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From bytes to blooms: Tech-driven transformation and green revenues

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ABSTRACT

Exploiting the staggered implementation of city-level Broadband China Pilot as an exogenous increase in digital transformation, this study investigates whether and how tech-driven transformation affects firms' green revenues. Using a difference-in-differences model, we find that firms' digital transformation enhances green revenues following the implementation of this policy. We document that higher environmental regulatory intensity and enhanced environmental protection practices serve as underlying mechanisms. Further analyses reveal that this impact is more pronounced among firms experiencing overinvestment and those with higher green capabilities. Our study contributes to the net-zero framework by providing a collaboration channel between micro- and macro-level institutional mechanisms to achieve a win-win scenario between economic efficiency and environment friendliness.

1. Introduction

This study addresses important yet overlooked queries of whether and how digital transformation increases green revenues. Green revenues refer to income earned through business segments operating in sustainable economic activities (Kooroshy et al., 2020). It is a key metric to indicate firms' performance in achieving economic profit while maintaining environmental sustainability (Bassen et al., 2023). The traditional business perspective frequently prioritizes economic motives over environmental sustainability (Cai et al., 2023). However, due to the escalating environmental issues, businesses are increasingly compelled also to preserve the environment. Further, the business challenges are intensified by the pressures from technological disruptions. These complexities are unavoidable, as negligence of environmental responsibility is subjected to penalty (Shevchenko, 2020), and ignorance of technological disruptions can be detrimental to the firms' competitiveness (Hsu and Cohen, 2021). Ideally, firms should orchestrate multiple challenges to create opportunities, including leveraging a digital transformation agenda to pursue sustainability performance. However, it is unclear whether digital transformation can significantly improve green revenues. This question is noteworthy because green revenues reconcile the dilemma between environment friendliness and profit maximization.

Pressures for businesses to embrace sustainability actions stem from the alarming trend of environmental issues. In 2023, the global average temperature rose by 1.48 °C above the pre-industrial level, approaching the critical 1.5 °C threshold for safe living space (European Commission, 2024; World Economic Forum, 2024). This worrying trajectory could add 250,000 health-related deaths per year; more than half of the global population suffers from water scarcity, and up to 80 million people are prone to hunger (IPCC, 2022; World Health Organization, 2023). Climate change has obviously resulted from irresponsible civilization since the 17th century (NASA, 2024). Therefore, various sustainability strategies are now embedded in human activities, including economic activities, to reduce environmental footprints. However, environmental sustainability is not aligned with the firms' traditional goal to maximize profit. Therefore, firms must establish specific strategies that can harmonize profit-seeking goals and environmental responsibility. In this matter, we contend that green revenues are one of the strategic choices for pursuing both economic and environmental objectives.

One of the crucial factors for achieving sustainable business is green innovation (Bose et al., 2021). However, green innovation is often associated with high-cost investment with significant failure risk (He et al., 2022). On a global scale, our society must anticipate investing 90 trillion United States dollars by 2030 in critical projects to keep temperatures below the 2 °C threshold (NCE, 2018). Despite its critical role, green innovation sometimes falls as a symbolic demonstration to meet social expectations (Lian et al., 2022). Amidst the heightening

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competition and regulation, companies should structure comprehensive yet efficient strategies to cope with multiple challenges. Therefore, we see that firms should gain momentum from the emerging digitalization and technological advancement.

Digital transformation is a strategic agenda to enhance the data flow effectiveness and resource allocation efficiency by leveraging state-of-the-art technologies, including big data, artificial intelligence, blockchain, and the Internet of Things (Wang et al., 2023a). It is also considered an integral part of economic and environmental initiatives at the macro and micro levels. At the macro level, we learn from Australia's intergenerational planning that embraces digital technology to structure national economic pathways and improve quality of life (Australian Government, 2023). Within the micro-economic domain, digital technology holds great potential to be integrated into a process-based framework to track and record operational activities as the basis for ESG information management (Zhao and Cai, 2023).

