-1}$	-0.022*	0.008	-0.022*	0.001	0.019**	-0.006	0.015	-0.011
	(-1.910)	(0.499)	(-1.694)	(0.070)	(2.051)	(-0.570)	(1.463)	(-1.011)
Inst $_{t-1}$	0.006	-0.012	0.010	-0.010	-0.006	0.006	-0.007	0.012
	(0.568)	(-0.581)	(0.884)	(-0.423)	(-0.331)	(0.316)	(-0.385)	(0.661)
STD_Net_Hire $_{t-1}$	-0.105***	-0.084**	-0.104***	-0.094**	-0.079***	-0.138***	-0.086***	-0.154***
	(-4.224)	(-2.081)	(-3.405)	(-2.076)	(-4.191)	(-3.085)	(-3.630)	(-2.731)
Labor_Intensity $_{t-1}$	-0.174***	-0.267***	-0.137**	-0.211***	-0.161***	-0.125***	-0.148***	-0.141***
	(-3.468)	(-4.324)	(-2.426)	(-3.307)	(-4.861)	(-3.062)	(-4.172)	(-3.157)
Union $_{t-1}$	-0.068	-0.045*	-0.071	-0.056***	-0.008	-0.022	-0.021	-0.024
	(-1.445)	(-1.685)	(-1.492)	(-3.116)	(-0.184)	(-0.576)	(-0.615)	(-0.538)
|Ab_Invest_Other| $_{t}$	0.060***	0.037*	0.044**	0.032	0.026**	0.023*	0.008	0.022
	(3.532)	(1.924)	(2.495)	(1.559)	(2.019)	(1.775)	(0.587)	(1.591)
MA $_{t-1}$	0.033**	0.043***	0.026*	0.041***	0.008	0.016	0.000	0.018
	(2.390)	(3.480)	(1.680)	(3.046)	(0.690)	(1.539)	(0.037)	(1.594)

First-stage regressors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.088***	0.038	0.092**	0.047	0.148***	0.007	0.173***	0.026
	(2.619)	(0.894)	(2.448)	(0.943)	(5.626)	(0.186)	(6.162)	(0.658)
Chi-squared stats	8.29***		3.59**		12.03***		9.01***	
Observations	14,668	14,586	12,722	12,441	18,072	18,319	15,275	16,516
R-squared	0.196	0.195	0.197	0.203	0.182	0.192	0.187	0.194
Clustered std err by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.3. Additional Analyses

We further analyze whether other firm characteristics, such as operation capital, labor adjustment costs, and the level of labor intensity, affect the association between regulatory intensity and labor investment efficiency.[14] Specifically, we conduct several sets of subsample analyses. First, we classify the sample into two subsamples based on labor investment inefficiency types, i.e., observations with positive abnormal hiring (firms over-investing in labor) and those with negative abnormal hiring (firms under-investing in labor). Second, we created subsamples based on labor adjustment costs using various dimensions, including the sample medians of lagged *R&D/Sales* (defined as the ratio of R&D expenses to sales), lagged organization capital, and human capital intensity industries. We construct organization capital as in Gao et al. (2021).[15] Following the literature (Ben-Nasr & Ghouma, 2018; Ertugrul, 2013; Ghaly et al., 2015), we classify telecommunications, high-tech, and healthcare industries as high human capital intensive industries, i.e., observations with the SIC codes of 283, 357, 36, 384, 48, and 80, with the rest of the sample being low human capital intensity industries. Third, we dissect our sample with the median values of labor intensity (*Labor_Intensity*). Our baseline results continue to hold for all these subsample analyses. Collectively, our results show that the positive impact of regulatory intensity on labor investment efficiency is unconditional on labor investment inefficiency types and labor adjustment costs. For brevity, the results are not tabulated but available upon request.

4. Conclusions

We investigate whether and how regulatory intensity affects corporate labor investment efficiency in U.S. firms. We measure labor investment inefficiency with the deviation of labor investment from the optimal level justified by a firm's economic fundamentals. We use the four newly developed firm-level regulatory intensity measures by Kalmenovitz (2023). These proxies are unique given that they are constructed on regulations relevant to a firm. They measure the number of active regulations and their estimated compliance costs, including the number of responses, time spent to comply, and dollars spent to comply. Additionally, we use two composite measures constructed from Principal Components Analysis (PCA) using the above regulatory intensity component variables.

[14]Organization capital facilitates the match between human resources and production facilities, and hence affects the efficiency of a firm (Bharadwaj, 2000; Eisfeldt & Papanikolaou, 2013).

[15]Refer to Gao et al. (2021) for details.

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We find that labor investment inefficiency decreases with firm-level regulatory intensity and the effect is driven by financially constrained firms. The results are robust to various model specifications and subsample analysis. The results are consistent with the view that regulations are beneficial, though costly, but firms can transfer regulatory burden to opportunities to develop competitive advantage. Our study complements Ince (2024) which documents that firms use within-industry acquisitions to spread compliance costs. Labor investment and within-industry M&As cannot be the only channels through which firms absorb regulatory compliance costs. We call for research on other potential vehicles.

As pointed out by Kalmenovitz (2023), causal inference of firm-level regulatory intensity on corporate decisions is challenging. Though we employ various strategies, we kindly advise our readers to excersize caution in interpreting the results. We do not claim that our finding is purely causal. However, the positive association between regulatory intensity and labor investment efficiency documented in this study should be of interest to regulatory bodies and regulated companies. Regulations are costly, but firms can find ways to digest regulatory costs through other firm decisions. Our results may provide important policy implications for heated policy discussions on the costs and benefits of paperwork reduction policies in the United States.

