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Organization capital and labor investment efficiency

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ABSTRACT

We examine whether a firm's organization capital (OC) affects its labor investment efficiency. We find that a higher level of OC is related to lower deviations from the optimal level of labor investment according to economic conditions (higher labor investment efficiency). We find that this result is empirically robust to a stacked difference-in-differences approach using exogenous CEO turnover as a quasi-natural experiment and planned CEO retirements and forced CEO turnovers as placebo tests. We identify that the ability to retain talented employees and reduction of agency costs are the two channels by which OC improves a firm's labor investment efficiency. Furthermore, we report that the positive effect of OC on labor investment efficiency is more pronounced in firms in highly competitive markets, firms with better access to external financing and firms with highly skilled labor.

1. Introduction

> "Talent, not [financial] capital, will be the key factor linking innovation, competitiveness and growth in the 21st century… Business, in particular, must rethink its role as a consumer of 'ready-made' human capital to proactively seek out, engage and develop people's potential. Better data and metrics are critical to this undertaking."
>
> - Klaus Schwab, Founder and Executive Chairman of the World Economic Forum, in his preface to *The Human Capital Report 2015*.

The abovementioned quotation highlights the importance of organization capital (OC) in the context of human capital (labor) investment. OC is a firm's unique knowledge, business procedures, and systems that allow firms to make better use of their financial resources (Evenson and Westphal, 1995). Therefore, firms are able to facilitate the matching of labor with physical production facilities. In this paper, we examine whether firms can utilize their OC to make more efficient labor investments.

Examining labor investment efficiency is important because efficient labor investment enhances competitive advantages (Becker, 1962), earnings and firm value (Merz and Yashiv, 2005). As a result, deviations from the optimal level of labor investment, namely, over- and under-investment, can result in overcapacity issues and poorer productivity, respectively (Williamson, 1963; Stein, 1989).[1] Over- and underinvestment problems related to labor become even more severe for human capital-intensive firms in modern knowledge-based economies (Zingales, 2000). This is evidenced by the recent attention given by BlackRock (the largest asset management firm) to labor investment concerns. For example, Blackrock's engagement priorities for 2020 state that they expect their board to supervise human capital management plans since most firms consider their personnel as their main vital assets. Therefore, Blackrock will hold its directors responsible if no disclosures are made regarding the board's involvement in overseeing the firm's human resource policies. As a result, a greater emphasis could be placed on whether streamlined business procedures, systems, and know-how (i.e., OC) can help or hinder firms in terms of efficiently investing in matching personnel, hence increasing or decreasing their labor investment efficiency.

To investigate the empirical association between OC and labor investment efficiency, we use a previously developed proxy for OC that has been used extensively (Lev et al., 2009; Eisfeldt and Papanikolaou, 2013; Li et al., 2018; Hasan and Cheung, 2018; Gao et al., 2021). We use capitalized selling, general, and administrative (SG&A) expenses, including those related to IT infrastructure, information systems, R&D and knowledge building. When calculating our labor investment efficiency metric, we follow Pinnuck and Lillis (2007). We begin by

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[1] Overinvestment in labor occurs when agency conflicts drive managers to engage in empire-building. Underinvestment, on the other hand, occurs when managers are pressured to meet earnings objectives by outside investors, as such, managers become concerned that high labor costs will limit short-term profitability.

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estimating the degree of labor investment that is justified by economic fundamentals such as profitability, leverage, and sales growth. Then, we use the absolute value of the regression residuals as our main dependent variable (Jung et al., 2014). A lower value of this main dependent variable suggests lower labor investment inefficiency.

Using a sample of 23,709 firm-year observations from the U.S. from 1991 to 2018, we show that OC is positively associated with labor investment efficiency. For example, a one-standard-deviation increase in OC is related to a 12.4 % (-0.0109 $\times$1.3381/0.1176) reduction in $|Ab\_Net\_Hire|$ from the mean (i.e., higher labor investment efficiency) after controlling for firm and year fixed effects. This finding supports our conjecture that firms with higher OC are more efficient in terms of labor investment due to their superior knowledge and expertise. Our results continue to hold if we employ alternative measures of OC and labor investment efficiency that are commonly used in the recent literature.

To identify the causal effect of OC on labor investment efficiency, we exploit a quasi-natural experiment using exogenous CEO turnover. Exogenous CEO turnover is defined as CEO turnover that is driven by non-firm-specific reasons such as health-related reasons. We conjecture that exogenous CEO turnover negatively shocks a firm's OC since Eisfeldt and Papanikolaou (2013) argue that CEOs are significant contributors to firms' OC. Then, we select firms that experience CEO departures due to health issues as our treatment firms. We expect the treatment firms to exhibit an upward trend in labor investment inefficiency after the CEO turnover events.

We conduct a stacked difference-in-differences (DID) regression similar to those of Lemmon and Roberts (2010), Gormley et al. (2013), and Gao et al. (2021). Specifically, we stack cohorts of treatment and control firms. The control firms in each turnover event cohort are in the same industry as the corresponding treatment firms, but they do not experience CEO departures three years before or after the treatment event. We use the nearest propensity scores and a caliper of 0.01 to select four control firms in each cohort that are comparable in terms of size and OC to the corresponding treatment firm. We find that firms respond to exogenous CEO departures by reducing their labor investment efficiency. A dynamic estimation that identifies the treatment effect timing supports the assumption of parallel trends in the DID setting. Using planned CEO retirement and forced CEO turnover as the placebo tests, we find no difference between the treatment and control groups. Overall, our findings suggest a positive relationship between OC and labor investment efficiency.

We identify two channels through which OC improves a firm's labor investment efficiency. Specifically, we show that firms with high OC are able to maintain better investments in labor resources because of their ability to attract and retain talented employees and their capacity to maintain better alignment of interests between managers and shareholders that reduce agency costs in the firm.

We also examine the moderating roles of other factors (e.g., product market competition, external financing, labor skills) in the OC-labor investment efficiency relationship. We argue that OC can help improve the labor investment efficiency of firms in highly competitive markets, as OC promotes firms' competitive advantage. Consistent with our conjecture, we show that the positive relationship between OC and labor investment efficiency is more pronounced in firms facing many competition threats. Moreover, we argue that efficient labor investment requires adequate financing. Firms that do not have sufficient funds are less likely to enjoy labor investment efficiency. Therefore, in the case of firms with better access to external financing, we conjecture that the role of OC in enhancing firms' ability to invest efficiently may be relatively important. Similarly, OC may play a relatively prominent role in improving the labor investment efficiency of firms that face higher labor adjustment costs due to their greater reliance on skilled labor (Oi, 1962; Dixit, 1997). Next, we investigate the role of nonlabor investment (i.e., capital expenditures, R&D expenditures, advertising expenditures, and acquisition expenditures) and demonstrate that the positive OC-labor investment efficiency relationship is not driven by the complementarity between nonlabor investments and labor investments. Finally, we show that firms with OC and low labor investment efficiency are rewarded with improved future operating performance (i.e., ROA) and an increase in firm value (Tobin's Q).

Our paper contributes to the literature in three important ways. First, we extend the emerging and rapidly growing body of literature on labor investment efficiency. For example, prior studies show that financial reporting quality (Jung et al., 2014), accounting comparability (Zhang et al., 2020), stock price informativeness (Ben-Nasr and Alshwer, 2016), institutional investors' horizons (Ghaly et al., 2020), and weak CEO-director ties (Khedmati et al., 2020) can increase labor investment efficiency. We extend this literature by investigating the effect of OC on labor investment efficiency. We provide strong evidence that OC fosters efficiency in labor investment by applying expertise and know-how to reduce agency conflicts in labor investment decisions. Our results are also economically significant because a one standard deviation increase in OC is associated with a 12.4 % decrease from the mean in labor investment inefficiency. Relative to other labor investment inefficiency predictors, the economic significance of OC is ranked as the third most important determinant (12.4 %) of labor investment inefficiency, ranking just after other abnormal investments (39.83 %) and firm size (17.08 %).

Second, our paper adds to the growing body of literature on the importance of OC. Proponents of this concept provide evidence that firms' OC is associated with superior performance (Corrado et al., 2009; Eisfeldt and Papanikolaou, 2013; Hasan and Cheung, 2018), value creation in M&As (Li et al., 2018), and competitive advantages (Lev et al., 2009). However, opponents argue that OC leads to information asymmetry due to the high complexity of information (Kim et al., 2021). Our findings suggest that OC is important for firm investment strategies and policies: higher OC facilitates better investments in human capital. Furthermore, identifying the two channels through which OC affects labor investment efficiency contribute to our understanding of how OC not only helps in attracting and retaining talent but also facilitates better managerial alignment with firm-wide goals with agency mitigating mechanisms. Thus, our paper makes a significant contribution to the literature on organizational capital and corporate governance.

Third, our research sheds light on policy implications for labor investment efficiency, which is already on regulators' and investors' agendas. For example, the Securities and Exchange Commission (SEC) enacted the final modification to Regulation S-K on November 9, 2020, requiring companies to disclose their human capital resources. The required information includes any human capital measures or objectives related to attracting, developing or retaining personnel. Furthermore, in their 2020 stewardship reports, major corporations such as Blackrock and Vanguard express concerns regarding labor investments.[2] Our study emphasizes how OC can help enhance labor investment efficiency, thus contributing to regulatory discussions and implementation. Moreover, investors, who usually evaluate firm performance by observing firms' investment decisions, can benefit from our findings, specifically our evidence regarding firms' OC and labor investment efficiency.

The remainder of this paper proceeds as follows. Section 2 discusses literature review and hypothesis development. Section 3 provides the research design. Section 4 describes our empirical results, and Section 5 shows our robustness tests. Section 6 concludes the work.

[2] See the following for more details:https://corpgov.law.harvard.edu/2020/10/31/incorporating-human-capital-management-disclosures-into-a-companys-annual-report/https://about.vanguard.com/investment-stewardship/perspectives-and-commentary/2021_investment_stewardship_annual_report.pdf

2. Literature review and hypothesis development

2.1. Literature review

Organizational capital (OC) has emerged as one of the most critical intangible assets in contemporary firms, significantly influencing various dimensions of firm performance, including labor investment efficiency. OC encompasses the accumulated knowledge, business processes, and employee expertise that collectively enable a firm to operate more effectively. Prior research has consistently highlighted the value of OC, positioning it as a pivotal driver of competitive advantage and enhanced firm performance.

OC is increasingly recognized as a vital component of a firm's intangible assets. Corrado et al. (2009) underscore the growing importance of OC, arguing that it has become one of the most valuable intangible assets in modern firms. Peters and Taylor (2017) build on this, developing a method to estimate OC and finding that it accounts for a significant portion of firm value. Eisfeldt and Papanikolaou (2014) further support this view, emphasizing that OC contributes to the firm's sustainable competitive advantage and is closely associated with superior financial performance. Lev et al. (2009) also link OC directly to enhanced firm productivity and overall performance. These studies collectively suggest that OC is not just a static asset but a dynamic resource that continuously enhances a firm's competitive positioning in the market.

OC's impact on firm productivity is well-documented. Atkeson and Kehoe (2005) demonstrate that firms with higher levels of OC exhibit greater productivity, owing to more efficient business processes and better-trained employees. Lev et al. (2009) further establish that OC plays a crucial role in facilitating mergers and acquisitions (M&A), as firms with substantial OC are better equipped to integrate new operations and maintain high performance post-acquisition. Li et al. (2018) extend this argument, showing that OC not only enhances M&A performance but also serves as a buffer against the risks associated with such transactions. These findings underscore the role of OC in driving productivity improvements and long-term firm success.

The relationship between OC and a firm's lifecycle has also been explored in the literature. Hasan and Cheung (2018) argue that firms with higher OC are less likely to enter unfavorable life cycle stages, such as decline or stagnation. This is because OC equips firms with the necessary resources to adapt to changing market conditions and sustain growth over time. By continuously investing in OC, firms can avoid the pitfalls associated with lifecycle challenges, thereby maintaining their competitive edge and ensuring sustained performance.