This study uses China as an empirical setting because its rapid economic development opposes environmental performance. Prominent economic growth is expected to continue, projecting that China will achieve the world's highest GDP based on purchasing power parity by 2050 (PwC, 2017). On the other hand, China faces serious environmental problems as it consistently ranked as the world's largest emitter of greenhouse gases since 2005 (World Resources Institute, 2022). The contrast between progressive economic development and worrying environmental issues provides appropriate settings for research on green revenues. Furthermore, China has emerged as an innovation hub by establishing more than 300 unicorns (WEF, 2023). The immersive business environment is then enforced by national initiatives to enhance the internet backbone through three stages of the Broadband China Pilot (BCP) from 2014 until 2016 (Wang et al., 2022). The advancement of this information highway is the rational foundation for considering digital transformation in this study. Beyond the Chinese setting, the paradox between flourishing economic activity and environmental trends is also prevalent in emerging countries (Wani et al., 2021). In addition, developing countries also face the momentum of digital evolution, which has the potential to rapidly transform their economies (Chakravorti et al., 2020). Therefore, this study establishes the foundation for a research framework applicable to various emerging countries.

Despite its potential to foster sustainability, green revenues receive limited scholarly attention. Existing studies discuss the green revenue metric development, the consequences, and its determinants. Green revenues are initially developed to classify firms' environmental performance (Kooroshy et al., 2020). Previous studies reveal that green revenues complement other metrics, such as brown revenue, carbon intensity, and fossil fuel reserves (Atta-Darkua et al., 2022; Nipper et al., 2022). Furthermore, previous studies find that green revenues have an impact on stock returns (Bassen et al., 2023), stock volatility (Noailly et al., 2022), firm performance (Kruse et al., 2020), and cash holding (Guo and Zhong, 2023). Despite the potential role of green revenues, research efforts focused on understanding the determinants of green revenues remain scarce. Mohnen et al. (2023) find that green innovation and technological spillover significantly drive firms' green revenues. To the best of our knowledge, no research has investigated the direct impact of digital transformation on green revenues.

This study employs a difference-in-differences (DiD) framework to test the hypothesis. We find that firms' digital transformation enhances corporate green revenues in the presence of the BCP. This finding aligns with the resource-based view and dynamic capability framework. Our study further finds this impact is strongly related to macro- and micro-level mechanisms. We identify higher environmental regulatory intensity and enhanced environmental protection practices as the underlying mechanisms. Further analyses reveal that this effect is more pronounced among firms with overinvestment tendencies and higher green capabilities.

We employ an array of robustness tests to mitigate endogeneity issues. First, given that the validity of the DiD estimates relies on the parallel trend assumption, we examine the pre-treatment trends between the treatment and control groups using a dynamic model. Our analysis reveals no significant differences in green revenues between these groups before adopting the BCP. Second, another potential source of endogeneity may arise from self-selection based on observables. To address the concern that changes in green revenues might be influenced by firm characteristics rather than digital transformation, we employ an entropy-balancing approach and propensity score matching approach. This approach matches each covariate between the treatment and control groups, ensuring these groups are comparable. Third, to test whether our estimates are sensitive to different specifications, we employ alternative specifications of digital transformation. Fourth, confounding factors, such as other concurrent regulations related to digital transformation that potentially affect treatment groups and green revenues, can threaten the validity of our estimates. Distinguishing the effects of the specific intervention from those of concurrent regulations is crucial to ensure the robustness of our findings. To address this potential endogeneity issue, we conduct a placebo test to mitigate the potential impact of other regulations, policies, or random factors on our estimates.

Fifth, one potential endogeneity is omitted variable bias, which may affect our estimates. If firms' characteristics are correlated with both their digital transformation and green revenues, omitting these characteristics could result in a correlation between digital transformation and the error term. To address this issue, we test for potential endogeneity concerns related to omitted variable bias using the method proposed by Oster (2019). Sixth, we further incorporate city-level control variables and an interaction term between region and year-fixed effects to mitigate concerns about the potential impact of city-specific characteristics and time-variant unobservable heterogeneity across cities on our estimates. Seventh, we employ an alternative estimation method to mitigate concerns of potential heterogeneity in treatment effects and variation in treatment timing, which may bias our estimates. Eighth, we use the Goodman-Bacon decomposition method to decompose the DiD estimates, checking the weight of biased components in total effect. Overall, our results remain consistent and robust across all endogeneity tests.

