Energy Economics 121 (2023) 106653

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

The impact of lowering carbon emissions on corporate labour investment: A quasi-natural experiment

June Cao [a], Wenwen Li [b,*], Iftekhar Hasan [c,d,e]

[a] School of Accounting, Economics and Finance, Curtin University, WA, Australia
[b] School of Accounting, Nanjing Audit University, Nanjing, China
[c] Fordham University, United States of America
[d] Bank of Finland, Finland
[e] University of Sydney, Australia

A R T I C L E I N F O

Keywords:
Carbon emission reduction
The economics of carbon emissions
Labour investment inefficiency
Skilled employee investment
Labour well-being

A B S T R A C T

We examine the impact of low-carbon city (LCC) initiatives on labour investment decisions (quantity, quality, and well-being). Using a time-varying difference-in-differences approach based on staggered implementations of such a pilot program, we report an inefficient outcome - absolute deviation of labour investment from the optimal net hiring – especially for firms in labour-intensive industries and firms with high financial slack or adjustment costs. We, however, observe increased investments in highly skilled personnel and compensated with employee stock ownership, especially by firms under intense pressure to reduce carbon emissions. Such initiatives are also closely associated with the significant enhancement of workplace safety. Overall, LCC helps to upgrade the corporate labour structure by hiring more skilled employees through reduced agency problems and heightened green innovation.

1. Introduction

As climate change has become a critical and urgent global issue, "companies are embarking on a war for talent" (PwC, 2021) to deal with climate risk. Our study investigates how carbon emission reduction initiatives affect human capital-related decisions. With carbon emissions rising from 22,149.4 million tons in 1990 to 36,390.3 million tons in 2018 (World Bank, 2020), the global community has recognised the need for urgent action to reduce carbon emissions to net zero (Khan et al., 2021). Cities are on the front line of efforts to address climate change, as 3.5 billion people live in cities, and cities are responsible for about 70% of global carbon emissions (United Nations 2019). As the world's biggest carbon polluter in terms of CO_2 emissions,[1] China has taken a battery of urgent actions to achieve its carbon peak and carbon-neutral goals (Huang et al., 2021a). One of the government's main strategies for reducing emissions is a low-carbon city (LCC) pilot programme. The key challenge in reducing carbon emissions is to internalize the full social and environmental costs of greenhouse gas emissions (Downar et al., 2021). A rigorous empirical examination of the LCC programme's real impact is necessary to determine whether and how this programme could be applied to the whole country and extended to other countries.

From the perspective of standard setters, it is important to provide the International Sustainability Standards Board (ISSB) with empirical evidence to support the ongoing development of high-quality disclosure standards related to climate and sustainability issues. To meet financial markets' high demand for information on companies' environmental, social, and governance (ESG) actions, the ISSB has developed Sustainability Disclosure Standards that include requirements for dealing with companies' environmental impact in relation to making investment decisions (IFRS Foundation 2021).[2] According to the concept of 'double materiality' in climate-related financial disclosures,[3] what accounting standards consider the material to disclose should include the impact of climate change on corporate activities as well as how corporate

* Corresponding author.
E-mail addresses: june.cao@curtin.edu.au (J. Cao), liwenwen@nau.edu.cn (W. Li), ihasan@fordham.edu (I. Hasan).

[1] According to Climate Trade report in 2021, China with over 10,065 million tons of carbon emissions is ranked as the world's biggest polluters. For more details, see https://climatetrade.com/which-countries-are-the-worlds-biggest-carbon-polluters/

[2] For more details, see https://www.valuereportingfoundation.org/news/ifrs-foundation-announcement/

[3] This is a hot topic among regulators and standard setters trying to bring environmental impacts into accounting standards.

https://doi.org/10.1016/j.eneco.2023.106653
Received 5 October 2022; Received in revised form 26 March 2023; Accepted 26 March 2023
Available online 5 April 2023

activities affect climate change (Täger, 2021). Drucker (1954) postulates that what gets measured also gets managed, indicating that measuring the impact of climate change on corporate finance and decisions and the impact of corporate activities on climate change is the first step towards a net-zero economy.

This study responds to the discussion of double materiality by empirically measuring the effects of carbon-reduction initiatives on corporate labour investment decisions. Human capital is a critical factor of production[4] and an organisation's most important asset (Pfeffer, 1994; Pfeffer and Veiga, 1999; Zingales, 2000), particularly in today's knowledge-based economy (Cao and Rees, 2020). In 2021, almost all directors indicate that their companies are taking action to address human capital issues, and around half of the directors stated that their companies were investing in upskilling or retraining employees (PwC, 2021). The employment situation experiences a significant change in China to respond to carbon peak and carbon neutrality goals. The Carbon Neutrality Committee of China reports that the demand for talents with carbon-related skills and knowledge expands 10 times each year, and the supply is far from meeting the demand. The number of employees related to carbon neutrality has increased from 10,000 to 100,000, and it is expected to increase to 500,000 to 1 million in 2025.[5] In addition, it is requested that intensive energy-consumed firms and sectors set energy management positions and full-time environmental protection personnel in China State Council in the "14th Five-Year Plan for Energy Conservation and Emission Reduction".[6] Listed firms made positive responses to this requirement. For example, the CITIC Pacific Special Steel Group Co., Ltd. (SZ.000708) states that the firm will accelerate the construction of talent teams and foster highly skilled personnel to strengthen R&D of energy-saving and emission-reduction technologies (The CITIC Pacific Special Steel Group Co., Ltd, 2021). This provides anecdotal evidence for our study. Labour investment efficiency is a major factor determining a firm's success (Jung et al., 2014; Khedmati et al., 2020). This study enhances understanding of the interplay between climate regulation and firm behaviour and thus informs standard setting on environmental information disclosure according to the double materiality concept.

This study differs from the literature on labour investment in the following ways. First, most studies only examine labour investment inefficiency (e.g., Ghaly et al., 2015; Caggese et al., 2019; Khedmati et al., 2020) but pay little attention to labour quality and labour welfare. We advance the literature by providing a relatively complete picture of labour-related decisions, including labour investment inefficiency (the absolute deviation of employee recruitment from the optimal hiring level predicted by firm economic fundamentals), skilled labour recruitment, unskilled labour dismissal, labour welfare (e.g., labour safety and accidents), labour training (professional and environmental training), and labour incentives. All these aspects of labour-related investment decisions are important given that organisational success depends on not only the size of the workforce but also its skills and motivation (Pfeffer, 1994). In addition, to the best of our knowledge, this study is the first to directly and comprehensively investigate how regulations to reduce carbon emissions affect a critical corporate investment decision: human capital investment. It is well documented that the reduction of carbon emissions mostly relies on technology and innovation (Huang et al., 2021b), and developing and implementing technology inevitably involves the workforce (Pfeffer, 1994; Zingales, 2000). Thus, this study helps to open the black box of corporate carbon-reduction activities and provides policymakers with information about the implications and effectiveness of regulations to reduce carbon emissions.

Moreover, understanding how such regulations affect labour investment decisions is important for the following reasons. First, carbon emissions reduction initiatives can have a profound and comprehensive effect on corporate policies and decisions. Theoretically, the Porter hypothesis shows that well-designed regulations can efficiently push firms to invest in technology development to offset compliance costs and increase resource efficiency (Ambec et al., 2013; Jaffe and Palmer, 1997; Porter and Van der Linde, 1995). Huang et al. (2021b) empirically present that the LCC implementation significantly increases corporate R&D investment. This suggests that firms may recruit more employees to enable the adoption of new technologies and green innovation because innovation can only be achieved by a talented workforce (Zingales, 2000). In addition, reducing carbon emissions is expected to raise shareholder value in the long run (Li et al., 2022) and help firms achieve sustainability. The LCC programme thus fosters a long-term orientation in managerial decisions, such that managers tend to optimise the allocation of labour capital investments to promote enterprises' long-term development (Zeng and Zhu, 2014).

However, according to neoclassical economic theory, environmental regulation negatively affects innovation and places economic burdens on firms (Gray and Shadbegian, 1993; Brunnermeier and Cohen, 2003; Kneller and Manderson, 2012). For example, the LCC programme requires firms to internalize the externalities of carbon emissions (Cao et al., 2022). Firms face high costs to comply with carbon-reduction targets and incur high penalties if they fail to meet them. This financial pressure may lead to decreased labour investment. Additionally, Huang et al. (2021a) find that the LCC programme induces uncertainty in corporate operations and enhances firm risk. Thus, making optimal investment decisions may be difficult. Therefore, an empirical examination of whether and how the LCC programme affects labour investment is relevant.

We investigate whether and how lowering carbon emission regulation in China affects human capital investment decisions. Our setting is suitable for addressing our research questions for the following several reasons. First, China, as the world's largest carbon emitter,[7] will reach its carbon emissions peak before 2030 and achieves carbon neutrality before 2060, which is critical to the success of the global climate change strategy and will significantly contribute to the global effort to prevent global warming from exceeding 1.5 °C (International Energy Agency (IEA), 2021). Thus, examining the real effect of the LCC programme in China is of global importance.

In addition, understanding the real effects of carbon-reduction initiatives in China is of interest to global investors, given that China has the largest clean energy innovation market, attracting more than 30% of the world's early-stage venture capital (IEA 2021). Information regarding carbon reductions in business activities is critical to the greening of the financial system (Dupré and Chenet, 2012). Therefore, investigating how carbon-reduction initiatives affect investment decisions in China is important and critical for global investors to make better investment decisions.

Importantly, the quasi-natural shock of LCC implementation provides us with the following identification advantages. First, the LCC pilot programme is exogenous to firms' investment decisions. The National Development and Reform Commission launched three rounds of lowering carbon emission pilot programme in 2010, 2012, and 2017. Thus, the LCC programme is independent of firms' labour investment decisions. This provides an ideal quasi-natural experimental setting to use a powerful time-varying difference-in-differences (DiD) approach to drawing causal inferences. In addition, the staggered enactment of the LCC pilot programme could mitigate the impact of other confounding factors that may contaminate our baseline results. This mitigates concerns about heterogeneity in the national institutional environment and

[4] Labour costs represent about two thirds of value added in an economy (Bernanke, 2004; Hamermesh, 1996; Jung et al., 2014).

[5] More details, see http://www.acet-ceca.com/desc/11410.html

[6] More details, see http://www.gov.cn/zhengce/content/2022-01/24/content_5670202.htm

[7] China contributes one third of global carbon emissions (IEA 2021).

simultaneous confounding events within the country.

We follow previous literature (Armstrong et al., 2012; Cao et al., 2022) to exploit city-level variation and investigate the effect of the LCC on firms' labour investment decisions between 2006 and 2019. In line with Jung et al. (2014), we define labour investment inefficiency as the absolute deviation in actual net hiring from a firm's expected normal hiring level (determined by the firm's economic fundamentals). We observe a positive correlation between the LCC and labour investment inefficiency. This relationship is also economically significant. The DiD estimates show that the firms subject to the LCC programme experience an increase in labour investment inefficiency, labour overinvestment, and labour underinvestment of approximately 6%, 12.55%, and 9.23% of the standard deviation of the treatment sample, respectively.

To validate our baseline results regarding labour investment inefficiency, we conduct a series of tests to check the validity of the DiD model. First, this study follows Bertrand and Mullainathan (2003) to test the parallel trend assumption of the DiD model using a dynamic analysis framework. We find that the significantly positive effect only presents after the LCC implementation. Moreover, following prior literature (Basu et al., 2022; Beck et al., 2022), we mitigate a possible endogeneity concern arising from time-varying differences between the treatment and control groups using an entropy balancing technique.[8] We re-estimate our baseline model using the matched sample. Our baseline results remain the same.

Third, to corroborate the sensitivity of our baseline results with respect to spurious correlations, we conduct two types of placebo tests. First, we randomly assign fictitious timing to each LCC implementation event. In the second, we randomly assign fictitious LCC pilot events to the firms in the control group. The results of placebo tests suggest that the baseline findings do not suffer from spurious correlation. This strengthens our causal inferences regarding the impact of the LCC initiative on labour investment inefficiency. Fourth, to control for non-parametrically correlated and time-specific shocks at the industry level, we incorporate industry-by-year fixed effects into the baseline model. Our baseline findings remain after controlling for those additional fixed effects.

Our cross-sectional tests indicate that the effect of the LCC on labour inefficiency, especially overinvestment, is stronger for firms with high financial slack relative to firms with low financial slack and for firms in industries that are human capital intensive. Moreover, the evidence shows that firms that have incurred penalties due to environmental violations are more likely to experience labour investment inefficiency issues.

We further investigate whether the LCC programme affects firms' labour structure upgrades, such as hiring skilled employees and firing unqualified workers. Studies document that initiatives to lower carbon emissions include favourable policies for affected firms, such as government subsidies and tax reductions (Cao et al., 2017). Consequently, this can promote labour structure upgrades (Sun et al., 2022). We thus examine how the LCC programme affects labour quality. Consistent with Sun et al. (2022), our findings show that the LCC programme improves firms' labour quality through the hiring of more highly skilled employees.

We explore the following three underlying economic mechanisms through which the LCC programme leads to the recruitment of more highly skilled employees. First, Li et al. (2022) and Zhang et al. (2021) find that environmental regulation can alleviate agency problems, which may lead to better decisions related to labour quality because mitigating agency problems helps to improve labour quality (Ghaly et al., 2020; Ha and Feng, 2018). We thus posit that the LCC programme improves labour quality by mitigating agency problems. Consistent with Xu et al. (2014) and Gul et al. (2011), we use excess perks as a proxy for the degree of agency problems. We find that firms with low excess perks tend to hire more highly skilled employees.

Second, R&D investment, as the main mechanism for lowering carbon emissions (Hong et al., 2021; Fu et al., 2021), can optimise firms' labour structures (Sun et al., 2022; Yamazaki, 2017; Guo et al., 2021; Carbone et al., 2020). We thus posit that the LCC programme upgrades labour structure through heightened green innovation investment. In our study, we particularly consider green innovation. Consistent with Huang et al. (2021b), we find that LCC significantly enhances corporate green innovation investment, and firms with higher green innovation investment after LCC are more likely to hire more highly skilled employees. Third, we find LCC induces great carbon emission reduction pressure on firms. Firms in regions with stronger carbon-reduction pressure are more likely to hire skilled employees after LCC. Our cross-sectional tests indicate that the LCC affects skilled labour employment strongly for firms with a high percentage of institutional investors. This is consistent with Cohen et al. (2022), who find that institutional investors are playing a crucial role in current efforts to transition to a sustainable economy.

