Received: 16 August 2021 | Revised: 14 August 2023 | Accepted: 22 January 2024

DOI: 10.1002/ijfe.2945

RESEARCH ARTICLE

WILEY

Looking in the rear-view mirror: Evidence from artificial intelligence investment, labour market conditions and firm growth

Ishmael Tingbani[1] | **Samuel Salia**[2] | **Christopher A. Hartwell**[3] | **Alhassan Yahaya**[4]

[1]Department of Accounting, Southampton Business School, University of Southampton, Southampton, UK

[2]Birmingham City Business School, Birmingham City University, Birmingham, UK

[3]International Management Institute, Department of International Business Zurich University of Applied Sciences, Winterthur, Switzerland

[4]Department of Accounting and Finance, Sunderland University, London, UK

Correspondence
Ishmael Tingbani, Department of Accounting, Southampton Business School, University of Southampton, Southampton, UK.
Email: i.s.tingbani@soton.ac.uk

Abstract

This paper presents evidence of the impact of AI investment on firm growth and how the relationship is sensitive to labour market conditions. Using the generalized method of moments (GMM) estimation on 1950 unique American firms over 1996–2016, we show that a 10% increase in AI investment leads to an increase in firm growth by 0.04%. However, this result is highly sensitive to labour market conditions, as labour productivity can positively impact firm growth, but labour cost and labour share negatively influence firm growth. These results offer original insights into an essential channel via which investment in AI may mediate firm growth.

KEYWORDS

artificial intelligence, firms growth, institutional quality, labour cost, labour market conditions, labour productivity, labour share

1 | INTRODUCTION

The lure of artificial intelligence (AI) has increased over the past decade, seemingly promising higher productivity, more competitive economies, a greater variety of products, and a key to unlocking long-term growth (Aghion et al., 2017; Bughin et al., 2018; Kakatkar et al., 2020). From the point of view of firms, channelling resources into AI has also been perceived as a way to remain on the technological frontier and avoid being "left behind" (see Balgobin & Pandit, 2001) as had happened in previous waves of technological advancement; instructive is the example of IBM, which is a case study in failing to stay on the frontier (Gao et al., 2019). Given the high promise of this new technology, firms have been investing in AI to spur growth, using, for example, AI-enabled automation to significantly influence the efficiency with which goods and services are produced (Furman & Seamans, 2019; Zdravković et al., 2022).

The burgeoning literature on microeconomics and firm-level effects of AI investment has focused on how AI can power firm growth (Babina et al., 2020, 2022; Schrage et al., 2023). Less attention has been paid to labour market conditions (e.g., labour cost, labour share and labour productivity) (see, for a critical review of this literature, Agrawal et al., 2019; Babina et al., 2020, 2022; Mitchell & Brynjolfsson, 2017; Rice et al., 2018; Wamba-Taguimdje et al., 2020). Implicitly ignoring the impact of labour is a critical enabler of innovation (Ipinnaiye et al., 2017; Liu et al., 2021). The benefit of AI is likely to be in its ability to save labour costs or to allow a firm to reallocate labour to higher-value tasks (Wamba-Taguimdje et al., 2020). Therefore, it is important to understand the sensitivity of AI-powered growth to labour market conditions since investments in new technologies are likely to respond differently to labour market shocks (Autor et al., 2016). For example, how does AI-powered growth react to unexpected increases in the cost of hiring AI-skilled labour? AI-skilled labour is a key input to AI implementation and accounts for a significant share of operating costs (Babina et al., 2020; Rampini et al., 2022). The implication is that price increases in the labour market will also increase the cost of operations, relatively more for an AI-powered firm. The increased cost of operation due to increases in hiring AI-skilled labour has the potential to translate into lowered profits and affect the prospect of firm growth (i.e., where profit is considered a measure of firm growth, e.g., Lui et al., 2022; Mishra et al., 2022).

Despite this, most previous studies have focused on only investment in AI and firm growth without jointly considering both AI investment and labour market conditions. A critical review of this strand of literature is in (Agrawal et al., 2019; Babina et al., 2020, 2022; Mitchell & Brynjolfsson, 2017; Rice et al., 2018; Wamba-Taguimdje et al., 2020). None of these studies incorporated both the AI investment and labour market conditions. The closest to our study has come from (Babina et al., 2020), who incorporated AI investment and firm growth into their model. Unlike our study, the (Babina et al., 2020) study did not incorporate labour market conditions, while Babina et al. (2022) only focused on AI investment and workforce educational attainment.

Against this backdrop, this paper addresses a critical gap in the literature by incorporating AI investment—labour market conditions—and firm growth into the analysis. Given the integration, we can trace the responses of AI-powered growth to shocks in each labour market condition. By considering these aspects jointly, a policy can be developed to address potential bottlenecks in essential channels via investment in new technologies moderate firm growth (Acemoglu et al., 2014; Acemoglu & Autor, 2011; Kleinknecht, 2020).

Our paper develops a resource-based framework, using investment in AI, labour market conditions, and firm growth as underlying parameters to explore the relationship among these three empirically. Specifically, we develop a GMM estimation model on a sample of 1950 unique US firms from 1996 to 2016, generating 21,743 firm-year observations. Evidence from this analysis shows that firm AI investment positively impacts firm growth, with a 10% increase in AI investment associated with increased firm growth of 0.04%. However, the results suggest that the positive relation between AI and a firm's growth is further reinforced when labour market conditions are efficient and favourable for the firm. Indeed, while labour productivity positively impacts firm growth in the presence of AI investment, both high labour costs and high labour have a negative effect. These results are robust to a series of tests controlling for endogeneity, alternative measures of the relevant variables, subsamples, and different periods.

These findings are consistent with prior research that indicates that investment in AI positively impacts firm growth (Babina et al., 2020; Dubey et al., 2019). By introducing the effects of labour market conditions, however, we contribute to the literature, demonstrating the moderating effects that labour markets have in enhancing growth (Murphy & Mercille, 2019; Quintana et al., 2016) through firms' investment in AI. Our study complements prior studies (Aghion et al., 2017; Alekseeva et al., 2021; Babina et al., 2020, 2022; Fedyk et al., 2022) by explicitly considering for the first time how labour markets influence the relationship between AI investment and firms' growth. By tracing the responses of AI-powered growth to shocks in a variety of labour market conditions, our study provides further insight and understanding of essential channels via which AI investment enhances firms' growth (Acemoglu et al., 2014; Acemoglu & Autor, 2011; Kleinknecht, 2020).

The paper proceeds as follows. Section 2 reviews the conceptual framework, previous literature and hypothesis for the study. Section 3 presents the data and the empirical model for the study using the identification strategy and estimation method. The empirical results and discussion are reported in Section 4; additional results and robustness checks are provided in Section 5, while Section 6 presents the conclusions.

2 | PRIOR RESEARCH AND HYPOTHESIS DEVELOPMENT

2.1 | Theoretical underpinning

Artificial intelligence, as a new form of technology, can further automation at the firm level to help firms optimize their resource allocation, better utilize scarce resources, and simultaneously serve their customer base more effectively (Acemoglu & Autor, 2011). Prior studies have addressed why firm-level output depends on the firm's ability to innovate and utilize unique resources (Alvarez & Barney, 2017; Davis & Simpson, 2017; Hoskisson et al., 2018; Mitchell & Brynjolfsson, 2017; Nason & Wiklund, 2018). The fundamental theory underlying this evidence is the resource-based view (RBV), which highlights strong internal resources and capabilities as key ingredients required by a firm to achieve positive output (Barney, 2001; Dubey et al., 2019; Shibin et al., 2020; Yen et al., 2019). Dubey et al. (2019), in particular, used RBV theory to examine the effect of big data culture on firm cost and operational performance; as with other papers in this vein, it showed how a firm's continuous exploits of Valuable, Rare, Inimitable, and Non-substitutable (VRIN) resources are central to competitiveness and the firm's ability to achieve above-average performance (Shibin et al., 2020).

AI as a competitive advantage that inures positive firm output is validated by the VRIN criteria described by Barney (2001) and Hoskisson et al. (2018). Consistent with the notion of rare, inimitable, non-substitutable and valuable assets, AI technology creates "thinking machines" capable of mimicking, learning, and replacing human intelligence (Davenport & Ronanki, 2018; Huang & Rust, 2018; Russell, 2016; Yoo, 2019). A cutting-edge technology that can undertake routine tasks with very minimal human involvement at a reduced cost of labour production (Hogarty et al., 2019; Kakatkar et al., 2020) is rare and only available to 21st-century business survivors who fear losing out on industry leadership (see Balgobin & Pandit, 2001). However, the significant investment required to deploy AI technology imposes a financial constraint on a firm's ability to imitate or easily substitute (Almeida & Campello, 2007; Chang et al., 2019; Lerskullawat, 2019; Yan et al., 2018). Related evidence of a laggard firm's inability to imitate AI is in Andrews et al. (2015), who observed that superstar firms are successful in blocking the imitation of their technology. Moreover, AI has the unique ability to address important technology needs of firms and streamline business expertise (Paschen et al., 2020), thereby making it a precious resource. However, AI is in a relatively nascent and evolving phase, and returns to it should be viewed as a long-term prospect (e.g., see Liu & Shong, 2018; Lu et al., 2018).

2.2 | Prior evidence

Mou (2019) notes that investment in AI can be found in virtually every industry today, with the unfolding evidence showing AI being used by firms to remain competitive and ensure long-term growth (Davenport & Ronanki, 2018); indeed, the evidence points to the reality that AI may improve a firm's efficiency, reduces operational cost, and increase profitability (Hsu et al., 2014; Makridakis, 2017). The way in which AI can be translated into more efficient processes within a firm operates through several channels. The first approach is the use of AI as a computational tool which performs tasks that traditionally have required human intelligence (Cockburn et al., 2018; Dwivedi et al., 2019; Fazal et al., 2018; Russell, 2016). Artificial intelligence can do administrative and operational tasks that consume much of employees' time faster, better, and at a lower cost. This aspect is explored in-depth by Fedyk et al. (2022), who found that Audit firms that invest in AI can displace human auditors, resulting in improved audit quality and reduced audit fees. Similarly, Kolbjørnsrud et al. (2016) found that the Associated Press expanded its quarterly earnings reporting from approximately 300 stories to 4400 with AI-powered software robots, as journalists were freed up to conduct more investigative and interpretive reporting.