This study contributes to literature and climate-change governance as follows. First, this study is the first to investigate the driving force of generating green revenues, that is, creating synergies and nexus between economic development and environment protection via leveraging technology advancement. Current research on green revenues limits its focus on micro-level factors, such as innovation and technology spillover (Mohnen et al., 2023). However, this study acknowledges the great potential of green revenue to mitigate environmental issues by embracing a multi-level digital transformation perspective. Our study considers government broadband policy as the macro-level strategy and the firms' technological initiatives at the micro level of digitalization.

Second, this study advances the evolving sustainability framework in business. We develop the net-zero framework in Fig. 1 by embracing the collaborative channel between micro- and macro-level institutional mechanisms in promoting green revenue as the win-win situation between economic efficiency and environment friendliness. Based on our findings, this study holds strategic and policy implications for embracing digital transformation and infrastructure as part of the collaborative mechanisms among multiple stakeholders. The holistic framework proposed in this study offers critical insights and strategies for regulators, policymakers, and other countries to address environmental issues through solid economic foundations and advanced technologies with the support of both macro and micro resources.

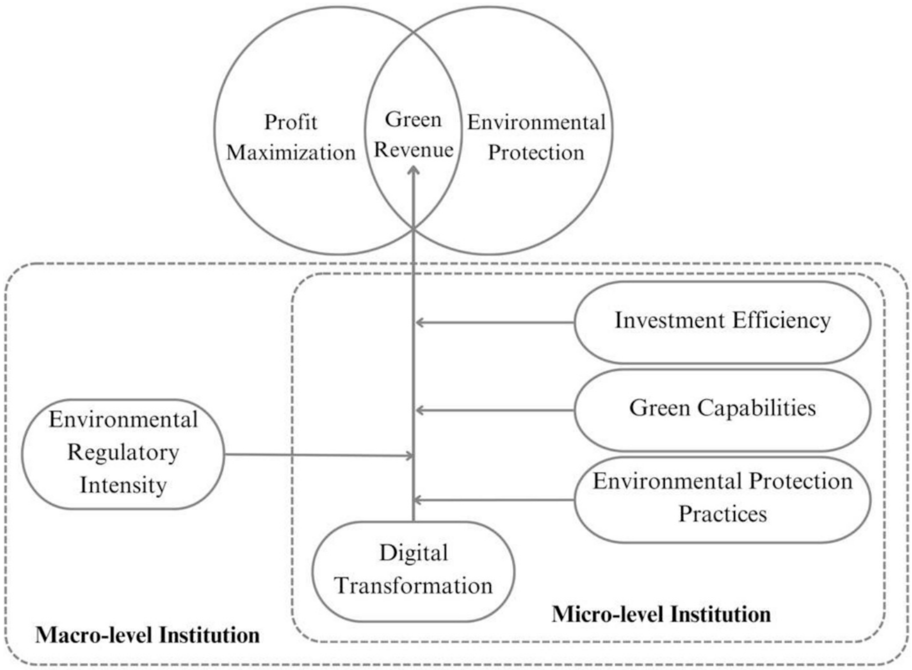

Fig. 1. Theoretical framework.

2. Theoretical mechanisms and hypothesis development

2.1. Institutional background

The construction of network infrastructure serves as a critical foundation and primary catalyst for the digital economy (Majchrzak et al., 2016). In recent years, numerous regions and countries worldwide have launched digital development strategies centered on broadband networks to enhance their standing in the global digital economy. Notable examples include the National Information Infrastructure Program in the United States,[1] Digital Britain in the United Kingdom,[2] and e-Japan in Japan.[3] In alignment with these international trends, China has implemented a thorough broadband development strategy, culminating in the broadband strategy and implementation plan, namely the BCP.