We further show that the LCC pilot programme implementation significantly encourages firms to offer employees stock ownership as an incentive. This effect is stronger in non-state-owned enterprises (non-SOEs) and firms with high human capital quality. Moreover, we find that firms subject to the LCC programme significantly enhance their safety management. Specifically, the results show that the frequency of labour accidents significantly decreases after the LCC programme is implemented. In addition, more firms enhance their safety management and become certified in occupational safety. Importantly, firms affected by the LCC programme are more likely to provide vocational education and training for their employees. Finally, our evidence shows that the LCC indeed improves firms' environmental governance after implementation, which is reflected in environmentally friendly product development, renewable energy use, adoption of the circular economy model, new policies on energy savings, and the establishment of green offices.

Collectively, we find that although the LCC programme reduces labour investment efficiency in the short run. It promotes the recruitment of skilled workers, motivates more favourable employee policies, and eventually has a real positive impact on firms' environmental governance, green products, and renewable energy generation.

This study advances the literature and contributes to corporate carbon emission reduction initiatives, policy-making, and standard setters in four ways. First, we enrich the emerging literature on the real impact of initiatives to reduce carbon emissions. For example, Huang et al. (2021b) show that the LCC programme increases R&D investment by 0.145% of total assets and 0.273% of sales. We extend these studies by investigating how the LCC programme affects one of the firms' most important investment decisions. We particularly shed light on the causal relationship between the LCC programme and labour investment inefficiency. We show that the LCC programme leads to greater inefficiency in labour investment. This provides important implications for firms' efficient allocation of resources and human capital structure optimisation.

Second, we advance prior studies on the impact of CSR (corporate social responsibility) or ESG on labour investment decisions (Pereira da Silva, 2019). We focus on not only labour investment inefficiency (in terms of abnormal net hiring) but also skilled versus unskilled labour recruitment, labour welfare (e.g., labour safety, accidents), labour training (professional education and environmental knowledge and skill training), and labour incentives.

Third, we explore a new factor that influences labour investment inefficiency. Studies investigate the effects of financial information quality (Jung et al., 2014), institutional investor horizon (Ghaly et al., 2015), stock price informativeness (Ben-Nasr and Alshwer, 2016), financial constraints (Caggese et al., 2019), and CEO–director ties (Khedmati et al., 2020). This study enriches the literature by considering

[8] To further check robustness of this result, we also use propensity score matching technique. We yield similar results as those based on entropy balancing technique.

an important determinant, carbon-reduction initiatives, of labour investment inefficiency.

Fourth, this study also makes a substantial conceptual contribution in terms of the double materiality of the disclosure of environmental impact information. Double materiality brings firms' environmental impact into focus in accounting standards (Täger, 2021). It highlights not only the effects of climate change on the company but also the impact of company activities on the climate. We provide solid evidence of the relationship between carbon-reduction initiatives and an important investment decision: employment. We add a new way to measure the materiality of firms' carbon-action information – in terms of its economically significant impact on labour investment inefficiency.

2. Model specification and sample selection

2.1. Research design

To test the impact of the LCC programme on labour investment inefficiency, we follow Zhu et al. (2023) and Beck et al. (2010) and conduct a time-varying DiD model:

$$INEFFICIENCY_{i,t} = \alpha_0 + \beta_1 LCC_{i,t} + \sum \gamma_k Control_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

whereLCC equals 1 if a firm is headquartered in a city subject to the LCC programme in year t (i.e., the treatment group) and zero otherwise (i.e., the control group). In 2010, the National Development and Reform Commission (NDRC) issued a "Notice on the Pilot of Low-carbon Provinces and Low-carbon Cities" and initiated the first batch of LCC experiments.[9] In 2012, NDRC initiated the second batch of LCC experiments,[10] and in 2017 initiated the third batch. We use the percentage change in the number of employees as a proxy for labour investment. Consistent with Jung et al. (2014), we measure labour investment inefficiency (*INEFFICIENCY*) as the absolute deviation in actual net hiring from a firm's expected normal hiring level, which is attributable to the firm's economic fundamentals. Specifically, we measure the expected level of labour hiring using the model of Pinnuck and Lillis (2007):

$$\begin{aligned} NETHIRE_{i,t} = {} & \alpha_0 + \beta_1 SALES\_GROWTH_{i,t-1} + \beta_2 SALES\_GROWTH_{i,t} + \beta_3 \Delta ROA_{i,t-1} \\ & + \beta_4 \Delta ROA_{i,t} + \beta_5 ROA_{i,t} + \beta_6 RETURN_{i,t} + \beta_7 SIZE\_R_{i,t-1} \\ & + \beta_8 QUICK_{i,t-1} + \beta_9 \Delta QUICK_{i,t-1} + \beta_{10} \Delta QUICK_{i,t} + \beta_{11} LEV_{i,t-1} \\ & + \beta_{12} LOSSBIN1_{i,t-1} + \beta_{13} LOSSBIN2_{i,t-1} + \beta_{14} LOSSBIN3_{i,t-1} \\ & + \beta_{15} LOSSBIN4_{i,t-1} + \beta_{16} LOSSBIN5_{i,t-1} + \theta_k + \varepsilon_{i,t} \end{aligned} \quad (2)$$

where *NETHIRE* is the percentage change in the firm's number of employees; *SALES_GROWTH* is the percentage change in the firm's sales revenue; *ROA* is net income scaled by beginning-of-year total assets; *ΔROA*is the change in *ROA*; *RETURN* is annual stock return; *SIZE_R* is the log of the market value of equity at the beginning of the year; *QUICK* is the sum of cash, short-term investment, and receivables divided by current liabilities; *ΔQUICK*is the change in *QUICK*; *LEV* is noncurrent liabilities divided by total assets at the beginning of the year; *LOSSBIN* represents indicator variables that equal 1 if a firm's previous-year *ROA* is between specific 0.005 intervals from 0 to −0.025, and 0 otherwise. For example, *LOSSBIN1* equals 1 if a firm's previous-year *ROA* is between −0.005 and 0; *LOSSBIN2* equals 1 if the previous-year *ROA* is between −0.010 and − 0.005, *LOSSBIN3* equals 1 if the previous-year *ROA* is between −0.015 and − 0.010, and so on. θ_k represents industry fixed effects.

A firm's expected net hiring based on Eq. (1) approximates its optimal labour investment. The absolute value of the residual obtained from Eq. (1) represents the absolute difference between a firm's actual net hiring and its optimal hiring level, indicating the level of labour investment inefficiency. Therefore, a positive residual represents labour overinvestment, and a negative residual indicates labour underinvestment. There may be concerns that the model of Pinnuck and Lillis (2007) lacks accuracy in predicting optimal labour investment because of model specification issues and variable measurement errors. Our results in Table A3 in Appendix indicate that the signs of the fundamental economic factors are consistent with those in previous studies (Ghaly et al., 2020; Jung et al., 2014). This suggests that our labour investment inefficiency model is well specified.

Following prior literature (e.g., Biddle and Hilary, 2006; Biddle et al., 2009; Khedmati et al., 2020), we incorporate a large number of control variables in the main analysis. Specifically, we control for financial factors that likely affect labour investment, including firm size (*SIZE*), leverage (*LEV*), return on assets (*ROA*), sales growth (*SALES_GROWTH*), dividend (*DIVIDEND*), the incidence of loss (*LOSS*), and liquidity (*QUICK*). *SOE* is included because politically connected firms generally have less labour investment efficiency (Luo et al., 2020).

Top shareholder ownership (*TOP1*) and institutional shareholding (*INS*) are also included because they are determinants of a firm's agency problems and thus affect labour investment (Ghaly et al., 2020; Fan et al., 2022). Following Le and Tran (2021), we choose board size (*BOARD*), the percentage of independent directors (*INDPR*), and CEO–Chairman duality (*DUAL*) to proxy for firms' internal governance. We also control for the external monitoring strength by considering whether a firm is audited by an international Big 4 or local Big 10 audit firm (*BIGN*), which is more effective at deterring managers' self-interested opportunistic behaviour (Becker et al., 1998; Chen et al., 2002). Labour intensity (*INTENSITY*) is included to account for labour adjustment costs (Anderson et al., 2003). Following Kong et al. (2018), we include growth in the percentage of employees with a bachelor's degree (*BACHEGROWTH*), growth in the percentage of employees with a master's degree (*MASTERGROWTH*), and growth in the percentage of employees with degrees below a bachelor's (*OTHERGROWTH*) to indicate specific growth of human capital.

2.2. Sample selection

The data on labour investment, financial fundamentals, regulatory compliance information, and office address are obtained from the China Stock Market and Accounting Research (CSMAR) database. This dataset is widely used in previous studies. Our initial sample consists of all listed firms and includes 35,253 firm-year observations from 2006 to 2019 inclusive. We exploit a time-varying DiD approach to investigate how the LCC programme affects labour investment decisions. This requires at least three years of data before and after the implementation of the LCC pilot programme. We thus begin the sample in 2006 because that is three years before the year of the first round of the LCC implementation (in 2010). We end the sample in 2019, which is three years after the third round of implementation (in 2017).

Table 1 shows the sample selection in detail. Specifically, we remove 711 financial firm-year observations according to the 2012 Industrial Classification of the China Securities Regulatory Commission Code J and

Table 1
Sample selection.

Total number of firm-year observations from 2006 to 2019	35,253
Less: financial and utilities firms	(711)
Less: firms that were delisted before the first round or went public after the third round	(124)
Less: observations with missing values for the dependent or control variables	(6471)
Less: observations without one observation in both the pre- and post-regulation periods	(5651)
Final sample	22,296
Number of unique firms	2048

[9] The first batch includes five provinces and eight cities.

[10] The second batch includes 28 cities, and the third batch covers 45 cities.

considering differences in their accounting fundamentals from other firms. Consistent with prior literature (e.g., Cao et al., 2022), we exclude 124 firms that were delisted before the first round of implementation or went public after the third round to balance the sample. We remove 6471 observations with missing values. DiD model requires firms with observations in both pre- and post-LCC pilot periods. 5651 observations are thus deleted for failing to meet this requirement. Eventually, this study obtains 22,296 firm-year valid observations from 2048 unique firms. We winsorise all continuous variables at the 1st and 99th percentiles to ensure that our results are not driven by outliers. The Appendix provides the variable definitions in detail.

3. Empirical results

3.1. Descriptive statistics

The descriptive statistics for the full sample are presented in Panel A, Table 2. The mean value of *INEFFICIENCY* is 0.439. About 38.2% (the mean value of *LCC* is 0.382) of the firm-year observations are subject to the LCC pilot programme. This also indicates the importance of investigating the real effects of the LCC programme on investment efficiency given that it covers more than one-third of China's cities. The average of *SIZE* is 22.170. This is also comparable to the results in relevant prior research (e.g., Huang et al., 2021b; Cao et al., 2022).

Panels B and C present the descriptive statistics for the treatment and control groups, respectively. The average of *INEFFICIENCY* for the treatment group (0.453) is higher than that for the control group (0.411). This indicates that labour investment inefficiency is more severer in firms affected by the LCC programme than in their counterparts. We also observe the differences in fundamental characteristics of the treatment and control groups. Therefore, we utilize an entropy balancing technique to create a matched sample and ensure comparability. Section 3.4 presents the details of the matching process.

3.2. Baseline results

Column (1) of Table 3 shows the results using the full sample. The estimated coefficient of *LCC* is positive (0.030) and significant at the 1% level ($p < 0.01$). This indicates that the LCC programme significantly reduces labour investment efficiency. We further partition the sample into overinvestment (i.e., net hiring greater than expected) and underinvestment (i.e., net hiring lower than expected) subsamples according to the sign of abnormal net hiring. Columns (2)–(3) show the results for the overinvestment and underinvestment subsamples, respectively. We find that the LCC programme leads to both overinvestment and underinvestment, particularly overinvestment. The magnitudes of the coefficients are economically significant. Specifically, the LCC programme increases the treated firms' labour investment inefficiency (overinvestment and underinvestment) by approximately 6%[11] (12.41%,[12] 8.72%[13]) of the standard deviation of the treatment group compared with the control group.

3.3. Pre-treatment trends

One assumption underlying the causal inferences of DiD estimations is that the trends in the dependent variable in the pre-treatment period are similar between treatment and control groups. Following Cao et al. (2022), we conduct a dynamic analysis to re-estimate our baseline regression after replacing *LCC* with seven dummy variables representing various years relative to LCC programme implementation, namely, three years (*LCC*-3), two years (*LCC*-2), and one year (*LCC*-1) prior to the LCC implementation, the year of implementation (*LCC*0), one year (*LCC*1), two years (*LCC*2), and three years and more (*LCC*3+) post-implementation.

Table 4 shows the results. The coefficients of *LCC*-3, *LCC*-2, and *LCC*-1 are close to 0 and statistically non-significant, indicating no significant difference between the trends of labour investment inefficiency (both overinvestment and underinvestment) for the treatment and control groups in the pre-implementation period. The results using the full sample are presented in Column (1) of Table 4. The positive and significant coefficient of *LCC*0 indicates that labour investment inefficiency incrementally increases in the treatment group. The positive and significant coefficients on *LCC*1, *LCC*2, and *LCC*3 indicate that the effect of the LCC programme on labour investment inefficiency persists in the ensuing three years, although the effect is weaker in the second and third years. We find that the decreasing trend mainly reflects a gradual decrease in overinvestment, as shown in Column (2), and slowly increasing underinvestment, as shown in Column (3). We further visualize the results of the parallel trend assumption test. As shown in Fig. 1, firm labour investment inefficiency increases significantly only after the LCC pilot regulation's implementation and we can see a dramatical increase in overinvestment after the LCC programme. This implies that the LCC programme has an immediate effect on firms' labour investment decisions, particularly overinvestment; the impact on underinvestment is more salient two years later.

3.4. Entropy balancing technique

In line with the literature (e.g., Beck et al., 2022; Cazier et al., 2020; Yoon, 2021), we use an entropy balancing technique to match the covariates across the treatment and control groups. This approach enables achieving greater covariate balance with fewer restrictive assumptions and without dropping any observations (Hainmueller, 2012). To assign scalar weights to all of the control firms, the entropy balancing technique balances the covariate distributions of the treatment and control groups across three moments: mean, variance, and skewness. We rerun the baseline analysis using the matched sample. The results in Table 5 suggest that the causal inferences hold for the matched sample based on entropy balancing. To check the robustness of this result, we further use the propensity score matching (PSM) technique to balance the treatment and control groups. The performance of PSM is presented in Fig. A in the Appendix and indicates that after matching, there are no significant differences between the two groups. The results are provided in Table A4 in Appendix. We yield similar results to those using the entropy balancing technique.