AI may also replace productive work rather than just administrative tasks in manufacturing. Extant research suggests that AI aids the design of better products in functionality, quality, and cost and improves predictive maintenance (Mou, 2019). Especially where the use of AI has resulted in increased product innovation, AI-investing firms experience increased growth in sales, employment and market valuation (Babina et al., 2020). In a similar vein, as reported in Furman and Seamans (2019), AI-enabled innovations have led to the development of various chat-bots and virtual assistance applications such as Alexa and Siri., while also allowing for tailoring product offerings and online ads to increase firm sales (Mihet & Philippon, 2019). In finance, (Trippi & Turban, 1993) have shown strong evidence of rapid adoption of AI for trading in securities markets, forecasting the economy and analysing credit risk (Cortes et al., 2018; Lee et al., 2018). Additional evidence from Farboodi et al. (2019) on the AI/big data nexus suggests that AI-intensive firms can enjoy economies of scale through better data utilization and analysis.

The advent of AI may also create positive labour market outcomes, both at the firm and macroeconomic levels. While many have highlighted the potential adverse effects of AI on labour markets (Frey & Osborne, 2017; Furman, 2016), AI investment may lead to an increased demand for highly skilled workers, as the extensive use of disruptive innovation skills tends to intensify labour quality, rebounding to the benefit of the firm in terms of labour productivity (Autor, 2015). Furman and Seamans (2019) provide evidence that this is the case in that AI has spurred high demand for workers with machine-learning or deep-learning skills. This is corroborated by Babina et al. (2022) as they found that firms investing in AI tend to transition to utilizing a more educated workforce.

This linkage comes on the heel of a large literature which has noted the association between technology and labour market conditions and how they impact firm productivity, competitiveness, and long-term growth (Autor, 2015; Rodríguez-Pose & Lee, 2020). For example, the concentration of highly skilled workers in STEM occupations explains the impact of innovations on firm growth (Atkinson & Mayo, 2010). An analysis of Arvanitis (2005) also indicates that the combined use of technology and human capital leads to the mutual strengthening of their impact on firm growth. Moreover, the effects of labour share on firms' information technology and market concentration are documented (Aghion et al., 2019; Crouzet & Eberly, 2019; Lashkari et al., 2018). These observations corroborate findings reported by Farboodi et al. (2019) that showed the deployment of technology led to a decline in long-term operational costs for banks than prior accumulated labour costs. This makes labour market conditions highly relevant for AI-powered growth (Alekseeva et al., 2020; Babina et al., 2020; Bartel et al., 2007).

2.3 | Hypothesis development

Given this extensive literature, as noted above, we posit that AI investment influences firm growth for several reasons. First, AI stimulates firm growth by streamlining operational tasks and by undertaking these tasks faster, better, and at a lower cost (Ghazwani et al., 2022). For example, AI-powered software robots are effective at eliminating errors and waste within the manufacturing process due to their high precision and efficiency in undertaking such a task (see Acemoglu et al., 2014; Graetz and Michaels, 2018). Similarly, AI-powered machine intelligence can enable firms to offer goods and services with little or no human involvement at comparatively low costs (Davenport & Ronanki, 2018). AI-powered cashier-less and cash-less grocery stores can offer products and services to customers even in the presence of staffing constraints (Ghazwani et al., 2022), while AI-powered Siri and Chat-bots can provide virtual assistance to customers in real-time, improving customer retention and market power (Mihet & Philippon, 2019). Evidence shows that, on average, firms with strong omnichannel communication[1] experience have an 89% customer retention rate compared to 33% for firms with weaker omnichannel communication (Aberdeen Group, 2020). The contribution of big data analytics to satisfactory customer service and sales growth is also reported by Hallikainen et al. (2020). AI technology can thus enable firms to respond to rapidly changing demands in the marketplace and from consumers, bypassing costly organizational or labour solutions (Singhal & Yerpude, 2018). Based on these theoretical channels and the corresponding empirical evidence, we propose the following hypothesis:

> **Hypothesis 1.** Investment in AI is positively correlated with firm growth.

Labour share alone represents some 50% of the gross domestic product (GDP) in the United States (US) (Donangelo et al., 2015); thus, labour market conditions play an important role in determining the effect of AI investment on firms in the US market (Acemoglu et al., 2014; Jung & Lim, 2020; Li et al., 2020). This argument is further grounded in the consideration that technology-driven production limits human involvement, which can reduce labour share (Hogarty et al., 2019; Jung & Lim, 2020; Kakatkar et al., 2020). To put it differently, a lower labour share (a lower unit labour cost) implies a higher degree of competitiveness as firms can lower the cost of labour compensation (wages, salaries, and other benefits). The resulting reduction in the cost of labour arising from firm investment in AI will, therefore, decrease the overall cost burden and release resources that can contribute to firm growth (Kwon & Stoneman, 1995). This can be expressed in our next two hypotheses:

> **Hypothesis 2.** High labour share negatively moderates the relationship between AI investment and firm growth.

> **Hypothesis 3.** There is a weak linear relationship between AI investment, high labour cost and firm growth.

Much as high labour costs can be reduced by AI investment, high labour productivity can reduce the amount of time an AI-automated plant spends to produce goods or provide services (Dalton et al., 2022). However, this productivity may come at a cost, as (high cost) employees with STEM skills are required due to their possession of specialist knowledge (i.e., sophisticated skills) that will enable them to manage AI-powered technologies (Acemoglu et al., 2014; Andrews & Saia, 2017; Arik & Geho, 2017). All other things being equal, this should lead to a reduction in production time, resulting in a decrease in the unit cost of production, but may be counterbalanced by an increase in unit labour costs. Similar arguments are explored in-depth in the literature (Chen, 2020; Khanna & Sharma, 2018; Liu et al., 2020; Ritter-Hayashi et al., 2019), leading to our final hypothesis:

> **Hypothesis 4.** The effects of AI investment on firm growth are stronger when labour productivity is high.

3 | EMPIRICAL STRATEGY

3.1 | Empirical model

To investigate the impact of AI investment on growth, we estimate the following model below:

$$Y_{i,t} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 AI_{i,t} + \beta_3 K_{i,t} + \beta_4 P_{i,t} + \mu_{i,t} + \lambda_t + \nu_{i,t}, \quad (1)$$

where Model (1) estimates the impact of AI investment on firm growth (Hypothesis H1), while Model (2) determines the moderating role of labour market conditions on AI investment and firm growth. The dependent variable denotes firms' growth for firm i in year t measured as a one-year growth rate of sales (SALE) at time t-1, constructed as $(\mathrm{SALE}_{t-1} - \mathrm{SALE}_{t-2})/\mathrm{SALE}_{t-2}$. We also consider various alternative measures of firm growth in our robustness checks in Section 5.1. In model (1), AI is the key independent variable which denotes AI investment measures as the total proportion of AI skills for a firm.

Given the difficulty in obtaining data on firm-level AI investment, we follow the approach of several prior studies (Alekseeva et al., 2021; Babina et al., 2022; Fedyk et al., 2022): given that AI-skilled labour is a key input to AI implementation, we construct a new measure of firm investments in AI based on the intensity of hiring in AI-skilled labour, relying on public job postings and employee profile databases. Adopting pre-specified lists of key terms and job positions directly involved in AI from Burning Glass Technologies (see Appendix A, Table A1), we search for these terms in every employment record and relevant biographical data of each individual in several publications, including Boardex, Marquis' "Who's Who," Prabook, Nndb, Relationship Science, and also via Wikipedia, Google, and Bing search engines. This search yielded information on 2558 out of 4909 AI-related North American firms. We then matched the employer's name to the names of publicly traded firms in the Compustat data set using the approach developed by Fedyk and Hodson (2023). Following Jiang and Lie (2016), we exclude firms from industries that are heavily regulated (given that their financial positions can be subject to regulatory supervision), resulting in excluding financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) from the sample. Moreover, to avoid survivorship bias, the sample includes survivors and non-survivors: using criteria proposed by Bartel et al. (2007) and McLean (2011), we require firms to have positive sales and assets. After this selection process, we were left with a sample of 1950 firms from 1996 to 2016.

To capture labour market conditions, P_{it} denotes the set of labour market condition variables, including labour share, labour cost, and labour productivity. We follow Donangelo et al. (2015) to construct empirical measures of labour share and Breit et al. (2019) for our construction of labour productivity and labour costs. Detailed definitions of these variables can be found in Table 1. Following prior research (Hanlon et al., 2017; Rahaman, 2011), we also include capital expenditure (CAPEX), market to book value (MBV), five-year repatriation tax cost (REPTAX), net tax loss carried forward (NOL) networking capital (NWC), effective tax rate (ETR), Altman score (ALTMAN), fixed assets growth (FAG), and firm size (FSIZE) as control variables to guide the study. The V_i is the unobserved firm effects (fixed effects), the parameter λ_t is the time dummy variable, ε_{it} the idiosyncratic shocks. β_{1-4} are vectors of parameters to be estimated. In the model, we control for firm-pair fixed effects (μ_{ij}) to control for the unobservable heterogeneity. λ_t controls for idiosyncratic shocks.α_0 is the constant. $\nu_{ij,t}$ represents the error term.

Next, to test Hypothesis 2, we capture the interactive effect of AI investment and Labour market conditions on firms' growth using the following regression models below:

$$Y_{i,t} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 AI_{i,t} + \beta_3 X_{i,t} + \beta_4 K_{i,t} + \beta_4 P_{i,t} + \mu_{i,t} + \lambda_t + \nu_{i,t}, \quad (2)$$

where $X_{i,t}$ is the interaction of AI Investment and labour market conditions (labour share, labour cost, and labour productivity). The rest of the variables are the same as in Model 1.

In terms of the estimator utilized, this panel model presents several econometric issues which need to be surmounted. In the first instance, OLS estimation will likely produce biased estimation due to the correlation between the unobserved firm-specific effects and the lagged dependent variable. Taking first differences could eliminate the firm-specific-effects problem. On the other hand, the first-difference transformation may lead to inconsistent OLS estimates when effects are spread out over time; additionally, the first differencing will eliminate time-invariant or slow-moving variables. Second, the question of AI and firm growth is a potentially endogenous relationship, given that some of the explanatory variables in our model are not strictly exogenous.