Several studies have examined the influence of OC on a firm's investment behavior and financial returns. Eisfeldt and Papanikolaou (2013) find that firms with higher OC experience increased expected returns and reduced investment-cash flow sensitivity, indicating a more efficient allocation of resources. Attig and Cleary (2014) support this finding, demonstrating that OC reduces market imperfections, making it easier for firms to attract and retain talented employees. Leung et al. (2018) further highlight that firms investing in OC are better positioned to capitalize on growth opportunities, thereby enhancing their overall financial performance.

The link between OC and labor investment efficiency is particularly compelling. Firms with higher OC can reduce labor investment inefficiencies by aligning managerial incentives with organizational goals, thereby fostering a more efficient allocation of human capital. Moreover, the improved performance and future success associated with high OC enable firms to minimize market imperfections. Attig and Cleary (2014) suggest that this reduction in market imperfections allows firms to more effectively attract and retain top talent, further enhancing labor investment efficiency. By maintaining a stable and skilled workforce, firms with high OC are better positioned to achieve sustained growth and competitive advantage.

In summary, the literature strongly supports the view that organizational capital is a critical determinant of labor investment efficiency. OC not only enhances firm productivity and performance but also can mitigate risks associated with overinvestment and underinvestment. By reducing market imperfections and aligning managerial incentives with firm objectives, OC plays a pivotal role in ensuring that labor investments are both efficient and strategically aligned with the firm's long-term goals. These insights lay the foundation for the hypotheses proposed in the subsequent section, which explores the dual effects of OC on labor investment efficiency.

2.2. Hypothesis development

We propose two competing hypotheses regarding the relationship between organizational capital (OC) and labor investment efficiency. On the one hand, OC can reduce labor investment inefficiency by mitigating agency costs, which are composed of two key elements: (1) the free cash flow problem and (2) the quiet life hypothesis.

First, agency costs, as discussed by Jensen and Meckling (1976), arise when managers have access to free cash flow, leading to overinvestment in projects that may not maximize shareholder value, such as empire building. OC, which includes effective business processes, well-trained employees, and technological know-how, can mitigate this issue. Firms with high OC require less managerial oversight and planning to maintain a competitive edge, thereby reducing the likelihood of overinvestment in labor. High-quality personnel and efficient systems allow firms to curb managers' tendencies to overinvest, thereby enhancing labor investment efficiency (Shleifer and Vishny, 1997).

Second, the quiet life hypothesis proposed by Bertrand and Mullainathan (2003), suggests that managers may underinvest in productive assets, including labor, to avoid the effort and stress associated with optimizing firm performance. OC can counteract this underinvestment by fostering an environment that encourages innovation and proactive decision-making. High OC enables firms to attract and retain top talent, particularly key employees, who drive corporate innovation—a critical force for maintaining competitiveness and achieving long-term growth (Porter, 1989; Francis et al., 2021). By reducing the propensity for underinvestment, OC contributes to better alignment of labor investments with the firm's strategic objectives (Kaplan and Norton, 2004).

Regarding employee retention, it is crucial to clarify how OC influences the retention of key talent who are vital for innovation. High OC helps prevent the loss of key talent by creating a supportive and engaging work environment, thereby reducing the probability of turnover. This ability to retain employees is essential for sustaining competitive advantage and fostering long-term growth through continuous innovation. However, the actual loss of key talent, although less likely in high-OC firms, can still have significant negative impacts due to the critical roles these employees play. Therefore, the expected loss of key talent can be expressed as:

$$E[\text{Loss of key talent}] = \text{Probability of losing key talent (low)} \times \text{Actual loss of key talent (high)}$$

This highlights the dual role of OC in managing employee retention—minimizing the probability of turnover while acknowledging the substantial impact if key employees do leave. Supporting this view, Eisfeldt and Papanikolaou (2013) demonstrate that high-OC firms have higher managerial quality scores, according to the measure of Bloom and Van Reenen (2007), spend more on information technology (IT), and are more likely to list "loss of key personnel" as a risk factor in their 10-K filings. This evidence underscores the importance of key talent in high-OC firms and the associated risks if such talent is lost.

On the other hand, organizational capital (OC) may lead to lower labor investment efficiency due to the hold-up problem. Key talent, who possess firm-specific skills and knowledge, are often difficult and costly to replace (Eisfeldt and Papanikolaou, 2014). This gives them significant bargaining power to negotiate better employment terms, such as higher compensation or additional benefits. Moreover, these employees can potentially hold up operations or strategic decisions by leveraging their importance to the firm. Such situations can exacerbate agency problems between shareholders and key employees, as the latter may prioritize their own interests over those of the firm. The increased bargaining power of key employees, akin to the hold-up problem described by Hart and Moore (1990) and Grossman and Hart (1986), can lead to inefficiencies in labor investment, as these employees may use their leverage to extract greater benefits, thereby complicating the alignment of interests between shareholders and the firm's key talent.

Based on the discussion above, we hypothesize the following:

H1a. : OC is positively associated with labor investment efficiency.

H1b. : OC is negatively associated with labor investment efficiency.

3. Research design

3.1. Sample and data

We collect finance and accounting data for OC and control variable construction from Compustat and institutional ownership information from Thomson Reuters. Moreover, we collect labor union data from Hirsch and Macpherson's (2003) updated Union Membership and Coverage database.[3] Our final sample contains firms (excluding financial and utility firms) traded on the NYSE, AMEX, and NASDAQ with information in each of these databases. Firms with missing data for any of the variables are excluded. Our final sample covers 2456 firms (23,709 firm-year observations) from 1991 to 2018.[4]

3.2. Independent variable: Organizational capital (OC)

Following literature on OC, such as Eisfeldt and Papanikolaou (2013), we proxy each firm's OC using its capitalized SG&A expenses. SG&A expenses include nonproduction costs, such as IT expenses, advertising and marketing expenses, R&D expenses, and information and distribution system investments. We use the perpetual inventory method to construct our OC variable. Specifically, we recursively compute OC stock by aggregating the deflated value of SG&A expenses as follows:

$$OC_{i,t} = (1-\delta_{OC})OC_{i,t-1} + \frac{SGA_{i,t}}{CPI_t}, \tag{1}$$

where δ_{OC} is the OC depreciation rate, which is set to 15 % by the Bureau of Economic Analysis in their R&D capital estimation; $SGA_{i,t}$ is the SG&A expenses of firm i in year t; and CPI_t is the consumer price index. We then value the initial OC stock of each firm as follows:

$$OC_{i,0} = \frac{SGA_{i,1}}{g+\delta_{OC}}, \tag{2}$$

where $SGA_{i,1}$ is the initial-year SG&A of firm i in the sample with no missing data and g represents the average real growth rate of firm-level SG&A expenses. Finally, we standardize the OC stock based on the firms' total assets to obtain our key OC measure.

3.3. Dependent variable: Labor investment efficiency

To measure labor investment efficiency, we follow the two-stage approach of Pinnuck and Lillis (2007). First, we regress the percentage change in the number of employees of each firm, *Net_Hire,* on economic fundamentals as follows:

$$\begin{aligned} Net\_Hire_{it} = {} & \beta_0 + \beta_1 Sales\_Growth_{it-1} + \beta_2 Sales\_Growth_{it} + \beta_3 \Delta ROA_{it-1} + \beta_4 \Delta ROA_{it} + \beta_5 ROA_{it} + \beta_6 Return_{it} + \beta_7 SizeR_{it-1} + \beta_8 Quick_{it-1} + \beta_9 \Delta Quick_{it-1} \\ & + \beta_{10}\Delta Quick_{it} + \beta_{11} Leverage_{it-1} + \beta_{12} AUR_{it-1} + \beta_{13} LossBin1_{it-1} + \beta_{14} LossBin2_{it-1} + \beta_{15} LossBin3_{it-1} + \beta_{16} LossBin4_{it-1} + \beta_{17} LossBin5_{it-1} \\ & + IndustryFE + \varepsilon_{it} \end{aligned} \tag{3}$$

where *Sales_Growth* is the percentage change in sales; *ROA* is return on assets; *Return* is the annualized stock return; *Size_R* is the percentile rank of firm size; *Quick* is defined as cash and short-term investments plus receivables scaled by current liabilities; *Leverage* is the ratio of long-term debt and debt in current liabilities to the book value of assets; *AUR* is measured as annual sales to total assets; *LossBin1* is equal to one if prior-year ROA is between −0.005 and 0 and zero otherwise; *LossBin2* is equal to one if prior-year ROA is between −0.010 and −0.005 and zero otherwise; and *LossBin3, LossBin4, LossBin5* are similarly constructed dummies with interval lengths of 0.005 ([-0.015: −0.010]; [-0.020: −0.015]; [-0.025: −0.020], respectively). Appendix 1 and Appendix 2 present the variable definitions and regression results of Eq. (3), respectively. We obtain the regression residual from Eq. (3) and label it abnormal net hiring. We then employ the absolute value of the residuals as abnormal net hiring *(|Ab_Net_Hire|),* following Khedmati et al. (2020). A higher $|Ab\_Net\_Hire|$ value indicates that *a* firm is less efficient in its human investment practices.

3.4. Control variables

Our first group of control variables includes growth options *(MTB),* firm size *(Size)*, liquidity *(Quick)*, leverage *(Leverage),* dividend payouts *(Divdum),* cash flow and sales volatilities *(Std_CFO, Std_Sales),* tangibility *(Tangible),* the incidence of losses *(Loss),* institutions *(Insti),* the firms' net hiring volatility *(Std_Net_Hire)* and labor intensity *(Labor_Intensity),* indirect impacts from other investments *(|Ab_Invest_Other|)* and accounting quality *(AQ)*. We control for firm characteristics such as growth options, firm size, liquidity, leverage, dividend payouts, cash flow and sales volatility, tangibility, losses, institution ownership, labor hiring, and other investment outcomes, following prior literature on labor investment efficiency (Biddle and Hilary, 2006; Biddle et al., 2009; Jung et al., 2014; Ben-Nasr and Alshwer, 2016). These factors are standard determinants of firm investment policies and, more specifically, labor investment policies. We also control for accounting quality *(AQ)* to determine whether firms with higher-quality accounting are more or less efficient in their net hiring practices (Jung et al., 2014).

[3] This database is available at http://www.unionstats.com.

[4] The starting year, 1991, was chosen because it marks the first year for which *Std_CFO* data was available for our analysis. *Std_CFO* represents the standard deviation of firm i's cash flows from operations (OANCF/AT) over the period from year t-5 to t-1. The end year of the sample is 2018, which ensures the most recent data prior to the COVID-19, maintaining the relevance and applicability of our findings without getting impacted by the COVID-19 pandemic.

Among them, the most complicated variable in terms of construction is *|Ab_Invest_Other|*, which represents the extent to which other nonlabor investments diverge from their optimal level. We denote the absolute value of the residual from the regression below as *(|Ab_Invest_Other|)*:

$$\text{Invest\_Other}_{it} = b_0 + b_1\text{Sales\_Growth}_{it-1} + e_{it} \quad (4)$$

where Invest_Other_{it} is the sum of other nonlabor investments such as capital expenditures, acquisition expenditures and R&D expenditures less cash receipts from the sale of property, plant, and equipment scaled by lagged total assets.

In addition, we consider managerial ability rank *(MA),* which potentially affects a firm's investment policies. Jung et al. (2014) suggest that higher managerial ability drives managers to invest in labor more efficiently.[5] Finally, we include the industry-level unionization rate *(Union)* to control the bargaining power of labor unions. We posit that firms in industries with more organized labor face much pressure in relation to their labor investment. The variable definitions are presented in Appendix 1.

To test our hypothesis on the relationship between OC and labor investment efficiency, we construct the following model:

$$|Ab\_Net\_Hire|_{it} = \beta_0 + \beta_1 OC_{it-1} + \beta_2 MTB_{it-1} + \beta_3 Size_{it-1} + \beta_4 Quick_{it-1} + \beta_5 Leverage_{it-1} + \beta_6 Divdum_{it-1} + \beta_7 Std\_CFO_{it-1} + \beta_8 Std\_Sales_{it-1} + \beta_9 Tangible_{it-1} + \beta_{10} Loss_{it-1} + \beta_{11} Insti_{it-1} + \beta_{12} Std\_Net\_Hire_{it-1} + \beta_{13} LaborIntensity_{it-1} + \beta_{14} AQ_{it-1} + \beta_{15}|Ab\_Invest\_Other|_{it-1} + \beta_{16} MA_{it-1} + \beta_{17} Union_{it-1} + Firm\ FE + Year\ FE + \varepsilon_{it} \quad (5)$$

All ratio variables are winsorized at the 1st and 99th percentiles. The regression model is estimated with firm and year fixed effects. Firm-level clustering is used to correct the standard errors.

