



Technological dynamism and labor investment efficiency: exploring strategic resilience

Mohamed Shaker Ahmed¹ · Charilaos Mertzanis^{2,3} · Satish Kumar^{4,5} ·
Mohamad Husam Helmi⁶ 

Received: 11 March 2026 / Accepted: 8 September 2026
© The Author(s) 2026

Abstract

This study contributes to the literature by exploring the impact of technological dynamism (TD) on labor investment efficiency, analyzing non-financial U.S. firms listed on the S&P 500 index from 1993 to 2023. Employing a novel TD measure based on industry-level R&D intensity, we find that firms in highly dynamic technological environments face greater challenges in achieving labor investment efficiency, with inefficiencies primarily driven by overinvestment rather than underinvestment. Robust across various sensitivity and endogeneity tests, the results highlight how rapid technological change complicates optimal labor allocation. Leadership characteristics significantly moderate this relationship, as external CEOs and extensive CEO media coverage weaken the link between TD and LIE, while longer CEO tenure enhances firms' alignment of labor investments with technological demands. Furthermore, corporate diversification, firm age, the adoption of the Inevitable Disclosure Doctrine, and business strategies emerge as key moderators through which TD influences LIE, demonstrating the interplay between organizational strategies and regulatory frameworks.

Keywords Labor investment efficiency · Technological dynamism · Research and development · Human capital · Managerial policies · Corporate investment

JEL Classification D22 · G30 · J23 · L25 · O32 · R11

1 Introduction

Firms compete in environments marked by shifting customers, rivals, and technologies. We frame technological dynamism (TD) as the dynamism dimension of the task environment, i.e., variation, instability, and unpredictability, that compels ongoing

Extended author information available on the last page of the article

ing resource reconfiguration (Aldrich 1979; Keats and Hitt 1988). In such contexts, dynamic capabilities guide adaptation but can have contingent, non-monotonic performance effects (Schilke 2014). Empirically, TD manifests through market-demand uncertainty, competitive shifts, and rapid technological change that stimulate corporate innovation (Uotila et al. 2009; Wang and Chen 2010; Wu et al. 2005).

Within this environment, labor investment efficiency (LIE), i.e., aligning hiring, retention, and redeployment with fundamentals, becomes central. Flexible, employee-centric HR systems (e.g., skill breadth, job rotation, contingent staffing) can support adjustment but are vulnerable to mis-calibration when managers misread signals (Wright and Snell 1998). LIE research shows that avoiding over- and under- investment in labor improves performance and market discipline (Ben-Nasr and Alshwer 2016; Khedmati et al. 2020), yet labor remains less studied than capital (Jung et al. 2014). In human-capital-intensive settings, efficient labor choices are key for advantage (Zingales 2000), especially given the mobility of skills and the need to manage knowledge leakage (Matsa 2018).

Managerial interpretation is a key transmission mechanism from TD to LIE. Managerial cognition and dynamic managerial capabilities shape how leaders read the environment and translate it into staffing, training, and redeployment (Helfat and Martin 2015). Competent leadership also affects market valuations and organizational resilience (Au et al. 2021). But misaligned incentives and constraints can degrade LIE: strategic human-capital investments help (Cao et al. 2023), whereas agency frictions and short-termism harm (Boubaker et al. 2022). A broad set of firm attributes, i.e., governance, strategy, information environments, and horizons, also co-determine labor choices (Habib and Hasan 2021; Khedmati et al. 2020; Le and Tran 2022; Cao and Rees 2020; Ghaly et al. 2020; Jung et al. 2014; Ben-Nasr and Alshwer 2016).

We explore whether industry-level TD predicts firms' LIE and under what managerial/organizational conditions. Consistent with our focus on external conditions, we proxy TD by 4-digit SIC industry R&D intensity (total industry R&D over total industry sales), which captures sector-wide innovation pressure beyond any single firm's policy and aligns with the OECD's R&D-intensity taxonomy (Belenzon et al. 2019). TD can also be triangulated by market-dynamism metrics based on time-trend volatility in industry sales (Keats and Hitt 1988). We measure LIE as the absolute abnormal net hiring from a standard two-stage model (Jung et al. 2014; Ben-Nasr and Alshwer 2016). This design fits the strategic view that external dynamics shape internal policies (Do et al. 2022). We study non-financial S&P 500 firms, constructing rolling histories from 1993 and estimating over 1997–2023. Non-financial S&P 500 firms are an ideal setting because they are large-cap, information-rich companies that disclose consistent employment and R&D data, span a highly innovative economy with meaningful cross-state institutional variation.

We find that higher TD is associated with lower LIE, with the effect concentrated in overinvestment, not underinvestment. A plausible mechanism is skill mismatches and talent scarcity under rapid change (Au et al. 2021), compounded by information frictions that complicate hiring and training (Helfat and Martin 2015). Managerial characteristics matter: externally hired CEOs and greater CEO media coverage attenuate TD-related inefficiency, whereas longer CEO tenure amplifies it, which is

consistent with fresh perspectives/discipline versus strategic persistence. Results are robust to alternative TD measures and estimators and remain after extensive endogeneity checks. We also document organizational/legal moderators, such as diversification, public-listing exposure, and state adoption of the Inevitable Disclosure Doctrine (IDD), and a strategy moderator (prospector orientation) through which TD shapes labor choices.

Our study makes three contributions to the literature. First, we shift the labor-investment literature from firm-internal determinants to the external technological environment, introducing industry-level TD as a predictor of LIE and decomposing effects into over- vs under-investment (Jung et al. 2014; Ben-Nasr and Alshwer 2016). Second, we justify and implement an industry-level TD measure rather than firm-level R&D, improving construct–measure alignment and comparability across firms (Belenzon et al. 2019) while complementing prior work that uses firm-level R&D to study risk-taking (Shao et al. 2013; Roychowdhury et al. 2019). Third, we open the black box between TD and LIE by testing managerial moderators (external CEO, tenure, media) and organizational moderators (diversification, exposure, IDD, strategy), connecting strategic management perspectives on external dynamics and innovation (Simerly and Li 2000; Wang et al. 2021; García-Villaverde et al. 2018).

2 Related literature

2.1 External conditions and corporate response

We theorize TD as a core facet of environmental dynamism, i.e., the volatility and unpredictability of customers, competitors, and technologies, that compels firms to realign resources and routines continually. Classic organization and strategy research emphasize that such dynamism heightens the need for strategic fit, learning, and rapid reconfiguration (Aldrich 1979; Keats and Hitt 1988; Schilke 2014). In this setting, labor is not a passive input: firms must adjust hiring, training, and redeployment to maintain performance (Wang and Chen 2010; Wu et al. 2005). Knowledge-based and absorptive-capacity views explain the micro-foundations of these adjustments, highlighting how distinctive know-how, problem-solving capability, and external knowledge integration support adaptation (Triguero and Córcoles 2013). Managerial cognition and dynamic managerial capabilities further shape how signals from a turbulent environment are interpreted and translated into staffing choices (Helfat and Martin 2015). At the HR policy level, workforce flexibility, i.e., skill breadth, job rotation, cross-functional teams, and contingent staffing, facilitates adjustment but can also produce mis-calibration if decision makers misread environmental cues (Wright and Snell 1998; Martínez-Sánchez et al. 2012).

2.2 Conceptualizing technological dynamism

To align construct and measurement with our research outcome, which is an intra firm deviation from fundamentals that we explicitly relate to the external environment, we treat TD as an external, industry-level condition and operationalize it using

4-digit SIC R&D intensity, i.e., total industry R&D divided by total industry sales. This measure captures peer competition and sectoral innovation pressure, smooths firm-specific noise, and comports with the OECD's taxonomy of R&D-intensive sectors (Uotila et al. 2009; Belenzon et al. 2019; Ćirović et al. 2026). As a cross-check, market dynamism can be proxied by the volatility of a time trend in industry sales, which further triangulates the construct (Keats and Hitt 1988). The literature also shows that TD itself emerges from multiple antecedents, i.e., networks and collaboration (Wu et al. 2005), policy internationalization (Schubert et al. 2018), entrepreneurial orientation (García Villaverde et al. 2018), governance (Cai and Tylecote 2008), and intra industry linkages (Gómez et al. 2022), reinforcing the view that TD is environmental rather than idiosyncratic to any single firm.

2.3 Theorizing moderators

Theory suggests two opposing perspectives on the relationship between technological dynamism (TD) and labor investment efficiency (LIE). An efficiency-enhancing view, grounded in the resource-based and strategic human-capital perspectives, argues that TD promotes upskilling, redeployment, and better alignment of human capital with production needs, thereby improving LIE (Gerhart and Feng 2021; Ployhart 2021). Dynamic-capabilities arguments similarly suggest that training, job rotation, and cross-functional teams facilitate timely workforce reconfiguration as technologies evolve (McKelvie and Davidsson 2009; Apascaritei and Elvira 2022). Transaction-cost and institutional perspectives further imply that targeted human-capital investments and innovation-oriented HR practices can reduce adaptation costs in dynamic environments (Fainshmidt et al. 2022).

In contrast, an efficiency-reducing view emphasizes agency frictions, short-termism, managerial misperception, and skill obsolescence, which may lead to empire-building over-hiring or underinvestment in labor (Boubaker et al. 2022; Erhemjamts and Huang 2019; Ensley et al. 2006; Torre et al. 2018). Empirical evidence also supports both perspectives. Innovation investment and HR flexibility can help retain scarce talent and improve labor allocation (Khedmati et al. 2020; Ee et al. 2022; Cao and Rees 2020; Li and Liu 2014; Simerly and Li 2000). Conversely, TD can intensify skill mismatches and reduce demand for routine labor, making efficient staffing more difficult. These mixed findings motivate our two-sided baseline and the decomposition of labor investment inefficiency into over- and underinvestment.

2.4 Managerial policies

Managers condition how external pressure maps into HR decisions. We focus on three moderators that are observable and economically meaningful in large-cap settings. First, externally hired CEOs can catalyze change and break inertial routines, potentially attenuating TD-related misallocation (Ertimur et al. 2018; Quigley et al. 2019; Bai and Mkrtchyan 2023; Arshad et al. 2026). Second, CEO tenure is often associated with strategic persistence; in high-TD settings, longer tenure may amplify misalignment if established schemas lag new technologies (Simerly and Li 2000; Wu et al. 2005). Third, CEO media coverage, as part of the broader information-interme-

diation infrastructure, can discipline managers and nudge policies toward efficiency (Cahan et al. 2015; Pfarrer et al. 2010; Chen et al. 2021; Milbourn 2003; Jian and Lee 2011; Tetlock 2007). These expectations mirror the interaction tests we run later.