To overcome these two challenges, we employ the system GMM dynamic panel estimator (Arellano & Bover, 1995; Blundell & Bond, 1998), which offers several advantages. First, it allows us to instrument the exogenous variables with their own lagged values if they are not correlated with the error term. Second, the system GMM addresses potential endogeneity issues across variables by estimating the equations jointly in differences

TABLE 1 Variables Definition.

Name	Definition	Data source
AI Investment	Proportion of AI skills (AI Share). Calculated as share of the firm's employees who are AI-skilled/ total number of employees	Based on Author's calculations
Firm growth	Measured as a one-year growth rate of sales (SALE) at time t-1. This constructed as $(SALE_{t-1} - SALE_{t-2})/SALE_{t-2}$	Compustat
Labour market conditions (LC)	(Labour share, labour cost and labour productivity)	
Labour share	Staff Expense – Total/(Operating Income Before Depreciation + Inventories –Finished Goods *). We set ΔINVFGit to zero when either INVFGit or INVFGi,t − 1 are missing. XLRit/OIBDPit +ΔINVFGit +XLRit	Compustat
Labour cost	Average cost of labour per unit of output produced LABEX is an imputed measure of labor expenses constructed as: LABEXit = WAGEit (EMPi,t − 1 + EMPit/2). Where EMP is the number of Employees, I denotes firm i's industry, and WAGEit the average of WAGEit = XLRjt ((EMPj,t − 1 + EMPjt)/2) across firms j ∈ I with non-missing values for these variables on year t.	Compustat
Labour Productivity	Total sales (SALE) divided by the number of employees (EMP) in a company	Compustat
Talent management (talent)	An index that measures how easy is it for a country retain talented people. [1 = the best and brightest leave to pursue opportunities in other countries; 7 = the best and brightest stay and pursue opportunities in the country]	Global Competitive index
Tobin's Q	The market value of equity (PRCC times CSHO) plus total assets (AT) minus the book value of equity (ceq + txdb), divided by total assets (AT)	Compustat
ROA	Operating income before depreciation (OIBDP) divided by total assets (AT).	Compustat
Book-to-market (MBV)	Book value of equity (CEQ) divided by market value of equity (PRCC times CSHO)	Compustat
Firm Size	Natural logarithm of book assets (AT)	Compustat
Effective Tax Rate	The ratio of tax expense (TXT) to pre-tax income (PI) (Lisowsky et al., 2013)	Compustat
5-year repatriation tax cost (REPTAX)	Income (PIFO) times (35%) and foreign income taxes paid (TXFO) over the previous 5 years.	Compustat
Net tax loss carry forward (NOL)	NOL as the balance of tax loss carryforwards scaled by total assets (TLCF/AT), where NOL is set equal to zero when tax loss carryforwards is missing	
Financial crisis	A dummy variable is a proxy for crisis 1 for the crisis periods (1991, 2001, 2007, 2008, and 2009) and 0 for any other years.	
Capital expenditures (CAPEX)	Capital expenditures (CAPX), scaled by total assets at the beginning of the period (AT).	Compustat
Net Working Capital	The ratio of working capital (ACT−LCT) minus cash and marketable securities (CHE) to total assets (AT)	Compustat
fixed assets growth (FAG)	The one-year growth rate of fixed assets (PPENT) at time t − 1: (PPENTt−1 − PPENTt−2)/PPENTt−2.	Compustat

and levels. Additionally, it also corrects any additional biases due to the correlation between the fixed-specific effects and the lagged dependent variable (Guney & Tepe, 2017).

In our estimation, we used the one-step system GMM estimation by using different sets of lagged instruments that best fit the commonly utilized diagnostics, namely the AR (2) and Hansen J-tests. Against this backdrop, different lag structures are needed to capture these dynamics. However, the Hansen J-test of overriding restrictions and the AR (2) confirms the validity of the instruments. In the dynamic model, we expect to have a first-order serial correlation (i.e., AR (1)) and no second-order serial correlation (i.e., AR (2)). The results of these tests are presented in each of the regression tables.

4 | EMPIRICAL RESULTS

4.1 | Descriptive statistics and univariate analysis

Table 2 reports the summary statistics for the study. The findings reveal that the average share of hired AI-skilled individuals to the total number of employees is 0.3%, with a standard deviation of 0.041%. The standard deviation figure shows a substantial variation in the average AI share in the sample. Of equal significance is firms' growth. Our findings suggest a mean firm's growth in the sample of 32 per cent with a median and standard deviation of 11% and 85%, respectively. The control variables' descriptive statistics are analogous to prior studies (see Ferrando & Mulier, 2013; Hanlon et al., 2017; Rahaman, 2011).

4.2 | Pearson's correlation matrix

Table 3 reports the results of the Pearson correlation matrix for the study. The evidence suggests a positive correlation between AI investment and firms' growth. This initial result reinforces our claim that AI investment positively impacts firm growth. The correlations among all the control variables are below 50%, consequently suggesting no multicollinearity issues among the individual variables.

4.3 | Baseline regression results

Table 4 reports the baseline regression estimations on the effect of AI investment on the firm's growth. We begin by estimating Model 1 without controlling for specific firm characteristics. The findings of these estimations have not been reported in the paper but could be presented upon request. Further, we control the unobservable heterogeneity and time trend effect on the AI investment-firm growth relationship in Table 4.

Column 1 of Table 4 presents the findings of the AI investment and firms' growth, and columns 2, 3, 4 and 5 for the relations between labour market conditions (labour share, labour cost and labour productivity) on firms' growth. Like the univariate analysis, the evidence reveals the relationship between AI investment and firms' growth to be significantly positive, supporting **hypothesis 1** of the study. The evidence suggests that secular investment in AI positively impacts the individual growth of firms. In particular, the results in column (1) of Table 4 suggest the coefficient of the AI investment be positive and statistically significant at the 1% level (= 0.00368, t-statistic = 2.15). The results show that a 10% decrease (increase) in AI investment leads to a decrease (increase) in firms' growth by 0.04%. This provides a strong and consistent pattern with similar studies (Babina et al., 2022), which suggests faster growth for firms that invest in AI. According to (Babina et al., 2020), industries that

TABLE 2 Descriptive statistics.

	Mean	SD	Perc 10	Median	Perc 90
Firm growth (%)	32	85	00	11	39
AI Share (ratio)	0.003	0.041	0	0	1
Labour share (%)	60	69	59	59	61
Labour cost (ratio)	1.67	1.14	0.00	1.88	3.17
Labour productivity (ratio)	1074.29	15656.7	0.00	16.11	322729.66
Market to book value (ratio)	5.05	2.22	2.25	3.24	7.96
REPOTAX	−0.005	0.028	0.00	0.00	0.12
NOL	11.9	441	0.00	0.079	3.42
Capital expenditure (ratio)	0.050	0.084	0.00	0.02	0.126
Net working capital (ratio)	3.78	1.89	1.35	3.92	332.27
FirmSize (Million $)	7.67	1.79	5.52	7.53	10.12
Fixed asset growth (%)	0.220	0.686	0.00	0.00	1.024
Altman Score (ratio)	5.01	2.04	2.4209	5.114	7.750
Effective tax rate (%)	0.06	18.07	0.000	0.10	0.404

Note: This table reports the descriptive statistics of the variables under consideration. All variable definitions are contained in Table 1.

TABLE 3 Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Firm growth	1													
2. AI investment	−0.043*	1												
3. Labour share	0.0107	−0.028*	1											
4. Labour cost	−0.002	0.0662*	−0.1058*	1										
5. Labour productivity	−0.0008	−0.0077	0.2996*	−0.725*	1									
6. NOL	−0.017*	0.202*	−0.0095	0.0113	0.0118	1								
7. REPOTAX	0.0117	−0.260*	0.009	−0.0119	0.0011	0.2587*	1							
8. Market to book value	−0.068*	−0.097*	0.0156	−0.0001	0.0108	0.005	0.1317*	1						
9. Capital Expenditure	0.1113*	0.0985*	0.0054	−0.0054	0.0015	0.0146*	−0.0017	−0.059*	1					
10. Net working capital	−0.027*	−0.445*	−0.0071	−0.0019	0.0039	0.2834*	0.2411*	0.5034*	−0.137*	1				
11. Firm size (million $)	−0.096*	−0.318*	0.0215*	−0.0098	0.0093	0.0590*	0.2814*	0.4651*	0.0342*	0.6403*	1			
12. Fixed asset growth (%)	0.503*	−0.079*	0.0202*	−0.0092	0.012	0.0227*	0.0445*	−0.0482	0.2527*	0.0046	0.0006	1		
13. Altman Score	−0.171*	−0.316*	0.0042	0.0019	0.001	0.2232*	0.2300*	0.5704*	−0.0339*	0.6388*	0.8366*	−0.1271*	1	
14. Effective Tax Rate	−0.059*	−0.145*	−0.0074	−0.0113*	−0.001	−0.013*	0.1757*	0.1430*	−0.038*	0.2447*	0.2714*	−0.024*	0.3381*	1

Note: This table reports the correlation matrix of the variables under consideration. All variable definitions are contained in Table 1. * indicates statistical significance at the 5%.

TABLE 4 Baseline regression: AI investment and firms' growth.

	Firm growth	Labour share	Labour cost	Labour productivity
Firm Growth	0.0354**	0.00204	0.0440***	−0.00421
	(2.31)	(0.10)	(9.92)	(−0.22)
AI investment	0.00368**	0.00374**	0.000964***	0.00316***
	(2.15)	(2.06)	(5.13)	(2.96)
LC		−0.06023***	−0.0206***	0.00922***
		(−4.10)	(−23.98)	(6.88)
MBV	0.0312***	0.0357***	0.0156***	0.0246***
	(4.52)	(4.70)	(14.51)	(4.43)
NOL	−0.0850***	−0.0261	−0.00379	−0.0137
	(−3.50)	(−0.92)	(−0.66)	(−0.68)
REPOTAX	2.373***	2.952***	0.647***	1.863***
	(3.30)	(2.83)	(8.50)	(3.62)
CAPEX	−0.292	−0.256	−0.341	−0.322
	(−1.21)	(−1.10)	(−7.13)	(−1.51)
NWC	0.0263	0.0314	0.0166***	0.00546
	(1.41)	(1.37)	(6.30)	(0.41)
Firm Size	0.152***	0.0587	0.158***	0.119***
	(4.97)	(1.46)	(26.85)	(5.93)
FAG	0.0629**	0.0801***	0.0758***	0.0545***
	(2.55)	(3.82)	(18.56)	(2.60)
Altman Score	−1.069***	−0.984***	−0.987***	−0.997***
	(−35.99)	(−25.91)	(−143.41)	(−34.01)
ETR	0.000623	0.00868	0.00514***	0.00776***
	(0.11)	(1.09)	(5.61)	(3.95)
N	486	486	486	486
AR1	0.14	0.24	0.12	0.15
AR2	0.001	0.001	0.001	0.001

Note: This table presents the results of the relationship between AI investment and Firms' growth. Column (1) provides the results of the relationship between AI investment and firms' growth. Column (2) reports the effect of labour share on firm grwoth. Column (3) presents the relationship between labour cost on firm growth. Column (4) presents the relationship between labour productivity on firm growth. Detailed definition of all the variables is in Table 1. Time and industry dummies are included in the estimations, but not reported. T statistic in brackets. Degrees of freedom in brackets. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

invest more in AI experience an overall increase in sales and employment.