3.5. Placebo tests

To further corroborate the causality and sensitivity of the above results with respect to spurious correlations and confounding factors, we conduct the following two placebo tests. First, in line with the literature (Cao et al., 2022; Ferri et al., 2018; Kyung et al., 2019), we randomise the timing of each round of the LCC but retaining the treatment and control group assignments to test whether the fictitious LCC programme timing (*FLCC1*) affects labour investment inefficiency. The results in Panel A of Table 6 show that the coefficient of *FLCC1* is statistically insignificant across all regression models. This supports the validity of the parallel trend assumption in our sample.

Second, another potential endogeneity issue is that other contemporaneous environmental regulations may affect our baseline findings. To mitigate this concern, we follow DeFusco (2018) and Edwards and

[11] This economic significance is calculated as the coefficient of LCC (0.030) divided by the standard deviation of *INEFFICIENCY* for the treatment group (0.500).

[12] This economic significance is calculated as the coefficient of LCC (0.089) divided by the standard deviation of *INEFFICIENCY* for the treatment group (0.717) when considering overinvestment in labour.

[13] This economic significance is calculated as the coefficient of LCC (0.017) divided by the standard deviation of *INEFFICIENCY* for the treatment group (0.195) when considering underinvestment in labour.

Table 2
Descriptive statistics.

Panel A: Descriptive statistics of the full sample

Variable	N	Mean	SD	P25	P50	P75	Max
INEFFICIENCY	22,296	0.439	0.483	0.131	0.284	0.606	3.302
NETHIRE	22,296	0.109	0.483	−0.047	0.012	0.110	3.427
ABNETHIRE	22,296	−0.186	0.626	−0.505	−0.181	0.059	3.302
LCC	22,296	0.382	0.486	0.000	0.000	1.000	1.000
SIZE	22,296	22.170	1.328	21.240	22.020	22.950	26.050
LEV	22,296	0.478	0.204	0.322	0.486	0.634	0.902
ROA	22,296	0.031	0.062	0.010	0.030	0.058	0.191
LOSS	22,296	0.113	0.316	0.000	0.000	0.000	1.000
SALES_GROWTH	22,296	0.188	0.515	−0.031	0.101	0.265	3.473
QUICK	22,296	1.278	1.426	0.543	0.871	1.413	10.710
SEGMENT	22,296	2.393	0.966	1.792	2.398	2.996	6.960
DIVIDEND	22,296	0.638	0.480	0.000	1.000	1.000	1.000
SOE	22,296	0.529	0.499	0.000	1.000	1.000	1.000
TOP1	22,296	0.346	0.149	0.227	0.324	0.451	0.740
INS	22,296	0.388	0.233	0.196	0.398	0.571	0.874
BOARD	22,296	2.467	0.308	2.303	2.485	2.639	3.178
INDPR	22,296	0.355	0.095	0.286	0.333	0.417	0.625
DUAL	22,296	0.179	0.383	0.000	0.000	0.000	1.000
BIGN	22,296	0.501	0.500	0.000	1.000	1.000	1.000
INTENSITY	22,296	0.005	0.022	−0.002	0.001	0.006	0.155
MASTERGROWTH	22,296	0.003	0.022	0.000	0.000	0.002	0.517
BACHEGROWTH	22,296	0.018	0.083	0.000	0.000	0.015	0.973
OTHERGROWTH	22,296	0.045	0.221	−0.013	0.000	0.002	1.219

Panel B: Descriptive statistics of the treatment group

Variable	N	Mean	SD	P25	P50	P75	Max
INEFFICIENCY	14,804	0.453	0.500	0.139	0.298	0.610	3.302
NETHIRE	14,804	0.117	0.507	−0.048	0.013	0.115	3.427
ABNETHIRE	14,804	−0.177	0.651	−0.509	−0.191	0.066	3.302
LCC	14,804	0.576	0.494	0.000	1.000	1.000	1.000
SIZE	14,804	22.240	1.386	21.270	22.090	23.070	26.050
LEV	14,804	0.490	0.203	0.336	0.499	0.645	0.902
ROA	14,804	0.031	0.060	0.011	0.030	0.057	0.191
LOSS	14,804	0.110	0.312	0.000	0.000	0.000	1.000
SALES_GROWTH	14,804	0.188	0.527	−0.033	0.099	0.262	3.473
QUICK	14,804	1.253	1.430	0.532	0.856	1.374	10.710
SEGMENT	14,804	2.475	0.982	1.792	2.485	3.091	6.960
DIVIDEND	14,804	0.642	0.480	0.000	1.000	1.000	1.000
SOE	14,804	0.574	0.494	0.000	1.000	1.000	1.000
TOP1	14,804	0.350	0.152	0.228	0.329	0.461	0.740
INS	14,804	0.400	0.233	0.215	0.411	0.584	0.874
BOARD	14,804	2.485	0.311	2.303	2.485	2.708	3.178
INDPR	14,804	0.351	0.096	0.286	0.333	0.400	0.625
DUAL	14,804	0.157	0.364	0.000	0.000	0.000	1.000
BIGN	14,804	0.511	0.500	0.000	1.000	1.000	1.000
INTENSITY	14,804	0.006	0.023	−0.002	0.001	0.006	0.155
MASTERGROWTH	14,804	0.003	0.024	0.000	0.000	0.002	0.517
BACHEGROWTH	14,804	0.020	0.089	0.000	0.000	0.016	0.973
OTHERGROWTH	14,804	0.047	0.222	−0.013	0.000	0.002	1.219

Panel C: Descriptive statistics of the control group

Variable	N	Mean	SD	P25	P50	P75	Max
INEFFICIENCY	7492	0.411	0.446	0.113	0.258	0.590	3.002
NETHIRE	7492	0.094	0.433	−0.045	0.011	0.103	3.427
ABNETHIRE	7492	−0.203	0.571	−0.495	−0.164	0.047	3.002
LCC	7492	0.000	0.000	0.000	0.000	0.000	0.000
SIZE	7492	22.030	1.193	21.190	21.910	22.720	26.050
LEV	7492	0.456	0.203	0.297	0.454	0.612	0.902
ROA	7492	0.031	0.066	0.009	0.031	0.061	0.191
LOSS	7492	0.119	0.324	0.000	0.000	0.000	1.000
SALES_GROWTH	7492	0.188	0.491	−0.026	0.107	0.269	3.473
QUICK	7492	1.328	1.417	0.562	0.908	1.490	10.710
SEGMENT	7492	2.230	0.911	1.609	2.197	2.773	6.607
DIVIDEND	7492	0.632	0.482	0.000	1.000	1.000	1.000
SOE	7492	0.439	0.496	0.000	0.000	1.000	1.000
TOP1	7492	0.338	0.145	0.225	0.316	0.432	0.740
INS	7492	0.365	0.233	0.163	0.370	0.545	0.874

(*continued on next page*)

Table 2 (*continued*)

Panel C: Descriptive statistics of the control group

Variable	N	Mean	SD	P25	P50	P75	Max
BOARD	7492	2.430	0.300	2.197	2.398	2.639	3.178
INDPR	7492	0.361	0.093	0.300	0.357	0.421	0.625
DUAL	7492	0.221	0.415	0.000	0.000	0.000	1.000
BIGN	7492	0.482	0.500	0.000	0.000	1.000	1.000
INTENSITY	7492	0.005	0.020	−0.002	0.001	0.005	0.155
MASTERGROWTH	7492	0.002	0.016	0.000	0.000	0.001	0.500
BACHEGROWTH	7492	0.014	0.071	0.000	0.000	0.014	0.923
OTHERGROWTH	7492	0.041	0.219	−0.012	0.000	0.001	1.024

Todtenhaupt (2020) to randomly assigns fictitious environmental regulation events to the firms in the control group. We code a counterfactual treatment indicator, *FLCC2*, that equals 1 if a firm is located in a pseudo-impacted city after the counterfactual implementation, and 0 otherwise. The results in Panel B of Table 6 show an insignificant coefficient of *FLCC2* across all regressions. This suggests that it is unlikely that confounding events affect our results.

This study simulates the placebo tests 5000 times and visualizes the probability distributions of the coefficients (*FLCC1* and *FLCC2*) in Fig. 2. Panels A–C, Fig. 2 show the distributions of *FLCC1* based on randomizing fictitious timing of the LCC implementation. Panels D—F of Fig. 2 reports the probability distributions of *FLCC2* based on the fictitious environmental regulation events assigned to the firms in the control group. The baseline result from Table 3 is represented as a vertical dotted line. Clearly, the six vertical dotted lines in Panels A–F of Fig. 2 are far from the distributions of the placebo coefficients. Overall, we provide convincing evidence that changes in labour investment inefficiency are due to implementing the LCC programme rather than confounding events.

3.6. Controlling other fixed effects

We follow Cao et al. (2022) to further incorporate city and industry-by-year fixed effects into our model considering nonparametrically correlated time-specific shocks at the industry level. The results in Table 7 show that, after adding the additional fixed effects, the baseline findings still hold.

3.7. Omitted variable test

To mitigate the omitted variable concern, following Oster (2019), we compare the coefficient estimate sensitivity and the R-square change between regressions with and without control variables. Specifically, we use an estimator to obtain consistent estimates of the true coefficients. We use two parameters, selection proportionality δ and R_{max}, which is the maximum goodness of fit for regression equations if omitted variables can be observed. We verify the robustness of our results by conducting the following two tests. First, δ takes value −1, and R_{max} takes the value of 1.3 times of adjusted R-square in the baseline result, and then we get the value of β^*. If β^* is in the 95% confidence interval of LCC, our baseline result is robust. Second, β^* takes the value 0, and R_{max} is the same as in test 1, then we get the value of δ. As discussed in Oster (2019), the result is robust if δ is larger than 1 or less than −1. The results in Table 8 indicate the robustness of baseline results.

4. Additional analyses

4.1. Financial constraints and financial slack

Labour investment includes variable costs such as wages as well as fixed costs such as hiring, firing, training, and other adjustment costs (Oi, 1962; Hamermesh, 1989; Hamermesh and Pfann, 1996), which require financing[14] (Benmelech et al., 2011). Studies (Cao and Rees, 2020; Khedmati et al., 2020; Pereira da Silva, 2019; Hamermesh and Pfann, 1996) document that financial constraints distort intertemporal labour decisions when considering upfront costs to improve future workforce productivity. As a result, firms could take suboptimal labour investment (Caggese et al., 2019). Specifically, Khedmati et al. (2020) argue that a firm with financial difficulties is less likely to efficiently invest in labour. They find that financial constraints exacerbate the negative effect of CEO–director ties on labour investment efficiency. Similarly, Ben-Nasr and Alshwer (2016) document the moderating effect of financial constraints on the relationship between stock price informativeness and labour investment efficiency. Pereira da Silva (2019) shows that the relationship between CSR performance and investment inefficiency in labour is more evident for less financially constrained firms. We thus posit that the LCC programme has stronger effects on firms' investment inefficiency in labour when they are financially constrained.

In addition, financial slack, which refers to financial resources uncommitted to any specific use (John et al., 2017), is strongly associated with agency conflicts. It is closely linked to agency issues from free cash flow (Kim et al., 2008, p. 405). Studies (e.g., Jensen, 1986) document that firms with more financial slack tend to overinvest. Pereira da Silva (2019) finds that the relationship between CSR performance and investment inefficiency in labour is more evident for less financially constrained firms than their peers. We thus expect the effect to be stronger in firms with financial slack.

The regression results are presented in Table 9. As expected, the baseline results show that the effect is stronger in firms with financial slack. We do not observe significant evidence about how financial constraints moderate the effect of the LCC programme on overall investment inefficiency in labour. However, a detailed analysis (Panel A of Table A2 in the Appendix) suggests that financial constraints play a significant role in over-hiring and over-firing.

Our finding that the effect is stronger for firms with financial slack is particularly significant for overinvestment. To explore this further, we follow Kim and Bettis (2014) and divide the sample into two subsamples according to the median value of financial slack in the firm's industry each year. To confirm the source of investment inefficiency in labour, we also disaggregate labour investment inefficiency into four types: over-hiring and under-firing (overinvestment) and under-hiring and over-firing (underinvestment). Panel B of Table A2 in the Appendix represents the results that show that financial slack moderate the effects of the LCC programme on investment inefficiency in labour, and this is particularly reflected in firms with over-hiring and over-firing. Collectively, these results indicate that financial slack is more likely to be

[14] Labour cost has a semi-fixed attribute (Hamermesh and Pfann, 1996). Firms must trade off upfront costs against future productivity when making labour investment decisions. When there is a mismatch between labour costs and the generation of cash flows, firms must finance their labour activities through the production process (Benmelech et al., 2011). As such, financial constraints may distort the optimal labour investment.

Table 3
Results of the baseline model.

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
LCC	0.030***	0.089***	0.017***
	(2.83)	(2.87)	(2.81)
SIZE	−0.041***	0.024	−0.133***
	(−4.44)	(0.89)	(−23.45)
LEV	0.034	−0.033	0.034
	(1.01)	(−0.31)	(1.46)
ROA	0.066	−0.843***	0.676***
	(0.75)	(−3.45)	(12.36)
LOSS	−0.011	−0.028	0.011
	(−0.94)	(−0.74)	(1.53)
SALES_GROWTH	0.202***	0.421***	0.032***
	(15.68)	(16.54)	(4.14)
QUICK	0.007	0.038***	−0.024***
	(1.49)	(3.16)	(−6.87)
SEGMENT	−0.003	−0.006	−0.021***
	(−0.33)	(−0.26)	(−4.34)
DIVIDEND	−0.028***	−0.027	−0.014***
	(−3.40)	(−1.08)	(−3.03)
SOE	−0.061***	−0.072	−0.044***
	(−3.07)	(−1.37)	(−3.43)
TOP1	0.171***	0.363***	−0.017
	(3.11)	(2.60)	(−0.58)
INS	−0.049**	−0.055	−0.041***
	(−2.24)	(−0.88)	(−3.32)
BOARD	0.065***	0.007	0.046***
	(3.59)	(0.15)	(4.22)
INDPR	0.025	0.118	0.007
	(0.58)	(0.96)	(0.28)
DUAL	0.005	−0.020	0.006
	(0.55)	(−0.72)	(0.93)
BIGN	−0.008	−0.010	−0.006
	(−0.88)	(−0.40)	(−1.11)
INTENSITY	−1.646***	−3.836***	0.015
	(−12.13)	(−9.96)	(0.15)
MASTERGROWTH	−1.028***	−2.431***	0.498***
	(−3.47)	(−2.93)	(3.80)
BACHEGROWTH	−0.125*	−0.553**	0.088**
	(−1.88)	(−2.26)	(2.40)
OTHERGROWTH	−0.011	0.112	−0.007
	(−0.32)	(0.81)	(−0.38)
Constant	0.961***	−0.331	3.004***
	(5.12)	(−0.60)	(26.36)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
P-value		0.000***	
N	22,296	6740	15,556
Adj.R^2	0.253	0.262	0.633

Notes: This table reports the DiD regression results for the impact of the LCC programme on firms' labour investment inefficiency. Following Jung et al. (2014), *INEFFICIENCY* is measured as the absolute value of the residuals obtained from the OLS estimation of Eq. (1), and a higher value for *INEFFICIENCY* suggests greater labour investment inefficiency. We divide the full sample into an *Overinvestment* subsample of firms with more employees than predicted and an *Underinvestment* subsample of firms with fewer employees than predicted. Following Cleary (1999), we test the difference in coefficient estimate for *LCC* between *Overinvestment* subsample and *Underinvestment* subsample, and the *P*-value of 0.000 suggests that the coefficient estimate of *LCC* is greater in *Overinvestment* subsample. The results show that firms have greater labour investment inefficiency, including labour overinvestment and labour underinvestment, after the implementation of the LCC pilot programme.
Robust standard errors (clustered at the firm level) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Pre-treatment trends.