4. Results

4.1. Descriptive statistics

In this section, we provide summary statistics and correlations of the variables used in our study. Panel A of Table 1 describes the summary statistics of the variables used in this paper. The average (median) of the OC variable is 1.4441 (1.1032), and its standard deviation is 1.3381. These numbers are relatively comparable to those reported by recent studies on OC. For example, Gao et al. (2021) show that the average and standard deviation of OC in their sample are 1.302 and 1.196, respectively. Furthermore, the descriptive statistics of the labor investment efficiency measures and firm characteristic variables are consistent with those in prior literature on labor investment, e.g., Jung et al. (2014), Ghaly et al. (2020), Chowdhury et al. (2022). Specifically, we note that the mean (median) of *|Ab_Net_Hire|* is 0.1176 (0.0727), which is very close to the value of 0.1126 (0.0704) reported by Jung et al. (2014). Furthermore, we note that our sample firms exhibit characteristics that are similar to those presented by Jung et al. (2014), namely, their *Quick* (1.9896 in our sample and 1.7169 in Jung et al.'s (2015) sample), *Leverage* (0.2049 in our sample and 0.2216 in their sample), *Loss* (0.2576 in our sample and 0.2217 in their sample) and *Union* (0.1137 in our sample vs. 0.1416 in their sample) values.[6]

Panel B of Table 1 reveals the pairwise correlation matrix of the variables. We show that OC is negatively correlated with |Ab_Net_Hire|, which supports our conjecture that *a* firm's OC has a positive (negative) impact on its labor investment efficiency (inefficiency)[7]. The correlations between the other variables are also consistent with those reported in prior literature (Jung et al., 2014; Ben-Nasr and Alshwer, 2016; Ghaly et al., 2020; Khedmati et al., 2020). For instance, *|Ab_Net_Hire|* is positively correlated with *Std_CFO, Std_Sales, Std_Net_Hire*, *Loss,* and *|Ab_Invest_Other|*. These results suggest that higher cash flow, sales and net hiring volatility, greater losses, and more indirect effects of other investments are related to greater divergence from the optimal level of net hiring.

4.2. Baseline results

Table 2 presents the estimation results on the association between OC and labor investment efficiency. Starting with the full sample in Column (1), we find that the coefficient of OC is negative and significant at the 1 % level (-0.0109, t = -4.91), which is consistent with our hypothesis *H1a* that OC enhances labor investment efficiency. Economically, the results indicate that a one-standard-deviation increase in OC is related to a 12.4 % (-0.0109 ×1.3381/0.1176) decrease in *|Ab_Net_Hire|* from the mean*,* which implies *a* 12.4 % increase in the labor investment efficiency level.

The other control variables also appear to be consistent with those in the literature. For example, smaller firms *(Size),* firms with fewer tangible assets *(Tangible),* firms with more liquid assets *(Quick),* and firms with higher abnormal nonlabor investment *(Ab_Invest_Other)* exhibit less efficient labor investments.

Next, to further emphasize the impact of OC on labor investment decisions, we examine two main forms of labor investment inefficiency: overinvestment and underinvestment.

Overinvestment in labor, often driven by managerial motives such as empire-building, can lead to inefficiencies when managers prioritize personal interests over shareholder value. Managers may excessively hire or retain underperforming employees to expand their influence or achieve short-term gains, which can detract from the firm's long-term profitability (Jensen and Meckling, 1976; Jensen, 1986). However, strong OC within a firm "enables superior operating, investment, and innovation performance, represented by the agglomeration of technologies—business practices, processes and designs" (Lev et al., 2009) that foster transparency and accountability (Panta and Panta, 2023). It helps align managerial decisions more closely with shareholder

[5] Alternatively, we consider managerial ability score as an alternative proxy and report results in Appendix 4. Our baseline finding remains qualitatively the same.

[6] The distributions of the other variables are also relatively comparable to those reported in prior studies. See Table 1 and Jung et al. (2014); Ben-Nasr and Alshwer (2016); Ghaly et al. (2020).

[7] Although some of the correlations are greater than 0.6, the unreported variance inflation factors (VIFs) of all the control variables from the regressions in Table 2 do not exceed 5. Hair et al. (1995) show that a VIF of less than 10 is an indication of inconsequential collinearity that does not poorly affect an analysis, while Marquardt (1970), Neter et al. (1989), and Mason et al. (1989) view VIF values greater than 10 as indicators of serious multicollinearity; this suggests that multicollinearity is not an issue in our model.

Table 1

Summary Statistics. This presents the summary statistics and correlation matrix of the variables used in our study. The sample contains 23,709 observations over a sample period from 1991 to 2018. Panel A presents the summary statistics of the variables. Panel B presents the correlation matrix. Variable definitions are provided in Appendix 1.

Panel A: Summary Statistics (N = 23,709)

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
|Ab_Net_Hire|	0.1176	0.1429	0.0335	0.0727	0.1425
OC	1.4441	1.3381	0.5431	1.1032	1.8915
MTB	3.2624	4.1223	1.3537	2.2233	3.7591
Size	6.3148	2.0285	4.8662	6.3104	7.6736
Quick	1.9896	1.9500	0.8828	1.3416	2.2869
Leverage	0.2049	0.1923	0.0222	0.1756	0.3181
Divdum	0.3847	0.4865	0.0000	0.0000	1.0000
Std_CFO	0.0695	0.0736	0.0279	0.0471	0.0808
Std_Sales	0.1826	0.1696	0.0734	0.1289	0.2289
Tangible	0.2557	0.2164	0.0894	0.1903	0.3553
Loss	0.2576	0.4373	0.0000	0.0000	1.0000
Insti	0.5766	0.297	0.3346	0.6149	0.8243
Std_Net_Hire	0.2115	0.2374	0.0723	0.1324	0.2476
Labor_Intensity	0.0071	0.0100	0.0022	0.0043	0.0079
AQ	−0.0809	0.0625	−0.1020	−0.0640	−0.0394
|Ab_Invest_Other|	0.1005	0.1158	0.0388	0.0739	0.1101
MA	0.5579	0.2808	0.3000	0.6000	0.8000
Union	0.1137	0.0518	0.0878	0.1128	0.153

Panel B: Pairwise Correlation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.|Ab_Net_Hire|	1.000																	
2.OC	**−0.036**	1.000																
3.MTB	**0.038**	**0.071**	1.000															
4.Size	**−0.110**	**−0.307**	**0.262**	1.000														
5.Quick	**0.125**	**−0.091**	**0.055**	**−0.110**	1.000													
6.Leverage	−0.012	**−0.193**	**−0.017**	**0.097**	**−0.335**	1.000												
7.Divdum	**−0.139**	**−0.070**	−0.011	**0.363**	**−0.209**	**0.066**	1.000											
8.Std_CFO	**0.183**	**0.167**	**0.157**	**−0.268**	**0.270**	**−0.167**	**−0.302**	1.000										
9.Std_Sales	**0.119**	**0.165**	**0.017**	**−0.254**	**0.025**	**−0.067**	**−0.194**	**0.372**	1.000									
10.Tangible	**−0.030**	**−0.273**	**−0.109**	**0.061**	**−0.297**	**0.301**	**0.181**	**−0.227**	**−0.153**	1.000								
11.Loss	**0.103**	**0.125**	0.009	**−0.257**	**0.107**	**0.054**	**−0.270**	**0.268**	**0.097**	**−0.052**	1.000							
12.Insti	**−0.092**	**−0.233**	**0.098**	**0.622**	**−0.052**	**0.070**	**0.134**	**−0.233**	**−0.209**	**−0.056**	**−0.135**	1.000						
13.Std_Net_Hire	**0.156**	**−0.049**	−0.012	**−0.167**	**0.054**	**0.043**	**−0.244**	**0.253**	**0.319**	**−0.043**	**0.146**	**−0.150**	1.000					
14.Labor_Intensity	−0.011	**0.187**	**−0.050**	**−0.224**	**−0.128**	**−0.041**	**−0.023**	**−0.048**	**0.141**	**0.049**	**−0.061**	**−0.164**	0.014	1.000				
15.AQ	**−0.115**	**−0.167**	**−0.119**	**0.162**	**−0.144**	**0.115**	**0.199**	**−0.518**	**−0.310**	**0.203**	**−0.156**	**0.115**	**−0.187**	**0.074**	1.000			
16.|Ab_Invest_Other|	**0.332**	**0.024**	**0.128**	**−0.065**	**0.094**	**−0.031**	**−0.142**	**0.195**	**0.078**	**−0.038**	**0.102**	**−0.033**	**0.061**	**−0.037**	**−0.109**	1.000		
17. MA	0.001	**0.209**	**0.136**	**0.108**	**0.063**	**−0.155**	**0.035**	**0.083**	**0.062**	**−0.087**	**−0.134**	**−0.048**	**−0.045**	**−0.045**	**−0.062**	**0.049**	1.000	
18. Union	0.006	−0.004	**−0.028**	**−0.112**	**0.068**	**−0.054**	**0.067**	**0.027**	**−0.083**	0.017	−0.002	**−0.207**	−0.004	**−0.164**	**0.063**	**−0.020**	**0.079**	1.000

Note: Figures in bold are statistically significant at least at the 10 % level or better.

Table 2
Organizational Capital and Labor Investment Efficiency. This table presents the baseline results of regressing the labor investment efficiency proxy on lagged OC. The dependent variable is |*Ab_Net_Hire*|. A higher value of Ab_Net_Hire represents lower labor investment efficiency. Column (1) presents the regression results for our full sample. Columns (2) and (3) present the regression results for the overinvestment and underinvestment subsamples, respectively. The full sample is split based on the sign of abnormal net hiring. The overinvestment subsample contains firms whose actual net hiring is greater than expected (i.e., positive abnormal net hiring), and the underinvestment subsample contains firms with negative abnormal net hiring. In all the specifications, we include firm and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	Full sample (1)	Overinvestment (2)	Underinvestment (3)
OC	−0.0109 * **	−0.0106 * **	−0.0113 * **
	(−4.91)	(−3.81)	(−2.65)
MTB	0.0008 * *	0.0012 * *	0.0009
	(2.20)	(2.49)	(1.41)
Size	−0.0099 * **	−0.0131 * **	−0.0025
	(−3.80)	(−4.60)	(−0.53)
Quick	0.0031 * **	0.0031 * *	0.0017
	(2.81)	(2.55)	(0.51)
Leverage	0.0042	0.0086	−0.0110
	(0.35)	(0.66)	(−0.41)
Divdum	0.0081 * *	0.0106 * *	−0.0007
	(2.09)	(2.29)	(−0.07)
Std_CFO	0.0433	0.0226	0.0839
	(1.40)	(0.64)	(1.02)
Std_Sales	0.008	0.0073	−0.0004
	(0.78)	(0.61)	(−0.01)
Tangible	−0.0442 *	−0.0656 * **	0.0009
	(−1.87)	(−2.89)	(0.02)
Loss	0.0014	0.0006	0.0033
	(0.5)	(0.16)	(0.66)
Insti	−0.0033	0.0053	−0.0181
	(−0.36)	(0.52)	(−1.05)
Std_Net_Hire	−0.0536 * **	−0.0513 * **	−0.0505 * **
	(−6.80)	(−5.76)	(−3.13)
Labor_Intensity	−0.8851	−1.3629 * *	3.8940 * *
	(−1.64)	(−2.14)	(2.17)
AQ	−0.0221	−0.0424	0.0468
	(−0.88)	(−1.43)	(0.84)
|*Ab_Invest_Other*|	0.4045 * **	0.4192 * **	0.2828 * **
	(22.79)	(22.49)	(4.41)
MA	−0.0051	−0.0134 * *	0.0167
	(−1.06)	(−2.49)	(1.56)
Union	−0.1152	−0.0668	−0.1728
	(−1.28)	(−0.68)	(−0.71)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	23,709	19,022	4687
Adj. R-squared	0.315	0.355	0.497

interests, thereby reducing the likelihood of overinvestment decisions. Moreover, the presence of high-quality personnel and efficient systems enables firms to restrain managers' tendencies toward overinvestment.