On August 16, 2013, the State Council of China introduced the *Broadband China Strategy and Implementation Plan* to accelerate the nationwide development of broadband infrastructure. This comprehensive strategic initiative mandates that all levels of government promptly adopt and enforce supportive policies to fulfill its objectives. The strategy is underpinned by four fundamental pillars: broadening the broadband user base, elevating broadband penetration rates, augmenting broadband access capabilities, and fostering the integration of broadband technology into both industrial processes and daily life.[4] The plan set ambitious targets to be achieved by the end of 2020, including increasing the number of fixed broadband subscription households to 400 million and the number of internet users to 1.1 billion (Wang et al., 2022). In addition, it aims to improve broadband speeds to 50 Mbps in urban areas and 12 Mbps in rural regions. These targets are strategically designed to establish a robust, high-speed, and widely accessible broadband network infrastructure across China. By enhancing connectivity, this strategy aims to stimulate innovation, support economic growth, and improve the quality of life for citizens (Zhang and Liu, 2023). The expansion of broadband infrastructure is anticipated to facilitate the digital transformation of industries, enhance educational and healthcare services, and promote social inclusion by bridging the digital divide between urban and rural areas.

To further advance this broadband implementation strategy, the Ministry of Industry and Information Technology, in collaboration with the National Development and Reform Commission, initiated the selection of BCP cities in January 2014. This initiative aims to facilitate the strategy's implementation through a rigorous selection process involving city applications, provincial pre-assessments, and expert reviews (He et al., 2024). Over a span of three years, from 2014 to 2016, a total of 117 cities were designated as BCP cities. Appendix A outlines the staggered implementation of the BCP across various cities and years. The spatial distribution of these cities suggests an impartial selection process, as there are no discernible geographical patterns influencing the designation of BCP cities. For example, Almeida and Kogut (1999) highlight the challenges that geographical distances pose to the free flow of technological knowledge. However, Storper and Venables (2004) emphasize the advantages of geographical proximity in facilitating communication and labor-force knowledge spillovers.

In addition, the adoption of the BCP not only underscores the commitment of the government to accelerate broadband infrastructure development but also ensures a balanced and equitable enhancement of digital connectivity across diverse regions (Wu et al., 2021). The exogenous selection of BCP cities indicates a strategic approach to inclusively bolster the nation's digital economy, aiming to bridge regional disparities and promote uniform technological advancement. Serving as the backbone of the contemporary digital economy, network infrastructure is pivotal in enabling the efficient allocation of resources for technological innovation. These facilities enhance the distribution of innovation resources across different regions and industries, thereby fostering greater interconnectivity and dynamism within the innovation ecosystem. Overall, the BCP initiative has profound implications for the digital economy, technological advancements, and social development.

[1] https://csrc.nist.gov/glossary/term/national_information_infrastructure (accessed on 15 July 2024).

[2] https://www.theguardian.com/technology/digital-britain (accessed on 15 July 2024).

[3] https://japan.kantei.go.jp/it/network/0122full_e.html (accessed on 15 July 2024).

[4] https://www.gov.cn/gongbao/content/2013/content_2473876.htm (accessed on 15 July 2024).

2.2. Resource-based view and dynamic capabilities framework

The underlying logic of this study lies in the resource-based view and dynamic capabilities framework. The resource-based view posits that firms need to secure the resources to shape their core competencies and competitiveness (Wernerfelt, 1984). In particular, only valuable, rare, inimitable, and non-substitutable resources are incremental to uphold firms' competitive advantages (Barney, 1991; Peteraf, 1993). At the further stage, Teece et al. (1997) extend the resource-based view with the dynamic capabilities framework to consider the rapid changes in the business environment. According to this framework, organizational mechanisms are continuously acquiring, integrating, and reconfiguring resources and capabilities to establish firms' competitiveness (Eisenhardt and Martin, 2000). Amidst the rapid disruption from technological changes, firms are prompted to align digital capabilities into their business strategies (Wang et al., 2023b). Specifically, the emerging digital economy motivates firms to embed their operation with digital business platforms and ecosystem transformation (Snihur and Markman, 2023). In this regard, we posit that digital transformation is part of strategic actions to shape distinctive competencies and secure critical resources. As expected, digital transformation helps firms gain greater competitive advantages (Ferreira et al., 2019).