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
LCC-3	0.006	0.047	−0.002
	(0.40)	(1.14)	(−0.27)
LCC-2	−0.013	−0.051	−0.011
	(−0.87)	(−1.24)	(−1.36)
LCC-1	−0.004	−0.086	−0.011
	(−0.28)	(−1.04)	(−1.42)
LCC0	0.032*	0.099**	0.004
	(1.91)	(1.97)	(0.44)
LCC1	0.050***	0.182***	−0.002
	(3.56)	(4.40)	(−0.30)
LCC2	0.025*	0.067*	0.025***
	(1.77)	(1.76)	(2.72)
LCC3	0.032*	0.033	0.019*
	(1.76)	(0.74)	(1.82)
Controls	Yes	Yes	Yes
Constant	0.962***	−0.338	3.003***
	(5.12)	(−0.61)	(26.32)
F: $L^{-3} + L^{-2} + L^{-1} = 0$ (p-value)	0.0002	0.0002	0.0283
F: $L^{0} + L^{+1} + L^{+2} + L^{+3} = 0$ (p-value)	0.7035	0.4386	0.1199
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,296	6740	15,556
Adj. R^2	0.254	0.266	0.633

Notes: This table reports the dynamic DiD regression results for the impact of the LCC programme on firms' labour investment inefficiency. *LCC-3*, *LCC-2*, and *LCC-1* are dummy variables that equal 1 for three years, two years, and one year before the LCC implementation, respectively. *LCC0*, *LCC1*, *LCC2*, and *LCC3* are dummy variables that equal 1 for the year of, one year, two years, and three years after the LCC implementation, respectively. The results show that the LCC pilot programme is significantly and positively associated with firms' labour investment inefficiency. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

linked with investment inefficiency in labour.

4.2. Labour intensity

Existing research (e.g., Ghaly et al., 2015; Khedmati et al., 2020; Pereira da Silva, 2019) documents that labour-intensive firms tend to invest more in labour than their non-labour-intensive peers. To make sure that our results are not mainly from less labour-intensive firms, we further investigate how labour intensity affects our baseline findings. We follow Pereira da Silva (2019) and use the number of employees per unit asset to measure labour intensity. A firm is seen as labour-intensive if its labour-intensity ratio is higher than the median. In Table 10, the coefficient of *LCC* is positive for labour-intensive firms, indicating that the effect is stronger for labour-intensive firms. In addition, we find that labour-intensive firms are more likely to overinvest in labour after the LCC implementation, which is reflected in labour-intensive firms having a higher coefficient than that of non-labour-intensive firms. This is similar to the finding of Khedmati et al. (2020) that labour-intensive firms have a greater need to adjust labour.

4.3. Environmental penalties

To further investigate how our baseline results vary between regions and firms, we conduct the following cross-sectional test on how environmental penalties affect our baseline results. The results in Table 11 indicate that firms that have incurred environmental penalties are more

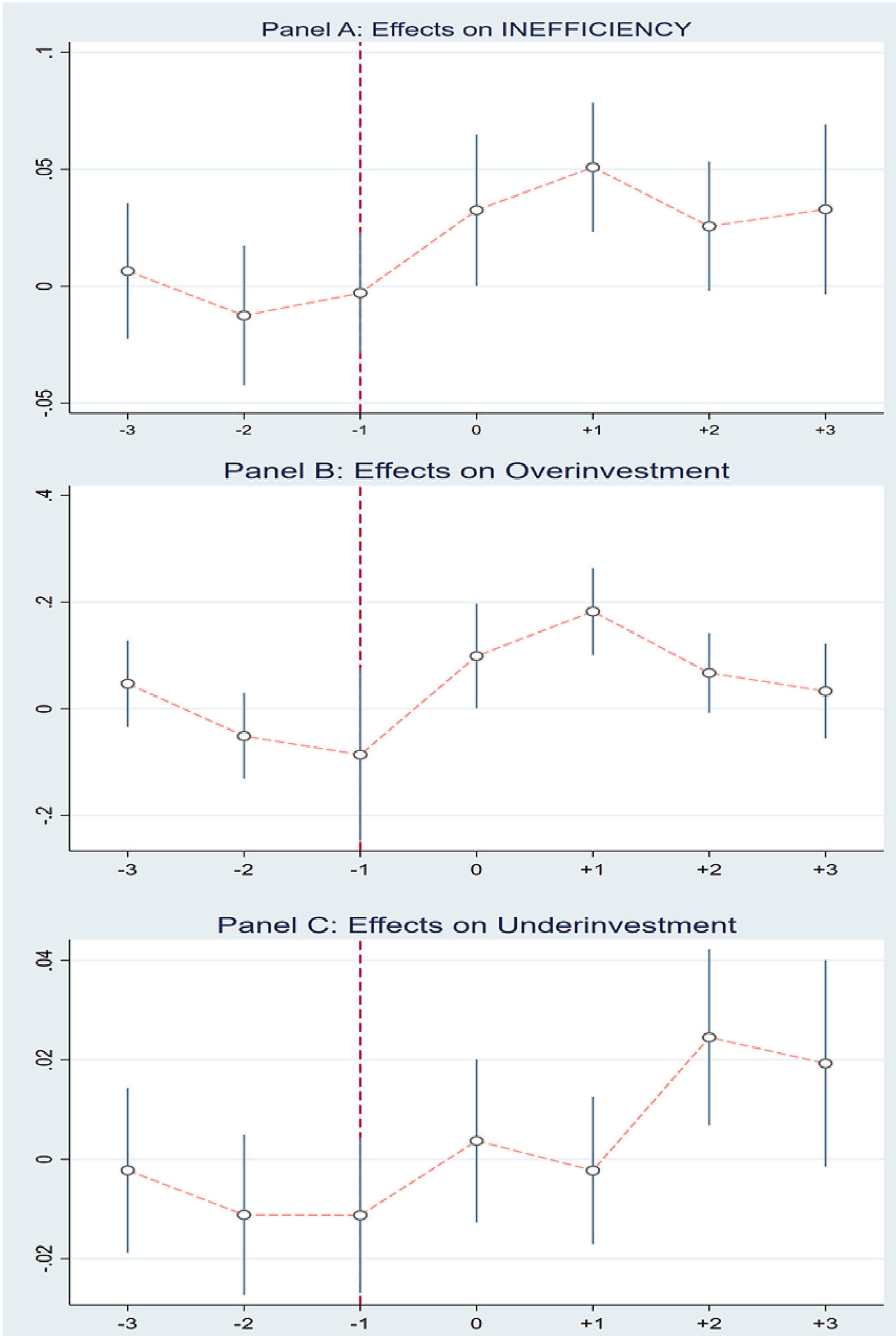

Fig. 1. Pre-treatment trends.
Notes: This figure illustrates the trends indicated by the regression coefficients reported in Table 5. Panels A–C show that the coefficients of *LCC*1, *LCC*2, and *LCC*3 are significantly greater than those of *LCC*-3, *LCC*-2, and *LCC*-1. The variable definitions are provided in Table A1.

Table 5
Entropy balancing approach.

Panel A: Differences in observables (Covariates) after entropy balancing

Covariate	Treat			Control			Std.	Var.
	Mean	Variance	Skewness	Mean	Variance	Skewness	Diff.	Ratio
SIZE	22.560	1.956	0.403	22.560	1.956	0.403	0.000	1.000
LEV	0.491	0.043	−0.108	0.491	0.043	−0.108	0.000	1.000
ROA	0.029	0.004	−1.736	0.029	0.004	−1.736	0.000	1.000
LOSS	0.114	0.101	2.437	0.114	0.101	2.437	0.000	1.000
GROWTH	0.176	0.280	3.908	0.176	0.280	3.908	0.000	1.000
QUICK	1.271	2.039	3.869	1.271	2.039	3.869	0.000	1.000
SEGMENT	2.668	1.009	0.217	2.668	1.009	0.217	0.000	1.000
DIVIDEND	0.677	0.219	−0.757	0.677	0.219	−0.757	0.000	1.000
SOE	0.559	0.247	−0.237	0.559	0.247	−0.237	0.000	1.000
TOP1	0.344	0.023	0.482	0.344	0.023	0.482	0.000	1.000
INS	0.456	0.044	−0.207	0.456	0.044	−0.207	0.000	1.000
BOARD	2.492	0.095	−0.080	2.492	0.095	−0.080	0.000	1.000
INDPR	0.353	0.009	0.427	0.353	0.009	0.427	0.000	1.000
DUAL	0.182	0.149	1.651	0.182	0.149	1.651	0.000	1.000
BIGN	0.578	0.244	−0.318	0.578	0.244	−0.317	0.000	1.000
INTENSITY	0.005	0.001	4.665	0.005	0.001	4.665	0.000	1.000
MASTERGROWTH	0.003	0.001	0.255	0.003	0.001	0.256	0.000	1.000
BACHEGROWTH	0.020	0.008	2.231	0.020	0.008	2.231	0.000	1.000
OTHERGROWTH	0.028	0.041	2.573	0.028	0.041	2.573	0.000	1.000

Panel B: Labour Investment Inefficiency after Entropy Balancing

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
LCC	0.040***	0.103***	0.017**
	(2.92)	(2.94)	(2.51)
Controls	Yes	Yes	Yes
Constant	0.718***	−0.449	2.927***
	(2.69)	(−0.67)	(20.95)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,220	6355	15,454
Adj. R^2	0.378	0.370	0.767

Notes: This table reports the DiD regression results for the impact of the LCC on firms' labour investment inefficiency after entropy balancing the sample. The results show that the LCC pilot programme is significantly and positively associated with firms' labour investment inefficiency. Robust standard errors (clustered at the firm level) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

likely to have labour investment inefficiency issues after the LCC programme. Consistent with the compliance costs and financing difficulty argument that firms with environmental issues may have more difficulty obtaining sufficient financing to invest in labour efficiently.

5. The impact of the LCC Programme on human capital quality

5.1. Labour quality

Collectively, our analysis indicates that the LCC programme leads to labour investment inefficiency. However, the results of our dynamic analysis in Table 4 indicate that this may be a temporary effect because the coefficient of *LCC3* is not highly significant for either overinvestment or underinvestment. Yu and Zhang (2021) find that the LCC programme increases carbon emissions efficiency by 1.7%. The main mechanisms of emissions reduction are technological innovation (Hong et al., 2021) and investment in research and development (Fu et al., 2021). R&D investment can optimise firms' labour structure (Sun et al., 2022; Yamazaki, 2017; Guo et al., 2021; Carbone et al., 2020). It is thus interesting and important to examine how the LCC programme affects firms' labour quality.

Previous research (e.g., Cao et al., 2017; Sun et al., 2022) has shown that carbon-emitting firms confronted with the LCC programme benefit from preferential policies, such as greater governmental financial support, tax reductions, and talent incentives. This drives firms to improve their labour structure by hiring more highly skilled employees and firing less highly skilled employees. To obtain in-depth insights into the changes in labour investment, we posit that the LCC programme may result in firms' upgrading their labour structure and enhancing labour quality. Consistent with Winters (2011), labour quality is defined as the percentage of all rank-and-file employees whose education level is higher than or equal to a bachelor's degree.

The coefficient of *LCC* in Column (1) of Table 12 is positive and statistically significant at the 1% level, which indicates that the LCC implementation drives firms to significantly improve their labour quality. The results in Columns (2)–(3) indicate that this effect is stronger in firms that overinvest in labour. Consistent with Sun et al. (2022), our results show that the LCC programme improves labour quality by leading firms to hire more highly skilled employees.

5.2. Underlying economic mechanisms

We further explore the mechanisms of the LCC programme motivating firms to recruit highly skilled employees. It has been found that environmental regulation can alleviate agency problems (e.g., Li et al., 2022; Zhang et al., 2021). This can further lead to better labour quality decisions because mitigating agency problems helps to improve labour quality (Ghaly et al., 2020; Jung et al., 2014; Ha and Feng, 2018). We

Table 6
Placebo tests.

Panel A: Random assignment of LCC implementation times to the treated firms

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
FLCC1	−0.007	−0.021	0.003
	(−0.67)	(−0.72)	(0.52)
Controls	Yes	Yes	Yes
Constant	0.953***	−0.392	3.003***
	(5.06)	(−0.70)	(26.23)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,296	6740	15,556
Adj. R^2	0.252	0.257	0.632

Panel B: Random Assignment of LCC Implementation Times to the Control Firms

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
FLCC2	−0.016	−0.025	−0.005
	(−1.37)	(−0.80)	(−0.80)
Controls	Yes	Yes	Yes
Constant	0.950***	−0.405	3.002***
	(5.05)	(−0.72)	(26.22)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,296	6740	15,556
Adj. R^2	0.252	0.257	0.632

Notes: This table reports the results of the first robustness test of the baseline results for the impact of the LCC programme on firms' labour investment inefficiency. As a placebo test, random LCC implementation years are assigned to the firms in the treatment group to fabricate alternative event times. The results show that the LCC programme is indeed significantly and positively associated with firms' labour investment inefficiency. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
Notes: This table reports the results of the second robustness test of the baseline results for the impact of the LCC programme on firms' labour investment inefficiency. As a placebo test, random LCC implementation years are assigned to the firms in the control group to fabricate an alternative treatment group. The results show that the LCC pilot programme is indeed significantly and positively associated with firms' labour investment inefficiency. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

argue that the reduction in agency problems is an underlying economic mechanism through which the LCC programme enhances labour quality. Following Xu et al. (2014) and Gul et al. (2011), we use excess perks to proxy for a firm's level of agency problems, and we calculate residual in the model (3) as the difference between actual perk consumption and expected perk consumption to measure excess perks:

$$Perk/Sales = \alpha_0 + \beta_1 LnTotalComp + \beta_2 LnAsset + \beta_3 LnTotalIncPerCap + \varepsilon \quad (3)$$

where *Perk/Sales* is actual perk consumption scaled by sales; *LnTotalComp*is the natural log of total compensation of employees; *LnAsset*is the natural log of total assets; and *LnTotalIncPerCap*is the natural log of total income per capita in the region where a firm's headquarters are located. Excess perks (*ABPERK*) are calculated as the residual of the above equation.