Underinvestment in labor occurs if there are managerial concerns about short-term firm performance (e.g., expected profit or cash flow reductions). In this situation, risk-averse managers may underinvest in essential areas like research and development, employee training, or infrastructure to minimize perceived risks and protect short-term financial outcomes (Jensen and Meckling, 1976). However, robust OC fosters a culture of strategic foresight and long-term planning, encouraging managers to allocate resources more effectively, even in the face of uncertainty. By embedding a framework that supports continuous learning, innovation, and alignment of investments with long-term goals, OC helps to counteract the tendencies that lead to underinvestment. Consequently, firms with high levels of OC are better positioned to overcome the inefficiencies associated with underinvestment, ultimately enhancing their competitive advantage and sustaining growth (Teece et al., 1997).

Table 3
Channel Tests. This table presents the effects of employee turnover on the relationship between labor investment efficiency and OC in Panel A, and the effects of managerial agency costs on the same relationship in Panel B. In Panel A, turnover rate is calculated as the natural logarithm of the ratio of non-executive employee stock option cancellations to the total number of stock options outstanding plus one. A dummy variable, *LowTO*, is defined as 1 if the turnover rate is lower than or equal to the in-sample mean (or median) and 0 otherwise. *HighOC* is another dummy variable that equals 1 if a firm's OC is higher than the in-sample mean (or median) and 0 otherwise. The dependent variable, *Underinvestment*, is a dummy that equals 1 for firms with negative abnormal net hiring and 0 otherwise. In Panel B, managerial agency costs are proxied by institutional ownership. *HighIO*, is created, which equals 1 if a firm's institutional ownership is higher than the in-sample mean (or median) and 0 otherwise. The dependent variable, *Overinvestment*, is a dummy that equals 1 for firms with positive abnormal net hiring and 0 otherwise. Both panels firm and year-fixed effects. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A: Employee Turnover		
Dependent variable: *Underinvestment*	In-sample mean (1)	In-sample median (2)
HighOC LowTO*	−0.0195 *	−0.0211 *
	(−1.74)	(−1.94)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	12,236	12,236
Adj. R-squared	0.360	0.360
Panel B: Agency Cost		
Dependent variable: *Overinvestment*	*In-sample mean* (1)	*In-sample median* (2)
*HighOC*HighIO*	−0.0102	−0.0169 *
	(−1.03)	(−1.80)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	23,709	23,709
Adj. R-squared	0.324	0.324

We decompose the full sample based on the signs of abnormal net hiring. Specifically, our overinvestment subsample includes firms whose actual net hiring is greater than expected (i.e., positive abnormal net hiring), and our underinvestment subsample includes firms with negative abnormal net hiring. Columns (2) and (3) report regression results for the overinvestment and underinvestment subsamples. We find that the coefficient estimates of OC presented in the two columns are both significantly negative, indicating that higher OC mitigates overinvestments and underinvestments in labor.

We further extend our main analysis by dividing the subsamples into over-hiring and under-firing (overinvestment) and under-hiring and over-firing (underinvestment). We rerun Eq. (5) based on these subsamples. We report the results in Appendix 3. We find that the coefficient for OC is statistically insignificant in over-hiring and under-hiring subsamples, but significantly negative in under-firing and over-firing subsamples. This suggests that OC is related to less under-firing and over-firing than hiring practices. It is because OC enhances a firm's ability to efficiently manage its workforce in alignment with its strategic objectives. Firms with high OC likely have better internal processes, communication, and strategic planning capabilities, which allows them to adjust their workforce more accurately. This leads to more stable employment conditions, where unnecessary layoffs or excessive reductions in staff are minimized, thus promoting higher retention rates among employees.

4.3. Channel tests

Our hypothesis (H1a) suggests two channels to explain the association between OC and labor investment efficiency. The first channel we mention is that OC facilitates a firm's ability to attract and retain talented employees, thereby reducing labor underinvestment. Specifically, firms with high OC achieve greater labor investment efficiency by successfully retaining top talent and experiencing lower employee turnover. To test this channel, we examine employee turnover rates in high OC firms. Following Babenko and Sen (2014) and Phua, Tham, and Wei (2018), we measure employee turnover rate as the natural logarithm of the ratio of non-executive employee stock option cancellations to the total number of stock options outstanding plus one. Using the in-sample mean and median, we create two dummy variables: low-level turnover *(LowTO)* and high-level firm OC *(HighOC)*. Specifically, *LowTO* takes a value of 1 if the turnover rate is lower than or equal to the in-sample mean (or median) and 0 otherwise. *HighOC* equals 1 if a firm's OC is higher than the in-sample mean (or median) and 0 otherwise. For the dependent variable, we use a dummy variable (*Underinvestment*) that equals 1 for firms with negative abnormal net hiring and 0 otherwise We incorporate the interaction between *LowTO* and *HighOC* in our baseline regression to evaluate this channel. The results are presented in Panel A of Table 3.

As predicted, the negatively significant coefficient on *HighOC* × *LowTO* suggests that low employee turnover enables firms with high organizational capital to improve labor investment efficiency by reducing labor underinvestment.[8]

The second channel we propose is that reduced agency costs in high OC firms enhance labor investment efficiency by reducing labor overinvestment. To test this, we employ institutional ownership as a proxy for how well a firm aligns managerial incentives with shareholders' interests due to its capacity to mitigate managerial opportunism through active monitoring and corporate governance influence. Shleifer and Vishny (1986) argue that large institutional investors have both the incentive and ability to monitor management effectively, reducing agency costs associated with managerial discretion. Hartzell and Starks (2003) show that higher institutional ownership serves a monitoring role in mitigating the agency problem between shareholders and managers. Similar to the previous analysis, we create an agency cost dummy variable: *HighIO*, which equals 1 if institutional ownership is above the in-sample mean (or median) and 0 otherwise. By construction, *HighIO* equals to 1 suggests a presence of low agency costs in a firm due to higher monitoring and stronger governance.

We include the interaction of *HighIO* with *HighOC* in the baseline regression, where the dependent variable is now *Overinvestment* – a dummy variable equal to 1 for firms with positive abnormal net hiring and 0 otherwise. Results, presented in Panel B of Table 3, show a negative and significant coefficient on *HighOC* × *HighIO*, suggesting that high OC firms facing low agency costs can reduce labor overinvestment and thereby increase labor investment efficiency. This result demonstrates that OC can indeed play a critical role in reducing potential conflicts between managers and shareholders, thereby enhancing labor investment efficiency.

4.4. The moderating role of product market competition

In this section, we show how competition can moderate the positive association between OC and labor investment efficiency. We conjecture that OC is more valuable for firms in highly competitive markets for three reasons. First, market competition threats and dynamics shape a firm's financial policies and managerial decisions on investments and operations (Hoberg et al., 2014; Karuna, 2007). Second, some scholars argue that market competition influences cost reduction initiatives (Hermalin, 1992, Schmidt, 1997). Therefore, market competitiveness can drive a firm's labor investment efficiency. Third, prior studies show that OC enhances firm competitiveness, performance and productivity (Atkeson and Kehoe, 2005; Lev et al., 2009). Taken together, we predict that competition will further strengthen the positive association between OC and labor investment efficiency.

We use Hoberg et al.'s (2014) *Fluidity* measure to proxy for market competition intensity.[9] *Fluidity* captures how rival firms change their product description words relative to a firm's vocabulary. We present the results in Table 4. We find that the coefficient of *OC*Fluidity* is negative and significant at the 1 % level (-0.0011, t = -2.80). This finding supports our conjecture that OC strengthens the labor investment efficiency of firms that are facing relatively intense product market threats.

Table 4
The Moderating Role of Product Market Competition. This table presents the moderating effect of product market competition on the relation between OC and labor investment efficiency. The dependent variable is |*Ab_Net_Hire*|. A higher value of Ab_Net_Hire represents lower labor investment efficiency. *Fluidity* measures product market intensity. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	Coefficient
OC	−0.0038
	(−1.26)
Fluidity	0.0016 *
	(1.85)
*OC*Fluidity*	−0.0011 * **
	(−2.80)
MTB	0.0009 * *
	(2.39)
Size	−0.0108 * **
	(−4.07)
Quick	0.0028 * *
	(2.56)
Leverage	0.0023
	(0.19)
Divdum	0.0077 *
	(1.94)
Std_CFO	0.0329
	(1.07)
Std_Sales	0.0114
	(1.11)
Tangible	−0.0422 *
	(−1.74)
Loss	0.0010
	(0.35)
Insti	−0.0005
	(−0.05)
Std_Net_Hire	−0.0504 * **
	(−6.31)
Labor_Intensity	−1.2007 * *
	(−2.28)
AQ	−0.0213
	(−0.84)
|*Ab_Invest_Other*|	0.4067 * **
	(22.94)
MA	−0.0050
	(−1.04)
Union	−0.1128
	(−1.20)
Firm FE	Yes
Year FE	Yes
Observations	22,841
Adj. R-squared	0.318

[8] We thank an anonymous reviewer for suggesting this test.

[9] Fluidity lies in the interval [0,1], and the data are updated every year. We thank the authors for making this dataset available for the period of 1989–2019 at https://hobergphillips.tuck.dartmouth.edu/industryconcen.htm.

Table 5
The Moderating Role External Financing. This table presents the moderating effect of external financing on the relation between OC and labor investment efficiency. The dependent variable is |*Ab_Net_Hire*|. A higher value of Ab_Net_Hire represents lower labor investment efficiency. External financing dependence *(EF)* is defined as the industry median of the difference between capital expenditures and cash flows from operations divided by capital expenditures. A higher EF value signifies that a firm requires more external financing for internal use. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	Coefficient
OC	−0.0104 * **
	(−4.80)
EF	0.0016 *
	(1.82)
*OC*EF*	−0.0007 *
	(−1.96)
Firm FE	Yes
Year FE	Yes
Observations	23,516
Adj. R-squared	0.315

4.5. The moderating role of external financing

Labor investment (relative to other variable costs) requires financing. Benmelech et al. (2011) show that labor costs are quasi-fixed costs incurred through hiring, maintaining, and replacing employees. Firms, especially those with insufficient internal funds, are relatively likely to resort to external funds to cover these labor costs. In this vein, we argue that firms with more efficient business systems and procedures can attract external financing more easily than other firms. As a result, they are more likely to use their expertise to allocate funds for labor investment efficiently.

We use external financing dependence *(EF),* which is defined as the industry median value of the difference between capital expenditures and cash flows from operations divided by capital expenditures (Foucault and Frésard, 2012; Ben-Nasr and Alshwer, 2016; and Khedmati et al., 2020), as a proxy for external financing. A higher EF value signifies that a firm requires more external financing for internal use. Table 5 shows that the coefficient of *OC*EF* is negatively significant at the 10 % level (-0.0007, t = -1.96), consistent with our conjecture that the positive relation between OC and labor investment efficiency is more pronounced in the presence of external financing.

4.6. The moderating role of high skilled labor

We further conjecture that the impact of OC on labor investment efficiency varies with the level of skilled labor within an industry. This is because firms with a greater reliance on skilled labor tend to pay higher labor adjustment costs (Oi, 1962; Dixit, 1997), which increase their labor investment inefficiency. In this connection, we argue that high OC enables firms to allocate and match their labor with physical resources efficiently, which help reduce the costs of highly skilled labor reliance. Therefore, the relationship between OC and labor investment efficiency is more pronounced for firms with skilled labor.

Following Ben-Nasr and Alshwer (2016), Khedmati et al. (2020), and Cao and Rees (2020), we obtain the average number of employees in each industry whose occupations are ranked 4th or 5th on *JobZones* in terms of skilled labor.[10,11] We create a dummy, *High_Skilled*, that equals one if the level of skilled labor in a firm's industry is higher than the in-sample median and 0 otherwise. Finally, we interact OC with *High_Skilled* (*OC*High_Skilled*) and report the results in Table 6.