Despite the strategies to run the business as usual, firms need to acknowledge the challenges and changes in their environment. Amidst the dynamic changes in the business environment, firms are urged to be responsive, agile, and adaptive by keeping their resources' capability to create a value market (Teece et al., 1997). According to the World Economic Forum (2023), contemporary business challenges are mainly rooted in environmental regulatory pressures and rapid digitalization. Under the heightened sustainability concerns, firms are urged to attain distinctive resources through green innovations and patents (Berrone et al., 2013; Helfat et al., 2023). In this matter, firms can also leverage their technological resources into their green strategies to improve sustainability performance (Ashraf et al., 2024). Therefore, our premise is that firms secure critical resources and core competencies by leveraging digital transformation, which will help them improve their competitive position amidst the pressures from sustainability concerns.

2.3. Green revenues

Firms generate green revenues from environmentally friendly businesses and industries (FTSE Russel, 2018). The presentation of green revenues indicates the firms' strategic endeavors to ease the tensions between profit-seeking and environmental conservation strategies (Bassen et al., 2023). In regard to this role, green revenues work by improving sustainability performance (Huang et al., 2024), restraining greenwashing (Cao et al., 2024), and bolstering financial performance (Kruse et al., 2020). However, a substantial transformation of firms' business portfolios is crucial for them to generate more green revenues (Hildebrandt et al., 2018). However, green transformations have the potential to expose firms to risk and uncertainty (Teng and Tan, 2023). Therefore, we argue that establishing green capabilities and allocating more investment to sustainability actions are the backbone of firms' capability to generate green revenues.

Beyond compliance with environmental regulations, green revenues hold the business potential to attract consumer markets and investors with sustainability consciousness. Even though stakeholders are diverse in terms of objectives and motives (Erhemjamts and Huang, 2019), some studies indicate favourable views on environmental performance. Amidst the emerging concerns on sustainability, the consumer market puts approval and higher intention to buy products or services from firms with better environmental performance (Grimmer and Bingham, 2013). Further, investors react positively toward firms with green performance (Cordeiro and Tewari, 2014). This evidence highlights that sustainability performance holds the potential to support firms' traditional business goals in terms of market and financing access. Accordingly, we contend that firms with more green revenues are more likely to maintain business continuity by securing legitimacy from stakeholders.

2.4. Digital transformation and green revenues

We posit that corporate digital transformation enhances green revenues in the presence of BCP. This proposition's logical framework is structured on the resource-based view and dynamic capability theory. According to the resource-based view, companies manage their resources and capabilities to shape the core competencies and gain competitive advantage (Wernerfelt, 1984). From this perspective, digital transformation represents a corporate resource characterized by value, rarity, imperfect imitation, and non-*substitutability* attributes (Sui et al., 2024). Therefore, this distinctive technological innovation empowers firms to develop and sustain their competitiveness (Sun et al., 2020). However, amidst the pressing challenge of the net-zero target, innovative solutions are critical to balance resource utilization, environmental sustainability, and economic motives (Wu et al., 2023). This study considers the "green business segment" and its green revenues as innovative solutions for reconciling the paradox between profit-seeking and environmental protection.

Dynamic capability framework suggests that firms strategically navigate changes in the business landscape by managing internal and external competencies to establish and sustain their competitive advantages (Teece et al., 1997). Firms acknowledge the disruptive nature of technology by continuously building their digital capabilities to discern the evolving trends and strategically align their business approach with emerging opportunities (Wang et al., 2023b). The BCP enables companies to initiate digital transformation, which improves organizational coordination and vertical integration (Zhang and Liu, 2023). Within the digital transformation, firms can optimize their business model and operational structure, which contributes to conserving energy and reducing emissions (Wang et al., 2023c). Therefore, digital transformation is pivotal in laying the groundwork for a more sustainable business strategy. Thus, we propose our hypothesis as follows:

H1. Corporate digital transformation enhances green revenues after the BCP.