Following the literature (Huang et al., 2021a, 2021b), we first examine the effects of the LCC programme on excess perks. Column (1) in Panel A of Table 13 represents the results that the LCC pilot programme significantly reduces excess perks. If the LCC programme affects labour quality through reductions of excess perks, we can observe firms with greater reductions experiencing stronger effects of the LCC programme on labour quality. Results represented in Column (2) show that the coefficient of *LCC*HighΔPERK* is positive and statistically significant at the 1% level. This indicates that the LCC programme affects labour quality through changes in excess perks.

The Porter Hypothesis suggests that well-designed environmental regulation can motivate firms to invest in new technologies and profit from that to offset compliance costs (Chakraborty and Chatterjee, 2017; Porter and Van der Linde, 1995). Innovation together with R&D investment, are the main mechanisms to lower carbon emissions (Hong et al., 2021; Fu et al., 2021). Huang et al. (2021a, 2021b) document that firms subject to LCC has a statistically significant increase in R&D investment in China. R&D investment can further optimise firms' labour structure (Sun et al., 2022; Yamazaki, 2017; Guo et al., 2021; Carbone et al., 2020). We posit that firms headquartered in regions affected by LCC are more likely to increase green innovation investment. This further upgrades firms' labour structure. Our results in Panel B of Table 13 indicate that LCC significantly increases green innovation investment. If the LCC programme affects labour quality through changes in green innovation investment, we can observe a stronger effect in firms with a greater increase in green innovation investment. In Column (2), the coefficient of *LCC* HighΔPatent* is positive and statistically significant at the 5% level, and it has a higher value than the coefficient of *LCC* LowΔPatent* significantly. This indicates that the LCC programme affects labour quality through changes in green innovation investment.

In addition, it is reasonable to predict that if LCC eventually upgrades the firm labour structure, then firms that have great pressure to lower carbon emissions should be more likely to hire skilled employees to meet carbon reduction requirements. We thus investigate how LCC affects firms' carbon reduction pressure and whether this further promotes labour structure. Our results in Panel C of Table 13 indicate that LCC significantly correlates with firms' carbon reduction pressure. In Column (2), the coefficient of *LCC*HighΔEnvPressure* is positive and significant statistically at the 1% level, indicating that the LCC programme affects labour quality due to heightened carbon reduction pressure.

5.3. Institutional investors

Cohen et al. (2022) document that institutional investors are playing a critical role in the current efforts to transition towards a sustainable economy. We further investigate the effects of institutional investors on the relationship between the LCC programme and labour quality. We posit that firms with more institutional investor shareholding tend to hire more highly skilled employees after the LCC implementation. The results in Table 14 indicate stronger effects of the LCC programme on labour quality in firms with a larger percentage of institutional investors than their peers.

5.4. Employee well-being and post-LCC environmental governance

Employees, as one of the firms' most important stakeholder groups, play a critical role in corporate environmental engagement and carbon-reduction actions (Kong and Wang, 2021). Research documents that companies grant employees stock ownership to motivate them to

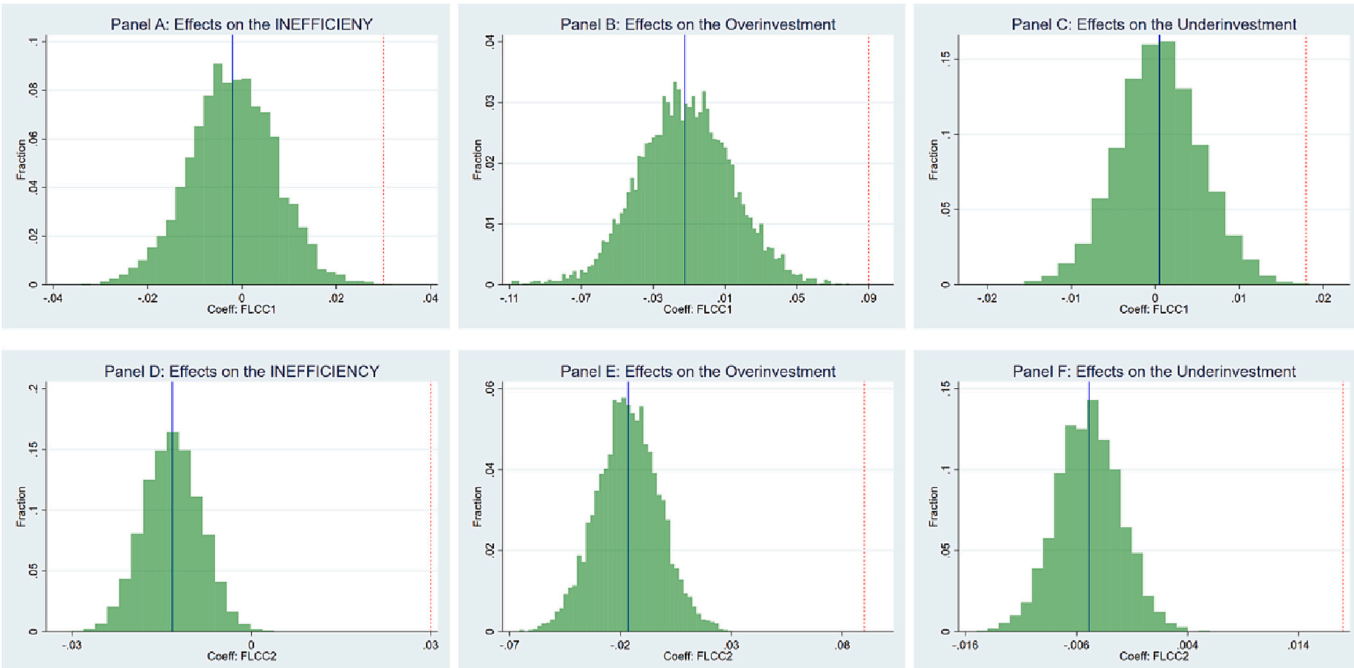

Fig. 2. The placebo estimations.
Notes: Graphs A, B, and C show histograms of 5000 estimates based on fictitious implementation event times. In each of the placebo estimations, we randomly assign (without replacement) a fictitious event time to each observation in the treatment group. Using these counterfactual times, we re-estimate our main model and plot the coefficients of *FLCC1*. Graphs D, E, and F show histograms of 5000 estimates based on fictitious environmental regulation events randomly assigned (without replacement) to the firms in the control group. Using these counterfactuals for the treated and untreated groups, we re-estimate our main model and plot the pseudo coefficients of *FLCC2*.

Table 7
Other fixed effects.

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
LCC	0.036***	0.109***	0.019***
	(3.25)	(3.50)	(3.02)
Controls	Yes	Yes	Yes
Constant	0.974***	−0.285	3.042***
	(4.92)	(−0.47)	(20.88)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year×Industry FE	Yes	Yes	Yes
N	22,296	6740	15,556
Adj. R^2	0.261	0.307	0.637

Notes: This table reports the results for the robustness test in which firm, year, city, and interactive fixed effects (Year × Industry FE) are included in the regression. The results show that the LCC pilot programme is significantly and positively associated with firms' labour investment inefficiency. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Omitted variable tests.

	Standard	Estimated value	Omitted variables bias
Panel A: LCC coefficients for the full sample			
(1)	$\beta^*(R_{max}, \delta) \in [0.0093, 0.0511]$	$\beta^*(R_{max}, \delta) = 0.0184$	Unlikely
(2)	$\delta > 1$ or $\delta < -1$	$\delta = -4.5601$	Unlikely
Panel B: LCC coefficients when overinvestment in labour			
(1)	$\beta^*(R_{max}, \delta) \in [0.0285, 0.1507]$	$\beta^*(R_{max}, \delta) = 0.0290$	Unlikely
(2)	$\delta > 1$ or $\delta < -1$	$\delta = -1.7289$	Unlikely
Panel C: LCC coefficients when underinvestment in labour			
(1)	$\beta^*(R_{max}, \delta) \in [0.0055, 0.0298]$	$\beta^*(R_{max}, \delta) = 0.0129$	Unlikely
(2)	$\delta > 1$ or $\delta < -1$	$\delta = -13.98$	Unlikely

Notes: This table reports the results for the omitted variable test. Following Oster (2019), we use the model $\beta^* = \beta^*(R_{max}, \delta)$ to obtain consistent estimates of the true coefficients, in which δ is the selection proportionality and R_{max} is the maximum goodness of fit for regression equations if omitted variables can be observed. Specifically, we do two tests to verify the robustness of our results. First, δ takes value −1, and R_{max} takes value of 1.3 times of adjusted R-square in the baseline result, then we get the value of β^* which is reported in Row (1) of Panels A, B, and C. Second, β^* takes value 0 and R_{max} is the same as in test 1, then we get the value of δ which is reported in Row (2) of Panels A, B, and C. As discussed in Oster (2019), if β^* is in the 95% confidence interval of *LCC* in the first test and δ is larger than 1 or less than −1 in the second test, there is unlikely omitted variables bias and the baseline result is robust.

enhance firm productivity and performance (Hochberg and Lindsey, 2010), retain qualified employees (Oyer, 2004) and attract employees (Bergman and Jenter, 2007). Kong and Wang (2021) find that employee shareholding significantly promotes firms' environmental engagement and environmental performance. We thus expect that to deal with environmental issues and respond to carbon-reduction regulation, firms complying with the LCC programme are more likely to grant their employees stock ownership, and the results in Panel A of Table 15 suggest that that is the case. This effect is particularly evident in non-SOEs and firms with high human capital quality. This is consistent with studies (Oyer, 2004; Bergman and Jenter, 2007) that show that employee shareholding is used to retain and attract a high-quality labour force and

Table 9
Financial constraints versus financial slack.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: INEFFICIENCY					
	Full Sample		Overinvestment		Underinvestment	
	Slack	Constraint	Slack	Constraint	Slack	Constraint
LCC	0.064***	0.013	0.125**	0.056	0.023**	0.003
	(3.81)	(0.90)	(2.56)	(1.19)	(2.12)	(0.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.217	1.509***	−3.553***	0.568	2.645***	3.220***
	(−0.62)	(6.13)	(−4.16)	(0.72)	(9.60)	(24.14)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
P-value	0.000***		0.060*		0.000***	
N	9430	12,866	2900	3840	6530	9026
Adj. R^2	0.294	0.241	0.330	0.167	0.639	0.640

Notes: This table reports the results for the difference in the effect of the LCC programme on labour inefficiency for firms with financial constraints versus those with financial slack. Following Pereira da Silva (2019), we compute the firms' KZ index using the model in Rajan and Zingales (1998), and a higher KZ index indicates greater financial constraints. We split the sample according to whether a firm's KZ index is above or below the industry median for that year. The *Slack* subsample includes all of the firms with a KZ index below the median for firms in the same year and industry, indicating they have fewer financial constraints than the median firm. The *Constraint* subsample includes all of the firms with a KZ index above the median for firms in the same year and industry, indicating they have more financial constraints than the median firm. Following Cleary (1999), we test the difference of coefficient estimate for *LCC* between *Slack* subsample and *Constraint* subsample, and the *P*-value of 0.000 for the full sample, P-value of 0.060 for overinvestment sample and P-value of 0.000 for underinvestment sample suggest that coefficient estimate of *LCC* is greater in *Slack* subsample. The results show that the effect of the LCC programme on labour inefficiency is stronger for firms with fewer financial constraints. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Labour intensity.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: INEFFICIENCY					
	Full Sample		Overinvestment		Underinvestment	
	High	Low	High	Low	High	Low
LCC	0.046***	0.021	0.135***	0.070	0.031***	0.011
	(2.89)	(1.41)	(2.92)	(1.47)	(2.63)	(1.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.019***	0.981***	−1.199	−0.049	2.959***	2.985***
	(3.51)	(3.95)	(−1.32)	(−0.06)	(14.64)	(19.16)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
P-value	0.005***		0.400		0.000***	
N	8527	13,769	2861	3879	5666	9890
Adj. R^2	0.219	0.262	0.193	0.247	0.612	0.643

Notes: This table reports the results for the difference in the effect of the LCC programme on labour inefficiency for firms with high versus low labour intensity. The *High* subsample includes the firms with labour intensity greater than the median of firms in the same year and industry, and the *Low* subsample includes the firms with lower labour intensity than the median of firms in the same year and industry. Labour intensity is measured as the number of employees divided by total assets at the end of year *t*-1 for firm *i*, following Pereira da Silva (2019). Following Cleary (1999), we test the difference of coefficient estimate for *LCC* between the *High* subsample and *Low* subsample, and the *P*-value of 0.005 for the full sample and P-value of 0.000 for the underinvestment sample suggest that the coefficient estimate of *LCC* is greater in *High labour intensity* subsample. The results show that effect of the LCC programme on labour inefficiency is stronger for firms with high labour intensity. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

to motivate them to enhance environmental performance and meet social expectations.

In addition to employee shareholding, we investigate other employee well-being strategies. Specifically, results are shown in Panel B of Table 15 that after the LCC implementation, firms significantly promote labour safety, which is reflected in fewer labour accidents, more effective safety management, and a greater likelihood of a firm's being certified in occupational safety. The results in Panel C of Table 15 indicate that firms complying with the LCC programme are motivated to improve their employees' skills through continuing vocational education and professional training.

To further validate our inference that firms complying with the LCC programme are more likely to hire skilled employees to promote their environmental engagement and reduce carbon emissions, we investigate firms' environmental governance after the LCC implementation. The results in Table 16 show that after the LCC implementation, firms are more likely to produce environmentally friendly products, use renewable energy, adopt a circular economy model, establish a green office, and implement new policies on energy savings and environmental protection.