Table 6
The Moderating Role of High- and Low-Skilled Labor. This table presents the moderating effect of skilled labor on the relation between OC and labor investment efficiency. The dependent variable is |*Ab_Net_Hire*|. A higher value of Ab_Net_Hire represents lower labor investment efficiency. The *High_Skilled* dummy equals 1 if the level of skilled labor within *a* firm's industry is greater than the in-sample median and 0 otherwise. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	Coefficient
OC	−0.0047
	(−1.34)
High_Skilled	0.0114
	(1.23)
*OC*High_Skilled*	−0.0096 * *
	(−2.48)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	23,516
Adj. R-squared	0.315

We find that the association between OC and labor investment efficiency is more pronounced for firms in industries with a greater reliance on skilled labor. This finding suggests that OC helps improve the net hiring practices of firms that face higher labor adjustment costs and are thus less likely to invest efficiently.

4.7. The effect of nonlabor investments

Some may argue that the association between OC and labor investment efficiency is attributable to other nonlabor investments due to the complementary nature of labor investments and other investments (Beard et al., 2014; Jung et al., 2014; Ben-Nasr and Alshwer, 2016; Khedmati et al., 2020). Thus, we examine the influence of other complementary investments on this relation. In particular, we employ the following four types of investment: capital expenditures *(CAPX),* R&D expenditures *(XRD),* advertising expenditures *(XAD),* and acquisition expenditures *(ACQ)*. We divide our sample into three subsamples based on the relationship between labor investment and these types of investment: (1) firms for which an increase (decrease) in net hiring is tied to an increase (decrease) in nonlabor investment; (2) firms for which an increase (decrease) in net hiring is tied to a decrease (increase) in nonlabor investment; and (3) firms with missing nonlabor investment information. We rerun our baseline Model (5) for each of these subsamples.

Panel A of Table 7 shows the results for the CAPX subsamples. We find that the positive relationship between OC and labor investment efficiency is centralized not only for firms that exhibit a positive relation between *CAPX* and labor investment but also for those that exhibit a negative relation. Panel B shows the results for the XRD subsamples. The coefficients of OC are negative and significant for two of the three specifications. Additionally, the coefficient of OC for the subsample with a positive relationship between *XRD* and labor investment is higher than

[10] The *JobZones* data is from the Occupational Information Network (O*Net),), which is available at http://www.onetonline.org/find/zone. The data on the number of employees by occupation is from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics.

[11] We thank the authors for making this industry-level skilled labor dataset available at https://sites.google.com/a/umn.edu/frederico-belo/.

Table 7
The Effect of Nonlabor Investment. This table presents the results regarding the impact of nonlabor investment on the relationship between OC and labor investment efficiency. Panel A presents the results for the subsample created based on capital expenditure (CAPX). Panel B presents the results for the subsamples created based on R&D expenses (XRD). Panel C presents the results for the subsamples created based on advertising expenses (XAD). Panel D presents the results for the subsamples created based on acquisition expenditures (AQC). Columns (1), (4), (7), and (10) present the results for the firms for which an increase (a decrease) in labor investment is tied to an increase (a decrease) in nonlabor investment (i.e., a positive relationship between labor and nonlabor investments). Columns (2), (5), (8), and (11) present the results for the firms that exhibit a negative relationship between labor and nonlabor investments. Columns (3), (6), (9), and (12) present the results for the firms without specific nonlabor investments (i.e., firms without CAPX, XRD, XAD or AQC, respectively). We report (for the sake of space) only the results regarding our variable of interest, OC. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Variable	Panel A: CAPX			Panel B: XRD			Panel C: XAD			Panel D: AQC		
	Positive	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OC	−0.0066 *	−0.0137 * **	−0.0328	−0.0164 * **	−0.0063 *	−0.0041	−0.0068 *	−0.0097 * *	−0.0142 * **	−0.0015	−0.0153 * **	−0.0082 * **
	(−1.87)	(−4.78)	(−0.49)	(−3.80)	(−1.76)	(−1.04)	(−1.66)	(−2.04)	(−4.14)	(−0.22)	(−3.00)	(−2.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,141	11,379	119	6690	6912	9429	4094	4302	14,687	6747	5151	10,663
Adj. R-squared	0.421	0.346	0.725	0.462	0.387	0.301	0.465	0.375	0.328	0.512	0.399	0.332

that for the subsample with negative relationships. This finding suggests that OC helps firms increase their labor investment efficiency through an increase in R&D investment. Panel C shows the results for the XAD subsamples. We find that the coefficient of OC is negatively significant at the 10 % level in Column (7), the 5 % level in Column (8), and the 1 % level in Column (9). Finally, Panel D shows the results for the AQC subsamples. The coefficient of OC is negative at the 1 % level in Columns (11) and (12), confirming that there is no positive association between OC and labor investment efficiency in the subsample of firms with a positive *AQC* correlation.

5. Robustness Tests

5.1. Quasi-natural experiment

In this section, we perform several additional analyses to confirm the OC-labor investment efficiency relation. Following Gao et al. (2021), we exploit exogenous CEO departures due to exogenous reasons such as health-related issues rather than firm-specific reasons. Such turnovers pose a negative shock to a firm's OC and can serve as a quasi-natural experiment. We expect that the treatment firms will exhibit a downward trend in labor investment efficiency following such events. We use Eisfeldt and Kuhnen's (2013) data on CEO turnover, which covers 2118 CEO turnovers from 1992 to 2006.[12] In this dataset, CEO departures are classified as "exogenous turnover" or "unclassified turnover". "Exogenous turnover" includes two categories: planned retirement and health problems. "Unclassified turnover" covers departures that do not fit in the two prior categories. For our analysis, we focus on only CEO departures due to health problems and remove any departures that are recorded as "RETIRED" on Execucomp (i.e., planned CEO retirements). Also, we do not include any forced CEO turnover in this sample. This is because firms know about and prepare for such events in advance. Thus, they are not "clean" negative shocks to the firms' OC.

We follow Lemmon and Roberts (2010), Gormley et al. (2013), and Gao et al. (2021) to create our stacked difference-in-differences approach. Particularly, we first stack cohorts of treatment and control firms. Treatment firms are firms that have experienced an exogenous CEO departure, while the control firms in each turnover event cohort are in the same industry as the corresponding treatment firms but have not experienced any CEO departures during the three years before or after the event. Next, we perform propensity score matching (PSM) to match the control and treatment firms using data from before the treatment events. We use the nearest propensity scores and a caliper of 0.01 to select four control firms in each cohort that are comparable in terms of size and OC to the treatment firm. The control firms are chosen with replacement. Firms are not required to be in the sample for the entire seven years. Finally, we group cohorts of treatment and control forms to create our matched sample for the DID analysis.

Table 8 provides the PSM diagnostic results for the samples before and after matching. We find that before matching, the treatment and control firms are significantly different in terms of OC level and other firm characteristics. However, after matching, the treatment and control firms in our sample are relatively comparable across all the firm characteristics examined, which is consistent with the PSM assumption. We then exploit a DID regression as follows:

$$|\mathrm{Ab\_Net\_Hire}|_{i,c,t} = \beta_0 + \beta_1 {*}\mathrm{Treatment}_{i,c} * \mathrm{Post}_{t,c} + \beta_n {*}\mathrm{Controls}_{i,t} + \omega_{i,c} + \gamma_{t,c} + \varepsilon_{i,c,t} \quad (6)$$

where $|Ab\_Net\_Hire|_{i,c,t}$ is the absolute value of the abnormal net hiring of firm *i* in cohort *c* during year *t*; $Treatment_{i,c}$ is *a* dummy variable that equals 1 if firm *i* is the treatment firm in cohort *c*; $Post_{t,c}$ is *a* dummy

[12] We thank the authors for making this dataset available at https://sites.google.com/site/andrealeisfeldt/.

Table 8

Propensity Score Matching Diagnostic. This table presents a pairwise comparison of our sample variables before and after propensity score matching (PSM). First, we stack cohorts of treatment and control firms. The treatment firms have experienced an exogenous CEO departure, while the control firms in each turnover event cohort are in the same industry as the corresponding treatment firms but have not experienced a CEO departure during the three years before or after the treatment events. We perform PSM to match the control and treatment firms using data from before the treatment events. We use the nearest propensity scores and a caliper of 0.01 to select four control firms in each cohort that are comparable in terms of size and OC to the treatment firm. The control firms are chosen with replacement. The firms are not required to be in the sample for the entire seven years. We group cohorts of treatment and control forms to create our matched sample for the DID analysis. Variable definitions are provided in Appendix 1. The numbers in parentheses are standard errors. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

	Pre-Match			Post-Match		
	Control	Treatment	Diff (Control-Treat)	Control	Treatment	Diff (Control-Treat)
OC	1.5673	1.1150	0.4523 * **	1.2198	1.1943	0.0256
MTB	3.7714	3.8536	−0.0822	3.4039	3.5376	−0.1337
Size	5.7260	7.7014	−1.9754 * **	6.9518	7.2342	−0.2823
Quick	2.4284	1.4850	0.9434 * **	1.9330	1.6877	0.2453
Leverage	0.1837	0.2062	−0.0225	0.1815	0.2008	−0.0193
Divdum	0.2705	0.6602	−0.3897 * **	0.4645	0.5286	−0.0641
Std_CFO	0.0969	0.0397	0.0572 * **	0.0539	0.0458	0.0081
Std_Sales	0.2317	0.1212	0.1104 * **	0.1365	0.1435	−0.0071
Tangible	0.2517	0.3280	−0.0764 * **	0.2779	0.2973	−0.0194
Loss	0.3088	0.0971	0.2117 * **	0.1585	0.1143	0.0442
Insti	0.4594	0.6354	−0.1760 * **	0.6221	0.6226	−0.0005
Std_Net_Hire	0.2889	0.1896	0.0993 * **	0.2137	0.2276	−0.0139
Labor_Intensity	0.0106	0.0134	−0.0028	0.0082	0.0093	−0.0011
AQ	−0.0805	−0.0575	−0.0230 * *	−0.0651	−0.0612	−0.0040
Ab_Invest_Other	0.1170	0.0784	0.0386 * *	0.0844	0.0797	0.0047
MA	0.1271	0.1320	−0.0049	0.1327	0.1337	−0.0009
Union	0.5740	0.5379	0.0361	0.5683	0.5514	0.0169
Observations	3164	103		187	70	

variable that equals 1 if year t is after the event year of cohort c (the event year is excluded from the estimation); $\omega_{i,c}$ is firm-cohort fixed effects; and $\gamma_{t,c}$ is year-cohort fixed effects.

Panel A of Table 9 reports the stacked DID regression results. We find that following exogenous CEO departures due to well-specified health issues, the treatment firms experience a greater decrease in labor investment efficiency than their control firms experience over the same period (0.04, t = 3.08). Consistent with our conjecture, CEO turnover hurts firm-specific OC, as CEOs are primary contributors to firm OC (Eisfeldt and Papanikolaou, 2013).

To ensure a valid DID estimation, we employ a parallel trend test. Specifically, we replace the *Post* dummy in the standard DID model with year-specific dummies. For example, d_{-2} is an indicator that equals one if a year falls two years before the focal exogenous CEO departure.

$$|\text{Ab\_Net\_Hire}|_{i,c,t} = \beta_0 + \beta_1 \text{Treatment}_{i,c} * d_{-2,t,c} + \beta_2 \text{Treatment}_{i,c} * d_{-1,t,c} + \beta_3 \text{Treatment}_{i,c} * d_{0,t,c}$$
$$+ \beta_4 \text{Treatment}_{i,c} * d_{1,t,c} + \beta_5 \text{Treatment}_{i,c} * d_{2,t,c} + \beta_6 \text{Treatment}_{i,c} * d_{3,t,c}$$
$$+ \beta_n * \text{Controls}_{i,t} + \omega_{i,c} + \gamma_{t,c} + \varepsilon_{i,c,t} \quad (7)$$

This dynamic DID model allows us to investigate the existence and timing of the treatment effect. For example, suppose the examined decrease in labor investment efficiency is caused by exogenous CEO departure. In that case, we should expect no difference between the treatment and control firms before the event. Therefore, we should expect nonsignificant β_1 and β_2, while β_3 could be either zero or positively significant because it takes time to respond to CEO turnover. Moreover, the post-event estimates, β_4, β_5, and β_6, should be positive and significant due to negative shocks to OC. In Panel B, we show that there is no significant difference between the change in labor investment efficiency of the treatment firms and that of the control firms before the events. However, after the event year, the treatment effect can be observed, and β_4 and β_6 have significantly positive coefficients. This finding indicates that the parallel assumption is well satisfied, and our DID estimation is valid.