2.5 Organizational and legal moderators

Beyond leaders, organizational and legal moderators shape the TD–LIE link. Corporate diversification can buffer shocks yet enable internal misallocation across segments (Khanna and Tice 2001; Ozbas and Scharfstein 2010; Kuppuswamy and Villalonga 2016; Wang 2023). Public listing age (exposure) may capture learning that improves allocation (countered by potential obsolescence; Kieschnick and Moussawi 2018; Balasubramanian and Lee 2008; Coad et al. 2016). Knowledge protection regimes, notably U.S. state adoption of the Inevitable Disclosure Doctrine (IDD), can help firms run leaner staffing models by lowering leakage risk (Klasa et al. 2018; Colak and Korkeamäki 2021; Canil et al. 2023; Qiu and Wang 2018). Business strategy (prospector vs. defender) conditions HR posture under TD; prospectors' long-term, stakeholder-oriented emphasis may reduce inefficiency (Zhou and Wu 2010; Bentley et al. 2013; Habib and Hasan 2021; Yuan et al. 2020; Chen and Jermias 2014). Because regional context shapes innovation inputs and labor markets, TD's association with LIE can be stronger in high-income states with deeper R&D ecosystems.

2.6 Hypotheses

Synthesizing these strands, we state an agnostic baseline: in dynamic industries, TD may either improve LIE by forcing timely reconfiguration and upskilling or worsen LIE through agency frictions, misperception, and skill obsolescence (McKelvie and Davidsson 2009; Ployhart 2021; Boubaker et al. 2022; Erhemjamts and Huang 2019). These hypotheses are stated as follows:

H1a (improvement) In dynamic industries, firms improve LIE by reconfiguring/upskilling the workforce to match technological change.

H1b (deterioration) Alternatively, TD worsens LIE via agency frictions, misperception, short termism, and skill obsolescence.

Beyond the agency- and information-based arguments outlined above, three complementary theoretical lenses help explain why technological dynamism should bias labor-investment inefficiency toward overinvestment rather than underinvestment.

First, real options theory suggests that when investment and disinvestment decisions are costly to reverse and future states of the world are uncertain, decision makers rationally delay downsizing and instead retain a buffer of resources whose option value exceeds the carrying cost of temporary excess capacity (Dixit and Pindyck 1994). Applied to staffing, firms operating in technologically dynamic industries face substantial uncertainty about which skills will be required as technologies evolve; because reducing headcount is far easier to reverse than rehiring comparable special-

ized talent once dismissed, managers have an incentive to hold "staffing options" open by over-retaining or over-hiring employees rather than shedding labor precisely when its future value is most uncertain (McGrath 1999). This logic implies that overinvestment, not underinvestment, is the theoretically predictable response of boundedly rational managers to irreversible, option-like staffing decisions under technological uncertainty.

Second, the irreversibility of specialized human capital reinforces this asymmetry. Unlike physical capital, technologically specialized human capital is costly and slow to reconstitute once dismissed: severance destroys firm-specific and tacit know-how that competitors can also bid away once released into the labor market, while rebuilding equivalent capability through new hiring entails lengthy search, matching, and training costs (Becker 1964). Under high TD, the expected cost of a future skill shortage is therefore disproportionately larger than the expected cost of temporarily carrying redundant labor, giving managers an asymmetric incentive to err toward overstaffing rather than risk irreversible losses of scarce, technologically relevant expertise.

Third, the knowledge-based view of the firm suggests that firms retain and expand their workforce beyond current fundamentals-implied needs in order to preserve tacit knowledge stocks and combinative capabilities that underpin competitive advantage (Grant 1996; Kogut and Zander 1992). Because tacit, technologically embedded knowledge is difficult to codify, transfer, or quickly re-acquire, and because employee mobility can transmit such knowledge to rivals, firms operating in technologically dynamic industries have a strategic incentive to over-retain talent as a defensive mechanism against knowledge attrition and spillovers, even when current fundamentals would justify a smaller workforce.

Together, these three lenses, real options reasoning, human-capital irreversibility, and the knowledge-based view, converge on a common prediction: under technological dynamism, the marginal cost of underinvesting in labor (foregone option value, lost tacit knowledge, costly re-acquisition of specialized skills) is perceived by managers as larger than the marginal cost of overinvesting (temporary excess capacity), even though both represent deviations from labor levels implied by current fundamentals. This provides an *ex ante* theoretical basis, rather than a purely post-hoc empirical account, for expecting technological dynamism to manifest primarily through labor overinvestment.

H₂ The negative effect of technological dynamism on labor investment efficiency is expected to be concentrated in labor overinvestment rather than labor underinvestment.

We then test directional moderator predictions: external CEOs and greater CEO media visibility should attenuate TD-related inefficiency; longer CEO tenure should amplify it; diversification should exacerbate misallocation; longer public exposure and IDD adoption should improve alignment; and prospector strategy should reduce inefficiency, predictions that correspond one-for-one to our interaction specifications and moderating analyses, anticipating the decomposition of LIE into over- and underinvestment.

3 Empirical strategy

3.1 Data

To examine how industry-level TD relates to firm-level LIE, we assemble a panel of U.S. S&P 500 non-financial firms with point-in-time index membership. Accounting and market data are drawn from DataStream; CEO characteristics used in the moderator analyses are compiled from BoardEx, company websites, Bloomberg, Crunchbase, and LinkedIn. The construction begins in 1993 to permit rolling histories; after forming five-year rolling measures (e.g., sales, cash-flow, and net-hiring volatilities), the estimation window spans 1997–2023, yielding 13,095 firm-years for 485 firms after standard data screens. This large-cap, widely followed universe provides consistent disclosure on employment and R&D, aligning the data with our research question on how external technological conditions shape internal labor allocation. To link each firm-year to its external technological environment, we later define TD at the 4-digit SIC industry-year level (industry R&D-to-sales), computed from the U.S. firm universe in DataStream and merged to firms by primary SIC. Measuring TD at the industry (rather than firm) level ensures the key regressor reflects environmental pressure outside the focal firm, consistent with our design to test whether industry dynamism predicts deviations from firm-fundamentals in hiring. All continuous variables are winsorized at the 1st/99th percentiles to mitigate outliers.

3.2 Key variables

We measure LIE using the standard two-stage approach (Pinnuck and Lillis 2007; Jung et al. 2014). Stage 1 benchmarks normal hiring by regressing a firm's net hiring on lagged fundamentals, with firm and year fixed effects. Equation (1) presents the Stage 1 estimation model:

$$\begin{aligned} Net_hire_{it} = & \beta_0 + \beta_1 Sales_Growth_{i,t-1} + \beta_2 Sales_Growth_{i,t} + \beta_3 \Delta ROA_{i,t-1} + \beta_4 \Delta ROA_{i,t} \\ & + \beta_5 ROA_{i,t} + \beta_6 Return_{i,t} + \beta_7 Size_{i,t-1} + \beta_8 Quick_{i,t-1} + \beta_9 \Delta Quick_{i,t-1} \\ & + \beta_{10} \Delta Quick_{i,t} + \beta_{11} Leverage_{i,t-1} + \beta_{12} AUR_{i,t-1} + \beta_{13} LossBin1_{i,t-1} \\ & + \beta_{14} LossBin2_{i,t-1} + \beta_{15} LossBin3_{i,t-1} + \beta_{16} LossBin4_{i,t-1} + \beta_{17} LossBin5_{i,t-1} \\ & + IndustryFE + \varepsilon_{i,t} \end{aligned} \quad (1)$$

Here, *Net_Hire* is the percentage change in employees from $t-1$ to t ; *Sales_Growth* is the percentage change in sales; *ROA* is the return on assets; *Return* is the annual stock price return; *Size* is the natural logarithm of total assets; *Quick* is cash and short-term investments plus receivables scaled by current liabilities; *Leverage* is the ratio of total debt to total assets; and *AUR* is asset turnover (sales/total assets). Moreover, in order to capture non-linear effects and account for financially stressed firms, we compute *LossBin_k* $k \in [1, 5]$ narrow loss-indicator dummies based on prior-year ROA: $[-0.005, 0)$, $[-0.010, -0.005)$, $[-0.015, -0.010)$, $[-0.020, -0.015)$, $[-0.025, -0.020)$. Variables such as *Size*, *Quick*, and *Leverage* enter only in Stage 2 (controls), not in Stage 1, to avoid absorbing variation we examine downstream. Finally, *IndustryFE* denotes industry-fixed effects.

Let $\hat{\varepsilon}_{i,t}$ be the residual from (1). We define: (i) Abnormal net hiring, $\text{Ab_Net_Hire}_{i,t} \equiv \hat{\varepsilon}_{i,t}$; (ii) Labor investment inefficiency, $|\text{Ab_Net_Hire}|_{i,t} = |\hat{\varepsilon}_{i,t}|$ (higher values = more inefficiency); and (iii) the decomposition used in later analyses: $\text{OverInvest}_{i,t} = \max(0, \hat{\varepsilon}_{i,t})$ and $\text{UnderInvest}_{i,t} = \max(0, -\hat{\varepsilon}_{i,t})$ (Khedmati et al. 2020). Thus, $|\text{Ab_Net_Hire}|$ captures the **absolute deviation** of actual net hiring from the level predicted by a firm's economic fundamentals, i.e., how much it over- or under-hires relative to what its economic fundamentals warrant, and therefore serves, by construction, as our measure of *labor investment inefficiency*. Consistent with prior literature, this measure captures deviations in workforce quantity from predicted levels and does not directly observe employee quality, skills, or human-capital composition. Stage 1 includes only the lagged fundamentals listed in Eq. (1), while broader financials and governance variables appear as regressors in Eq. (4).

Our primary regressor measuring technological dynamism (*Dynamism*) is industry-level R&D intensity at the 4-digit SIC–year:

$$TD_{j,t} = \frac{\sum_{m \in j} R\&D_{m,t}}{\sum_{m \in j} \text{Sales}_{m,t}} \quad (2)$$

We compute TD using the U.S. firm universe in DataStream (not just S&P 500 constituents) and merge to firms by primary SIC. Using an industry-level measure captures the external innovation environment, e.g., peer competition and sector-wide technological change and competitive pressure, rather than a firm's own policy choice, and aligns with OECD R&D-intensity taxonomy practice. This operationalization directly serves our research question by linking environmental technological pressure to deviations from fundamentals in firm hiring. This industry-wide TD proxy captures the external innovation environment while avoiding the policy endogeneity inherent in firm-level R&D. Aggregation smooths firm-specific noise, improves cross-firm comparability, and aligns with the OECD's R&D-intensity taxonomy and prior strategy work that links industry R&D intensity to environmental dynamism (Uotila et al. 2009). Conceptually, this choice matches our research design: we test whether environment-level technological pressure predicts deviations from fundamentals in firm hiring ($|\text{Ab_Net_Hire}|$), so TD reflects conditions outside the focal firm.