Collectively, our study shows that the LCC programme significantly reduces labour investment efficiency in the short run but promotes human capital quality through the hiring of skilled employees and the implementation of favourable employee treatment policies and plans,

Table 11
Environmental penalties.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: INEFFICIENCY					
	Full Sample		Overinvestment		Underinvestment	
	Punish = 1	Punish = 0	Punish = 1	Punish = 0	Punish = 1	Punish = 0
LCC	0.316**	0.021*	0.455***	0.090***	0.145**	0.004
	(2.13)	(1.93)	(2.94)	(2.86)	(2.32)	(0.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.358	1.041***	−7.335***	−0.169	6.033***	3.162***
	(0.79)	(5.71)	(−2.75)	(−0.30)	(4.44)	(29.63)
P-value	0.000***		0.000***		0.000***	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	557	21,739	172	6568	385	15,171
Adj. R^2	0.334	0.247	0.725	0.259	0.605	0.638

Notes: This table reports the results for the difference in the effects of the LCC programme on labour inefficiency for firms that have incurred environmental penalties versus those that have not. The results show that the effect is stronger for firms that have previously received penalties. *Punish* equals 1 for firms that have been punished for environmental issues in a year, and the firm's observations in and after that year are allocated to the *Punish* subsample. Otherwise, *Punish* equals 0. Following Cleary (1999), we test the difference in the coefficient estimate for *LCC* between *Punish* subsample and *without-punish* subsample, and the *P*-value of 0.000 suggests that the coefficient estimate of *LCC* is greater in *Punish* subsample. The results show that effect of the LCC programme on labour inefficiency is stronger for firms with environmental penalties. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12
Effect of the LCC programme on human capital quality.

	(1)	(2)	(3)
	Dependent variable: LABORQUALITY		
	Full Sample	Overinvestment	Underinvestment
LCC	0.038***	0.040***	0.038***
	(7.24)	(4.83)	(6.43)
Controls	Yes	Yes	Yes
Constant	−0.453***	−0.473***	−0.373***
	(−4.82)	(−3.54)	(−3.59)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,296	6740	15,556
Adj.R^2	0.605	0.628	0.607

Notes: This table reports the DiD regression results for the impact of the LCC programme on firms' human capital quality. Following Winters (2011), *LABORQUALITY* is calculated as the proportion of all rank-and-file employees with an education level higher than or equal to a bachelor's degree, and a higher value of *LABORQUALITY* suggests higher human capital quality. We divide the full sample into two subsamples: *Overinvestment* includes the firms with more employees than predicted, and *Underinvestment* includes the firms with fewer employees than predicted. The results show that the firms in both subsamples have higher human capital quality after the LCC implementation. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

eventually generating real impacts on firms' environmental governance.

6. Conclusion

Lowering carbon emissions is an increasingly important global issue of great interest to standard setters, policy makers, regulators, researchers, and practitioners. To further enrich the growing body of literature on carbon-emissions regulation, this study focuses on the real impact of the LCC programme on investment decisions related to human capital, which constitutes a key factor of firms' competitive advantages. Employees, as one of the most important groups of stakeholders in firms, play a critical role in addressing firms' environmental issues and implementing net-zero strategies.

Specifically, employing the event of the LCC programme staggered implemented across provinces in China as a quasi-natural shock, we adopt a powerful DiD approach to investigate how carbon emissions reduction initiatives affect labour investment decisions. First, we examine how the LCC programme affects labour investment efficiency. Our results indicate that labour investment is significantly less efficient for firms complying with the LCC programme after its implementation.

A series of robustness tests have been conducted to validate the sensitivity of our main results. First, dynamic analysis is conducted to examine whether the causal inference of our DiD estimation applies the parallel trend assumption. Second, to balance the covariates across the treatment and control groups, we use entropy balancing to create a matched sample and rerun the regression, and the results support our baseline conclusion. Third, to mitigate spurious correlations and confounding factors in terms of other contemporaneous environmental regulations, we conduct the following two placebo tests. We first construct fictitious timing of the LCC implementation by randomly assigning a fictitious timing to the treatment firms. We also construct a fictitious treatment group by randomly assigning three batches of LCC implementation to firms in the control group. The results of these tests eliminate the impact of potential confounding events on labour investment inefficiency. Fourth, we incorporate city and industry-by-year fixed effects to control for unobserved factors at the city level and time-specific factors at the industry level. Fifth, we address the omitted variable concern following Oster (2019).

To distinguish potential factors influencing the relationship between initiatives to lower carbon emissions and labour investment inefficiency, we adopt a series of cross-sectional tests. First, we investigate how financial constraints and financial slack affect our baseline inferences. We do not find a significant effect of financial constraints on labour investment efficiency. However, we observe a stronger effect of the LCC programme on labour investment inefficiency in firms with financial slack than for their peers. Second, we observe a stronger effect of the LCC programme on labour investment inefficiency in labour-intensive firms relative to their peers. Third, the LCC programme has a more significant influence on labour investment inefficiency for firms headquartered in regions with greater pressure to reduce carbon emissions and firms that have incurred government penalties for environmental violations.

Interestingly, although we find that the LCC programme reduces labour investment efficiency in the short run, it significantly improves

Table 13
Mechanisms of the LCC programme's effect on human capital quality.

Panel A: Excess Perks

	(1)	(2)
	ABPERK	Labourquality_Growth
LCC	−0.001**	
	(−2.10)	
LCC* HighΔPERK (β1)		0.236***
		(3.40)
LCC* LowΔPERK (β2)		0.024
		(0.50)
Controls	Yes	Yes
Constant	0.027***	−1.441**
	(4.48)	(−2.41)
F: β_1 - β_2 (p-value)		0.0033***
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	22,296	22,296
Adj. R^2	0.012	0.076

Panel B: Green Innovation Investment

	(1)	(2)
	Patent	LABORQUALITY
LCC	0.066***	
	(2.86)	
LCC* HighΔPatent (β1)		0.387**
		(1.99)
LCC* LowΔPatent (β2)		−0.031
		(−0.21)
Control	Yes	Yes
Constant	−3.961***	−13.256**
	(−9.18)	(−2.00)
F: β_1 - β_2 (*p*-value)		0.0669*
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	22,296	22,296
Adj.R^2	0.185	0.018

Panel C: Environmental Pressure

	(1)	(2)
	EnvPressure	Labourquality_Growth
LCC	0.020**	
	(2.08)	
LCC* HighΔEnvPressure (β1)		0.340***
		(2.76)
LCC* LowΔEnvPressure (β2)		−0.010
		(−0.05)
Controls	Yes	Yes
Constant	0.639***	−13.470**
	(4.95)	(−2.00)
F: β_1 - β_2 (*p*-value)		0.0857*
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	22,296	22,296
Adj.R^2	0.137	0.018

Notes: This table reports the regression results for the test of a proposed mechanism by which the LCC programme affects firms' human capital quality. *HighΔPERK* equals 1 if a treated firm's change in excess perk consumption (*ABPERK*) from before to after the LCC implementation is greater than the median for the treatment group, and 0 otherwise. *LowΔPERK* equals 1 if a treated firm's change in *ABPERK* from before to after the LCC implementation is less than the median for the treatment group and 0 otherwise. The results show that the effect of the LCC pilot programme on firms' human capital quality is through the channel of decreasing perk consumption by managers. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: This table reports the regression results for the test of a proposed mechanism by which the LCC programme affects firms' human capital quality. *HighΔPatent* equals 1 if a treated firm's change in the number of green patent applications (*Patent*) from before to after the LCC implementation is greater than the median for the treatment group, and 0 otherwise. *LowΔPatent* equals 1 if a treated firm's change in *Patent* from before to after the LCC implementation is less than the median for the treatment group, and 0 otherwise. The results show that the effect of the LCC pilot programme on firms' human capital quality is through the channel of increasing green patent applications. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: This table reports the regression results for the test of a proposed mechanism by which the LCC programme affects firms' human capital quality. We use the environmental regulatory index of a zone where firms are located to measure a firm's environmental pressure (*EnvPressure*). *HighΔEnvPressure* equals 1 if a treated firm's change in environmental pressure (*EnvPressure*) from before to after the LCC implementation is greater than the median for the treatment group, and 0 otherwise. *LowΔEnvPressure* equals 1 if a treated firm's change in *EnvPressure* from before to after the LCC implementation is less than the median for the treatment group and 0 otherwise. The results show that the effect of the LCC pilot programme on firms' human capital quality is through the channel of heightened carbon reduction pressure. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 14
Influence of institutional investors.

	(1)	(2)
	Labourquality_Growth	Labourquality_Growth
	HighIns	LowIns
LCC	0.245**	0.057
	(2.20)	(0.24)
Controls	Yes	Yes
Constant	0.434	−1.957
	(0.20)	(−1.13)
Firm FE	Yes	Yes
Year FE	Yes	Yes
P-value	0.000***	
N	11,223	11,073
Adj. R^2	0.097	0.037

Notes: This table reports the results for the difference in the effect of the LCC programme on labour quality for firms with more versus less institutional shareholding. The *HighIns* subsample includes firms with more institutional investors than the median of firms in the same year and industry, and the *LowIns* subsample includes those with fewer institutional investors than the median. Following Cleary (1999), we test the difference of coefficient estimate for *LCC* between *HighIns* subsample and *LowIns* subsample, and the *P*-value of 0.000 suggests that coefficient estimate of *LCC* is greater in *HighIns* subsample. The results show that effect is stronger for firms with more institutional shareholders. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

firms' labour structure, as reflected in the hiring of more highly skilled employees, and this is particularly true for firms with more institutional investors shareholding. The underlying economic mechanisms are the mitigation of excess perks, increased green innovation investment, and heightened carbon reduction pressure after the LCC programme has been implemented, which motivates better decisions related to labour structure. We also provide evidence that the LCC programme motivates

Table 15
Employee Well-being.

Panel A: Employee Shareholding

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Employee shareholding				
	Full Sample	SOE	Non-SOE	High LABORQUALITY	Low LABORQUALITY
LCC	0.099**	−0.036	0.242***	0.243***	−0.001
	(2.04)	(−0.71)	(2.86)	(2.65)	(−0.03)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	−4.958***	−1.884**	−5.159***	−7.754***	−3.898***
	(−5.89)	(−2.09)	(−4.08)	(−5.07)	(−3.84)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
P-value		0.000***		0.000***	
N	22,296	11,792	10,504	11,145	11,151
Adj. R^2	0.162	0.058	0.243	0.163	0.158

Panel B: Safety at Work

	(1)	(2)	(3)
	ACCIDENT	SAFEMANAGE	SAFECERTIFICAT
LCC	−0.522**	0.213**	0.251**
	(−2.34)	(2.22)	(1.99)
Controls	Yes	Yes	Yes
Constant	−5.573***	−21.837***	−16.861***
	(−2.69)	(−18.76)	(−13.35)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,296	22,296	22,296
Pseudo R^2	0.098	0.199	0.107

Panel C: Vocational Education and Training

	(1)	(2)	(3)	(4)	(5)	(6)
	VOCEDU			VOCTRAIN		
	Full sample	Overinvestment	Underinvestment	Full sample	Overinvestment	Underinvestment
LCC	0.215**	0.389***	0.119	0.189**	0.387***	0.088
	(2.26)	(3.19)	(1.11)	(2.01)	(3.23)	(0.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−20.983***	−22.042***	−19.995***	−23.567***	−25.605***	−22.462***
	(−17.75)	(−12.76)	(−14.54)	(−19.84)	(−15.64)	(−16.78)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22,296	6740	15,556	22,296	6740	15,556
Pseudo R^2	0.184	0.215	0.157	0.238	0.285	0.202

Notes: This table reports the regression results for the impact of the LCC programme on firms' employee shareholding. Employee shareholding is measured as the percentage of a firm's shares held by its employees. The results in Column (1) show that employee shareholding increases significantly after the LCC implementation. Following Cleary (1999), we test the difference of coefficient estimate for *LCC* between the *SOE* subsample and *Non-SOE* subsample, as well as the coefficient estimate for *LCC* between *High LABORQUALITY* subsample and *Low LABORQUALITY* subsample and the P-value of 0.000 suggests the significant difference between subsamples. The results in Columns (2) and (3) show that the effect of the LCC programme on employee shareholding is stronger in non-SOEs. We divide our sample into high and low *LABORQUALITY* subsamples according to the median of *LABORQUALITY*, and the results in Columns (4) and (5) show that the effect is also stronger for firms with high labour quality before the LCC implementation. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: This table reports the regression results for the impact of the LCC programme on firm safety, and the results show that there are significant improvements in safety management and fewer accidents after the LCC implementation. *ACCIDENT* equals 1 if a firm experiences any serious safety production accidents in year *t*, and 0 otherwise. *SAFEMANAGE* equals 1 if a firm adopted a safety management system in year *t*, and 0 otherwise. *SAFECERTIFICAT* equals 1 if a firm became certified in occupational safety in year *t*, and 0 otherwise. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: This table reports the regression results for the impact of the LCC programme on vocational education and training for employees, and the results show that employees are more likely to receive vocational education and training after the LCC implementation, especially in firms that are overinvested in labour after the LCC implementation. *VOCEDU* equals 1 if a firm provides vocational education for employees, and 0 otherwise. *VOCTRAIN* equals 1 if a firm provides vocational training for employees, and 0 otherwise. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 16
Post-implementation environmental governance progress.

	(1)	(2)	(3)	(4)
	ECOPRODUCT	RECYCLE	ENERGYSAVE	GREENOFFICE
LCC	0.125**	0.115**	0.129**	0.157***
	(2.42)	(2.04)	(2.46)	(2.75)
Controls	Yes	Yes	Yes	Yes
Constant	−12.549***	−12.430***	−13.119***	−7.857***
	(−22.54)	(−19.68)	(−20.74)	(−12.20)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	22,296	22,296	22,296	22,296
Adj. R^2	0.225	0.203	0.238	0.119

Notes: This table reports the regression results for the impact of the LCC programme on firms' environmental governance after the LCC implementation, and the results show that firms take multiple environmental protection measures after the LCC implementation. *ECOPRODUCT* equals 1 if a firm develops or uses environmentally friendly products, devices, or technology, and 0 otherwise. *RECYCLE* equals 1 if a firm enacts policies and measures to use renewable energy or adopts a circular economy model, and 0 otherwise. *ENERGYSAVE* equals 1 if a firm implements energy-saving policies, measures, or technologies, and otherwise 0. *GREENOFFICE* equals 1 if a firm establishes green office policies or measures, and 0 otherwise. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year-fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

firms to enhance employees' well-being by granting employees stock options and stock ownership plans, enhancing employee safety, providing vocational education and professional training, and strengthening environmental governance.

Overall, our results contribute to a growing body of literature that suggests that regulations to reduce carbon emissions can play an important role in firms' investment decisions and have real economic consequences. This study has important implications for the double materiality concept in the ISSB Sustainability Disclosure Standards, as it empirically supports the effects of firms' low carbon and sustainability strategies on factors such as human capital quality and employee well-being. We also provide regulators with *ex-ante* evidence on improving the effectiveness of the LCC programme or other carbon emissions policies. Finally, as the zero-carbon goal becomes a globally accepted goal, this study's findings will be of interest to international investors and regulators.

CRediT authorship contribution statement

June Cao: Conceptualization, Methodology, Supervision, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Validation, Writing - original draft, Writing - review & editing. **Wenwen Li:** Conceptualization, Methodology, Data curation, Formal analysis, Funding acquisition, Investigation, Software, Validation, Visualization, Writing - review & editing. **Iftekhar Hasan:** Conceptualization, Supervision, Formal analysis, Project administration, Validation, Writing - review & editing.