We further report a plot of firms' abnormal net hiring both pre and post exogenous CEO turnovers for our treatment and control groups. Specifically, Fig. 1 illustrates the difference in mean residuals of abnormal net hiring (|*Ab_Net_Hire*|) over seven years. Recent studies show that abnormal net hiring typically hinges on several key determinants at the firm level: MTB, size, leverage, labor intensity, and other variables included in our baseline Eq. (5). We conduct a regression analysis to isolate and remove their influence and report the mean residuals of abnormal net hiring in Fig. 1.

We show that in the pre-treatment period, the trend in abnormal net hiring residuals remains relatively stable, fluctuating slightly above zero, indicating that both the treatment and control groups exhibited similar hiring behaviors, which supports the parallel trends assumption crucial for the validity of the DID approach. However, in the turnover year, there is a noticeable decline in abnormal net hiring residuals, which continues to drop significantly in the post-turnover period, reaching its lowest point around the first year after the event and stabilizing at a lower level in the subsequent years. This downward trend suggests that exogenous CEO turnovers, causing a reduction in OC, lead to a substantial and sustained reduction in net hiring activities compared to firms in the control group that did not experience a CEO turnover. The analysis indicates that CEO turnover induced reductions in OC have a marked and lasting impact on a firm's hiring practices.

Next, we use planned CEO retirements and a CEO's forced turnover (Peters and Wagner, 2014; Jenter and Kanaan, 2015) as pseudo-treatment events because these events, by definition, are mostly known by firms in advance.[13] Therefore, we do not expect them to inflict unexpected negative shocks to the examined firms' OC stock; moreover, they should have no positive treatment effect on labor investment efficiency. We apply the same stacked DID process and report the results in Table 10. The treatment effect is not statistically significant in Column (1) (planned CEO retirements) and Column (2) (forced CEO turnover), suggesting that planned CEO retirements and forced CEO turnovers do not affect a firm's OC and labor investment efficiency.

[13] We thank Florian Peters to make CEO forced turnover data publicly available at https://www.florianpeters.org/data/.

Table 9
Stacked Difference-in-Differences. This table presents the results of the stacked difference-in-differences regression that investigates the effect of exogenous CEO departure due to health-related problems on labor investment efficiency. *Treatment* is a dummy that equals 1 for firms that experienced exogenous CEO turnover due to well-specified health issues and 0 otherwise. The control firms in each cohort are in the same industry as the corresponding treatment firms and have not experienced CEO turnover during the three years before or after the treatment events. The control firms are matched with treatment firms using the PSM method. We use the nearest propensity scores and a caliper of 0.01 to choose four control firms for each treatment firm in each turnover event cohort. The control firms are selected with replacement. Firms are not required to be in the sample for the entire seven years. We group cohorts of treatment and control forms to create our matched sample for the DID analysis. Panel A presents the results of a standard DID, while Panel B presents the results of a dynamic model. *Post* is a dummy that equals 1 for years after the event year and 0 otherwise. The year-specific indicator d_j equals 1 if a year is the jth year after the focal exogenous CEO turnover event. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed t-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A: Standard Difference-in-Differences	
Dependent variable: |*Ab_Net_Hire*|	Coefficient
*Treatment*Post*	0.0400 * **
	(3.08)
Controls	Yes
Firm-Cohort FE	Yes
Year-Cohort FE	Yes
Observations	1303[a]
Adj. R-squared	0.441
Panel B: Dynamic difference-in-differences	
Dependent variable: |*Ab_Net_Hire*|	Coefficient
Treatmentd_{-2}	0.0063
	(0.27)
Treatmentd_{-1}	0.0055
	(0.25)
Treatmentd_0	0.0240
	(1.15)
Treatmentd_1	0.0452 * *
	(1.99)
Treatmentd_2	0.0359
	(1.48)
Treatmentd_3	0.0470 *
	(1.85)
Controls	Yes
Firm-Cohort FE	Yes
Year-Cohort FE	Yes
Observations	1557
Adj. R-squared	0.415

[a] The event year is not included in this regression, following Gao et al. (2021).

5.2. Impact threshold for confounding variable (ITCV) test

In alignment with previous research, we employed the impact threshold of a confounding variable (ITCV) test to assess the potential for uncontrolled confounding factors in the study (Frank, 2000; Pan and Frank, 2004; Busenbark et al., 2022; Hill et al., 2023, Chen et al., 2024). The ITCV test address the potential biases due to unobservable omitted variables and quantifies the minimum partial correlations necessary between a confounding variable and both the outcome and predictor variables to challenge the validity of our findings within the context of our analysis (e.g., sample size, included predictors, estimated values) (Frank, 2000; Busenbark et al., 2022). Our analysis, reported in Table 11, revealed that the most significant ITCV for the organization capital was 0.146 at a 10 % significance level. This finding implies that a confounding variable would need to correlate at least 0.146 with the outcome and −0.146 with the predictor of interest to question our conclusions. Mathematically, the impact of such a variable would be calculated as −0.146 * 0.146 = -0.0212 to challenge an inference. Nevertheless, the most substantial (and the second most significant) observed covariates' partial impacts were −0.0205 and −0.0109,

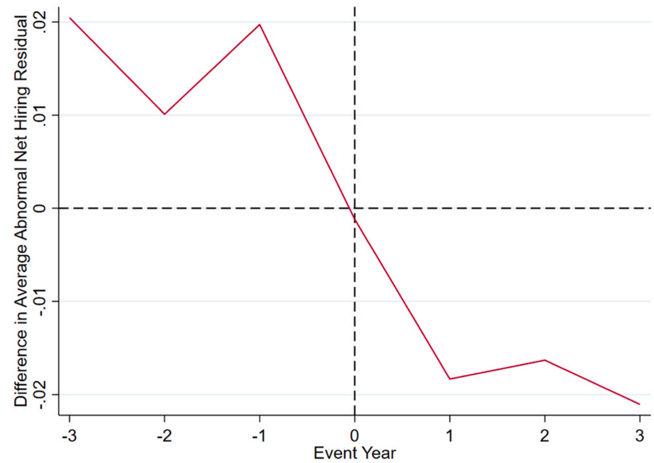

Fig. 1. The difference in average abnormal net hiring residuals around the exogenous CEO turnovers. Fig. 1 shows the difference in average residuals of abnormal net hiring for the three years before and after a CEO turnover event. Abnormal net hiring is typically driven by key factors such as MTB, size, leverage, labor intensity, and other variables outlined in our baseline model (Eq. 5). We apply a regression approach to remove the effects of these determinants and then plot the resulting mean residuals of abnormal net hiring. The treatment group includes firms with an exogenous CEO departure, while the control group consists of firms that are in the same industry as the corresponding treatment firms but have not experienced any CEO departures during the three years before or after the event. The event year refers to the year in which a CEO turnover occurs.

Table 10
Placebo Test. This table presents the results of the stacked difference-in-differences regression that investigates the effect of exogenous CEO departure due to planned retirement on labor investment efficiency in Column (1) and the effect of forced CEO departure on labor investment efficiency in Column (2). *Treatment* is a dummy that equals 1 for firms that have experienced exogenous CEO turnover due to planned retirement (Column (1)) or forced CEO departure (Column (2)) and 0 otherwise. The control firms in each cohort are in the same industry as the corresponding treatment firms and have not experienced CEO turnover during the three years before or after the treatment events. They are matched with treatment firms using the PSM method. We use the nearest propensity scores and a caliper of 0.01 to choose 4 control firms for each treatment firm in each turnover event cohort. The control firms are selected with replacement. Firms are not required to be in the sample for the entire seven years. We group cohorts of treatment and control firms to create our matched sample for the DID analysis. *Post* is a dummy that equals 1 for years after the event year and 0 otherwise. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed t-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	(1)	(2)
*Treatment*Post*	−0.0059	−0.0020
	(−0.23)	(−0.23)
Controls	Yes	Yes
Firm-Cohort FE	Yes	Yes
Year-Cohort FE	Yes	Yes
Observations	447	4578
Adj. R-squared	0.454	0.441

respectively, calculated as [Cov(v,X)*Cov(v,Y)], which do not surpass −0.0212. These results suggest that the ITCV exceeds the nearest practical impact of observed covariates by at least 4.4 % (and up to 96.3 %), indicating that the potential for bias due to omitted variables is minimal (Hill et al., 2023).

Table 11
ITCV Test. This table presents the results of the impact threshold of a confounding variable (ITCV) test. Partial correlation results are reported. In column (1), X denotes *OC*. In column (2) Y denotes |*Ab_Net_Hire*|. Variable definitions are provided in Appendix 1.

Dependent variable: |*Ab_Net_Hire*|	Cor(v, X) (1)	Cor(v, Y) (2)	Impact (3)
MTB	0.1146	−0.0037	−0.0004
Size	−0.2346	−0.0069	0.0016
Quick	−0.2618	0.0782	−0.0205
Leverage	−0.1343	0.0277	−0.0037
Divdum	0.0730	−0.0245	−0.0018
Std_CFO	0.0141	0.0400	0.0006
Std_Sales	0.0166	0.0298	0.0005
Tangible	−0.2747	0.0218	−0.0060
Loss	0.1279	0.0149	0.0019
Insti	−0.0436	−0.0258	0.0011
Std_Net_Hire	−0.1211	0.0901	−0.0109
Labor_Intensity	0.1223	0.0007	0.0001
AQ	−0.0685	−0.0126	0.0009
|*Ab_Invest_Other*|	−0.0160	0.3006	−0.0048
MA	0.2338	−0.0128	−0.0030
Union	−0.0318	0.0048	−0.0002
ITCV for OC			−0.0212

Table 12
Alternative OC proxies. This table presents the results we obtain when using alternative OC proxies. *RANK_OC* is defined as the annual decile rank of a firm's OC based on the Compustat universe. *INDADJ_OC* is defined as a firm's OC minus the industry median OC divided by total assets; *RANK_INDADJ_OC* is the annual decile rank of industry-adjusted OC. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed t-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	*RANK_OC* (1)	*INDADJ_OC* (2)	*RANK_INDADJ_OC* (3)
OC	−0.0074 * **	−0.0102 * **	−0.0042 * **
	(−5.05)	(−4.74)	(−4.91)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	23,709	23,709	23,709
Adj. R-squared	0.315	0.315	0.315

5.3. Alternative OC specification

Following Gao et al. (2021), we create the following alternative OC proxies to ensure the robustness of our findings: (i) the annual decile rank of a firm's OC based on the Compustat universe *(RANK_OC);* (ii) industry-adjusted OC *(INDADJ_OC)*, defined as OC minus the industry median of OC divided by total assets; and (iii) the annual decile rank of industry-adjusted OC *(RANK_INDADJ_OC)*. We rerun our baseline model (Eq. 5) and report the results in Table 12. We find support for our earlier finding, namely, that OC is positively associated with labor investment efficiency, as the coefficients of all three alternative OC measures are negatively significant at the 1 % level.