Column (2) covers the results of the effect of labour market conditions on firms' growth. The evidence shows a statistically negative and significant coefficient of the labour share variable (= −0.0602, t-statistics = −4.10) on firm growth at the 1% level, suggesting that a decrease (increase) in the share of income going to labour results in an increase (decrease) growth of firms which is consistent with (Stanford, 2018). The evidence suggests that a 10% increase (decrease) in the total amount of labour share is likely to increase (decrease) a firm's growth by 0.6%. According to Stanford (2018), a lower labour share (a lower unit labour cost) implies a higher degree of competitiveness and growth as firms can lower the cost of labour compensation (wages, salaries, and other benefits).

Similarly, we also find a significantly negative relationship between labour costs and firms' growth. Column 3 of Table 4 results show that the labour cost is negative and statistically significant at the 1% level (= − 0.0206, t-statistic = −23.98).

Finally, we examine the effect of labour productivity on firms' growth and report the findings in Column 4 of

TABLE 5 AI investment, labour market condition and firms' growth.

	Labour share	Labour cost	Labour productivity
Firm growth	0.0290	−0.0294***	0.0268***
	(1.57)	(−6.24)	(6.80)
AI investment	−0.00348**	−0.00166***	−0.00122**
	(−2.06)	(−3.11)	(−2.13)
MBV	0.0231***	0.0114***	0.00631***
	(3.32)	(4.19)	(3.39)
NOL	−0.0686***	−0.0216***	−0.0643***
	(−3.55)	(−4.13)	(−5.25)
REPOTAX	1.358**	0.254	1.858***
	(2.38)	(1.56)	(10.38)
CAPEX	0.00519	−0.114	−0.0971
	(0.03)	(−1.34)	(−1.03)
NWC	0.0687***	−0.0300***	0.0126***
	(4.18)	(−5.36)	(2.62)
Firm size	0.0792***	0.209***	0.0404***
	(3.11)	(15.23)	(3.41)
FAG	0.0840***	0.0239***	0.0335***
	(4.37)	(4.67)	(4.40)
Altman score	−1.099***	−1.000***	−1.057***
	(−32.52)	(−69.84)	(−75.52)
ETR	0.00386	−0.00785***	−0.00556**
	(0.70)	(−4.41)	(−2.11)
LC X AI investment	0.0245***	0.00791**	0.0151***
	(3.33)	(2.19)	(10.50)
N	486	305	195
AR1	0.74	0.123	0.123
AR2	0.001	0.005	0.002

Note: This table presents the results of the relationship between AI investment, labour market conditions and Firms' growth. Column (1) provides the results of the relationship between AI investment, labour market conditions (measured by labour share) and firms' growth. Column (2) presents the relationship between AI investments, labour market conditions (measured by labour cost) on firm growth. Column (3) presents the relationship between AI investments, labour market conditions (measured by Labour productivity) on firm growth. Detailed definition of all the variables is in Table 1. Time and industry dummies are included in the estimations, but not reported. T statistic in brackets. Degrees of freedom in brackets. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 4. The results find labour productivity to be positive and statistically significant at 1% (= 0.009, t-statistic =6.88) on firm growth. Economically, the results suggest that a 10% increase (decrease) in labour productivity results in a 0.09% increase (decrease) in firms' growth. The overall evidence from Columns (1)–(4) suggests that labour market frictions significantly impact firms' level of growth, as observed by previous studies (Mourre, 2009; Stanford, 2018).

The study finds their estimated coefficients to be broadly consistent with theoretical and empirical literature (Babina et al., 2020; Ferrando & Mulier, 2013; Rahaman, 2011). We find a significant and positive relation between firm size and firms' growth in all the models except Model 2, indicating that larger firms are faster compared to small firms. However, we find a positive and significant relationship between NWC and firms' growth in Columns (3), which suggests that an increase in investment in NWC is likely to boost firms' growth. Ferrando and Mulier (2013) discovered that adopting working capital is theoretically justified and empirically helpful in testing firms' growth behaviour. Interestingly, we also find a significantly positive relationship between MTB, REPOTAX and FAG. ETR was only found to be positive and significant in Columns (3) and (4).

In contrast, we find a significantly negative relationship between Altman on firms' growth in all Columns (1)–(4). Similarly, we find a negative relationship between NOL and firm growth in Columns (1). In contrast, we find an insignificant relationship between CAPEX and firm growth throughout all the Columns (1)–(4).

4.4 | Moderation effect of labour market conditions on AI investment—Firms growth relationship

The overall evidence in Table 4 underscores the significance of AI investment and labour market conditions on firms' growth outcomes. We assess AI investment's effect on firm growth through labour market conditions to develop more precise insight into our results' economic impact. To accomplish this, we interact with labour market conditions with AI. We maintain that an efficient labour market outcome is particularly relevant, enhancing AI growth opportunities for firms. We expect AI investments to spur firms' growth through adequate labour market conditions.

Table 5 presents evidence of our baseline results of Equation 2. We find that the coefficient of the interactive term of AI and labour market conditions (AI*LC) is significantly positive throughout all the Columns (1)–(3). The findings suggest that labour market conditions moderate the relationship between AI investment and firms' growth. The findings suggest efficient labour market conditions further reinforce the positive relationship between AI and firms' growth. This supports our hypotheses (H2–H4) of the study.

The significantly positive relationship between the interaction of AI and Labour market conditions on firms' growth supports the empirical evidence, which suggests that favourable labour market conditions support firms' investment (Fajgelbaum, 2020; Garcia-Vega et al., 2019). Favourable labour market conditions decrease firm growth—AI investment sensitivity by providing favourable production costs to support firms' AI investment for growth. This aligns with prior studies (Babina et al., 2020; Giunta et al., 2012; Laeven et al., 2018). The control variables are broadly consistent with extant literature, as established in previous Table 4.

5 | ADDITIONAL RESULTS AND ROBUSTNESS CHECKS

5.1 | Alternative measures of firm growth

To further enhance our results' robustness, we assess whether our analysis is sensitive to alternative measures of firms' growth. In the previous estimation, we defined firm growth as the ratio of the one-year growth rate of sales (SALE). To enhance the robustness of our results, we capture firms' growth using employment growth. Further, we align the empirical estimations with the model by replicating the tests of the model's estimates while using employment growth instead of sales growth as the dependent variable. This prevents any disconnections between the theoretical characterization of firms' growth and their acknowledged empirical counterpart.

Following similar firms' level-growth-related studies (Babina et al., 2020; Rahaman, 2011), we construct employment growth using the log transformation firms' total employees (EMP) from the COMPUSTAT database to normalize the distribution of the data. The findings are presented in Table 6. Column 1 of Table 6 reveals evidence of a significant impact of secular government AI investment on firms' employment growth. Specifically, we find the coefficient of AI to remain positive and statistically significant with our alternative measure of firm growth, as previously established in Table 4.

Columns (2)–(4) reveal the empirical results of the interaction of labour market conditions and AI on firms' employment growth. The evidence throughout Columns (2)–(4) suggests that all three labour market conditions measurements moderate the relation between AI investment and firms' growth. Overall, the findings displayed in Table 6 confirm that our empirical results are not influenced by using an alternative measure of growth. The evidence suggests that AI investment can have a much more significant spillover effect on firms' sales and employment growth in markets with adequate labour market conditions. Such conditions streamline the production cost and increase productivity. This aligns with Fajgelbaum's (2020) findings, which find labour market frictions to constrain firms' fixed revenue-enhancing investment opportunities essential for growth. Similarly, according to (Kugler, 2007), firms operating in more rigid labour markets face higher costs and delays when hiring workers. This invariably has a spillover adverse effect on their ability to undertake viable investment opportunities to support their sales and employment growth (Table 7).

TABLE 6 Alternative measure of growth and labour market conditions.

	Employment growth	Labour share	Labour cost	Labour productivity
Firm growth	−0.00305	0.0565***	−0.0272***	−0.00299***
	(−0.58)	(36.21)	(−12.81)	(−4.51)
AI investment	0.00277***	0.000816	0.00354	0.00110
	(3.96)	(0.57)	(1.26)	(0.86)
MBV	0.00804***	−0.0182***	0.0373***	−0.0110***
	(2.92)	(−6.14)	(5.30)	(−3.51)
NOL	0.0246***	0.169***	0.105***	0.160***
	(3.33)	(8.74)	(3.80)	(7.53)
REPOTAX	−1.231***	−4.107***	0.319	−0.333***
	(−5.14)	(−21.33)	(0.82)	(−2.90)
CAPEX	0.425***	−0.293***	−1.519***	−0.152**
	(3.07)	(−3.24)	(−17.12)	(−2.22)
NWC	0.0141**	0.0546***	0.0304***	−0.00661*
	(2.26)	(17.88)	(4.40)	(−1.78)
Firm size	0.894***	0.322***	1.332***	1.297***
	(75.40)	(26.44)	(30.28)	(86.77)
FAG	0.0387***	0.336***	0.134***	0.0739***
	(4.10)	(74.86)	(16.88)	(8.51)
Altman score	−0.101***	0.322***	0.0291	−0.206***
	(−6.67)	(26.44)	(1.08)	(−15.51)
ETR	0.0201***	−0.0464***	−0.0210***	−0.00361*
	(5.50)	(−43.79)	(−5.41)	(−1.72)
LC		−0.176***	−0.0578***	−0.0120819
		(−41.12)	(−4.41)	(−1.63)
AI investment X LC		0.03037***	0.102***	0.009893***
		(5.96)	(3.40)	(3.34)
N	343	342	289	188
AR1	0.171	0.125	0.126	0.147
AR2	0.001	0.002	0.002	0.001

Note: This table reports the relationship between AI, labour market conditions using alternative measures of growth. We define growth using the employment growth instead of sales growth as the dependent variable. Column (1) provides the results of the relationship between AI investment and firms employment growth. Column (2) provides the results of the relationship between AI investment and labour market conditions (measured by labour share) and firms' growth. Column (3) presents the relationship between AI investments, labour market conditions (measured by labour cost) on firm growth. Column (4) presents the relationship between AI investments, labour market conditions (measured by Labour productivity) on firm growth. Detailed definitions of all the relevant variables can be found in Table 1. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

5.2 | The real effect of labour market conditions

The overall findings imply that labour market conditions significantly impact firms' ability to invest in AI to enhance their sales and employment growth. We offer in this section evidence of the real effect of that labour market conditions in accelerating firms' AI investment decisions for growth.