Acknowledgement

Dr. Wenwen Li and Dr. June Cao would like to acknowledge financial support from Jiangsu University Philosophy and Social Science Research Project (Grant No. 2022SJYB0354); Nanjing Audit University Research and Cultivation Program for Young Teachers (Grant No. 2021QNPY013); Nanjing Audit University Special Project for Internationalization (Grant No. 22GJHGY11); Nanjing Audit University Research Project of Higher Education (2022JG033). Dr. Wenwen Li would like to acknowledge financial support from National Natural Science Foundation of China (Grant No. 72272077); Dr. June Cao would like to acknowledge financial support from School of Accounting, Economics and Finance of Curtin University. We would like to thank Zheng Qiao, Ziye Huang (discussant) and all participants of *2023 China Accounting and Finance Conference* for their valuable comments and suggestions.

Appendix A

Table A1
Variable definitions.

Variable	Definition
Variables used in the estimation of Eq. (1)	
NETHIRE	The percentage change in the number of firm employees from year *t*-1 to *t* for firm *i* (Jung et al., 2014)
ROA	A firm's net income divided by its beginning-of-year total assets
ΔROA	The change in a firm's ROA
RETURN	A firm's total annual return
SIZE_R	The percentile rank of the natural logarithm of a firm's market value of equity
LEV	A firm's long-term debt divided by its total assets
QUICK	The quick ratio, measured as the sum of cash, short-term investments, and receivables divided by current liabilities, in year t for firm i
ΔQUICK	The change in a firm's quick ratio
SALES_GROWTH	The percentage change in a firm's sale revenues
LOSSBIN1	An indicator variable that equals 1 if a firm's ROA in the previous year is between −0.005 and 0, and 0 otherwise
LOSSBIN2	An indicator variable that equals 1 if a firm's ROA in the previous year is between −0.01 and − 0.005, and 0 otherwise
LOSSBIN3	An indicator variable that equals 1 if a firm's ROA in the previous year is between −0.015 and − 0.01, and 0 otherwise
LOSSBIN4	An indicator variable that equals 1 if a firm's ROA in the previous year is between −0.02 and − 0.015, and 0 otherwise
LOSSBIN5	An indicator variable that equals 1 if a firm's ROA in the previous year is between −0.025 and − 0.02, and 0 otherwise
Variables used in the baseline regression	
ABNETHIRE	The residuals obtained from the estimation of Eq. (1), following Jung et al. (2014)
INEFFICIENCY	The absolute value of AbNetHire
LABORQUALITY	A firm's human capital quality, calculated as the proportion of all rank-and-file employees with an education level higher than or equal to a bachelor's degree
Labourquality_Growth	The percentage change in proportion of all rank-and-file employees with an education level higher than or equal to a bachelor's degree from year t-1 to t for firm i
LCC	An indicator variable that equals 1 if a firm's headquarters is in a city subject to the LCC pilot programme in year t (treatment group), and 0 otherwise (control group)
SIZE	A firm's size, measured as the log of the sum of 1 plus the firm's total assets
LEV	A firm's long-term debt divided by its total assets
ROA	A firm's net income divided by its beginning-of-year total assets

(*continued on next page*)

Table A1 (*continued*)

Variable	Definition
LOSS	An indicator variable that equals 1 if a firm has negative profit, and 0 otherwise
SALES_GROWTH	The percentage change in a firm's sale revenues
QUICK	The quick ratio, measured as the sum of cash, short-term investments, and receivables divided by current liabilities, in year *t* for firm *i*
SEGMENT	The natural log of the number of segments
DIVIDEND	An indicator variable that equals 1 if the firm pays dividends, and 0 otherwise
SOE	An indicator variable that equals 1 if a firm is state-owned, and 0 otherwise
TOP1	The percentage of shares held by the largest shareholder
INS	The percentage of shares held by institutional investors
BOARD	The natural log of board size
INDPR	The proportion of independent directors (the ratio of independent directors to the total number of directors)
DUAL	An indicator variable that equals 1 if the chairman of the board is also the general manager, and 0 otherwise
BIGN	An indicator variable that equals 1 if the company is audited by a top-4 global audit firm or a top-10 local audit firm in China, and 0 otherwise
INTENSITY	Labour intensity, measured as the number of employees divided by total assets at the end of year *t*-1 for firm *i*
MASTERGROWTH	The percentage change in the number of employees with a master's degree or above from year *t*-1 to year *t* for firm *i*
BACHEGROWTH	The percentage change in the number of employees with a bachelor's degree from year *t*-1 to *t* for firm *i*
OTHERGROWTH	The percentage change in the number of employees with degrees below a bachelor's from year *t*-1 to *t* for firm *i*
Variables used in the economic channel tests	
ABPERK	A firm's excess perk consumption, calculated by Eq. (1), following Xu et al. (2014)
High∆PERK	An indicator variable that equals 1 if a treated firm's change in *ABPERK* from before to after the LCC implementation is above the median for the treatment group, and 0 otherwise
Low∆PERK	An indicator variable that equals 1 if a treated firm's change in *ABPERK* from before to after the LCC implementation is below the median for the treatment group, and 0 otherwise
Patent	The number of green patent application, indicating green innovation investment
High∆Patent	An indicator variable that equals 1 if a treated firm's change in *Patent* from before to after the LCC implementation is above the median for the treatment group, and 0 otherwise
Low∆Patent	An indicator variable that equals 1 if a treated firm's change in *Patent* from before to after the LCC implementation is below the median for the treatment group, and 0 otherwise
EnvPressure	The environmental regulatory index of a zone where firms located
High∆EnvPressure	An indicator variable that equals 1 if a treated firm's change in *EnvPressure* from before to after the LCC implementation is above the median for the treatment group, and 0 otherwise
Low∆EnvPressure	An indicator variable that equals 1 if a treated firm's change in *EnvPressure* from before to after the LCC implementation is below the median for the treatment group, and 0 otherwise
Variables used in the endogeneity correction and subsample analyses	
LCC-3	A categorical variable indicating three years prior to treatment
LCC-2	A categorical variable indicating two years prior to treatment
LCC-1	A categorical variable indicating one year prior to treatment
LCC0	A categorical variable indicating the year of treatment
LCC1	A categorical variable indicating one year after treatment
LCC2	A categorical variable indicating two years after treatment
LCC3	A categorical variable indicating three years after treatment
FLCC1	A fabricated LCC variable constructed by randomly assigning event years to the firms in the treatment group
FLCC2	A fabricated LCC variable constructed by randomly assigning event years to the control group
Punish	An indicator variable that equals 1 if a firm was punished for environmental issues in a year, and 0 otherwise; the observations in and after the punishment year are allocated to the *Punish* subsample
Variables used in the additional analyses	
SHAREHOLDING	The number of employee shareholders in logarithm form
ACCIDENT	An indicator variable that equals 1 if a firm experienced serious safety accidents in year *t*, and 0 otherwise
SAFEMANAGE	An indicator variable that equals 1 if a firm adopted a safety management system in year *t*, and 0 otherwise
SAFECERTIFICAT	An indicator variable that equals 1 if a firm became certified in occupational safety in year *t*, and 0 otherwise
VOCEDU	An indicator variable that equals 1 if a firm provides vocational education for employees, and 0 otherwise
VOCTRAIN	An indicator variable that equals 1 if a firm provides vocational training for employees, and 0 otherwise
ECOPRODUCT	An indicator variable that equals 1 if a firm develops or uses environmentally friendly products, devices, or technology, and 0 otherwise
RECYCLE	An indicator variable that equals 1 if a firm has policies and takes measures to use renewable energy or adopts a circular economy model, and 0 otherwise
ENERGYSAVE	An indicator variable that equals 1 if a firm has policy measures or technologies to save energy, and 0 otherwise
GREENOFFICE	An indicator variable that equals 1 if a firm has green office policies or measures, and 0 otherwise

Table A2
Financial constraints and financial slack.

Panel A: Financial constraints								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: INEFFICIENCY							
	Over-hiring		Under-firing		Under-hiring		Over-firing	
	Low	High	Low	High	Low	High	Low	High
LCC	0.161***	0.044	0.000	−0.022	0.023	0.007	0.035***	0.007
	(2.69)	(0.70)	(0.01)	(−0.66)	(1.48)	(0.53)	(2.62)	(0.66)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−3.219***	0.339	−3.516***	−1.674*	2.296***	2.974***	2.929***	3.390***
	(−2.85)	(0.31)	(−3.48)	(−1.95)	(5.36)	(14.23)	(8.81)	(19.64)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A2 (*continued*)

Panel A: Financial constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: INEFFICIENCY							
	Over-hiring		Under-firing		Under-hiring		Over-firing	
	Low	High	Low	High	Low	High	Low	High
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2340	2761	549	1054	3378	3841	3096	5016
Adj. R^2	0.331	0.190	0.332	0.368	0.687	0.720	0.746	0.732

Panel B: Financial slack

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: INEFFICIENCY							
	Over-hiring		Under-firing		Under-hiring		Over-firing	
	High	Low	High	Low	High	Low	High	Low
LCC	0.124**	0.030	−0.015	−0.014	0.026*	0.014	0.030**	0.017
	(2.10)	(0.49)	(−0.36)	(−0.48)	(1.85)	(0.99)	(2.56)	(1.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.792	−0.730	−2.984***	−1.670***	3.044***	2.657***	3.216***	3.181***
	(−0.72)	(−0.64)	(−3.82)	(−3.90)	(9.10)	(8.64)	(13.36)	(13.81)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1983	2145	583	539	3232	3076	3567	3694
Adj. R^2	0.317	0.302	0.732	0.584	0.796	0.787	0.843	0.824

Notes: This table reports the results for the difference in the effect of the LCC programme on labour inefficiency for firms with high versus low financial constraints. Following Pereira da Silva (2019), we compute a firm's KZ index score using the model in Rajan and Zingales (1998), and a higher score indicates greater financial constraints. We split the sample according to whether a firm's score is above or below the industry median for the year. The *Low* subsample includes the firms with a score lower than the industry median that year. The *High* subsample includes the firms with a score higher than the industry median for that year. The results show that the effect of the LCC implementation on labour inefficiency (i.e., *over-hiring* and *over-firing*) is stronger for the less financially constrained firms. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
Notes: This table reports the results for the difference in the effects of the LCC programme on labour inefficiency in firms with high versus low financial slack. Following Kim and Bettis (2014), Financial slack, or cash holdings, is measured as the ratio of cash and marketable securities to current liabilities. The sample is divided into two subsamples according to the median value of a firm's financial slack. The *High* subsample includes all of the firms with greater slack than the median of firms in the same year and industry, and the *Low* subsample includes all of the firms with less slack than the median of firms in the same year and industry. The results show that the effect of the LCC programme on labour inefficiency (i.e., over-hiring, under-hiring, and over-firing) is stronger for the firms with low financial slack. Robust standard errors (clustered at the firm level and robust to heteroskedasticity) are in parentheses. The variable definitions are in Table A1. The continuous variables are winsorised at 1% and 99%. Firm and year fixed effects are included in the regression estimations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3
Regression results for Eq. 1 (Dependent variable = NetHire).

	Coeff.	*P*-value
Constant	−0.0231	0.705
$SALES\_GROWTH_{t}$	0.3445	0.000
$SALES\_GROWTH_{t-1}$	0.0000	0.619
ROA_t	0.3881	0.000
ΔROA_{t-1}	−0.0007	0.857
ΔROA_t	−0.2355	0.000
$SIZE\_R_{t-1}$	0.0024	0.381
$RETURN_t$	0.0150	0.022
$QUICK_{t-1}$	−0.0028	0.111
$\Delta QUICK_{t-1}$	0.0027	0.092
$\Delta QUICK_t$	−0.0152	0.000
LEV_{t-1}	−0.0514	0.011
$LOSSBIN1_{t-1}$	−0.0251	0.480
$LOSSBIN2_{t-1}$	−0.0229	0.568
$LOSSBIN3_{t-1}$	−0.0668	0.146
$LOSSBIN4_{t-1}$	−0.0029	0.948
$LOSSBIN5_{t-1}$	−0.0694	0.126
Industry FE		Yes
Adj. R^2		14.09%
N		22,296

Notes: This table reports the estimation results for Eq. (1). The signs of the explanatory variables are consistent with those reported in prior studies, suggesting that our labour investment model is well estimated. ROA, stock returns, lagged change in the quick ratio, sales growth, and lagged sales growth are statistically significant and positively associated with net hiring, whereas leverage, change in ROA, lagged change in ROA, the change in the quick ratio, and loss bins are negatively associated with net hiring. The coefficient *QUICK* is negative which differs from the results in prior studies.

Table A4
Propensity score matching.

	(1)	(2)	(3)
	Dependent variable: INEFFICIENCY		
	Full Sample	Overinvestment	Underinvestment
LCC	0.037***	0.111***	0.018***
	(3.16)	(3.17)	(2.64)
Controls	Yes	Yes	Yes
Constant	0.929***	−0.639	2.971***
	(4.31)	(−1.01)	(23.04)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	18,224	5580	12,644
Adj.R^2	0.237	0.261	0.622

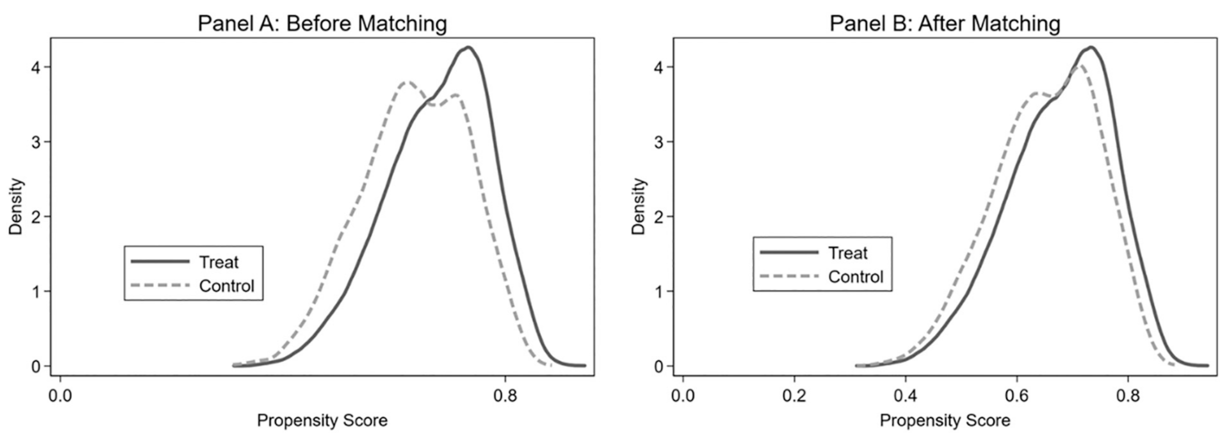

Fig. A. The density distribution.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106653.