2.5. Macro mechanism: environmental regulation intensity

According to institutional theory, organizations are embedded in a hierarchical framework comprising the macro- and micro-level institutional environments (Gao et al., 2017). As part of the macro-level mechanisms, Pan et al. (2018) document that regional institutional development plays a role in shaping the firms' sustainability strategies. In this study, we posit that the environmental regulatory intensity at the regional level induces better environmental performance. Under global pressures on sustainable business practices, authorities have emerged to establish environmental regulations to curb emissions and conserve nature. In this regard, environmental regulations are embedded with "carrots" and "sticks" that introduce incentive and coercive pressures (Sun et al., 2024). Therefore, the stronger the pressure from environmental regulations, the more firms are motivated to take immediate action to reduce environmental footprints (Aragon-Correa et al., 2008).

From the firm-level perspective, the outcomes of firms' strategic responses toward environmental regulations vary. Some firms can establish well-performed actions covering both environmental and economic goals (Aragon-Correa et al., 2008; Aragón-Correa and Sharma, 2003). In contrast, failed strategies lead to penalties due to regulatory violations (Shevchenko, 2020). Therefore, firms may consider various available resources to support their strategic decisions, including leveraging digital transformation. Digital transformation has great potential to improve firms' sustainability performance through business process optimization (Wang et al., 2023c). Further, the advancement of firms' technological processes helps them to establish green innovation to improve business efficiency and sustainable value creation (Bos-Brouwers, 2010). In this matter, we argue that firms with a stronger capability to embed efficiency and sustainability into their business are more likely to generate green revenues. Therefore, we posit that the intensity of environmental regulations works as the catalyst for the impact of digital transformation on green revenues.

H2. This impact is more pronounced among firms operating under intensive environmental regulations.

2.6. Micro mechanism: environmental protection practices

Digital transformation plays a pivotal role for firms pursuing their strategic objectives. Traditionally, the digital infrastructure helps them improve competitiveness, business processes efficiency, and reduce information costs (Han et al., 2024; Li et al., 2024; Sui et al., 2024). However, emerging sustainability concerns lead firms to expand their business goals beyond traditional economic objectives. They are required to contribute to climate change mitigation through sustainability actions. As a consequence, firms need to structure businesses that are both economically feasible and environmentally friendly (Erbetta et al., 2022). To pursue these complex business objectives, firms need to allocate their resources to maintain economic profit while adapting to the changes. In this matter, digitalization can serve firms beyond the traditional economic goal to improve their sustainability performance (Cai et al., 2023).

Firms with well-developed digital transformation will have more opportunities to improve their operational efficiency as well as sustainability performance (Cai et al., 2023; Han et al., 2024). In addition, firms with better environmental practices are more likely to establish and maintain better economic performance and reduced environmental impact (Dahlmann et al., 2019; Ortiz-de-Mandojana and Bansal, 2015; Riggs et al., 2024). Upon improving environmental practices, firms accumulate capabilities that help them structure green business strategies (Ashraf et al., 2024). Therefore, we posit that better environmental practices catalyze the utilization of digital infrastructure in establishing green revenues.

H3. This impact is more pronounced among firms with more environmental protection practices.

3. Sample, data, and research design

3.1. Sample and data

We collect data on China's A-share listed firms from 2009 to 2021, including five years before the first round of the BCP in 2014 and five years after the last round of the BCP in 2016. We collect firms' revenues from diverse business activities using the WIND database and firms' annual reports to construct corporate green revenues. We collect corporate financial data from China's Stock Market & Accounting Research Database (CSMAR). We remove specially treated (ST) firms and financial firms as their accounting fundamentals are different from those of other firms. We eliminate firm-year observations with missing financial data. Our final sample consists of 31,716 firm-year observations involving 4141 unique firms across 78 industries. We winsorize continuous variables at the 1st and 99th percentiles to mitigate the impact of outliers on our results.