A limitation of our technological dynamism measure is that industry-level R&D intensity primarily captures innovation effort and technological opportunity rather than technological turbulence itself. Although R&D intensity is widely employed in the strategy and innovation literature as an indicator of technologically dynamic environments, industries exhibiting similar R&D-to-sales ratios may nevertheless differ in the pace, unpredictability, and disruptive nature of technological change. Alternative measures, such as patent citation volatility, technology-class entropy, patent renewal dynamics, or product-market disruption indices, may capture complementary dimensions of technological dynamism. However, our objective is to capture the external innovation pressure faced by firms rather than firm-specific innovation outcomes. Industry-level R&D intensity is particularly well suited to this purpose because it reflects sector-wide innovation investment, is consistently available over

the long sample period, and minimizes endogeneity concerns associated with firm-level innovation measures. Nevertheless, future research may benefit from examining whether our findings generalize to alternative indicators that more directly capture technological turbulence and disruption.

We also create two robustness proxies: (i) a High-TD indicator (1 if $TD_{j,t}$ is above the annual median), and (ii) a market-dynamism metric following Keats and Hitt (1988): in rolling five-year windows, we regress $\ln(\text{industry sales})$ on a time trend and use the standard error of the time coefficient (normalized by mean sales) as dynamism. Results are consistent across measures.

3.3 Controls

Consistent with prior research (Ee et al. 2022; Cao and Rees 2020), we include a comprehensive set of firm-level controls that may influence LIE. These include firm size (Size), measured as the natural logarithm of total assets, and the market-to-book ratio (MTB), which captures growth opportunities. The quick ratio (Quick) measures short-term liquidity, while Leverage reflects reliance on debt financing. Dividends (Dividend) proxy for financial health and shareholder value. Operational risk is captured by the volatility of operating cash flows (Std. CF) and sales (Std. Sales), whereas Tangibility measures the proportion of physical assets. We also control for losses (Loss), a binary indicator of negative earnings, and the volatility of net hiring (Std. net hiring), which reflects labor-market dynamics. Labor intensity captures the importance of labor in production, while CEO duality indicates whether the CEO also serves as board chair and may influence decision-making efficiency. Finally, we control for other (non-labor) investment efficiency ($|Ab_Invest_Other|$), constructed using the investment model of Biddle et al. (2009). This measure captures deviations in non-labor investments (e.g., capital expenditures, R&D, and acquisitions) scaled by beginning assets. We estimate firm- and year-fixed-effects regressions and use the absolute residuals as our measure of non-labor investment inefficiency, as follows:

$$|Ab_Invest_Other|_{it} = \beta_0 + \beta_1 Sales_Growth_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

Other (non-labor) investment efficiency accounts for the company's efficiency in allocating resources to investments other than labor, such as capital expenditures. This absolute value of the residuals obtained from the above equation measures the extent to which other investments (e.g., capital expenditures, R&D expenditures, and acquisitions) deviate from the optimal level. Table 1 provides detailed definitions of these variables.

3.4 Estimation model

Identifying a detectable association effect of TD on LIE is challenging because unobserved factors may be correlated with both. Our baseline therefore uses panel OLS with firm and year fixed effects, which absorb time-invariant firm heterogeneity (e.g., strategy, culture) and common shocks (e.g., macro conditions, technology cycles). We treat estimates as associations and report clustered standard errors by firm to

Table 1 Definition of variables

Variable	Definition
Model (1) variables	
Net_Hire _{it}	Percentage change in the number of employees of firm <i>i</i> from year <i>t-1</i> to <i>t</i>
Sales_growth _{it}	Percentage change in sales of firm <i>i</i> in year <i>t</i>
ROA _{it}	Return on assets of firm <i>i</i> in year <i>t</i>
Return _{it}	Total stock price return of firm <i>i</i> during year <i>t</i>
Size _{it}	Natural logarithm of firm's total assets of firm <i>i</i> at the end of year <i>t</i>
Quick _{it}	Cash plus short-term investments plus receivables over current liabilities of firm <i>i</i> in year <i>t</i>
Leverage _{it}	Total debt scaled by total assets of firm <i>i</i> in year <i>t</i>
LossBin1, LossBin2, LossBin3, LossBin4, LossBin5	LossBin1 is equal to one if prior-year ROA is between -0.005 and 0 and zero otherwise. LossBin2, LossBin3, LossBin4, and LossBin5 are identically constructed dummies with interval lengths of 0.05 ([-0.010 and -0.005]; [-0.015 and -0.010]; [-0.020 and -0.015]; [-0.025 and -0.020], respectively)
AUR _{it}	Annual sales to total assets of firm <i>i</i> in year <i>t</i>
Model (3) variables	
Dynamism _{it}	Industry-level R&D intensity at year <i>t</i> , computed as the ratio of R&D expenditures to total sales for all firms in an industry. Industries are specified using the four-digit SIC code in a specific year
Ab_Net_Hire _{it}	The absolute value of residuals as abnormal net hiring. This absolute value is extracted from Model (1)
MTB _{it}	Market to book ratio in year <i>t</i> for firm <i>i</i>
Divd _{it}	Dividend payouts in year <i>t</i> for firm <i>i</i>
Cash_flow_volatility _{it}	Standard deviation of operating cash flows over five-years period
Sales_volatility _{it}	Standard deviation of the ratio of sales to total assets over five-years period
Tangibility _{it}	The ratio of property, plant, and equipment (non-current) to total assets
Loss _{it}	Dummy variable that takes one if a firm has a negative ROA and zero otherwise
Net_hire_volatility _{it}	Standard deviation of net hire over five-years period
Labor_intensity _{it}	Ratio of number of employees to total assets in year <i>t</i> for firm <i>i</i>
Ab_Invest_Other _{it}	Absolute value of residuals of Model (3)
CEO duality	A dummy variable that takes the value of one if the CEO is also the chairperson of the board of director and zero otherwise
R&D	Ratio of R&D expenditure to total assets

allow for arbitrary heteroskedasticity and serial/cross-sectional correlation. To probe residual endogeneity, we later implement sensitivity analyses and bias-mitigation checks. Analyses use non-missing observations. The estimation equation assumes the following form:

$$\begin{aligned}
 |Ab_Net_Hire|_{it} = & \beta_0 + \beta_1 Dynamism_{i,t-1} + \beta_2 MTB_{i,t-1} + \beta_3 Size_{i,t-1} \\
 & + \beta_4 Quick_{i,t-1} + \beta_5 Leverage_{i,t-1} + \beta_6 Dividends_{i,t-1} + \beta_7 Std_CF_{i,t-1} \\
 & + \beta_8 Std_sales_{i,t-1} + \beta_9 Tangibility_{i,t-1} + \beta_{10} Loss_{i,t-1} \\
 & + \beta_{11} Std_Net_Hire_{i,t-1} + \beta_{12} LaborIntensity_{i,t-1} + \beta_{13} Duality_{i,t-1} \\
 & + \beta_{14} |Ab_Invest_Other|_{i,t-1} + \beta_{15} R\&D_{i,t-1} + FirmFE + YearFE \\
 & + \varepsilon_{i,t}
 \end{aligned} \quad (4)$$

where $|Ab_Net_Hire|$ is the absolute abnormal net hiring from Eq. (1); $TD_{j(i),t}$ is industry-level technological dynamism for firm i 's 4-digit SIC industry j ; vector $X_{i,t-1}$ collects the controls and ε_{it} , representing the regression's error parameter. Coefficient β_I captures how exposure to technological change is associated with labor-investment inefficiency, after conditioning on firm fundamentals and time effects. We interpret coefficients as associations ("predict") rather than causal effects and therefore complement the baseline with sensitivity analyses and endogeneity checks.

4 Results

4.1 Descriptive analysis

Table 2 reports substantial variation across firms, reflecting differences in financial health, growth, governance, and market conditions. Net Hire averages 0.053 (SD: 0.145), indicating variation in employee growth, while Dynamism averages 0.030 (SD: 0.053), reflecting differences in industry R&D intensity. $|Ab\ Net\ Hire|$ averages 0.084 (SD: 0.109), suggesting meaningful deviations from predicted hiring levels. Firm Size averages 16.539 (SD: 1.225), while MTB 1.667 (SD: 1.708). The Quick Ratio (0.087–7.727) and Leverage (0.073–4.016) indicate substantial differences in liquidity and financing. Dividends range from 0 to 8.0, while Sales Volatility (SD: 0.665) and Tangibility (0.068–0.999) reveal heterogeneity in operating conditions and asset structures. Most firms are profitable (Loss SD: 0.231), although hiring volatility varies considerably (mean: 0.142, SD: 0.127). Labor Intensity shows limited dispersion, whereas CEO Duality is present in nearly half the sample. Overall, the descriptive statistics indicate considerable cross-sectional diversity.

Table 2 Descriptive statistics

Variable	Mean	SD	Min	Max	Obs
Net Hire	0.053	0.145	−0.285	0.802	12,225
Dynamism	0.030	0.053	0.000	0.176	12,596
$ Ab_Net_Hire $	0.084	0.109	0.010	0.700	10,938
Size	16.539	1.225	13.176	19.592	12,266
MTB	1.667	1.708	0.000	9.631	12,238
Quick	1.780	1.356	0.087	7.727	12,255
Leverage	0.678	0.477	0.073	4.016	12,351
Dividends	1.113	1.355	0.000	8.000	12,074
Std. CF	0.001	0.001	−0.001	0.001	12,758
Std. Sales	0.760	0.665	0.036	3.510	12,595
Tangibility	0.632	0.239	0.068	0.999	12,351
Loss	0.056	0.231	0.000	1.000	12,595
Std. net hiring	0.142	0.127	0.022	0.800	12,597
Labor intensity	0.001	0.001	0.000	0.001	12,184
$ Ab_Invest_Other $	−0.001	0.143	−0.438	0.598	11,886
CEO duality	0.472	0.499	0.000	1.000	12,114
R&D	0.026	0.051	0.000	0.293	12,351

This table presents descriptive statistics. Definitions of variables are presented in Table 1