Appendix A. Variable definitions

	Definition
Laborinefft	Labor investment inefficiency, constructed as the absolute values of the residuals from Eq. (1) in financial year t.
RegIn_Reg $_{t-1}$	Logarithm of the number of active paperwork regulations in calendar year t-1. The data is obtained from https://sites.google.com/view/jkalmenovitz .
RegIn_Resp $_{t-1}$	Logarithm of the total number of responses received ("how much paperwork") in calendar year t-1.
RegIn_Time $_{t-1}$	Logarithm of total hours invested by the public to comply with paperwork regulation in calendar year t-1, including the time it takes to collect the information, read the instructions, and file the paperwork.
RegIn_Dollar$_{t-1}$	Logarithm of total dollars invested by the public for compliance in calendar year t-1.
RegIn_Comp3$_{t-1}$	The component generated from the first three regulatory intensity proxies with an eigenvalue above 1 using the PCA analysis in calendar year t-1.
RegIn_Comp4$_{t-1}$	The component generated from all four regulatory intensity proxies with an eigenvalue above 1 using the PCA analysis in calendar year t-1.
NetHire$_{t-1}$	Percentage change in the number of employees (EMP) from financial year t-1 to financial year t
SGR$_{t-1}$	Percentage change in sales in financial year t-1.
SGR$_t$	Percentage change in sales in financial year t for firm i.
ΔROA$_t$	Change in return on assets (NI/lag (AT)) in financial year t.
ΔROA$_{t-1}$	Change in return on assets in financial year t-1.
ROA$_t$	Return on assets in financial year t.
Return$_t$	Total stock return during financial year t.
FirmSize_R $_{t-1}$	Percentile rank of firm market capitalization (CSHO*PRCC_F) at the end of year t-1.
Quick $_{t-1}$	Quick ratio ((CHE+RECT)/LCT) at the end of financial year t-1.
ΔQuick $_{t-1}$	Percentage change in the quick ratio in financial year t-1.

$\Delta Quick_t$	Percentage change in the quick ratio in financial year t.
Lev_{t-1}	The sum of debt in current liabilities and total long-term debt (DLC+DLTT) scaled by total assets (AT) at the end of financial year t-1.
AUR_{t-1}	Ratio of annual sales to total assets in financial year t-1.
$LossBin1_{t-1}$ $LossBin2_{t-1}$ $LossBin3_{t-1}$ $LossBin4_{t-1}$ $LossBin5_{t-1}$	There are five separate loss bins for each 0.005 interval of ROA from 0 to −0.025 in period t-1. LossBin1 equals 1 if ROA ranges from −0.005 to 0. LossBin2 equals 1 if ROA ranges from −0.005 to −0.010. LossBin3 equals 1 if ROA ranges from −0.010 to −0.015. LossBin4 equals 1 if ROA ranges from −0.015 to −0.020. LossBin5 equals 1 if ROA ranges from −0.020 and−0.025.
AQ_{t-1}	Accounting quality, constructed as in Dechow and Dichev (2002) model modified by McNichols (2002) and Francis et al. (2005). We regress working capital accruals on one-year-lagged, current, and one-year-ahead cash flows from operations, the change in revenue, and property, plant, and equipment cross-sectionally by industry-year and estimate the residuals. We multiply the standard deviation of firm i's residuals over the past 5 years (t-5 to t-1) by −1 (so that it increases with accounting quality). Finally, we rank the resulting measure into deciles by year.
MTB_{t-1}	Market-to-book ratio (CSHO*PRCC_F/SEQ) in year t−1.
$DivDum_{t-1}$	Indicator variable that equals 1 if firm i paid dividends (DVPSP_F) in financial year t-1 and zero otherwise.
STD_CFO_{t-1}	Standard deviation of cash flows from operations (OANCF) from financial year t-5 to t-1.
STD_Sales_{t-1}	Standard deviation of sales from year t-5 to t-1.
$Tangibles_{t-1}$	Property, plant, and equipment (PPENT) scaled by total assets, both measured at the end of financial year t-1.
$Loss_{t-1}$	Indicator variable that equals 1 if firm i had negative ROA for financial year t-1 and zero otherwise.
$Inst_{t-1}$	Percentage of institutional shareholdings at the end of financial year t-1.
$STD\_Net\_Hire_{t-1}$	Standard deviation of the change in the number of employees (EMP) from financial year t-5 to t-1 for firm i.
$Labor\_Intensity_{t-1}$	Labor intensity, constructed as the number of employees divided by total assets at the end of financial year t-1.
$Union_{t-1}$	Industry-level labor unionization rate for financial year t-1, obtained from www.unionstats.com.
$\lvert AB\_Abnormal\_InvestOther_t$	Abnormal non-labor investments, constructed the absolute values of the residual from the following equation: Invest_Otherit=β0+β1SGRit-1+εit , where Invest_Other is the sum of capital expenditure (CAPEX), research and development expenditures (XRD), less cash receipts from the sale of property, plant, and equipment (SPPE), all scaled by lagged total assets.
MA_{t-1}	The industry-year decile rank of managerial ability scores constructed by Demerjian et al. (2012).

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