5.2.1 | Institutional quality: Efficient use of talents and information asymmetry

Several studies have highlighted the relevance of institutional quality on the financial market's efficiency (see Djankov et al., 2007; Haselmann et al., 2010). The overall evidence gathered from these studies suggests that the level of information asymmetry between market players is minimized within markets with a high-quality

TABLE 7 AI investment, institutional quality and firm growth.

	Firm size	High performance	High R&D
Firm growth	0.0434*	0.0332***	0.0332***
	(1.75)	(4.38)	(4.38)
AI investment	0.00435**	0.00177*	0.00177*
	(2.22)	(1.69)	(1.69)
AI investment x information asymmetry	0.178***	0.0777***	0.0777***
	(3.62)	(3.36)	(3.36)
MBV	0.0366***	0.0135***	0.0135***
	(5.83)	(3.52)	(3.52)
NOL	−0.0820**	−0.0868***	−0.0868***
	(−2.45)	(−5.03)	(−5.03)
REPOTAX	3.255***	1.767***	1.767***
	(4.61)	(3.94)	(3.94)
CAPEX	−0.113	−0.507***	−0.507***
	(−0.39)	(−3.28)	(−3.28)
NWC	0.0625***	0.0148	0.0148
	(3.27)	(1.49)	(1.49)
Firm size	0.120***	0.133***	0.133***
	(3.75)	(5.23)	(5.23)
FAG	0.0188	0.0370***	0.0370***
	(0.62)	(4.63)	(4.63)
Altman score	−1.048***	−1.065***	−1.065***
	(−28.22)	(−54.48)	(−54.48)
ETR	0.0175**	−0.00822***	−0.00822***
	(2.28)	(−2.81)	(−2.81)
N	486	278	278
AR1	0.115	0.134	0.187
AR2	0.001	0.001	0.01

Note: This table reports the institutional relationship quality on the relationship between LC, AI and growth. Institutional quality is measured using the talent management information asymmetry. Detailed definitions of all the relevant variables can be found in Table 1. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

institutional framework. In line with (Lei et al., 2018), we adopt three information asymmetry proxies to determine how information asymmetry impacts AI, Labour market conditions, and firms' growth decisions. (1) firm size, (2) firms' growth opportunities denoted by Tobin Q and (3) R&D intensity measured by the ratio of R&D expenditure to sales. The evidence is presented in Columns (1)–(3) using the median of three information asymmetry proxies.

We find throughout the sample that the coefficient of the interactive term for AI and information asymmetry (AI x Information asymmetry) has a higher magnitude and statistical significance for firms with high information asymmetry (Small, high Tobin's Q or R&D intensity). The evidence suggests that high institutional quality reduces information asymmetry among firms investing for growth.

5.3 | Firm policy and AI investment

This section investigates the link between labour market conditions and firms' policies to determine its implication on firms' AI investment growth decisions. The overall argument from our preceding evidence indicates that favourable labour market conditions aid firms' AI investment growth decisions. Prior studies contend that favourable labour market conditions allow firms to explore investment opportunities for growth (Fajgelbaum, 2020; Kugler, 2007; Stanford, 2018). Fajgelbaum (2020) finds that labour market frictions constrain firms' fixed revenue-enhancing investment opportunities essential for growth. According to (Stanford, 2018), a lower labour share (a lower unit labour cost) implies a higher degree of competitiveness and growth as firms can lower the cost of labour compensation (wages, salaries, and other benefits). Therefore, with favourable labour market conditions and inputs, firms with favourable financial policies are better positioned to invest more in AI for growth.

Against this backdrop, we assess the effect of firm policy on AI-firms' growth relationship. To achieve this, we evaluate AI's sensitivity-firms' growth relationship using three firms' policies. Following prior studies (Bianchi & Tosun, 2018; Faulkender & Petersen, 2012), the study adopts the following three firm policies: innovation, dividend payments and firms investment. The firm's innovation policy is measured using the R&D ratio approximated as R&D expenses over total assets.

TABLE 8 AI investment, firm policies and growth.

	R&D	**Dividend**	**Investment**	**R&D**	**Dividend**	**Investment**
	Labour share	Labour share	Labour share	Labour cost	Labour cost	Labour cost
Firm growth	0.00937	−0.00552	0.0297**	−0.0293***	−0.00824	0.0114
	(0.90)	(−0.28)	(2.24)	(−5.32)	(−1.07)	(0.66)
AI investment	−0.00259**	−0.00190	−0.00323**	−0.00183***	−0.00215***	−0.00336**
	(−2.56)	(−0.79)	(−2.06)	(−4.11)	(−3.20)	(−2.04)
MBV	0.0103***	0.0179***	0.0241***	0.0135***	0.0210***	0.0339***
	(3.30)	(3.10)	(3.69)	(5.69)	(5.54)	(5.12)
NOL	−0.0563***	−0.0296	−0.0653***	−0.0275***	−0.0590***	−0.0549***
	(−5.79)	(−1.24)	(−3.52)	(−5.02)	(−4.44)	(−3.37)
REPOTAX	0.997**	1.079*	1.412***	0.0359	0.302	0.260
	(2.53)	(1.65)	(2.60)	(0.23)	(1.31)	(0.44)
CAPEX	0.307**	−0.543**	−0.0207	−0.175**	0.262**	−0.449**
	(2.00)	(−1.98)	(−0.11)	(−2.17)	(2.23)	(−1.96)
NWC	0.0195**	0.0543***	0.0602***	0.00383	0.0303***	0.0116
	(2.03)	(3.81)	(3.54)	(0.57)	(3.05)	(0.74)
Firm size	0.0768***	0.0518**	0.0827***	0.221***	0.0384**	0.248***
	(4.76)	(2.07)	(3.37)	(19.72)	(2.42)	(6.81)
FAG	0.0741***	0.150***	0.0871***	0.0215***	0.0655***	0.0667***
	(6.13)	(7.42)	(4.57)	(4.51)	(7.71)	(3.34)
Altman score	−0.943***	−1.105***	−1.095***	−1.001***	−1.175***	−1.102***
	(−45.97)	(−44.32)	(−41.74)	(−64.01)	(−96.99)	(−29.39)
ETR	0.00367	0.0151**	0.00673	−0.0101***	−0.0130***	−0.0154***
	(1.17)	(2.20)	(1.34)	(−6.32)	(−6.12)	(−3.36)
AI investment X LC	0.0394***	0.0483***	0.0237***	0.00744***	0.0269***	0.0178***
	(7.67)	(4.69)	(3.43)	(2.79)	(5.64)	(2.98)
N	366	383	486	305	320	411
AR1	0.142	0.123	0.154	0.189	0.146	0.116
AR2	0.001	0.002	0.005	0.002	0.001	0.001

Note: This table presents the results of the relationship between AI investment, firm policies and growth. Firm policies are measured by three firms' policies, namely: innovation, dividend payments and firms' investment. Firms' innovation policy is measured using R&D ratio approximated as R&D expenses over total assets. Dividend payments are measured as a dummy variable that takes a value of one if a firm paid a dividend over the last fiscal year and zero if otherwise. We adopt three investment policies (fixed-income investment, capital expenditure and cash acquisition). We measured investment policies, as a dummy variable that takes a value of one of the values of the three investment policies are greater than their median values and zero if otherwise. Detailed definition of all the variables is in Table 1. A year and industry dummies are included in the estimations. T statistic in brackets. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Also, we constructed dividend payments using a dummy variable that takes a value of one if a firm paid dividends over the last fiscal year and zero if otherwise. We also measured firms' investments using three investment policies (capital expenditure, fixed-income investment, and cash acquisition). We denote a dummy variable (favourable financial policies) assuming the value of one (1) if each of the values of the three investment policies is higher than their median values and zero (0) if otherwise.

Table 8 presents the results on the impact of firm policies on AI investment. The evidence presented in Columns (1)–(6) reveals the empirical results of the interaction of labour market conditions and AI on firms' growth using the three firm policies. The evidence throughout Columns (1)–(6) suggests that all three labour market conditions measurements are positively and significantly moderate the relation between AI investment and firms' growth. Overall, the findings displayed in Table 8 suggest that firms with favourable financial policies conditions AI investments, labour market conditions and firms' growth relationship.

5.4 | Firm performance and growth

Next, in this section, we explore the implications of AI investment on firms' economic performance. We construct firms' performance using two measures return on assets (ROA) (Aktas et al., 2015) and stock market performance (Tobin's Q) (Martínez-Sola et al., 2013). However, we have only reported ROA results, given that the results

TABLE 9 AI, labour market conditions on firm performance.