Table 3 Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Abs net hiring	1															
2. Dynamism	0.004***	1														
3. MTB	-0.011**	0.028***	1													
4. Size	-0.032***	-0.041	0.117***	1												
5. Quick	0.010***	0.070***	0.255***	-0.107***	1											
6. Leverage	-0.007	0.006	0.042***	-0.042***	0.005	1										
7. Dividends	-0.031***	-0.020***	-0.062	0.180***	-0.040***	0.010	1									
8. Std. CF	0.070***	0.071***	0.358***	-0.009	0.166***	0.034***	-0.116***	1								
9. Std. Sales	-0.008	-0.017***	-0.101***	0.378***	-0.131***	-0.018	0.051***	-0.011***	1							
10. Tangibility	0.014	-0.060***	-0.263***	0.023**	-0.313***	-0.050***	0.107***	-0.185***	-0.011**	1						
11. Loss	0.072***	0.081***	-0.003	-0.121***	0.047***	-0.009**	-0.055***	0.279***	-0.011	-0.017**	1					
12. Std. net hiring	0.127***	-0.001	-0.055***	0.004	0.031**	-0.008	-0.028***	0.027***	0.099	-0.001***	0.025***	1				
13. Labor intensity	0.040**	-0.015**	0.248***	-0.070***	0.007**	0.155***	-0.067***	0.091	0.006	-0.132	-0.041	-0.029	1			
14. Duality	-0.034***	-0.030***	-0.074***	0.078***	-0.130***	-0.023	0.051***	-0.097***	0.026	0.069***	-0.016**	-0.072***	-0.028	1		
15. Ab_Invst_Oth	0.205***	0.058***	0.071***	-0.022***	0.027**	0.004	-0.013**	0.231**	-0.028***	-0.203***	0.177**	0.043	0.007	-0.038***	1	
16. R&D	0.025***	-0.036**	0.224***	-0.111	0.025***	0.405***	0.123***	-0.236***	-0.153	0.299***	0.309***	0.315***	0.155***	0.325***	-0.278**	1
VIF	1.984															

This table presents the pairwise correlations of all variables. Symbols ***, **, and * denote 1%, 5%, and 10%, respectively. VIF is the regression's variable inflation factor

Table 3 presents pairwise correlations among the main variables. Abs Net Hiring is weakly positively correlated with Dynamism (0.004, 1% level) and negatively correlated with MTB (-0.011 , 5%) and Size (-0.032 , 1%). Dynamism is positively associated with MTB (0.028), Quick Ratio (0.070), and Cash Flow Volatility (0.071), all at the 1% level. MTB is positively related to Size (0.117) but negatively related to Sales Volatility (-0.101). Quick Ratio is negatively correlated with Size (-0.107) and Tangibility (-0.313), while Leverage is positively related to MTB (0.042) and negatively related to Size (-0.042). Dividends are negatively associated with Abs Net Hiring, whereas Labor Intensity is weakly negatively related to Dynamism (-0.015). CEO Duality is negatively correlated with both Abs Net Hiring (-0.034) and Dynamism (-0.030). Overall, the correlations reveal complex interrelationships among firm characteristics and labor investment inefficiency. The VIF of 1.984 is well below the threshold of 4, indicating no serious multicollinearity concerns.

4.2 Inferential analysis

The regression results of Panel A in Table 4 show that industry-level technological dynamism (TD) is positively associated with our inefficiency metric, $|Ab_Net_Hire|$: the TD coefficient is 0.543 ($t = 2.43$), and a one-standard-deviation increase in TD raises labor-investment inefficiency by 34.26%, consistent with H1b (deterioration)

Table 4 Panel A Baseline results

Variables	Labor investment inefficiency (1)	Overinvestment (2)	Underinvestment (3)
Dynamism (TD)	0.543 (2.43)	1.157 (2.10)	-0.158 (-0.84)
MTB	6.061 (1.81)	2.369 (3.63)	1.090 (4.36)
Size	-0.029 (-4.50)	-0.055 (-3.29)	0.010 (1.98)
Quick	-0.317 (-1.14)	-0.561 (-0.81)	0.258 (0.97)
Leverage	-0.050 (-2.14)	-0.034 (-0.92)	0.044 (1.54)
Dividend	0.168 (0.50)	-0.217 (-0.27)	-0.210 (-1.03)
Std CF	0.125 (2.84)	0.231 (2.873)	0.068 (1.57)
Std Sales	0.059 (5.12)	0.045 (2.26)	0.070 (6.173)
Tangibility	-0.155 (-4.88)	0.056 (4.64)	0.036 (1.23)
Loss	-0.297 (-0.32)	-0.293 (-3.88)	-0.607 (-0.73)
Std net hire	0.058 (8.09)	-0.015 (-0.57)	0.059 (8.43)
Labor intensity	-3.944 (-2.24)	-1.623 (-3.43)	-3.007 (-1.64)
Duality	-0.871 (-1.43)	0.152 (0.84)	0.691 (1.39)
Ab_Invest_Other	0.083 (4.34)	0.159 (2.71)	-0.078 (-5.04)
R&D	0.766 (2.76)	-0.563 (-1.59)	0.519 (3.44)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	19.87	36.13	28.52
F-statistic (pv)	8.48 (0.000)	5.38 (0.000)	8.79 (0.000)
N	13,095	5798	7297

This table reports the baseline effects of technological dynamism (TD) on labor investment inefficiency (Model 1), overinvestment (Model 2), and underinvestment (Model 3). Reported in parentheses are t-statistics. All regressions are estimated using panel OLS with firm and year fixed effects, and standard errors are clustered at the firm level. Control variables include firm-specific financial and governance characteristics. Detailed definitions of all variables are provided in Table 1

and reinforcing the theory that external technological pressure can degrade firm-level labor-investment precision. Decompositions indicate that this association is concentrated in overinvestment: TD = 1.157 ($t = 2.10$), with no detectable effect on underinvestment: TD = -0.158 ($t = -0.84$). These results show that external, industry-level technological change predicts lower labor-investment efficiency for large U.S. firms, primarily through excessive net hiring rather than insufficient hiring.

Market-to-book (MTB) is positively related to inefficiency ($\beta = 6.061$, $t = 1.81$). Firm size lowers inefficiency ($\beta = -0.029$, $t = -4.50$) and overinvestment ($\beta = -0.055$, $t = -3.29$), while the Quick ratio carries a negative but imprecise coefficient for inefficiency ($\beta = -0.317$, $t = -1.14$). Leverage reduces inefficiency ($\beta = -0.050$, $t = -2.14$). Operating-cash-flow volatility ($\beta = 0.125$, $t = 2.84$) and sales volatility ($\beta = 0.059$, $t = 5.12$) exacerbate inefficiency. In the overinvestment model, tangibility ($\beta = 0.056$, $t = 4.64$) and other (non-labor) investment inefficiency ($|Ab_Invest_Other|$: $\beta = 0.159$, $t = 2.71$) raise overinvestment, whereas labor intensity reduces it ($\beta = -1.623$, $t = -3.43$). In the underinvestment model, MTB ($\beta = 1.090$, $t = 4.36$) and size ($\beta = 0.010$, $t = 1.98$) are positively associated with underinvestment, labor intensity is negatively signed ($\beta = -3.007$, $t = -1.64$), and $|Ab_Invest_Other|$ mitigates underinvestment ($\beta = -0.078$, $t = -5.04$). Finally, firm-level R&D intensity is positively related to both total inefficiency ($\beta = 0.766$, $t = 2.76$) and underinvestment ($\beta = 0.519$, $t = 3.44$). Collectively, these patterns suggest that larger, less volatile, and less leveraged settings are better able to align hiring with fundamentals, while growth pressure (high MTB), real-asset intensity, and instability complicate that alignment.

It is worth noting that the correlation between $|Ab_Net_Hire|$ and Dynamism is reported as 0.004*** (Table 3), a statistically significant but near-zero raw correlation, compared with a regression coefficient of 0.543 in the multivariate model (Tables 4, 5). We argue that the near-zero pairwise correlation reported in Table 3 reflects the unconditional association between technological dynamism and labor investment inefficiency across all firm-year observations. In contrast, the coefficient

Table 5 Panel B unified specification: dynamism $\times$ overinvestment interaction (full sample)

Variables	Coefficient
Dynamism (TD)	0.492 (2.91)
overinvestment	0.947 (2.09)
TD $\times$ overinvestment	0.058 (3.17)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Adj. R ²	26.44
F-statistic (pv)	9.22 (0.000)
N	13,095

This table reports estimates from a unified full-sample specification testing whether the association between technological dynamism (TD) and labor investment inefficiency is asymmetric across over- and underinvestment states. The dependent variable is $|Ab_Net_Hire|$. OverInvest is an indicator equal to 1 if the firm's abnormal net hiring residual is positive (i.e., in an overinvestment state) in year t , and 0 otherwise. All specifications include firm and year fixed effects; standard errors are clustered by firm. t -statistics are reported in parentheses

reported in Tables 4 and 5 is estimated from a multivariate specification that includes an extensive set of control variables together with firm and year fixed effects. These controls absorb substantial cross-sectional and temporal variation that is unrelated to technological dynamism but correlated with labor investment decisions. Consequently, the regression coefficient reflects the within-firm association between changes in technological dynamism and labor investment inefficiency after accounting for observable and unobservable confounding factors. It is therefore not uncommon for a weak unconditional correlation to become economically and statistically meaningful once suppressing factors are controlled for.

To provide direct empirical support for this suppression-effect interpretation, Appendix B reports a stepwise regression in which fixed effects and control variables are introduced sequentially, starting from the bivariate association and building up to the full baseline specification. The coefficient on Dynamism rises steadily at each step: 0.005 in the bivariate specification with no fixed effects or controls (Adj. $R^2 = 0.20\%$), closely mirroring the near-zero unconditional correlation reported in Table 3; 0.105 once firm and year fixed effects are added (Adj. $R^2 = 8.68\%$); 0.308 once a first block of firm-fundamentals controls (MTB, Size, Quick, Leverage, Dividends) is further introduced (Adj. $R^2 = 14.11\%$); and 0.543 in the full baseline specification (Adj. $R^2 = 19.87\%$), matching Tables 4, 5. This monotonic increase in both the coefficient and the share of explained variance shows that the gap between the unconditional correlation and the multivariate coefficient is not an estimation artifact, but reflects fixed effects and control variables absorbing confounding variation that otherwise suppresses the observable association between technological dynamism and labor investment inefficiency.

Why does TD worsen LIE, and why mainly via overinvestment? In technologically intensive industries, managers often resort to frequent workforce adjustments to buffer volatility and preserve knowledge stocks, e.g., over-hiring or delaying separations, which can raise $|Ab_Net_Hire|$ even if the intent is resilience. Over-hiring can be a defensive way to build intellectual capital, while under-firing helps retain tacit knowledge and limit leakages from mobile human capital (Ee et al. 2022). Scarcity of specialized skills pushes firms toward costly recruitment and training surges that create timing mismatches and amplify deviations from fundamentals (Au et al. 2021). At the same time, TD heightens dependence on intangibles and widens information asymmetries, complicating investor–manager alignment on staffing needs (Chowdhury et al. 2025). Perceived technological uncertainty can also depress long-horizon human-capital bets because of obsolescence risk, again increasing deviations from “normal” hiring (Helfat and Martin 2015). This finding supports our second hypothesis H_2 .