3.2. Research design

3.2.1. Model specification

Exploiting the gradual adoption of city-level BCP in China as an exogenous increase in regional digital transformation, we employ a staggered DiD model with continuous variables (Angrist and Pischke, 2009). This model is aimed at investigating the impact of firms' digital transformation on corporate green revenues in the presence of the BCP:

$$\mathrm{GR}_{i,t} = \alpha + \beta_1 \mathrm{DT}_{i,t} \times \mathrm{BCP}_{i,t} + \beta_2 \mathrm{DT}_{i,t} + \beta_3 \mathrm{BCP}_{i,t} + \theta \mathrm{X}_{i,t} + \gamma_j + \delta_r + \mu_t + \varepsilon_{i,t} \tag{1}$$

where the subscripts *i*, *r*, *t*, and *j* denote the firm, city, year, and industry, respectively. The outcome variable $GR_{i,t}$ represents the ratio of corporate green revenues to total revenues. The independent variables $DT_{i,t}$ represents the intensity of corporate digital transformation. The indicator variable $BCP_{i,t}$ equals one when firm *i* is headquartered in a city covered by the BCP in the post-adoption year (treatment group), and zero otherwise (control group). Section 3.2.4 shows the details of the identification of $BCP_{i,t}$. The vector $X_{i,t}$ is a set of firm-specific control variables comprising firms' size (*Size*), nature of ownership (*SOE*), listed age (*Age*), leverage (*LEV*), net working capital (*NWC*), cash holdings (*Cash*), quick ratio (*Quick*), book-to-market ratio (*BTM*), return on assets (*ROA*), Tobin's Q value (*TobinsQ*), fixed assets (*Fixed*), financial constraints (*SA*). The industry-fixed effect (γ_j) accounts for time-invariant unobservable heterogeneity of diverse industries. The region-fixed effect (δ_r) controls for time-invariant unobservable variations across cities. The year-fixed effect (μ_t) captures unobservable time-specific heterogeneity. $\varepsilon_{i,t}$ represents the error term. Robust standard errors are clustered at the industry, firm, or region level to mitigate heteroskedasticity and autocorrelation. The definitions of each variable are detailed in Appendix B.

Our key coefficient of interest is the DiD estimator β_1, which captures the effect of corporate digital transformation on green revenues of firm-year observations located in cities that enact the BCP relative to those in cities that do not enact the BCP. We expect β_1 to be positive, as discussed in *H1*, implying that corporate digital transformation enhances green revenues after the implementation of the BCP.

3.2.2. Measures of green revenues (GR)

Green revenues are defined as firms' revenues derived from business activities pertinent to green and environmental sustainability (FTSE Russel, 2018). The presentation of green revenues reflects firms' strategic efforts to reconcile profit-seeking objectives with environmental conservation strategies (Bassen et al., 2023). We, therefore, acquire data on firms' revenues from different business activities and industries through the WIND database and firms' annual reports. We classify business activities pertinent to green and environmental sustainability based on the *2019 Green Industry Guiding Catalogue* (GIGC) issued by China's National Development and Reform Commission.[5] The GIGC encompasses information on six primary categories of business activities related to green and environmental sustainability, comprising a total of thirty first-tier subcategories and 211 second-tier subcategories. We define corporate green revenues as firms' revenues derived from business activities listed in the GIGC. We quantitatively measure corporate green revenues (*GR*) by scaling aggregated corporate green revenues by total revenues, thereby mitigating the potential influence of revenue scale. Thus, *GR* denotes the ratio of corporate green revenues to total revenues.