	Firm performance growth	Labour share	Labour cost	Labour productivity
Firm Growth	0.182***	0.224***	−0.0473	0.199***
	(3.93)	(5.33)	(−0.86)	(7.21)
AI investment	0.00335***	0.00518***	0.00452***	0.00369***
	(2.66)	(4.25)	(3.65)	(4.38)
MBV	0.0159***	0.0152***	0.0146***	0.0114***
	(7.09)	(7.92)	(5.73)	(7.39)
NOL	−0.0602***	−0.0387***	−0.0262**	−0.0163***
	(−5.59)	(−4.63)	(−2.27)	(−2.66)
REPOTAX	−1.153***	−0.956***	−0.444	−1.053***
	(−3.52)	(−4.27)	(−1.44)	(−4.57)
CAPEX	−0.316**	−0.208*	0.0163	−0.539***
	(−2.01)	(−1.75)	(0.11)	(−4.01)
NWC	0.0141**	0.0170***	0.0149**	0.00410
	(2.36)	(3.19)	(2.02)	(1.06)
Firm Size	−0.150***	−0.137***	0.0507***	−0.0870***
	(−11.66)	(−12.58)	(2.75)	(−9.74)
FAG	−0.0489***	−0.0363***	−0.0234***	−0.0106***
	(−6.69)	(−6.31)	(−3.72)	(−2.79)
Altman Score	0.157***	0.141***	0.109***	0.217***
	(12.70)	(13.31)	(6.01)	(23.64)
ETR	0.0120***	0.0138***	0.00752***	0.00745**
	(5.07)	(8.07)	(3.99)	(2.55)
AI Investment X LC		0.111***	0.0127***	0.0127***
		(4.55)	(5.72)	(6.98)
N	361	361	305	195
AR1	0.102	0.139	0.124	0.189
AR2	0.001	0.001	0.01	0.001

Note: This table reports the relationship between AI, labour market conditions on firm performance. We define firm performance using ROA. Detailed definitions of all the relevant variables can be found in Table 1. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

of the two measures are virtually the same. Table 9 presents the effect of AI investment on firm growth using firm performance as a measure of growth. The evidence presented in Table 9 is statistically significant, like those presented in Table 4. We find AI investment to positively and significantly affect firms' performance. In terms of economic significance, the results in Column (1) of Table 9 suggest that a 10% increase in AI investment is associated with a 0.03% increase in the performance growth of an average sample firm.

Similarly, empirical results of the interaction of labour market conditions and AI on firms' performance are presented in Columns (2)–(4) of Table 9. Columns (2)–(4) reveal the empirical results of the interaction of Labour market conditions and AI on firms' employment growth. The evidence throughout Columns (2)–(4) suggests that all three labour market conditions measurements are positively and significantly moderate the relation between AI investment and firms' performance.

5.5 | The sensitivity of the crisis period

Further, we explore the sensitivity of our analysis of financial crises. Our argument is inspired by prior evidence that firms' investments in innovation are

TABLE 10 The crises effect.

	Firm growth	Labour share	Labour cost	Labour productivity	
Firm growth	0.0299**	0.0297**	0.0403	0.0616***	
	(2.05)	(2.24)	(1.51)	(4.68)	
AI investment	0.00328**	−0.00323**	−0.00260	0.00158	
	(2.29)	(−2.06)	(−1.21)	(1.04)	
MBV	0.0135**	0.0241***	0.0499***	0.00927	
	(2.42)	(3.69)	(5.21)	(1.56)	
NOL	−0.0441***	−0.0653***	−0.0488	−0.132***	
	(−2.76)	(−3.52)	(−1.53)	(−7.42)	
REPOTAX	−2.006***	−0.360	−1.391*	−1.472***	
	(−4.62)	(−0.78)	(−1.81)	(−3.92)	
CAPEX	−0.0397	−0.0207	−0.817**	−1.008***	
	(−0.20)	(−0.11)	(−2.37)	(−4.14)	
NWC	0.0238**	0.0602***	0.00163	0.0193	
	(2.06)	(3.54)	(0.06)	(1.55)	
Firm size	0.163***	0.0827***	0.152***	0.221***	
	(6.07)	(3.37)	(2.73)	(5.99)	
FAG	0.00790	0.0327**	0.0687**	0.127***	
	(0.55)	(2.13)	(2.24)	(7.54)	
Altman score	−0.959***	−1.095***	−1.126***	−1.147***	
	(−26.09)	(−41.74)	(−19.28)	(−46.03)	
ETR	−0.00484	0.00673	−0.0183**	−0.0150***	
	(−1.47)	(1.34)	(−2.33)	(−3.16)	
AI investment X LC		0.0237***	0.0332**	0.0121***	
		(3.43)	(2.21)	(3.77)	
	361	486	411	265	
AR1	0.112	0.152	0.174		0.19
AR2	0.001	0.001	0.01		0.001

Note: This table presents the results of the effects of financial crises on the relationship between AI investment and growth. A dummy variable is a proxy for crisis 1 for the crisis periods (1991, 2001, 2007, 2008, and 2009) and 0 for any other years. Columns (1) of Table 10 reports the results on the impact of AI investment on firms growth during the crisis periods, while Columns (2)–(4) presents results on the interactive effect of LC and AI investment on firms growth during financial crisis periods. Detailed definition of all the relevant variables can be found in Table 1. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

procyclical and adversely affected during economic downturns (Francois & Lloyd-Ellis, 2003). Paunov (2012) finds that many firms need to abandon their ongoing innovative investment projects during crises due to the increasing demand uncertainties. Aghion et al. (2017) attribute the cyclicality of firms' investments in innovation during an economic crisis to the tighter credit constraints firms face during economic downturns. According to the evidence, when firms face tight credit constraints, long-term investment becomes procyclical, thus increasing volatility and lowering firm growth for a given investment rate. This evidence suggests that the effect of AI on firms' growth may be unique to the crisis periods. We divide our sample into crisis and non-crisis periods to investigate this possibility. Using the information on the US business cycle expansions and contractions available from the National Bureau of Economic Research, we identify the years: 1991, 2001, 2007, 2008 and 2009 as crisis years and present the results in Table 10. A dummy variable is a proxy for crisis 1 for the crisis periods (1991, 2001, 2007, 2008 and 2009) and 0 for any other years.

Column (1) of Table 10 reports the results on the impact of AI investment on firms' growth during the crisis periods, while Columns (2)–(4) present results on the interactive effect of labour market conditions and AI investment on firms' growth during financial crisis periods. The evidence throughout all Columns (1)–(4) of Table 10 supports our previous evidence that AI and labour market conditions significantly impact firms' growth decisions.

6 | CONCLUSION

This study explored the impact of investment in artificial intelligence on US firms' growth. Using a sample of publicly traded US firms from the COMPUSTAT annual file from 1996 to 2016, the study finds strong evidence that AI investment positively impacts firm growth. The positive association between AI investment and firm growth suggests that the rise in growth of firms in the US was partly driven by the increase in AI investment among US firms over the past decade.

We posit several explanations to comprehend the performance of US firms during the review period. We demonstrate that the operating landscape shapes the growth of these firms. We find convincing evidence that adequate labour market conditions moderate the sensitivity of AI investment on firm growth. Our study's empirical implication demonstrates that labour market conditions influence corporate investment decisions and firm growth. Labour market conditions in labour cost, labour share and labour productivity induce AI investment-firm growth sensitivity.

The results of our investigation offer meaningful contributions to current literature. First, it is one of the earliest investigations of the effect of AI investment on firm growth. Second, our model also, for the first time, sheds light on the crucial role that labour market conditions play in determining the effect of AI investment on firm growth. Our finding shows that labour market conditions moderate a firm's growth sensitivity, and AI investment highlights an essential channel through which adequate labour market conditions support firms' growth. This also sheds light on the significance of adequate labour market conditions in enhancing economic growth (Murphy & Mercille, 2019; Quintana et al., 2016).

Our results should be interpreted, considering some relevant limitations. First, we concentrated on US-traded firms; thus, the findings might not be generalized to other countries where the effect of AI investment on firm growth may vary relative to the prevailing social-economic factors. To put it differently, the result might not be replicable in different countries. It is recommended that future studies consider a cross-country analysis. Another limitation worth acknowledging is that our study covered a limited period from 1996 to 2016. Thus, our results may suffer from an in-depth chronology.

ACKNOWLEDGEMENTS

No funding was provided for this paper.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Data will be provided upon request.

ORCID

Ishmael Tingbani https://orcid.org/0000-0002-4012-1224
Samuel Salia https://orcid.org/0000-0002-5651-5009
Alhassan Yahaya https://orcid.org/0000-0001-6700-635X

ENDNOTE

[1] Omnichannel communication approach enables consistent messaging and branding across channels such as mobile apps, social media accounts, websites, and so forth.

REFERENCES

Aberdeen Group. (2020). Multichannel vs. Omnichannel Communications - Liquid State. https://liquid-state.com/multichannel-vs-omnichannel-communications/

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2014). Return of the Solow paradox? It is productivity and employment in US manufacturing. *American Economic Review*, *104*(5), 394–399. https://doi.org/10.1257/aer.104.5.394

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P., & Li, H. (2019). A theory of falling growth and rising rents. *The Review of Economic Studies*, *90*, 2675–2702. https://doi.org/10.3386/w26448

Aghion, P., Jones, B., & Jones, C. (2017). *Artificial intelligence and economic growth*. NBER. https://doi.org/10.3386/w23928

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. *Innovation Policy and the Economy*, *19*(1), 139–159. https://doi.org/10.1086/699935

Aktas, N., Croci, E., & Petmezas, D. (2015). Is working capital management value-enhancing? Evidence from firm performance and investments. *Journal of Corporate Finance*, *30*(1), 98–113. https://doi.org/10.1016/j.jcorpfin.2014.12.008

Alekseeva, L., Azar, J., Gine, M., Samila, S., & Taska, B. (2020). *The demand for AI skills in the labor market*. Elsevier.

Alekseeva, L., Azar, J., Gine, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labour market. *Labour Economics*, *71*, 102002.

Almeida, H., & Campello, M. (2007). Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies*, *20*(5), 1429–1460. https://doi.org/10.1093/rfs/hhm019

Alvarez, S. A., & Barney, J. B. (2017). Resource-based theory and the entrepreneurial firm. In *Strategic entrepreneurship* (pp. 87–105). Blackwell Publishing Ltd. https://doi.org/10.1002/9781405164085.ch5

Andrews, D., Criscuolo, C., & Gal, P. N. (2015). Frontier firms, technology diffusion and public policy: Micro evidence from OECD countries (OECD productivity papers, 2015–02).

Andrews, D., & Saia, A. (2017). *Coping with creative destruction*. OECD iLibrary. https://doi.org/10.1787/BBB44644-EN

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Arik, M., & Geho, P. (2017). Resource-based theory and STEM workforce dynamics: Strategic implications for businesses and regions. *Global Journal of Business Disciplines*, *1*(1), 16–35.