Estimating the overinvestment and underinvestment models on separate subsamples may raise concerns that differences in coefficients could partially reflect compositional differences across firms rather than a genuine asymmetry in the effect of technological dynamism. To address this concern, we conducted an additional analysis by estimating a unified specification on the full sample, including an interaction between technological dynamism and an overinvestment indicator. Panel B of Table 5 reports the related results. The interaction term is positive and statistically significant at the 1% level, indicating that the association between technological

dynamism and labor investment inefficiency is significantly stronger when firms are in an overinvestment state. These additional analyses strengthen our conclusion that the documented asymmetry reflects a genuine feature of the TD–LIE relationship rather than differences in sample composition.

4.3 Robustness

We test the robustness of the baseline TD–LIE association using alternative TD proxies and estimation methods. These analyses reduce reliance on a single construct definition or modeling assumption and address concerns related to measurement error, heteroskedasticity, autocorrelation, and clustering. Results are reported in Table 6. Panel A replaces the continuous TD measure with (a) a High-TD indicator (1 if industry TD exceeds the annual median) and (b) a market-dynamism proxy based on the volatility of the time trend in 4-digit SIC industry sales. Both measures confirm the baseline finding: The High-TD indicator is positive and significant (0.018, 5% level), as is the market-dynamism proxy (0.211, 5% level). These consistent results indicate that the TD–LIE relationship is not driven by the baseline R&D-intensity measure and is robust to an alternative demand-side measure of environmental variability (Keats and Hitt 1988; Kafouros et al. 2024). Panel B shows that the positive association between TD and LIE persists across estimators with different error structures. System-GMM yields a positive coefficient (0.399, 1% level), WLS produces 0.620 (1%), Newey–West standard errors yield 0.325 (1%), Petersen’s two-way clustering produces 0.589 (1%), and a Tobit model accounting for censoring in $|Ab_Net_$

Table 6 Robustness

Variable	Panel A. Alternative measures		Panel B. Alternative models				
	Dummy (1A)	Market dynamism (2A)	Sys-GMM (1B)	WLS (2B)	Newey-West (3B)	Petersen (4B)	Tobit (5B)
Dynamism	0.018 (2.03)	0.211 (1.99)	0.399 (4.74)	0.620 (2.72)	0.325 (2.67)	0.589 (3.26)	0.663 (9.60)
Dynamism _{t-1}			− 0.068 (− 3.82)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan stat (pv)			449.91 (0.572)				
AR(2)			0.952 (0.341)				
Adj. R ²	15.69	13.24				13.21	2.97
F-statistic (pv)	104.81 (0.000)	52.65 (0.000)		255.43 (0.000)	23.24 (0.000)	43.25 (0.000)	
N	12,675	12,977	12,295	12,295	12,875	13,075	12,777

This table reports robustness checks using alternative measures of technological dynamism (TD) and estimation methods. t-statistics are in parentheses. The dependent variable is labor investment inefficiency ($|Ab_Net_Hire|$), with firm and year fixed effects. Panel A shows results using a binary above-median TD indicator (Model 1A) and a market-dynamism proxy based on industry sales volatility (Model 2A). Panel B applies alternative estimators: system-GMM (1B), WLS (2B), Newey–West (3B), Petersen two-way clustering (4B), and Tobit (5B). Variable definitions are provided in Table 1

Hire| returns 0.663 (1%). Together, these results indicate that the baseline finding is not driven by heteroskedasticity, serial or cross-sectional correlation, or censoring. Across alternative proxies and estimators, higher industry-level TD consistently predicts greater absolute abnormal net hiring, i.e., lower LIE, confirming that the external technological environment is an important driver of firms' labor misallocation rather than a modeling artifact.

4.4 Endogeneity

Endogeneity may bias the estimated effect of technological dynamism (TD) on labor investment inefficiency (LIE) through reverse causality, measurement error, sample selection, and omitted variables. We therefore complement fixed-effects models with several identification and sensitivity tests, including instrumental variables, reweighting, matching, and coefficient stability analyses. Results are summarized in Table 7. First, to address reverse causality, we employ Lewbel's (2012) heteroskedasticity-based IV approach, which generates internal instruments from residual variation in exogenous covariates. The IV estimate remains positive and economically large (TD = 3.267, $t = 9.44$). Model fit is satisfactory ($R^2 = 33.14\%$; $F = 8.10$, $p = 0.000$), and the Hansen J test ($p = 0.288$) supports instrument validity. The larger IV coefficient suggests that measurement error or related biases may attenuate the baseline OLS estimate. Beyond measurement-error attenuation, part of this gap may also reflect a distinction between local and average treatment effects. Because Lewbel's (2012) approach generates instruments internally from heteroskedasticity in the first-stage residuals rather than from an external source of exogenous variation, the identifying variation is concentrated among firm-years where this heteroskedasticity is most pro-

Table 7 Endogeneity

Variables	Lewbel (1)	Entropy balancing (2)	PSM (3)	Oster (4)
Dynamism	3.267 (9.44)	0.121 (30.76)		0.243 (10.561)
Controls	Yes	Yes		Yes
Firm FE	Yes	Yes		Yes
Year FE	Yes	Yes		Yes
Adj. R^2	33.14	31.72		33.45
F-statistic (pv)	8.10 (0.000)	76.64 (0.000)		
Hansen J (pv)	0.288			
Above-median TD			0.010	
Below-median TD			0.008	
Difference (pv)			0.002 (0.044)	
Controlled beta / R_c^2				0.543/0.204
Uncontrolled beta / R_{un}^2				0.665/0.001
Delta				[0.465, 0.468]
N	12,885	7859	7859	13,085

This table summarizes endogeneity checks for the relationship between technological dynamism (TD) and labor investment inefficiency ($|Ab_Net_Hire|$). t-statistics (or pvs, where noted) are reported in parentheses. Model (1) applies the Lewbel (2012) heteroskedasticity-based IV approach; Model (2) uses entropy balancing to re-weight treatment and control groups; Model (3) implements propensity-score matching; and Model (4) applies Oster's (2019) coefficient-stability test. All models include firm and year fixed effects. Variable definitions are provided in Table 1

nounced. If the effect of technological dynamism on labor investment inefficiency is heterogeneous across firms, for instance, stronger among firms most exposed to the real-options and knowledge-retention mechanisms underlying H2, the IV estimate is better interpreted as a local average treatment effect for this subpopulation (Imbens and Angrist 1994) rather than the population-average effect that OLS targets. Attenuation bias and treatment-effect heterogeneity are not mutually exclusive explanations, and both plausibly contribute to the observed gap between the OLS and IV estimates. Second, to address design imbalance, we use entropy balancing to reweight below-median TD firm-years to match the above-median TD group. TD remains positive and significant (0.121, 1% level; $F = 76.64$, $p = 0.000$), indicating that the baseline result is not driven by observable differences between treated and control firms. Third, to address sample selection, we implement propensity score matching (Rosenbaum and Rubin 1983). Matched firms with above-median TD exhibit higher LIE inefficiency (0.010 vs. 0.008), with the difference remaining significant ($t = 2.02$, $p = 0.044$). Thus, greater TD is associated with higher hiring misalignment even after aligning observables. Fourth, we assess omitted variable bias using Oster's (2019) coefficient stability test. The controlled beta (0.543; $R^2 = 0.204$) remains close to the uncontrolled beta (0.665; $R^2 = 0.001$), and the implied δ range [0.465, 0.468] suggests that unobservables would require implausibly strong selection to eliminate the TD effect.

To further address omitted variables, Table 8 augments the baseline with additional firm-level and state-level controls. Panel A adds CEO education, market beta, cash holdings, growth, and profitability (Boubaker et al. 2022; Chen et al. 2017). Across specifications, the TD coefficient remains positive and significant. Panel B adds state income, income per capita, and income growth individually and jointly (Qiu and Wang 2018; Gong et al. 2023). The TD coefficient likewise remains robust, indicating that regional economic conditions do not explain the main findings. Across these complementary tests, industry-level TD consistently predicts higher $|Ab_Net_Hire|$, validating H1b that technological dynamism can reduce labor investment efficiency. Given that the baseline effect is concentrated in overinvestment, these analyses further support the interpretation that external technological pressure systematically pushes firms toward labor overinvestment rather than underinvestment. Overall, the evidence strengthens our central claim that industry-level technological change is an important external driver of labor misallocation among S&P 500 non-financial firms.

5 Moderating analysis

5.1 Role of management

We focus on external CEO, CEO tenure, and CEO media coverage because these characteristics directly influence managerial adaptability, information processing, and external monitoring, three moderators that are particularly important when firms operate in technologically dynamic environments. In particular, external CEO reflects the extent to which a chief executive brings new knowledge, perspectives, and strategic approaches that may help firms adapt to rapidly changing technological environments. CEO tenure captures managerial experience and organizational

Table 8 New controls

Panel A. Firm-level controls						Panel B. State-level controls					
Variables	(1A)	(2A)	(3A)	(4A)	(5A)	All	Variables	(1B)	(2B)	(3B)	All
Dynamism	0.288 (3.14)	0.503 (2.15)	0.561 (2.48)	0.437 (2.23)	0.544 (2.47)	0.261 (2.92)	Dynamism	0.585 (2.89)	0.629 (2.36)	0.627 (2.97)	0.623 (3.08)
Firm growth	0.131 (7.61)					0.132 (7.70)	State income	- 3.172 (- 2.19)			- 0.068 (- 3.71)
Cash holdings		- 11.757 (- 3.34)				- 8.393 (- 2.35)	State income per capita		10.177 (1.68)		0.161 (2.30)
Profitability			0.001 (5.62)			3.452 (1.63)	State income growth			0.090 (1.05)	0.111 (1.30)
Company beta				0.787 (1.93)		1.068 (2.13)					
MBA CEO					0.891 (1.86)	0.699 (1.43)					
Controls	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Adj. R ²	15.39	12.75	12.44	13.81	19.89	16.67		13.51	13.49	13.47	13.63
F-stat (p ^v)	59.28 (0.000)	8.93 (0.000)	39.16 (0.000)	7.03 (0.000)	4.41 (0.000)	73.37 (0.000)		491.31 (0.000)	5.55 (0.000)	7.80 (0.000)	22.00 (0.000)
N	13,085	13,085	13,078	12,905	12,657	12,635		13,075	12,935	12,875	12,875

This table reports robustness tests that add additional firm- and state-level controls to the baseline specification. t-statistics are shown in parentheses. Panel A. includes firm-specific variables: firm growth (Model 1A), cash holdings (Model 2A), profitability (Model 3A), market beta (Model 4A), and MBA CEO (Model 5A). Panel B incorporates state-level factors: state income (Model 1B), state income per capita (Model 2B), and state income growth (Model 3B). All regressions are estimated with panel OLS, firm and year fixed effects, and firm-clustered standard errors. Standard baseline controls (firm financial and governance characteristics plus state-level factors) remain included in all models. Definitions of all variables are provided in Table 1

embeddedness, which can either facilitate informed decision-making or create strategic inertia when technological conditions evolve quickly. CEO media coverage reflects external scrutiny and information dissemination, which may discipline managerial behavior and improve the alignment of labor investment decisions with firm fundamentals. In particular, we examine whether leadership choices condition the link between TD and LIE. Moderators clarify *when* and for *whom* TD worsens (or improves) hiring alignment, sharpening inference and offering actionable levers for boards. Guided by the upper echelons and information intermediation literatures, we study three moderators: outsider CEO origin, CEO tenure, and CEO media coverage, implemented as interactions with TD in the fixed effects baseline. Table 9 reports the estimates.