References

Ambec, S., Cohen, M.A., Elgie, S., Lanoie, P., 2013. The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? Rev. Environ. Econ. Policy 7, 2–22.

Anderson, M.C., Banker, R.D., Janakiraman, S.N., 2003. Are selling, general, and administrative costs 'sticky'? J. Account. Res. 41 (1), 47–63.

Armstrong, C.S., Balakrishnan, K., Cohen, D., 2012. Corporate governance and the information environment: evidence from state antitakeover laws. J. Account. Econ. 53, 185–204.

Basu, R., Naughton, J.P., Wang, C., 2022. The regulatory role of credit ratings and voluntary disclosure. Account. Rev. 97 (2), 25–50.

Beck, T., Levine, R., Levkov, A., 2010. Big bad banks? The winners and losers from bank deregulation in the United States. J. Financ. 65 (5), 1637–1667.

Beck, M.J., Nicoletti, A.K., Stuber, S.B., 2022. The role of audit firms in spreading depositor contagion. Account. Rev. 97 (4), 51–73.

Becker, C.L., DeFond, M.L., Jiambalvo, J., Subramanyam, K.R., 1998. The effect of audit quality on earnings management. Contemp. Account. Res. 15 (1), 1–24.

Benmelech, E., Bergman, N.K., Seru, A., 2011. Financing Labour (Working Paper No. w17144). National Bureau of Economic Research. https://www.nber.org/papers/w17144.

Ben-Nasr, H., Alshwer, A.A., 2016. Does stock price informativeness affect labour investment efficiency? J. Corp. Finan. 38, 249–271.

Bergman, N.K., Jenter, D., 2007. Employee sentiment and stock option compensation. J. Financ. Econ. 84 (3), 667–712.

Bernanke, B.S., 2004. Monetary Policy and the Economic Outlook. Speech Delivered at the Meetings of the American Economic Association, San Diego, California, January 4. Available online at: http://www.federalreserve.gov/boarddocs/speeches/2004/20040104/default.htm (retrieved on 28 July 2022).

Bertrand, M., Mullainathan, S., 2003. Enjoying the quiet life? Corporate governance and managerial preferences. J. Polit. Econ. 111 (5), 1043–1075.

Biddle, G.C., Hilary, G., 2006. Accounting quality and firm-level capital investment. Account. Rev. 81 (5), 963–982.

Biddle, G.C., Hilary, G., Verdi, R.S., 2009. How does financial reporting quality relate to investment efficiency? J. Account. Econ. 48 (2–3), 112–131.

Brunnermeier, S.B., Cohen, M.A., 2003. Determinants of environmental innovation in US manufacturing industries. J. Environ. Econ. Manag. 45, 278–293.

Caggese, A., Cuñat, V., Metzger, D., 2019. Firing the wrong workers: financing constraints and labour misallocation. J. Financ. Econ. 133 (3), 589–607.

Cao, Z., Rees, W., 2020. Do employee-friendly firms invest more efficiently? Evidence from labor investment efficiency. J. Corp. Finan. 65, 101744.

Cao, W., Wang, H., Ying, H., 2017. The effect of environmental regulation on employment in resource-based areas of China–an empirical research based on the mediating effect model. Int. J. Environ. Res. Public Health 14 (12), 1598.

Cao, J., Li, W., Bilokha, A., 2022. Low-carbon city initiatives and analyst behaviour: a quasi-natural experiment. J. Financ. Stab. 101042.

Carbone, J.C., Rivers, N., Yamazaki, A., Yonezawa, H., 2020. Comparing applied general equilibrium and econometric estimates of the effect of an environmental policy shock. J. Assoc. Environ. Resour. Econ. 7 (4), 687–719.

Cazier, R.A., Merkley, K.J., Treu, J.S., 2020. When are firms sued for qualitative disclosures? Implications of the safe harbor for forward-looking statements. Account. Rev. 95 (1), 31–55.

Chakraborty, P., Chatterjee, C., 2017. Does environmental regulation indirectly induce upstream innovation? New evidence from India. Res. Policy 46, 939–955.
Chen, S., Sun, Z., Wang, Y., 2002. Evidence from China on whether harmonized accounting standards harmonize accounting practices. Account. Horiz. 16 (3), 183–197.
Cleary, S., 1999. The relationship between firm investment and financial status. J. Financ. 54 (2), 673–692.
Cohen, S., Kadach, I., Ormazabal, G., Reichelstein, S., 2022, 1 April. Executive Compensation Tied to ESG Performance: International Evidence (Finance Working Paper No. 825/2022). European Corporate Governance Institute. SSRN: https://ssrn.com/abstract=4097202.
DeFusco, A.A., 2018. Homeowner borrowing and housing collateral: new evidence from expiring price controls. J. Financ. 73 (2), 523–573.
Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., Zaklan, A., 2021. The impact of carbon disclosure mandates on emissions and financial operating performance. Rev. Acc. Stud. 26 (3), 1137–1175.
Drucker, P.F., 1954. The Practice of Management. Harper Business.
Dupré, S., Chenet, H., 2012. Connecting the dots between climate goals, portfolio allocation and financial regulation. In: Portfolio Allocation and Financial Regulation.
Edwards, A., Todtenhaupt, M., 2020. Capital gains taxation and funding for start-ups. J. Financ. Econ. 138 (2), 549–571.
Fan, R., Weng, R., Pan, J., 2022. How property rights affect firm's labour investment efficiency? Evidence from a property law enactment in China. Emerg. Mark. Financ. Trade 58 (2), 381–397.
Ferri, F., Zheng, R., Zou, Y., 2018. Uncertainty about managers' reporting objectives and investors' response to earnings reports: evidence from the 2006 executive compensation disclosures. J. Account. Econ. 66, 339–365.
Fu, Y., He, C., Luo, L., 2021. Does the low-carbon city policy make a difference? Empirical evidence of the pilot scheme in China with DEA and PSM-DID. Ecol. Indic. 122, 107238.
Ghaly, M., Dang, V.A., Stathopoulos, K., 2015. Cash holdings and employee welfare. J. Corp. Finan. 33, 53–70.
Ghaly, M., Dang, V.A., Stathopoulos, K., 2020. Institutional investors' horizons and corporate employment decisions. J. Corp. Finan. 64, 101634.
Gray, W.B., Shadbegian, R.J., 1993. Environmental Regulation and Manufacturing Productivity at the Plant Level (Working Paper No. 4321). National Bureau of Economic Research.
Gul, F.A., Cheng, L.T., Leung, T.Y., 2011. Perks and the informativeness of stock prices in the Chinese market. J. Corp. Finan. 17 (5), 1410–1429.
Guo, S., Song, Q., Qi, Y., 2021. Innovation or implementation? Local response to low-carbon policy experimentation in China. Rev. Policy Res. 38 (5), 555–569.
Ha, J., Feng, M., 2018. Conditional conservatism and labour investment efficiency. J. Contemp. Account. Econ. 14 (2), 143–163.
Hainmueller, J., 2012. Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Polit. Anal. 20 (1), 25–46.
Hamermesh, D.S., 1989. What do we know about worker displacement in the US? Ind. Relat.: J. Econ. Soc. 28 (1), 51–59.
Hamermesh, D.S., 1996. Labour demand. Princeton University Press.
Hamermesh, D.S., Pfann, G.A., 1996. Adjustment costs in factor demand. J. Econ. Lit. 34 (3), 1264–1292.
Hochberg, Y.V., Lindsey, L., 2010. Incentives, targeting, and firm performance: an analysis of non-executive stock options. Rev. Financ. Stud. 23 (11), 4148–4186.
Hong, M., Chen, S., Zhang, K., 2021. Impact of the 'low-carbon city pilot' policy on energy intensity based on the empirical evidence of Chinese cities. Front. Environ. Sci. 9, 717737.
Huang, J., Cao, J., Hasan, T., Zhao, J., 2021a. Low-carbon city initiatives and firm risk: a quasi-natural experiment in China. J. Financ. Stab. 57, 100949.
Huang, J., Zhao, J., Cao, J., 2021b. Environmental regulation and corporate R&D investment—evidence from a quasi-natural experiment. Int. Rev. Econ. Financ. 72, 154–174.
International Energy Agency (IEA), 2021. An Energy Sector Roadmap to Carbon Neutrality in China. https://www.iea.org/reports/an-energy-sector-roadmap-to-carbon-neutrality-in-china.
Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: A panel data study. Rev. Econ. Stat. 79, 610–619.
Jensen, M.C., 1986. Agency costs of free cash flow, corporate finance, and takeovers. Am. Econ. Rev. 76 (2), 323–329.
John, K., Li, Y., Pang, J., 2017. Does corporate governance matter more for high financial slack firms? Manag. Sci. 63 (6), 1872–1891.
Jung, B., Lee, W.J., Weber, D.P., 2014. Financial reporting quality and labour investment efficiency. Contemp. Account. Res. 31 (4), 1047–1076.
Khan, Z., Ali, S., Dong, K., Li, R.Y.M., 2021. How does fiscal decentralization affect CO_2 emissions? The roles of institutions and human capital. Energy Econ. 94, 105060.
Khedmati, M., Sualihu, M.A., Yawson, A., 2020. CEO-director ties and labour investment efficiency. J. Corp. Finan. 65, 101492.
Kim, C., Bettis, R.A., 2014. Cash is surprisingly valuable as a strategic asset. Strateg. Manag. J. 35, 2053–2063.
Kim, H., Kim, H., Lee, P.M., 2008. Ownership structure and the relationship between financial slack and R&D investments: evidence from Korean firms. Organ. Sci. 19 (3), 404–418.
Kneller, R., Manderson, E., 2012. Environmental regulations and innovation activity in UK manufacturing industries. Resour. Energy Econ. 34, 211–235.
Kong, D.M., Wang, Y.N., 2021. Employee Stock Ownership Plans and Corporate Environmental Engagement. Woking Paper. SSRN: https://ssrn.com/abstract=3915366.
Kong, D., Liu, S., Xiang, J., 2018. Political promotion and labour investment efficiency. China Econ. Rev. 50, 273–293.
Kyung, H., Lee, H., Marquardt, C., 2019. The effect of voluntary clawback adoption on non-GAAP reporting. J. Account. Econ. 67, 175–201.
Le, A.T., Tran, T.P., 2021. Corporate governance and labour investment efficiency: international evidence from board reforms. Corp. Gov.: Int. Rev. 30 (5), 555–583.
Li, W., Chen, X., Huang, J., Gong, X., Wu, W., 2022. Do environmental regulations affect firm's cash holdings? Evidence from a quasi-natural experiment. Energy Econ. 112, 106151.
Luo, J., Li, X., Chan, K.C., 2020. Political uncertainty and labour investment efficiency. Appl. Econ. 52 (43), 4677–4697.
Oi, W.Y., 1962. Labour as a quasi-fixed factor. J. Polit. Econ. 70 (6), 538–555.
Oster, E., 2019. Unobservable selection and coefficient stability: theory and evidence. J. Bus. Econ. Stat. 37 (2), 187–204.
Oyer, P., 2004. Why do firms use incentives that have no incentive effects? J. Financ. 59 (4), 1619–1650.
Pereira da Silva, P., 2019. Corporate Social Responsibility and Labour Investment Efficiency. Woking Paper (Available at SSRN 3418906).
Pfeffer, J., 1994. Competitive advantage through people. Calif. Manag. Rev. 36 (2), 9–28.
Pfeffer, J., Veiga, J.F., 1999. Putting people first for organizational success. Acad. Manag. Perspect. 13 (2), 37–48.
Pinnuck, M., Lillis, A.M., 2007. Profits versus losses: does reporting an accounting loss act as a heuristic trigger to exercise the abandonment option and divest employees? Account. Rev. 82 (4), 1031–1053.
Porter, M.E., Van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9, 97–118.
PwC, 2021. Annual Corporate Directors Survey-The Director's New Playbook: Taking on Change. https://www.pwc.com/us/en/services/governance-insights-center/assets/pwc-2021-annual-corporate-directors-survey.pdf.
Rajan, R.G., Zingales, L., 1998. Financial dependence and growth. Am. Econ. Rev. 88, 559–586.
Sun, X., Zheng, Y., Zhang, C., Li, X., Wang, B., 2022. The effect of China's pilot low-carbon city initiative on enterprise labour structure. Front. Energy Res. 9, 821677.
Täger, M., 2021. 'Double Materiality': What is it and Why Does it Matter? LSE Grantham Research Institute on Climate Change. https://greencentralbanking.com/research/double-materiality-what-is-it-and-why-does-it-matter/.
The CITIC Pacific Special Steel Group Co., Ltd, 2021. Annual Report in 2021. http://www.cninfo.com.cn/new/disclosure/detail?plate=szse&orgId=gssz0000708&stockCode=000708&announcementId=1212540500&announcementTime=2022-03-11.
Winters, J.V., 2011. Human capital, higher education institutions, and quality of life. Reg. Sci. Urban Econ. 41 (5), 446–454.
World Bank, 2020. World Development Indicators. http://databank.worldbank.org/data/reports.aspx?source=World%20Development%20Indicators.
Xu, N., Li, X., Yuan, Q., Chan, K.C., 2014. Excess perks and stock price crash risk: evidence from China. J. Corp. Finan. 25, 419–434.
Yamazaki, A., 2017. Jobs and climate policy: evidence from British Columbia's revenue-neutral carbon tax. J. Environ. Econ. Manag. 83, 197–216.
Yoon, A.S., 2021. The role of private disclosures in markets with weak institutions: evidence from market liberalization in China. Account. Rev. 96 (4), 433–455.
Yu, Y., Zhang, N., 2021. Low-carbon city pilot and carbon emission efficiency: quasi-experimental evidence from China. Energy Econ. 96, 105125.
Zeng, J., Zhu, H., 2014. R&D human capital allocation in high-tech industries and its economic effects. In: 2014 Seventh International Joint Conference on Computational Sciences and Optimization. IEEE, pp. 218–222.
Zhang, A., Li, X., Jin, J., Wu, W., Yang, X., 2021. Environmental regulation, agency cost and corporate performance-empirical evidence from listed companies in the chemical industry. Account. Res. 08, 83–93 (In Chinese).
Zhu, D., Chen, K., Sun, C., Lyu, C., 2023. Does environmental pollution liability insurance promote environmental performance? Firm-level evidence from quasi-natural experiment in China. Energy Econ. 118, 106493.
Zingales, L., 2000. In search of new foundations. J. Financ. 55 (4), 1623–1653.