5.4. Alternative proxies for labor investment efficiency

We also obtain alternative labor investment efficiency proxies, in line with Biddle et al. (2009) and Ben-Nasr and Alshwer (2016). First, we regress actual net hiring on sales growth, following Biddle et al. (2009), and note the residuals of this regression. We then compute the difference between actual net hiring and the residuals and take the absolute value. Second, we add more variables to Eq. (3), including the logarithm of GDP per capita *(LGDPC)*, the industry unionization rate *(UNION)*, capital expenditures *(CAPX)*, research and development expenses *(XRD)*, acquisition expenses *(AQC)*, and the lagged value of actual labor

Table 13
Alternative Labor Investment Efficiency Proxies. This table presents the results we obtain when using alternative labor investment efficiency proxies. In Column (1) of Panel A, we use the absolute value of the difference between actual net hiring and the residuals of a regression of actual net hiring on sales growth. In Column (2), the measure is calculated based on the process above, but we add more variables to Eq. (3) (i.e., *LGDPC, UNION, CAPX, XRD, AQC,* and the lagged value of actual labor investment). In Column (3), we compute our proxy for labor investment efficiency as the difference between actual net hiring and the residuals of an industry-level version of Column (2). In Panel B, we use labor cost stickiness as a dependent variable. In Panel C, we address potential measurement errors in the two-step process by following the two alternative techniques suggested by Chen et al. (2018). Column (1) presents the regression result of regressing our dependent variable |*Ab_Net_Hire*| after combining all the two-step regressors in Eqs. (3) and (5). Column (2) shows the results of regressing our dependent variable |*Ab_Net_Hire*| on the residuals obtained from regressing *X2* and *X3* on *X1*, where *X1* is a set of first-step regressors in Eq. (3), *X2* is our *OC* and *X3* is a set of our second-step regressors in Eq. (5). Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed t-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A:			
Dependent variable:	Alternative measures of labor investment efficiency		
	(1)	*(2)*	*(3)*
OC	−0.0055 * **	−0.0074 * **	−0.0060 * **
	(−13.68)	(−4.76)	(−4.78)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	23,709	15,387	23,709
Adj. R-squared	0.371	0.442	0.397

Panel B: Labor cost stickiness	
Dependent variable:	Labor cost stickiness
Log ($Rev_{i,t}/Rev_{i,t-1}$)	0.7023 * **
	(11.63)
$Decr_{i,t}$ * $Log\ (Rev_{i,t}/Rev_{i,t-1})$	−0.3463 *
	(−1.67)
$Decr_{i,t}$ *$OC_{i,t}$ * $Log\ (Rev_{i,t}/Rev_{i,t-1})$	0.1241 *
	(1.86)
$Decr_{i,t}$ * $AI_{i,t}$ * $Log\ (Rev_{i,t}/Rev_{i,t-1})$	−0.0768
	(−0.83)
$Decr_{i,t} * Succ\_Decr_{i,t}$	0.3226 * *
	(2.05)
$Decr_{i,t}$ * $Loss_{i,t-1}$ * $Log\ (Rev_{i,t}/Rev_{i,t-1})$	−0.0915
	(−0.43)
$OC_{i,t}$	−0.0238 * **
	(−3.00)
$AI_{i,t}$	0.0300 * *
	(2.33)
$Loss_{i,t-1}$	−0.0417 * **
	(−3.76)
$Succ\_Decr_{i,t}$	0.0079
	(0.51)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	1332
Adj. R-squared	0.695

Panel C: Addressing potential measurement errors in the two-step process		
Dependent variable:	|*Ab_Net_Hire*| (1)	|*Ab_Net_Hire*| (2)
OC/ OC_Residual in (2)[a]	−0.0081 * **	−0.0085 * **
	(−3.23)	(−3.00)
MTB	0.0004	0.0004
	(1.10)	(0.87)
Size	−0.0131 * **	0.0027
	(−2.66)	(0.56)
Quick	0.0021 *	0.0031 * *
	(1.77)	(2.29)
Leverage	−0.0020	−0.0338 * **

(*continued on next page*)

investment. We then recalculate the absolute value of the difference between actual net hiring and the residuals from the abovementioned regression. Finally, we repeat the prior process at the industry level. The results are presented in Table 13. The coefficients of OC are negative and significant at the 1 % level; this is strongly consistent with our prior findings.

In Panel B, we examine the effect of OC on wages paid to employees and severance payments made to fired workers. Specifically, we employ labor cost stickiness as a proxy for labor investment efficiency. Sticky costs are more sensitive to increases in activity than decreases. This means that labor costs increase more when activity surges than they decrease when activity drops. It is argued in prior studies (Dierynck et al., 2012; Prabowo et al., 2018; Hall, 2016) that managerial self-interest drives managers to increase labor cost stickiness through empire building and risk aversion incentives. We expect that labor cost stickiness decreases with OC given that firms with high OC experience more efficient business processes and systems and have well-trained top managers and employees. We follow Ben-Nasr and Alshwer (2016) and use the following model:

$$\begin{aligned}Log\left(\frac{LaborCost_{i,t}}{LaborCost_{i,t-1}}\right) = \beta_0 + \beta_1 Log\left(\frac{Rev_{i,t}}{Rev_{i,t-1}}\right) + \beta_2 Decr_{i,t} \\ * Log\left(\frac{Rev_{i,t}}{Rev_{i,t-1}}\right) + \beta_3 Decr_{i,t} * OC_{i,t} \\ * Log\left(\frac{Rev_{i,t}}{Rev_{i,t-1}}\right) + \beta_4 Decr_{i,t} * AI_{i,t} \\ * Log\left(\frac{Rev_{i,t}}{Rev_{i,t-1}}\right) + \beta_5 Decr_{i,t} * Succ\_Decr_{i,t} \\ * Log\left(\frac{Rev_{i,t}}{Rev_{i,t-1}}\right) + \beta_6 Decr_{i,t} * Loss_{i,t-1} \\ * Log\left(\frac{Rev_{i,t}}{Rev_{i,t-1}}\right) + \beta_7 OC_{i,t} + \beta_8 Controls_{i,t} + \gamma_t + \varepsilon_{i,t}\end{aligned} \tag{8}$$

where *LaborCost* is staff expense from Compustat; *Rev* is total revenue; *Decr* is an indicator that equals one if total revenue decreased from the previous year and zero otherwise; *OC* is our main OC proxy; and *Controls* includes asset intensity (*AI*—defined as total assets scaled by total revenue), a variable denoting whether each firm faced a decrease in revenue between the current and the previous year *(Succ_Decr)*, and a dummy variable denoting whether each firm reported a loss during the last year *(Loss)*.

We report the results of our estimation of Eq. (8) in Panel B of Table 13. We find that β_1 is significantly positive and β_2 is significantly negative, indicating that labor costs are sticky. This is consistent with prior literature (Anderson et al., 2003; Chen et al., 2012a, 2012b; Prabowo et al., 2018). The coefficient β_3 is positive and significant (0.1241, t = 1.86), suggesting that firms with higher OC have fewer problems related to empire building and thereby face less labor cost stickiness. Once again, these results confirm our finding that the relation between OC and labor investment efficiency is not driven by a specific labor investment efficiency proxy.

Chen et al. (2018) elucidate that the two-step estimation process frequently includes incorrect assumptions, potentially presenting challenges for researchers who may not fully recognize these estimation issues. Furthermore, the inherent structure of the two-step procedure can conceal research design problems that might otherwise become apparent if alternative estimation methods were employed. To address potential coefficient bias arising from the two-step procedure, we implement two tests grounded in the methodology proposed by Chen et al. (2018). First, we perform a regression that includes our primary dependent variable |*Ab_Net_Hire*| alongside all two-step regressors. Second, we conduct a two-step regression. According to the Frisch–Waugh–Lovell Theorem, the same coefficients and standard errors from a single regression can be obtained using a two-step process. The residual from the first-step regression, our |*Ab_Net_Hire*|, is regressed on the residuals from regressing *X2* and *X3* on *X1*, where *X1* is a set of first step regressors in Eq. (3), *X2* is our *OC* and *X3* is a set of our second-step regressors in Eq. (5). The findings, detailed in Columns (1) and (2) of Panel C, Table 13 demonstrate that our main variable of interest exerts a significantly negative impact on labor investment inefficiency, thereby supporting our primary hypothesis. This also substantiates that the negative effect of our main variable on labor investment efficiency is both consistent and significant, indicating that the

Table 13 (*continued*)

Panel C: Addressing potential measurement errors in the two-step process		
Dependent variable:	|*Ab_Net_Hire*| (1)	|*Ab_Net_Hire*| (2)
	(−0.17)	(−2.74)
Divdum	0.0110 * **	0.0128 * **
	(2.87)	(3.15)
Std_CFO	0.0223	0.0139
	(0.72)	(0.41)
Std_Sales	0.0096	0.0064
	(0.95)	(0.60)
Tangible	−0.0356	−0.0445 *
	(−1.54)	(−1.89)
Loss	0.0049	0.0102 * *
	(1.61)	(2.55)
Insti	0.0062	0.0252 * **
	(0.70)	(2.66)
Std_Net_Hire	−0.0498 * **	−0.0541 * **
	(−6.46)	(−6.62)
Labor_Intensity	−0.9852 *	−1.4180 * *
	(−1.71)	(−2.28)
AQ	−0.0188	−0.0246
	(−0.78)	(−0.94)
|*Ab_Invest_Other*|	0.3440 * **	0.3564 * **
	(19.80)	(18.96)
MA	0.0025	0.0018
	(0.53)	(0.37)
Union	−0.1386	−0.5219 * **
	(−1.57)	(−5.68)
First-step controls	Yes	No
Firm FE	Yes	No
Year FE	Yes	No
Observations	23,709	23,709
Adj. R-squared	0.338	0.208

[a] Similarly, we use the residuals from regressing our controls in Eq. (5) on a set of first-step regressors in Eq. (3), labeling them as *Control_Residuals* (e.g., *MTB_Residual, Size_Residual*, etc.). For simplicity and clarity, we do not place them on the table.

Table 14
Effect on Future Firm Performance. This table presents the results of regressing future firm performance on labor investment efficiency, OC, and their interaction. We measure firm performance using ROA and Tobin's Q. Based on the in-sample mean, we create two dummy variables: high-level labor investment efficiency *(HighLIE)* and high-level firm OC *(HighOC)*. We then interact them and include the interaction in our regression: $Firm\ Performance_{it+1} = \beta_0 + \beta_1 HighLIE * HighOC_{it} + \beta_n Controls_{it} + Firm\ FE + Year\ FE + \varepsilon_{it}$. Columns (1) and (2) present the regression results for ROA and Tobin's Q respectively. In all the specifications, we include firm and year-fixed effects. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable:	ROA (1)	Tobin's Q (2)
*HighLIE*HighOC*	0.0040 * *	10.8491 * **
	(2.09)	(2.80)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	21,963	20,794
Adj. R-squared	0.592	0.721

coefficients are not substantially influenced by measurement biases.

5.5. Effect on future firm performance

In this section, we examine the extent to which labor investment efficiency, enhanced by organizational capital (OC), positively impacts firm performance. We hypothesize that higher labor investment efficiency, driven by robust OC, should positively affect firm performance metrics such as Return on Assets (ROA) and Tobin's Q.

Our empirical analysis, presented in Table 14, examine the relationship between firm performance, labor investment efficiency, OC, and their interaction. To capture the effect of OC on labor investment efficiency, we introduce an interaction term between high-level labor investment efficiency (*HighLIE*) and high-level firm OC (*HighOC*). The results, as shown in Columns (1) and (2) of Table 14, indicate a positive and significant relationship between this interaction term and firm performance. Specifically, the coefficients for the interaction term ($HighLIE \times HighOC$) are 0.0040 ($p < 0.05$) for ROA and 10.8491 ($p < 0.01$) for Tobin's Q. These findings suggest that firms with high OC, which are also efficient in their labor investments, tend to exhibit superior financial performance. This outcome aligns with our initial predictions and reinforces the notion that organizational capital plays a crucial role in enhancing labor investment efficiency, thereby contributing to improved firm outcomes. The importance of retaining skilled employees is further underscored by Bernstein (2015), who documented that the departure of key inventors in firms post-IPO leads to a decline in subsequent innovation activity. Our results also resonate with the findings in our channel test presented in Table 3, which shows that high OC firms with low employee turnover achieve better labor investment efficiency.

These results not only confirm the theoretical framework posited by prior literature but also provide robust empirical evidence that OC can serve as a significant lever for firms seeking to optimize labor investment efficiency and enhance overall performance. The implications of these findings are particularly relevant for managers and policymakers who aim to leverage OC to drive firm success.

6. Conclusion

This paper demonstrates that firms with high organizational capital (OC) are better equipped to invest in human capital more efficiently than their counterparts with lower OC. We examine this relationship through a robust empirical analysis that shows a positive association between OC and labor investment efficiency. We find that high OC improves a firm's labor investment efficiency by reducing both labor underinvestment (employee retention channel) and labor overinvestment (mitigation of agency cost channel). Our results remain consistent across various measures of OC and labor investment efficiency. Furthermore, we strengthen our findings with evidence from a quasi-natural experiment using exogenous CEO turnover and a stacked difference-in-differences (DID) approach. In line with expectations, a placebo test using planned CEO retirements and forced CEO turnovers yielded no significant differences, reinforcing the validity of our results.