First, we explore the role of external CEOs. Outsider appointments are intended to reset routines and accelerate strategic renewal in turbulent settings (Ertimur et al. 2018; Quigley et al. 2019; Bai and Mkrtchyan 2023). We code External CEO = 1 when the incumbent was hired from outside the firm (0 otherwise) and interact it with TD. Consistent with the view that fresh schemas mitigate inertia, the interaction $TD \times \text{External CEO}$ is negative and significant (-0.151 , $t = -2.23$, 5% level), indicating that outsider leadership *attenuates* TD-induced hiring misalignment. Substantively, bringing in an external CEO can partially offset the baseline deterioration in LIE observed in high TD industries, aligning workforce adjustments more tightly with fundamentals.

Second, we explore the role of CEO tenure. Longer tenure is often associated with strategic persistence and entrenched cognitive frames (Simerly and Li 2000; Wu et al. 2005). We define CEO Tenure = 1 when tenure exceeds the sample median in year t (results are robust to years in office as a continuous measure). The $TD \times \text{CEO Tenure}$ interaction is positive and significant (0.064 , $t = 2.84$), implying

Table 9 Managerial attributes as moderators

Variables	External CEOs (1)	CEO tenure (2)	CEO media coverage (3)
Dynamism	0.002 (1.99)	-0.060 (-2.71)	0.002 (2.18)
External CEO	0.844 (1.79)		
Dynamism $\times$ External CEO	-0.151 (-2.23)		
CEO tenure		-0.426 (-1.48)	
Dynamism $\times$ CEO tenure		0.064 (2.84)	
CEO media coverage			0.285 (0.34)
Dynamism $\times$ CEO media coverage			-0.085 (-2.46)
Initial Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	8.97	5.55	4.04
F-statistic (pv)	15.95 (0.000)	9.08 (0.000)	9.04 (0.000)
N	13,077	12,997	12,897

This table reports baseline regressions augmented with moderating variables: the presence of an external CEO (Model 1), CEO tenure (Model 2), and CEO media coverage (Model 3). t -statistics are shown in parentheses. All models include the standard set of controls (firm-specific and state-level characteristics) and are estimated using panel OLS with firm and year fixed effects and firm-clustered standard errors. Variable definitions are provided in Table 1

that, in dynamic technological environments, long-tenured CEOs *amplify* hiring inefficiency, consistent with slower adaptation to shifting skill needs. This pattern cautions boards that stability at the top can carry an efficiency cost when external change is rapid.

Lastly, we further focus on CEO media coverage because technological dynamism creates substantial uncertainty regarding future workforce requirements, skill needs, and the timing of labor investments. Under such conditions, managers possess private information about technological opportunities and human-capital requirements, which can increase information asymmetry between managers and external stakeholders. Greater CEO media coverage can reduce these frictions by increasing public scrutiny, enhancing transparency, and strengthening reputational concerns. CEOs who receive extensive media attention are more likely to face external monitoring from investors, analysts, and other stakeholders, making it costlier to engage in labor investment decisions that deviate from economic fundamentals. Consequently, media coverage is particularly relevant in technologically dynamic environments, where uncertainty surrounding future labor needs is greatest and where managerial discretion over hiring and retention decisions is correspondingly higher. We therefore expect CEO media coverage to weaken the positive association between technological dynamism and labor investment inefficiency (Ahmed et al. 2024). External scrutiny can discipline managers and improve policy alignment (Cahan et al. 2015; Pfarrer et al. 2010; Chen et al. 2021). We count CEO mentions in major U.S. business outlets over the prior year and use an above-median indicator (robust to $\log(1+\text{mentions})$; Milbourn 2003; Jian and Lee 2011). The $\text{TD} \times \text{Media}$ interaction is negative and significant (-0.085 , $t = -2.46$, 5% level): greater CEO visibility *tempers* the rise in LIE associated with TD, consistent with media acting as an information intermediary that nudges labor decisions toward fundamentals.

These moderators show that the baseline association is not *mechanical*: governance and information environments shape how strongly TD translates into hiring misalignment. Appointing outsider CEOs and increasing external scrutiny (media attention) dampen the inefficiency channel, whereas longer CEO tenure reinforces it. For firms operating under intense technological change, these results imply concrete levers, i.e., leadership selection, tenure management, and transparency, that can partially neutralize TD's adverse impact on labor allocation and help keep staffing closer to fundamentals.

5.2 Organizational and institutional moderators

Here, we examine four organizational and institutional moderators that capture firms' capacity to adapt to technological change: organizational complexity (diversification), organizational learning (IPO age), knowledge protection (IDD adoption), and strategic orientation (business strategy). These factors are particularly relevant because they influence how firms allocate and retain human capital when operating in technologically dynamic environments. Diversification reflects the complexity of internal resource allocation and coordination across business segments. IPO age captures organizational learning and accumulated experience in responding to external pressures. IDD adoption represents the institutional protection of knowledge

Table 10 Moderating analysis

Variables	Product diversification (1)	Firm age (2)	Adoption of IDD (3)	Business strategy (4)
Dynamism	0.570 (8.73)	0.621 (2.72)	0.593 (9.97)	0.105 (15.27)
Diversification	- 16.496 (-3.10)			
Dynamism $\times$ Diversification	0.642 (2.12)			
Firm age		- 0.500 (-0.69)		
Dynamism $\times$ Firm age		- 0.169 (-1.83)		
Adoption of IDD			0.251 (0.53)	
Dynamism $\times$ Adoption of IDD			- 0.081 (-2.09)	
Business strategy				0.015 (13.60)
Dynamism $\times$ Business strategy				- 0.482 (-16.03)
Initial Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R ²	19.14	19.91	19.07	26.30
F-statistic (pv)	41.52 (0.000)	6.96 (0.000)	91.13 (0.000)	56.53 (0.000)
N	12,667	13,095	13,095	12,699

This table reports baseline regressions augmented with variables that capture potential moderators through which technological dynamism (TD) affects labor investment inefficiency. These moderators include corporate diversification (Model 1), firm age/public exposure (Model 2), state adoption of the Inevitable Disclosure Doctrine (IDD; Model 3), and business strategy (Model 4). t-statistics are reported in parentheses. All models include the standard set of controls (firm-specific characteristics and state-level factors) and are estimated using panel OLS with firm and year fixed effects and firm-clustered standard errors. Detailed definitions of variables are provided in Table 1

assets and human capital, which is particularly important in technologically intensive environments where employee mobility may create knowledge spillovers. Business strategy reflects firms' long-term orientation and approach to innovation, influencing how labor resources are deployed in response to technological change. Collectively, these variables allow us to examine how organizational complexity, organizational learning, institutional protection, and strategic orientation shape the relationship between technological dynamism and labor investment efficiency. Table 10 presents the results.

First, we examine product diversification. Diversification can buffer shocks in dynamic environments (Khanna and Tice 2001) and improve productivity during crises (Kuppuswamy and Villalonga 2016; Erl et al. 2025), yet it may also reduce investment efficiency through misallocation and uncoordinated divisional decisions (Ozbas and Scharfstein 2010; Wang 2023). Consistent with this trade-off, Model 1 reports a positive and significant interaction between TD and diversification (dynamism $\times$ corporate diversification = 0.642, $t = 2.12$, 5% level), indicating that diversified firms in high-TD industries exhibit lower labor investment efficiency than focused firms. Thus, TD-induced complexity amplifies internal frictions and pushes hiring away from fundamentals. Second, we examine corporate public exposure. Longer time since IPO may either create organizational rigidity (Balasubramanian and Lee 2008) or enhance learning and dynamic capabilities (Kieschnick and Mous-

sawi 2018). Using an indicator for above-median listing age, Model 2 yields a negative TD interaction ($\text{dynamism} \times \text{firm exposure age} = -0.169, t = -1.83$), supporting a learning effect whereby more seasoned public firms allocate labor more efficiently under TD than younger firms. Thus, organizational experience mitigates TD-related hiring misalignment.

Third, we examine state adoption of the Inevitable Disclosure Doctrine (IDD). Knowledge-protection regimes can reduce human-capital leakage and support more strategic staffing (Klasa et al. 2018; Colak and Korkeamäki 2021; Canil et al. 2023). Model 3 reports a negative TD interaction where IDD is adopted ($\text{dynamism} \times \text{IDD adoption} = -0.081, t = -2.09$), suggesting that legal protection improves LIE by enabling firms to hire closer to fundamentals when the risk of talent spillovers is lower. Lastly, we examine business strategy. Strategic orientation shapes HR decisions under uncertainty (Zhou and Wu 2010; Bentley et al. 2013). Although prospectors may overexpand and misjudge labor needs (Habib and Hasan 2021), their long-term orientation can also enhance efficiency (Yuan et al. 2020; Chen and Jeremias 2014). Using the Bentley et al. (2013) classification, Model 4 shows a negative TD interaction ($\text{dynamism} \times \text{business strategy} = -0.482, t = -16.03$), indicating that prospector firms experience lower labor investment inefficiency in high-TD industries. Thus, strategic orientation can counteract TD's tendency to push hiring away from fundamentals. Overall, the TD–LIE relationship is context dependent. It is amplified by organizational complexity (diversification) but attenuated by organizational experience, knowledge-protection institutions (IDD), and prospector strategies that promote long-term human-capital alignment.

6 Conclusions

This paper examines whether and how industry-level technological dynamism (TD) shapes firms' labor investment efficiency (LIE). Using non-financial S&P 500 firms, we find that greater TD is associated with lower LIE, with the effect concentrated in labor overinvestment rather than underinvestment. Extensive robustness and endogeneity tests support this result, indicating that the external technological environment is an important predictor of deviations from fundamentals-based hiring. Overall, exposure to faster industry-wide technological change leads to less efficient labor allocation, primarily through excessive net hiring. The evidence also reveals important heterogeneity. On the managerial side, externally hired CEOs and greater CEO media visibility mitigate TD-related misallocation, whereas longer CEO tenure amplifies it, consistent with fresh perspectives and external discipline versus strategic persistence. On the organizational side, diversification worsens hiring misalignment, while greater public-listing experience, state adoption of the Inevitable Disclosure Doctrine, and a prospector strategy reduce inefficiency by facilitating learning, knowledge retention, and long-term workforce alignment. Regionally, the TD–LIE link is stronger in economically advanced states, suggesting that deeper R&D ecosystems and tighter talent markets intensify both the challenges and benefits of staffing decisions. Together, these findings show that leadership, organizational structure, and institutional context shape the magnitude of TD's effect on LIE.