Arvanitis, S. (2005). Computerisation, workplace organisation, skilled labour and firm productivity: Evidence for the Swiss business sector. *Economics of Innovation and New Technology*, *14*(4), 225–249. https://doi.org/10.1080/1043859042000226257

Atkinson, R. D., & Mayo, M. J. (2010). *Refuelling the US innovation economy: Fresh approaches to science, technology, engineering and mathematics (STEM) education*. Information Technology and Innovation Foundation.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D. H., Dorn, D., & Hanson, G. H. (2016). The China shock: Learning from labour-market adjustment to large changes in trade. *Annual Review of Economics*, *8*, 205–240.

Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2020). Artificial intelligence, firm growth, and product innovation. https://papers.ssrn.com/abstract=3651052

Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2022). Firm Investment in *Artificial Intelligence Technologies and Changes in Workforce Composition*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4060233

Balgobin, R., & Pandit, N. (2001). Stages in the turnaround process: The case of IBM UK. *European Management Journal*, *19*(3), 301–316. https://doi.org/10.1016/S0263-2373(01)00027-5

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management*, *27*(6), 643–650. https://doi.org/10.1177/014920630102700602

Bartel, A., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. *The Quarterly Journal of Economics*, *122*(4), 1721–1758. https://doi.org/10.1162/qjec.2007.122.4.1721

Bianchi, D., & Tosun, O. K. (2018). Cyber attacks and stock market activity. *SSRN Electronic Journal*, *76*, 101795. https://doi.org/10.2139/ssrn.3190454

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Breit, E., Song, X., Sun, L., & Zhang, J. (2019). CEO power and labour productivity. *Accounting Research Journal*, *32*(2), 148–165.

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier modeling the impact of AI on the world economy.

Chang, K., Zeng, Y., Wang, W., & Wu, X. (2019). The effects of credit policy and financial constraints on tangible and research & development investment: Firm-level evidence from China's renewable energy industry. *Energy Policy*, *130*, 438–447. https://doi.org/10.1016/j.enpol.2019.04.005

Chen, C. (2020). Capital-skill complementarity, sectoral labour productivity, and structural transformation. *Journal of Economic Dynamics and Control*, *116*, 103902. https://doi.org/10.1016/j.jedc.2020.103902

Cockburn, I., Henderson, R., & Stern, S. (2018). *The Impact of Artificial Intelligence on Innovation*. NBER. https://doi.org/10.3386/w24449

Cortes, D. G., Cortes Jofre, A. J., & Martin, L. S. (2018, December 21). Artificial intelligence-based method for portfolio selection. *2018 Congreso Internacional de Innovacion y Tendencias En Ingenieria, CONIITI 2018 - Proceedings*. https://doi.org/10.1109/CONIITI.2018.8587104

Crouzet, N., & Eberly, J. (2019). *Understanding weak capital investment: The role of market concentration and intangibles*. NBER. https://doi.org/10.3386/w25869

Dalton, P., Pamuk, H., Ramrattan, R., van Soest, D., & Uras, B. (2022). E-payment technology and business finance: A randomized controlled trial with Mobile money. www.tilburguniversity.edu/dfid-innovation-and-growth

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *1*(96), 108–116.

Davis, P. J., & Simpson, E. (2017). Resource-based theory, competition and staff differentiation in Africa: Leveraging employees as a source of sustained competitive advantage. *American Journal of Management*, *17*, 19–33.

Djankov, S., McLiesh, C., & Shleifer, A. (2007). Private credit in 129 countries. *Journal of Financial Economics*, *84*(2), 299–329. https://doi.org/10.1016/j.jfineco.2006.03.004

Donangelo, A., Gourio, F., & Palacios, M. (2015). The cross-section of labour leverage and equity returns, working paper.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, *30*(2), 341–361. https://doi.org/10.1111/1467-8551.12355

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Fajgelbaum, P. D. (2020). Labour market frictions, firm growth, and international trade. *The Review of Economic Studies*, *87*(3), 1213–1260. https://doi.org/10.1093/restud/rdz063

Farboodi, M., Mihet, R., Philippon, T., & Veldkamp, L. (2019). Big data and firm dynamics. *AEA Papers and Proceedings*, *109*, 38–42. https://doi.org/10.1257/pandp.20191001

Faulkender, M., & Petersen, M. (2012). Investment and capital constraints: Repatriations under the American jobs creation act. *The Review of Financial Studies*, *25*(11), 3351–3388. https://doi.org/10.1093/rfs/hhs092

Fazal, M. I., Patel, M. E., Tye, J., & Gupta, Y. (2018). The past, present and future role of artificial intelligence in imaging. *European Journal of Radiology*, *105*, 246–250. https://doi.org/10.1016/j.ejrad.2018.06.020

Fedyk, A., & James, H. (2023). Trading on talent: Human capital and firm performance. *Review of Finance*, *27*(5), 1659–1698.

Fedyk, A., Hodson, J., & Khimich, N. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, *27*, 938–985. https://doi.org/10.1007/s11142-022-09697-x

Ferrando, A., & Mulier, K. (2013). Do firms use the trade credit channel to manage growth? *Journal of Banking and Finance*, *37*(8), 3035–3046. https://doi.org/10.1016/j.jbankfin.2013.02.013

Francois, P., & Lloyd-Ellis, H. (2003). Animal spirits through creative destruction. *American Economic Review*, *93*(3), 530–550. https://doi.org/10.1257/000282803322156972

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Furman, J. (2016). Is this time different? The opportunities and challenges of artificial intelligence. Presentation, AI Now: The Social and Economic Implications of Artificial Intelligence Technologies in the Near Term.

Furman, J., & Seamans, R. (2019). AI and the economy. *Innovation Policy and the Economy*, *19*(1), 161–191. https://doi.org/10.1086/699936

Gao, Y., Liu, X., & Ma, X. (2019). How do firms meet the challenge of technological change by redesigning the innovation ecosystem? A case study of IBM. *International Journal of Technology Management*, *80*(3–4), 241–265.

Garcia-Vega, M., Kneller, R., Stiebale, J., García-Vega, M., Barr, A., Bentolila, S., Braun, S., Jose Dolado, J., Felgueroso, F., & Jansen, M. (2019). Labour market reform and innovation: Evidence from Spain labor market reform and innovation: Evidence from Spain.

Ghazwani, S., van Esch, P., Cui, Y. G., & Gala, P. (2022). Artificial intelligence, financial anxiety and cashier-less checkouts: A Saudi Arabian perspective. *International Journal of Bank Marketing*, *40*(6), 1200–1216. https://doi.org/10.1108/IJBM-09-2021-0444/FULL/XML

Giunta, A., Nifo, A., & Scalera, D. (2012). Subcontracting in Italian industry: Labour division, firm growth and the north-south divide. *Regional Studies*, *46*(8), 1067–1083. https://doi.org/10.1080/00343404.2011.552492

Guney, M. S., & Tepe, Y. (2017). Classification and assessment of energy storage systems. In *Renewable and sustainable energy reviews* (Vol. 75, pp. 1187–1197). Elsevier Ltd. https://doi.org/10.1016/j.rser.2016.11.102

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768.

Hallikainen, H., Savimäki, E., & Laukkanen, T. (2020). Fostering B2B sales with customer big data analytics. *Industrial Marketing Management*, *86*, 90–98. https://doi.org/10.1016/j.indmarman.2019.12.005

Hanlon, M., Maydew, E. L., & Saavedra, D. (2017). The taxman cometh: Does tax uncertainty affect corporate cash holdings? *Review of Accounting Studies*, *22*(3), 1198–1228. https://doi.org/10.1007/s11142-017-9398-y

Haselmann, R., Pistor, K., & Vig, V. (2010). How law affects lending. *The Review of Financial Studies*, *23*(2), 549–580. https://doi.org/10.1093/rfs/hhp073

Hogarty, D. T., Mackey, D. A., & Hewitt, A. W. (2019). Current state and future prospects of artificial intelligence in ophthalmology: A review. *Clinical & Experimental Ophthalmology*, *47*(1), 128–139. https://doi.org/10.1111/ceo.13381

Hoskisson, R. E., Gambeta, E., Green, C. D., & Toby, X. L. I. (2018). Is my firm-specific investment protected? Overcoming the stakeholder investment dilemma in the resource-based view. *Academy of Management Review*, *43*(2), 284–306. https://doi.org/10.5465/amr.2015.0411

Hsu, P.-H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, *112*(1), 116–135. https://doi.org/10.1016/J.JFINECO.2013.12.002

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Ipinnaiye, O., Dineen, D., & Lenihan, H. (2017). Drivers of SME performance: A holistic and multivariate approach. *Small Business Economics*, *48*, 883–911.

Jiang, Z., & Lie, E. (2016). Cash holding adjustments and managerial entrenchment. *Journal of Corporate Finance*, *36*, 190–205.

Jung, J. H., & Lim, D. G. (2020). Industrial robots, employment growth, and labour cost: A simultaneous equation analysis. *Technological Forecasting and Social Change*, *159*, 120202. https://doi.org/10.1016/j.techfore.2020.120202

Kakatkar, C., Bilgram, V., & Füller, J. (2020). Innovation analytics: Leveraging artificial intelligence in the innovation process. *Business Horizons*, *63*(2), 171–181. https://doi.org/10.1016/j.bushor.2019.10.006

Khanna, R., & Sharma, C. (2018). Testing the effect of investments in IT and R&D on labour productivity: New method and evidence for Indian firms. *Economics Letters*, *173*, 30–34. https://doi.org/10.1016/j.econlet.2018.09.003

Kleinknecht, A. (2020). The (negative) impact of supply-side labour market reforms on productivity: An overview of the evidence.

Cambridge Journal of Economics, *44*(2), 445–464. https://doi.org/10.1093/cje/bez068

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2016). How artificial intelligence will redefine management. *Harvard Business Review*, *2*(1), 3–10.

Kugler, A. (2007). The effects of employment protection in Europe and the US Opuscule.

Kwon, M. J., & Stoneman, P. (1995). The impact of technology adoption on firm productivity. *Economics of Innovation and New Technology*, *3*(3–4), 219–234. https://doi.org/10.1080/10438599500000004

Laeven, L., Mcadam, P., & Popov, A. (2018). After the credit squeeze: How labour market flexibility can strengthen firm growth and employment.