Our analysis also reveals that the positive impact of OC on labor investment efficiency is more pronounced in firms facing higher market competition, those with better access to external financing, and those heavily reliant on skilled labor. Additionally, we demonstrate that firms with high OC and low labor investment inefficiency are rewarded with stronger future operating performance, as measured by return on assets (ROA), and higher firm value, as reflected in Tobin's Q.

These findings contribute to the growing body of literature on the significance of OC in influencing firm labor investment decisions and have important economic implications, particularly in light of the increasing role of OC in shaping market outcomes. Our study underscores the critical role that OC plays not only in improving labor investment efficiency but also in enhancing overall firm performance and value.

CRediT authorship contribution statement

Tan Kelvin Jui Keng: Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Chowdhury Hasibul:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Le Trinh Hue:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

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Appendix A. Variable Definition

This table presents the definitions and data sources of all the variables used in our regressions. The Compustat acronyms are presented in italics and parentheses.

Variables	Description and *Acronyms*
Net_Hire	Percentage change in the number of employees *(EMP)* from financial year *t−1* to financial year *t* for firm *i*.
Sales_Growth	Percentage change in sales
ROA	Return on assets
ΔROA	Change in return on assets
Return	Annualized stock return
Size_R	Percentile rank of firm size
Quick	Cash and short-term investments plus receivables scaled by current liabilities *(CHE + RECT)/LCT)*
ΔQuick	Percentage change in the quick ratio
Leverage	The ratio of long-term debt and debt in current liabilities to the book value of assets *(DLTT+DLC)/AT*
AUR	Annual sales to total assets *(SALE/AT)*
LossBin1	A dummy that equals one if prior-year ROA is between −0.005 and 0 and zero otherwise
LossBin2	A dummy that equals one if prior-year ROA is between −0.010 and −0.005 and zero otherwise
LossBin3	A dummy that equals one if prior-year ROA is between −0.015 and - 0.010 and zero otherwise
LossBin4	A dummy that equals to one if prior-year ROA is between −0.020 and - 0.015 and zero otherwise
LossBin5	A dummy that equals one if prior-year ROA is between −0.025 and - 0.020 and zero otherwise

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Variables	Description and *Acronyms*
Labor Cost	Staff expense *(XLR)*
OC	OC measured as the stock of OC (for details, see Section 2.2)
RANK_OC	The annual decile rank of a firm's OC based on the Compustat universe
INDADJ_OC	The organization capital minus the industry median OC, scaled by total assets.
RANK_INDADJ_OC	The annual decile rank of industry-adjusted OC
MTB	The market-to-book ratio *(CSHO * PRCC_F/SEQ)*
Size	Firm size
Divdum	A dummy variable that equals one if a firm paid dividends *(DVPSP_F)* and zero otherwise.
Std_CFO	Standard deviation of firm *i*'s cash flows from operations *(OANCF/AT)* from year *t−5* to *t−1*.
Std_Sales	Standard deviation of firm *i*'s sales *(REVT/AT)* from year t−5 to t−1
Tangible	Property, plant, and equipment *(PPENT)* divided by total assets
Loss	A dummy variable that equals one if a firm has a negative ROA and zero otherwise
Insti	Institutional shareholdings
Std_Net_Hire	The standard deviation of firm *i*'s change in the number of employees from year *t−5* to *t−1*
Labor_Intensity	Labor intensity; measured as the number of employees divided by total assets *(EMP/AT)*.
AQ	An accounting quality measure based on the model of (Dechow and Dichev, 2002) as 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. After running the model cross-sectionally by industry and year, we compute the standard deviation of firm *i*'s residuals over the years *t−5* to *t−1* and multiply the result by −1.
|Ab_Invest_Other|	Abnormal other investments is defined as the absolute value of the residual of the following model: $Invest\_Other_{it} = b_0 + b_1 Sales\_Growth_{it-1} + e_{it}$, where $Invest\_Other_{it}$ is the sum of other nonlabor investments such as capital expenditures, acquisition expenditures and R&D expenditures less cash receipts from the sale of property, plant, and equipment scaled by lagged total assets.
MA	Managerial ability rank
Union	The industry-level rate of labor unionization
EF	The industry median value of the difference between capital expenditures and cash flows from operations divided by capital expenditures
High_Skilled	A dummy variable that equals one if the level of skilled labor in a firm's industry is higher than the in-sample median and zero otherwise
Treatment	A dummy variable that equals one for firms that have experienced exogenous CEO turnover due to well-specified health issues and zero otherwise
Post	A dummy variable that equals one for years after the event year and zero otherwise
Decr	A dummy variable that equals one if total revenue decreased from the previous year and zero otherwise
AI	The ratio of total assets to total revenue
Succ_Decr	A dummy variable that equals one if a firm faced a decrease in revenue between the current and previous year and zero otherwise.
HighOC	A dummy variable that equals one if a firm's OC is higher than the in-sample mean (median) and zero otherwise.
LowTO	A dummy variable that equals one if an employee turnover rate is lower than or equal to the in-sample mean (median) and zero otherwise. Employee turnover rate is calculated as the natural logarithm of a firm's ratio of non-executive employee stock option cancellations to its total number of stock options outstanding plus one [ln(1 +optca/optosey)].
Underinvestment	A dummy variable that equals one for firms with negative abnormal net hiring and zero otherwise.
HighIO	A dummy variable that equals one if a firm's institutional ownership is higher than the in-sample mean (median) and zero otherwise.
Overinvestment	A dummy variable that equals one for firms with positive abnormal net hiring and zero otherwise.

Appendix B. Economic fundamentals and net hiring practices

This table presents the results of regressing the percentage change in the number of employees, *Net_Hire*, on economic fundamentals. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: *Net_Hire*	Full sample (1)
$Sales\_Growth_{it-1}$	0.0296 * **
	(11.78)
$Sales\_Growth_{it}$	0.3054 * **
	(67.66)
ΔROA_{it-1}	−0.0310 * **
	(−5.02)
ΔROA_{it}	−0.2144 * **
	(−25.20)
ROA_{it}	0.1166 * **
	(15.30)
$Return_{it}$	0.0572 * **
	(31.81)
$Size\_R_{it-1}$	0.0004 * **
	(12.57)
$Quick_{it-1}$	0.0060 * **
	(10.26)
$\Delta Quick_{it-1}$	0.0313 * **
	(18.56)
$\Delta Quick_{it}$	−0.0177 * **
	(−8.75)
$Leverage_{it-1}$	−0.0555 * **
	(−10.64)

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Dependent variable: *Net_Hire*	Full sample (1)
AUR_{it-1}	0.0093 * **
	(5.96)
$LossBin1_{it-1}$	−0.0241 * **
	(−3.53)
$LossBin2_{it-1}$	−0.0217 * **
	(−3.34)
$LossBin3_{it-1}$	−0.0273 * **
	(−3.85)
$LossBin4_{it-1}$	−0.0141 * *
	(−2.22)
$LossBin5_{it-1}$	−0.0137
	(−1.63)
Industry FE	Yes
Observations	104,765
R-squared	0.255

Appendix C. : Subsamples of overinvestments and underinvestments

This table presents the baseline results for the four subsamples. Columns (1) and (2) present the regression results for the overhiring and underfiring subsamples, which are related to overinvestments. Columns (3) and (4) show the regression results for the underhiring and overfiring subsamples, which are related to underinvestments. The full sample is split based on the sign of abnormal net hiring. Over-hiring is actual net hiring that exceeds the expected number (based on Eq. (3)) when expected net hiring is positive. Under-firing is actual net hiring that exceeds the expected number when expected net hiring is negative. Under-hiring is actual net hiring that is less than the expected number when the expected number is positive. Over-firing is actual net hiring that is less than the expected number when the expected number is negative. The dependent variable is |*Ab_Net_Hire*|. A higher value of *Ab_Net_Hire* represents lower labor investment efficiency. In all the specifications, we include firm and year-fixed effects. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

	Overinvestments		Underinvestments	
Dependent variable:	Overhiring (1)	Underfiring (2)	Underhiring (3)	Overfiring (4)
OC	−0.0028	−0.0133 * **	0.0031	−0.0211 * **
	(−0.49)	(−4.65)	(0.47)	(−3.69)
MTB	0.0026 * **	−0.0000	0.0007	0.0018 * *
	(3.02)	(−0.05)	(0.60)	(2.31)
Size	−0.0118 * *	−0.0145 * **	0.0172 * *	−0.0127 *
	(−2.05)	(−5.28)	(2.20)	(−1.94)
Quick	0.0037	0.0014	0.0077	0.0019
	(1.42)	(1.08)	(1.28)	(0.48)
Leverage	0.0246	0.0101	−0.0468	0.0708 * *
	(0.99)	(0.78)	(−0.89)	(2.21)
Divdum	0.0248 * *	0.0018	−0.0296	0.0096
	(2.26)	(0.48)	(−1.64)	(0.78)
Std_CFO	0.0495	0.0394	0.1608	0.1288
	(0.74)	(1.11)	(1.01)	(1.24)
Std_Sales	0.0324	−0.0317 * *	−0.0184	−0.0330
	(1.38)	(−2.42)	(−0.34)	(−0.90)
Tangible	−0.1095 * *	−0.0624 * **	0.0826	−0.0273
	(−2.14)	(−3.18)	(1.02)	(−0.39)
Loss	−0.0144 *	0.0148 * **	0.0060	−0.0019
	(−1.80)	(4.21)	(0.72)	(−0.26)
Insti	0.0177	−0.0019	−0.0358	−0.0175
	(0.80)	(−0.19)	(−1.18)	(−0.69)
Std_Net_Hire	−0.0748 * **	−0.0247 * **	−0.0860 * **	−0.0548 * *
	(−4.25)	(−2.70)	(−2.67)	(−2.20)
Labor_Intensity	−7.4261 * **	2.4926 * **	−5.2379 * **	8.2132 * **
	(−5.32)	(3.82)	(−3.23)	(3.78)
AQ	−0.0759	−0.0363	0.0839	−0.0016
	(−1.22)	(−1.23)	(0.82)	(−0.02)
|*Ab_Invest_Other*|	0.5068 * **	0.0654 * **	0.3573 * **	0.0515
	(20.95)	(2.97)	(4.07)	(0.80)
MA	0.0177	−0.0211 * **	0.0344 *	0.0098
	(1.51)	(−3.83)	(1.66)	(0.65)
Union	0.0003	−0.0973	−0.3436	−0.0426
	(0.00)	(−1.12)	(−0.82)	(−0.11)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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	Overinvestments		Underinvestments	
Dependent variable:	Overhiring (1)	Underfiring (2)	Underhiring (3)	Overfiring (4)
Observations	7,301	11,721	2,009	2,678
Adj. R-squared	0.514	0.414	0.703	0.568

Appendix D. Controlling for managerial ability score

This table presents the results of our baseline model after replacing managerial ability rank control variable with managerial ability score. The dependent variable is |*Ab_Net_Hire*|. A higher value of *Ab_Net_Hire* represents lower labor investment efficiency. We include firm and year-fixed effects. Heteroskedasticity-robust standard errors are clustered at the firm level. Variable definitions are provided in Appendix 1. The numbers in parentheses are two-tailed *t*-statistics. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent variable: |*Ab_Net_Hire*|	Full sample
OC	−0.0108 * **
	(−4.86)
MA Score	−0.0206
	(−1.55)
MTB	0.0008 * *
	(2.20)
Size	−0.0096 * **
	(−3.69)
Quick	0.0030 * **
	(2.78)
Leverage	0.0040
	(0.34)
Divdum	0.0080 * *
	(2.08)
Std_CFO	0.0432
	(1.39)
Std_Sales	0.0083
	(0.81)
Tangible	−0.0438 *
	(−1.86)
Loss	0.0012
	(0.43)
Insti	−0.0033
	(−0.37)
Std_Net_Hire	−0.0537 * **
	(−6.83)
Labor_Intensity	−0.8844
	(−1.64)
AQ	−0.0218
	(−0.87)
|*Ab_Invest_Other*|	0.4048 * **
	(22.82)
Union	−0.1136
	(−1.26)
Firm FE	Yes
Year FE	Yes
Observations	23,709
Adj. R-squared	0.315

Data Availability

The authors do not have permission to share data.

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