Rapid technological change increases demand for scarce specialized skills and reliance on intangible assets, exacerbating information frictions and agency conflicts in hiring and retention. Firms often respond by adjusting their workforce to preserve flexibility and knowledge assets; however, these responses may overshoot, leading to excessive hiring and delayed separations that appear as labor-investment inefficiency. Skill mismatches, heightened uncertainty, and difficult-to-observe effort further complicate fundamentals-consistent staffing, helping explain why TD primarily affects the overinvestment margin. For executives and boards, the results highlight the importance of governance and HR policies that moderate TD-induced hiring swings. Strengthening workforce analytics, expanding internal redeployment and training, and using monitoring mechanisms to curb empire building can improve labor allocation. Leadership choices also matter: outsider CEOs and greater reputational scrutiny can help align staffing decisions with fundamentals, whereas longer CEO tenure may require safeguards against inertia. For policymakers, legal protections that safeguard knowledge assets, such as IDD adoption, appear to support more targeted labor policies in technologically dynamic sectors.

Our study focuses on large U.S. non-financial firms and measures TD using industry R&D intensity. While this improves alignment with an external environmental concept, it may not capture all dimensions of technological turbulence. Likewise, LIE is inferred from abnormal net-hiring residuals and therefore reflects workforce quantity rather than all aspects of workforce quality or task reconfiguration. Although we conduct extensive endogeneity tests, the analysis remains observational. Future research could examine smaller firms, non-U.S. settings, skill-based labor measures, alternative TD proxies, and policy shocks to further illuminate the link between technological change and workforce allocation.

Appendix A: Legal cases of precedent-setting adopting/rejecting the Inevitable Disclosure Doctrine

State	Precedent-setting case(s)	Date	Decision
AR	Southwestern Energy Co. v. Eickenhorst, 955 F. Supp. 1078 (W.D. Ark. 1997)	March 18, 1997	Adopt
	Cellco Partnership v Langston, No. 4:09CV00928JMM (W.D. Ark. 2009)	December 11, 2009	Reject
CA	Whyte v Schlage Lock Co., 101 Cal. App. 4th 1443 (2002)	September 12, 2002	Reject
CT	Branson Ultrasonics Corp. v. Stratman, 921 F. Supp. 909 (D. Conn. 1996)	February 28, 1996	Adopt
DE	E.I. duPont de Nemours & Co. v. American Potash & Chem. Corp., 200 A.2d 428 (Del. Ch. 1964)	May 5, 1964	Adopt
FL	Fountain v. Hudson Cush-N-Foam Corp., 122 So. 2d 232 (Fla. Dist. Ct. App. 1960)	July 11, 1960	Adopt
	Del Monte Fresh Produce Co. v. Dole Food Co. Inc., 148 F. Supp. 2d 1326 (S.D. Fla. 2001)	May 21, 2001	Reject
GA	Essex Group Inc. v. Southwire Co., 501 S.E.2d 501 (Ga. 1998)	June 29, 1998	Adopt

State	Precedent-setting case(s)	Date	Decision
	Holton v. Physician Oncology Servs., LP. No. S13A0012, 2013WL 1859294 (Ga. 2013)	May 20, 2013	Reject
IL	Teradyne Inc. v. Clear Communications Corp., 707 F. Supp. 353 (N.D. 111. 1989)	February 9, 1989	Adopt
IN	Ackerman v. Kimball Int'l Inc., 652 N.E.2d 507 (Ind. 1995)	July 12, 1995	Adopt
IA	Uncle B's Bakery v. O'Rourke, 920 F. Supp. 1405 (N.D. Iowa 1996)	April 1, 1996	Adopt
KS	Bradbury Co. v. Teissier-duCros, 413 F. Supp. 2d 1203 (D. Kans. 2006)	February 2, 2006	Adopt
MA	Bard v. Intoccia, 1994 U.S. Dist. LEXIS 15,368 (D. Mass. 1994)	October 13, 1994	Adopt
	US Elec. Servs. V. Schmidt, Civil Action No. 12–10845-DJC (U.S. Dist. CT. for the Dist. of Mass. 2012)	May 14, 2012	Reject
MD	LeJeune v. Coin Acceptors, Inc., 381 Md. 288 (Md. 2004)	May 13, 2004	Reject
MI	Allis-ChalmersManuf. Co. v. Continental Aviation & Eng. Corp., 255 F. Supp. 645 (E.D.Mich. 1966)	February 17, 1966	Adopt
	CMI Int'l, Inc. v. Internet Int'l Corp., 649 N.W.2d 808 (Mich. Ct. App. 2002)	April 30, 2002	Reject
MN	Surgidev Corp. v. Eye Technology Inc., 648 F. Supp. 661 (D.Minn. 1986)	October 10, 1986	Adopt
MO	H&R Block Eastern Tax Servs. Inc. v. Enchura, 122 F. Supp. 2d 1067 (W.D. Mo. 20 0 0)	November 2, 2002	Adopt
NC	Travenol Laboratories Inc. v. Turner, 228 S.E.2d 478 (N.C. Ct. App. 1976)	June 17, 1976	Adopt
	RCR Enterprises, LLC v. McCall, 2014 WL 7591977 (N.C. Super Ct. Dec. 19, 2014)	October 2, 2014	Reject

Source: Canil et al. (2023)

Appendix B: Stepwise evolution of the Dynamism coefficient

Variables	(1) bivariate	(2) + Firm & Year FE	(3) + Fundamentals	(4) Full baseline
Dynamism (TD)	0.005 (2.26)	0.105 (2.88)	0.308 (2.52)	0.543 (2.43)
Controls	No	No	Partial	Yes
Firm FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Adj. R ²	0.200	8.68	14.11	19.87

Variables	(1) bivariate	(2) + Firm & Year FE	(3) + Fundamentals	(4) Full baseline
F-statistic (pv)	6.25 (0.000)	7.10 (0.000)	8.20 (0.000)	8.48 (0.000)
N	13095	13095	13095	13095

This table reports the stepwise evolution of the coefficient on technological dynamism (TD) as fixed effects and control variables are sequentially introduced. The dependent variable is `|Ab_Net_Hire|` throughout, consistent with the baseline specification in Table 4. Model (1) reports a bivariate regression of `|Ab_Net_Hire|` on Dynamism alone, with no fixed effects and no control variables; this specification corresponds most closely to the unconditional pairwise correlation reported in Table 3. Model (2) adds firm and year fixed effects but no control variables. Model (3) retains firm and year fixed effects and adds a first block of firm-fundamentals controls (MTB, Size, Quick, Leverage, Dividends). Model (4) reports the full baseline specification from Table 4, Model (1), adding the remaining control variables (Std. CF, Std. Sales, Tangibility, Loss, Std. net hiring, Labor intensity, Duality, `|Ab_Invest_Other|`, and R&D) to the specification in Model (3). t-statistics, reported in parentheses, are estimated using standard errors clustered at the firm level throughout. Detailed definitions of all variables are provided in Table 1

Declarations

Competing Interests The authors declare that they have no competing interests.

Use of Artificial Intelligence During the preparation of this manuscript, the author(s) used Claude (Anthropic) to proofread the text for grammatical errors, inconsistencies, and formatting issues. After using this tool, the author(s) reviewed and verified all suggested changes and take full responsibility for the content of this publication.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

References

- Ahmed MS, Kumar S, Gupta P, Bamel N (2024) CEO media coverage and cash holdings. *Int Rev Financ Anal* 91:103041
- Aldrich HE (1979) *Organizations and environments*. Prentice-Hall, Englewood Cliffs, NJ
- Apascanite P, Elvira MM (2022) Dynamizing human resources: an integrative review of SHRM and dynamic capabilities research. *Hum Resour Manag Rev* 32(4):100878
- Arshad MU, Khan FN, Ilyas M, Haider W (2026) Academic-experienced CEOs and investment efficiency of Chinese listed firms: moderating role of cash holdings. *Rev Manag Sci* 20:1793–1843
- Au S-Y, Dong M, Tremblay A (2021) Employee flexibility, exogenous risk, and firm value. *J Financ Quant Anal* 56(3):853–884
- Bai J, Mkrtchyan A (2023) What do outside CEOs really do? Evidence from plant-level data. *J Financ Econ* 147(1):27–48
- Balasubramanian N, Lee J (2008) Firm age and innovation. *Ind Corp Change* 17(5):1019–1047
- Becker GS (1964) *Human capital: a theoretical and empirical analysis with special reference to education*, 1st ed. Columbia University Press, New York
- Belenzon S, Shamshur A, Zarutskiy R (2019) CEO's age and the performance of closely held firms. *Strateg Manag J* 40(6):917–944