Lashkari, D., Bauer, A., & Boussard, J. (2018). Information technology and returns to scale. Available at SSRN 3458604. https://ssrn.com/abstract=3458604

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial artificial intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters*, *18*, 20–23. https://doi.org/10.1016/j.mfglet.2018.09.002

Lei, J., Qiu, J., & Wan, C. (2018). Asset tangibility, cash holdings, and financial development. *Journal of Corporate Finance*, *50*, 223–242. https://doi.org/10.1016/J.JCORPFIN.2018.03.008

Lerskullawat, A. (2019). Financial development, financial constraint, and firm investment: Evidence from Thailand. *Kasetsart Journal of Social Sciences*, *40*(1), 55–66. https://doi.org/10.1016/j.kjss.2018.01.010

Li, J., Shan, Y., Tian, G., & Hao, X. (2020). Labour cost, government intervention, and corporate innovation: Evidence from China. *Journal of Corporate Finance*, *64*, 101668. https://doi.org/10.1016/j.jcorpfin.2020.101668

Lisowsky, P., Robinson, L., & Schmidt, A. (2013). Do publicly disclosed tax reserves tell us about privately disclosed tax shelter activity?. *Journal of Accounting Research*, *51*(3), 583–629.

Liu, F., Dutta, D. K., & Park, K. (2020). From external knowledge to competitive advantage: Absorptive capacity, firm performance, and the mediating role of labour productivity. *Technology Analysis & Strategic Management*, *1–13*, 18–30. https://doi.org/10.1080/09537325.2020.1787373

Liu, F., Dutta, D. K., & Park, K. (2021). From external knowledge to competitive advantage: Absorptive capacity, firm performance, and the mediating role of labour productivity. *Technology Analysis & Strategic Management*, *33*(1), 18–30.

Liu, L., & Shong, Y. C. (2018). Study on innovation performance of big data and artificial intelligence listed companies. In *ACM international conference proceeding series* (Vol. 57–62). ACM. https://doi.org/10.1145/3305275.3305287

Lu, Y., Meng, Q., & Cai, Y. (2018). Research on the relationship between R & D investment and corporate value of "unicorn" companies: Based on the financial flexibility of artificial intelligence company data. *Open Journal of Business and Management*, *06*(4), 953–962. https://doi.org/10.4236/ojbm.2018.64070

Lui, A. K., Lee, M. C., & Ngai, E. W. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*, 1–16.

Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60. https://doi.org/10.1016/J.FUTURES.2017.03.006

Martínez-Sola, C., García-Teruel, P. J., & Martínez-Solano, P. (2013). Corporate cash holding and firm value. *Applied Economics*, *45*(2), 161–170. https://doi.org/10.1080/00036846.2011.595696

McLean, R. D. (2011). Share issuance and cash savings. *Journal of Financial Economics*, *99*(3), 693–715.

Mihet, R., & Philippon, T. (2019). The economics of big data and artificial intelligence. In *International finance review* (Vol. 20, pp. 29–43). Emerald Group Publishing Ltd. https://doi.org/10.1108/S1569-376720190000020006

Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science*, *50*(6), 1176–1197.

Mitchell, T., & Brynjolfsson, E. (2017). Track how technology is transforming work. *Nature*, *544*(7650), 290–292. https://doi.org/10.1038/544290a

Mou, X. (2019). Artificial Intelligence: Investment Trends and Selected Industry Uses.

Mourre, G. (2009). What explains the differences in income and labour utilisation and drives labour and economic growth in Europe? A GDP accounting perspective (No. 354). *Directorate General Economic and Financial Affairs (DG ECFIN), European Commission*.

Murphy, E., & Mercille, J. (2019). (Re)making labour markets and economic crises: The case of Ireland. *The Economic and Labour Relations Review*, *30*(1), 22–38. https://doi.org/10.1177/1035304619829015

Nason, R. S., & Wiklund, J. (2018). An assessment of resource-based theorizing on firm growth and suggestions for the future. *Journal of Management*, *44*(1), 32–60. https://doi.org/10.1177/0149206315610635

Paschen, U., Pitt, C., & Kietzmann, J. (2020). Artificial intelligence: Building blocks and an innovation typology. *Business Horizons*, *63*(2), 147–155. https://doi.org/10.1016/j.bushor.2019.10.004

Paunov, C. (2012). The global crisis and firms' investments in innovation. *Research Policy*, *41*(1), 24–35. https://doi.org/10.1016/j.respol.2011.07.007

Quintana, C. D. D., Mora, J.-G., Pérez, P. J., & Vila, L. E. (2016). Enhancing the development of competencies: The role of UBC. *European Journal of Education*, *51*(1), 10–24. https://doi.org/10.1111/ejed.12162

Rahaman, M. M. (2011). Access to financing and firm growth. *Journal of Banking and Finance*, *35*(3), 709–723. https://doi.org/10.1016/j.jbankfin.2010.09.005

Rampini, L., Khodabakhshian, A., & Re Cecconi, F. (2022). Artificial intelligence feasibility in the construction industry. *Computing in Construction*, *3*, 1–8.

Rice, E., Yoshioka-Maxwell, A., Petering, R., Onasch-Vera, L., Craddock, J., Tambe, M., Yadav, A., Wilder, B., Woo, D., Winetrobe, H., & Wilson, N. (2018). Piloting artificial intelligence to enhance HIV prevention interventions for youth experiencing homelessness. *Journal of the Society for Social Work and Research*, *9*(4), 551–573. https://doi.org/10.1086/701439

Ritter-Hayashi, D., Knoben, J., & Vermeulen, P. A. M. (2019). Success belongs to the flexible firm: How labour flexibility can retain firm innovativeness in times of downsizing. *Long Range Planning*, *53*(3), 101914. https://doi.org/10.1016/j.lrp.2019.101914

Rodríguez-Pose, A., & Lee, N. (2020). Hipsters vs. geeks? Creative workers, STEM and innovation in US cities. *Cities*, *100*, 102653. https://doi.org/10.1016/j.cities.2020.102653

Russell, S. (2016). Rationality and intelligence: A brief update. In *Fundamental issues of artificial intelligence* (pp. 7–28). Springer International Publishing. https://doi.org/10.1007/978-3-319-26485-1_2

Schrage, M., Kiron, D., Candelon, F., Khodabandeh, S., & Chu, M. (2023). AI is helping companies redefine, not just improve, performance. *MIT Sloan Management Review*, *64*(3), 1–7.

Shibin, K. T., Dubey, R., Gunasekaran, A., Hazen, B., Roubaud, D., Gupta, S., & Foropon, C. (2020). Examining sustainable supply chain management of SMEs using resource-based view and institutional theory. *Annals of Operations Research*, *290*(1–2), 301–326. https://doi.org/10.1007/s10479-017-2706-x

Singhal, T. K., & Yerpude, S. (2018). Internet of things based customer relationship management-a research perspective. *Article in International Journal of Engineering and Technology*, *7*(2), 444–450. https://doi.org/10.14419/ijet.v7i2.7.10860

Stanford, J. (2018). The declining labour share in Australia: Definition, measurement, and international comparisons. *Journal of Australian Political Economy*, *81*, 11–32.

Trippi, R. R., & Turban, E. (1993). *Neural networks in finance and investing : Using artificial intelligence to improve real-world performance*. Probus Pub. Co.

Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*, 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Yan, B., Zhang, Y., Shen, Y., & Han, J. (2018). Productivity, financial constraints and outward foreign direct investment: Firm-level evidence. *China Economic Review*, *47*, 47–64. https://doi.org/10.1016/j.chieco.2017.12.006

Yen, K. F., Wang, X., Ma, F., Lee, G., & Li, X. (2019). Critical success factors of supply chain integration in container shipping: An application of resource-based view theory. *Maritime Policy & Management*, *46*(6), 653–668. https://doi.org/10.1080/03088839.2019.1597289

Yoo, H. J. (2019). 1.2 intelligence on silicon: From deep-neural-network accelerators to brain mimicking AI-SoCs. In *Digest of technical papers - IEEE international solid-state circuits conference, 2019-February* (pp. 20–26). IEEE. https://doi.org/10.1109/ISSCC.2019.8662469

Zdravković, M., Panetto, H., & Weichhart, G. (2022). AI-enabled enterprise information systems for manufacturing. *Enterprise Information Systems*, *16*(4), 668–720.

How to cite this article: Tingbani, I., Salia, S., Hartwell, C. A., & Yahaya, A. (2024). Looking in the rear-view mirror: Evidence from artificial intelligence investment, labour market conditions and firm growth. *International Journal of Finance & Economics*, 1–22. https://doi.org/10.1002/ijfe.2945

APPENDIX A

TABLE A1 List of skills in the Burning Glass Technologies job vacancies data set used to identify AI vacancies.

N	Skill	N	Skill
1	AI ChatBot	37	Mlpy
2	AI KIBIT	38	Modular audio recognition framework (MARF)
3	ANTLR	39	MoSes
4	Apertium	40	MXNet
5	Artificial intelligence	41	Natural language processing
6	Automatic speech recognition (ASR)	42	Natural language toolkit (NLTK)
7	Caffe deep learning framework	43	ND4J (software)
8	Chatbot	44	Nearest neighbour algorithm
9	Computational linguistics	45	Neural networks
10	Computer Vision	46	Object recognition
11	Decision trees	47	Object tracking
12	Deep learning	48	OpenCV
13	Deeplearning4j	49	OpenNLP
14	Distinguo	50	Pattern recognition
15	Google cloud machine learning platform	51	Pybrain
16	Gradient boosting	52	Random forests
17	H_2O (software)	53	Recommender systems
18	IBM Watson	54	Semantic driven subtractive clustering method (SDSCM)
19	Image processing	55	Semi-supervised learning
20	Image recognition	56	Sentiment analysis/opinion mining
21	IPSoft Amelia	57	Sentiment classification
22	Ithink	58	Speech recognition
23	Keras	59	Supervised learning (machine learning)
24	Latent dirichlet allocation	60	Support vector machines (SVM)
25	Latent semantic analysis	61	TensorFlow
26	Lexalytics	62	Text mining
27	Lexical acquisition	63	Text to speech (TTS)
28	Lexical semantics	64	Tokenization
29	Libsvm	65	Torch (machine learning)
30	Machine learning	66	Unsupervised learning
31	Machine translation (MT)	67	Virtual agents
32	Machine vision	68	Vowpal
33	Madlib	69	Wabbit
34	Mahout	70	Word2Vec
35	Microsoft cognitive toolkit	71	Xgboost
36	MLPACK (C++ library)		