- Ben-Nasr H, Alshwer AA (2016) Does stock price informativeness affect labor investment efficiency? *J Corp Financ* 38:249–271
- Bentley KA, Omer TC, Sharp NY (2013) Business strategy, financial reporting irregularities, and audit effort. *Contemp Account Res* 30(2):780–817
- Biddle GC, Hilary G, Verdi RS (2009) How does financial reporting quality relate to investment efficiency? *J Account Econ* 48(2–3):112–131
- Boubaker S, Dang VA, Sassi S (2022) Competitive pressure and firm investment efficiency: evidence from corporate employment decisions. *Eur Financ Manag* 28(1):113–161
- Cahan SF, Chen C, Chen L, Nguyen NH (2015) Corporate social responsibility and media coverage. *J Bank Finance* 59:409–422
- Cai J, Tylecote A (2008) Corporate governance and technological dynamism of Chinese firms in mobile telecommunications: a quantitative study. *Res Policy* 37(10):1790–1811
- Canil J, Karpavičius S, Yu C-F (2023) CEO mobility and corporate payouts. *J Bus Finance Account* 50(9–10):1743–1778
- Cao Z, Rees W (2020) Do employee-friendly firms invest more efficiently? Evidence from labor investment efficiency. *J Corp Finance* 65:101744
- Cao Z, Rees W, Zhang Z (2023) The effect of real earnings smoothing on corporate labour investment. *Br Account Rev* 55(6):101178
- Chen R, El Ghoul S, Guedhami O, Wang H (2017) Do state and foreign ownership affect investment efficiency? Evidence from privatizations. *J Corp Finance* 42:408–421
- Chen W, Zhang Y, Zhao J, Hu G, Zou G (2021) CEO media coverage and corporate investment. *J Int Account Res* 20(3):1–19
- Chen Y, Jermias J (2014) Business strategy, executive compensation and firm performance. *Account Finance* 54(1):113–134
- Chowdhury H, Le TH, Tan KJ (2025) Organization capital and labor investment efficiency. *J Financ Stab* 77:101384
- Ćirović D, Dabić M, Melović B, Backović T (2026) Unleashing SME innovation in small open economies: the strategic role of market dynamism, R&D, and organizational capabilities. *RMS* 20:737–773
- Coad A, Segarra A, Teruel M (2016) Innovation and firm growth: does firm age play a role? *Res Policy* 45(2):387–400
- Colak G, Korkeamäki T (2021) CEO mobility and corporate policy risk. *J Corp Financ* 69:102037
- Dixit AK, Pindyck RS (1994) *Investment under uncertainty*. Princeton University Press, Princeton, NJ
- Do H, Budhwar P, Shipton H, Nguyen H-D, Nguyen B (2022) Building organizational resilience, innovation through resource-based management initiatives, organizational learning and environmental dynamism. *J Bus Res* 141:808–821
- Ee MS, Hasan I, Huang H (2022) Stock liquidity and corporate labor investment. *J Corp Financ* 72:102142
- Ensley MD, Pearce CL, Hmieleski KM (2006) The moderating effect of environmental dynamism on the relationship between entrepreneur leadership behavior and new venture performance. *J Bus Ventur* 31(2):243–263
- Erhemjants O, Huang K (2019) Institutional ownership horizon, corporate social responsibility and shareholder value. *J Bus Res* 105:61–79
- Erl L, Kiesel F, Schiereck D (2025) The diversity of divestiture—stock market reactions around the announcements of divestiture programs. *Rev Manag Sci* 19:2729–2773
- Ertimur Y, Rawson C, Rogers JL, Zechman SL (2018) Bridging the gap: evidence from externally hired CEOs. *J Account Res* 56(2):521–579
- Fainshmidt S, Smith AW, Aguilera RV (2022) Where do born globals come from? A neoconfigurational institutional theory. *Organ Sci* 33(4):1251–1272
- García-Villaverde PM, Rodrigo-Alarcón J, Parra-Requena G, Ruiz-Ortega MJ (2018) Technological dynamism and entrepreneurial orientation: the heterogeneous effects of social capital. *J Bus Res* 83:51–64
- Gerhart B, Feng J (2021) The resource-based view of the firm, human resources, and human capital: progress and prospects. *J Manag* 47(7):1796–1819
- Ghaly M, Dang VA, Stathopoulos K (2020) Institutional investors' horizons and corporate employment decisions. *J Corp Financ* 64:101634
- Gómez J, Pérez-Arados B, Salazar I (2022) How to beat early movers: the role of competitive strategy and industry dynamism on followers' performance in the telecommunications industry. *Long Range Plann* 55(5):102244
- Gong N, Guo L, Wang Z (2023) Shareholder litigation and workplace safety. *J Corp Financ* 82:102467
- Grant RM (1996) Toward a knowledge-based theory of the firm. *Strateg Manag J* 17(52):109–122

- Habib A, Hasan MM (2021) Business strategy and labor investment efficiency. *Int Rev Financ* 21(1):58–96
- Helfat CE, Martin JA (2015) Dynamic managerial capabilities: review and assessment of managerial impact on strategic change. *J Manag* 41(5):1281–1312
- Imbens GW, Angrist JD (1994) Identification and estimation of local average treatment effects. *Econometrica* 62(2):467–475
- Jian M, Lee KW (2011) Does CEO reputation matter for capital investments? *J Corp Financ* 17:929–946
- Jung B, Lee W-J, Weber DP (2014) Financial reporting quality and labor investment efficiency. *Contemp Account Res* 31(4):1047–1076
- Kafourous M, Aliyev M, Piperopoulos P, Au A, Ho JW, Wong SY (2024) The role of institutional quality and industry dynamism in explaining firm performance in emerging economies. *Glob Strateg J* 14(1):56–83
- Keats BW, Hitt MA (1988) A causal model of linkages among environmental dimensions, macro organizational characteristics, and performance. *Acad Manag J* 31(3):570–598
- Khanna N, Tice S (2001) The bright side of internal capital markets. *J Finance* 56(4):1489–1528
- Khedmati M, Sualihu MA, Yawson A (2020) CEO-director ties and labor investment efficiency. *J Corp Finance* 65:101492
- Kieschnick R, Moussawi R (2018) Firm age, corporate governance, and capital structure choices. *J Corp Finance* 48:597–614
- Klasa S, Ortiz-Molina H, Serfling M, Srinivasan S (2018) Protection of trade secrets and capital structure decisions. *J Financ Econ* 128(2):266–286
- Kogut B, Zander U (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. *Organ Sci* 3(3):383–397
- Kuppuswamy V, Villalonga B (2016) Does diversification create value in the presence of external financing constraints? Evidence from the 2007–2009 financial crisis. *Manag Sci* 62(4):905–923
- Le A-T, Tran TP (2022) Corporate governance and labor investment efficiency: international evidence from board reforms. *Corp Gov Int Rev* 30(5):555–583
- Lewbel A (2012) Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *J Bus Econ Stat* 30(1):67–80
- Li D-y, Liu J (2014) Dynamic capabilities, environmental dynamism, and competitive advantage: evidence from China. *J Bus Res* 67(1):2793–2799
- Martínez-Sánchez A, Vela-Jiménez M-J, Pérez-Pérez M, de-Luis-Carnicer P (2012) The dynamics of labour flexibility: Relationships between employment type and innovativeness. *J Manag Stud* 48(4):715–736
- Matsa DA (2018) Capital structure and a firm's workforce. *Annu Rev Financ Econ* 10:387–412
- McGrath RG (1999) Falling forward: real options reasoning and entrepreneurial failure. *Acad Manag Rev* 24:13–30
- McKelvie A, Davidsson P (2009) From resource base to dynamic capabilities: an investigation of new firms. *Br J Manag* 20(S1):S63–S80
- Milbourn TT (2003) CEO reputation and stock-based compensation. *J Financ Econ* 68(2):233–262
- Oster E (2019) Unobservable selection and coefficient stability: theory and evidence. *J Bus Econ Stat* 37(2):187–204
- Ozbas O, Scharfstein DS (2010) Evidence on the dark side of internal capital markets. *Rev Financ Stud* 23(2):581–599
- Pfarrer MD, Pollock TG, Rindova VP (2010) A tale of two assets: the effect of firm reputation and celebrity on earnings surprises and investors' reactions. *Acad Manag J* 33(5):1131–1152
- Pinnuck M, Lillis AM (2007) Profits versus losses: does reporting an accounting loss act as a heuristic trigger to exercise the abandonment option and divest employees? *Account Rev* 48(4):1031–1053
- Ployhart RE (2021) Resources for what? Understanding performance in the resource-based view and strategic human capital resource literatures. *J Manag* 47(7):1771–1786
- Qiu B, Wang T (2018) Does knowledge protection benefit shareholders? Evidence from stock market reaction and firm investment in knowledge assets. *J Financ Quant Anal* 53(3):1341–1370
- Quigley TJ, Hambrick DC, Misangyi VF, Alessandra R (2019) CEO selection as risk-taking: a new vantage on the debate about the consequences of insiders versus outsiders. *Strat Manag J* 40(9):1453–1470
- Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41–55
- Roychowdhury S, Shroff N, Verdi RS (2019) The effects of financial reporting and disclosure on corporate investment: a review. *J Account Econ* 68(2–3):101246

- Schilke O (2014) On the contingent value of dynamic capabilities for competitive advantage: the nonlinear moderating effect of environmental dynamism. *Strateg Manag J* 35(2):179–203
- Schubert T, Baier E, Rammer C (2018) Firm capabilities, technological dynamism and the internationalisation of innovation: a behavioural approach. *J Int Bus Stud* 49:70–95
- Shao L, Kwok CC, Zhang R (2013) National culture and corporate investment. *J Int Bus Stud* 44:745–763
- Simerly RL, Li M (2000) Environmental dynamism, capital structure and performance: a theoretical integration and an empirical test. *Strateg Manag J* 21(1):31–49
- Tetlock PC (2007) Giving content to investor sentiment: the role of media in the stock market. *J Finance* 62(3):1139–1168
- Torre ED, Zatzick CD, Sikora D, Solari L (2018) Workforce churning, human capital disruption, and organisational performance in different technological contexts. *Hum Resour Manag J* 28(1):112–127
- Triguero Á, Córcoles D (2013) Understanding innovation: an analysis of persistence for Spanish manufacturing firms. *Res Policy* 42(2):340–352
- Uotila J, Maula M, Keil T, Zahra SA (2009) Exploration, exploitation, and financial performance: analysis of S&P 500 corporations. *Strateg Manag J* 30(2):221–231
- Wang H, Chen W-R (2010) Is firm-specific innovation associated with greater value appropriation? The roles of environmental dynamism and technological diversity. *Res Policy* 39(1):141–154
- Wang X, Sun J, Tian L, Guo W, Gu T (2021) Environmental dynamism and cooperative innovation: the moderating role of state ownership and institutional development. *J Technol Transf* 46:1344–1375
- Wang YY (2023) Corporate diversification, investment efficiency and the business cycle. *J Corp Financ* 78:102353
- Wright PM, Snell SA (1998) Toward a unifying framework for exploring fit and flexibility in strategic human resource management. *Acad Manag Rev* 23(4):756–772
- Wu S, Levitas E, Priem RL (2005) CEO tenure and company invention under differing levels of technological dynamism. *Acad Manag J* 48(5):859–873
- Yuan Y, Lu LY, Tian G, Yu Y (2020) Business strategy and corporate social responsibility. *J Bus Ethics* 162:359–377
- Zhou KZ, Wu F (2010) Technological capability, strategic flexibility, and product innovation. *Strateg Manag J* 31(5):547–561
- Zingales L (2000) In search of new foundations. *J Finance* 55(4):1623–1653

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Mohamed Shaker Ahmed¹ · Charilaos Mertzanis^{2,3} · Satish Kumar^{4,5} ·
Mohamad Husam Helmi⁶ 

✉ Mohamad Husam Helmi
mhelmi@ra.ac.ae

Mohamed Shaker Ahmed
Mohamed.ahmed@aaau.ac.ae

Charilaos Mertzanis
charilaos.mertzanis@adu.ac.ae

Satish Kumar
satishk@sunway.edu.my

¹ Al Ain University, Abu Dhabi, United Arab Emirates

² Abu Dhabi University, Abu Dhabi, United Arab Emirates

³ National and Kapodistrian University of Athens, Athens, Greece

⁴ Sunway Business School, Sunway University, Subang Jaya, Malaysia

- ⁵ Jaipuria Institute of Management Lucknow, Lucknow, India
- ⁶ Rabdan Academy, Abu Dhabi, United Arab Emirates