For example, Dayu Irrigation Group Co., Ltd. (stock code: SZ300021) is a specialized provider of comprehensive industrial chain solutions that integrates intelligent services in the fields of agricultural water conservation, rural sewage treatment, urban and rural water supply, and modern irrigation districts. In 2014, this firm generated revenues from four distinct business activities: water-saving materials (63.04 %), water-saving engineering income (35.27 %), design income (1.6 %), and

[5] To address concerns regarding ambiguous business activity terms reported in Chinese by the WIND database and GIGC, we also cross-reference green-related business activities using the FTSE Russell Green Revenues Classification System available on the Refinitiv platform.

other business activities (0.1 %). Among these business activities, water-saving materials (63.04 %) and water-saving engineering income (35.27 %) are identified by the GIGC as contributing to green and environmental sustainability. As a result, 98.31 % of the corporate revenues of Dayu Irrigation Group in 2014 are classified as green revenues. Zhong Chuang Environment Group (stock code: SZ300056), a listed company in China specializing in high-temperature bag filtration and dust removal, generated revenues from four distinct business activities in 2013: filter bag series (93.74 %), filter felt series (4.08 %), environmental engineering (1.3 %), and other businesses (0.88 %). According to the GIGC, environmental engineering (1.3 %) qualifies as a green-related business activity. Thus, 1.3 % of the revenues of Zhong Chuang Environment Group in 2013 are classified as green revenues.

3.2.3. Measures of firms' digital transformation (DT)

We follow Zhou and Li (2023) and Zhang et al. (2024) to measure firms' digital transformation using a textual analysis. We assess the intensity of firms' digital transformation by computing the frequency of keywords relevant to digital within the annual reports issued by listed firms. Specifically, we employ Python to collect and organize the annual reports of A-share listed firms in China. Employing the JavaPDF Box library (Zhou and Li, 2023), all textual content from these annual reports is extracted and utilized as a data pool for subsequent feature term selection. Drawing on the policy documents and research reports pertinent to digital transformation issued by the government, we construct the key terms of digital transformation based on the *Special Action Plan for the Digital Empowerment of Small and Medium Enterprises*, the *2020 Digital Transformation Trend Report*, *Data Utilization, and Intelligence Empowerment Action to Cultivate New Economic Development*, and *Chinese Government Work Reports*. Appendix C provides the details of these key terms pertinent to digital transformation. The glossary of key terms relevant to digital transformation encompasses five dimensions: *Transformation of Artificial Intelligence*, *Transformation of Big Data*, *Transformation of Blockchain*, *Transformation of Cloud Computing*, and *Transformation of Digital Technology*. This glossary includes 71 unique key terms associated with firms' digital transformation. We then measure firms' digital transformation (*DT*) by taking the logarithmic value of one plus the frequency of keywords relevant to digital transformation.

3.2.4. Identification of broadband China pilot (BCP)

The Ministry of Industry and Information Technology and the National Development and Reform Commission initiated the selection of BCP cities to promote the development of regional broadband infrastructure in January 2014. Over the three-year period from 2014 to 2016, a total of 115 cities were designated as BCP cities. Specifically, 41 cities adopted the BCP in 2014, followed by 38 cities in 2015 and 36 cities in 2016. We manually compile data on the implementation of the BCP across cities, primarily utilizing resources such as the official website of China's State Council, municipal government websites, and local news outlets. Appendix A presents a detailed summary of the staggered rollout of the BCP in different cities over various years. To ensure accuracy, we cross-reference this information with previous studies that employ the BCP as the research setting. We find that the data we collected on the implementation of the BCP across various cities and years are consistent with those in previous studies (i.e., Tang et al., 2021; Wang et al., 2022; He et al., 2024).

We then capture the implementation of the BCP by employing an indicator variable (*BCP*), which is the DiD term. Aligning with previous studies (e.g., Tang et al., 2021; He et al., 2024), we define *BCP* as equal to one for firms located in cities that enacted the BCP policy during the post-enactment period (treatment group), and zero otherwise (control variables). For example, as shown in Appendix A, Beijing implemented the BCP policy in 2014. Therefore, for firm-year observations in Beijing, the indicator variable *BCP* equals one in and after 2014, and zero for years prior to 2014. Chongqing enacted the BCP policy in 2015. Thus, for firm-year observations in Chongqing, the *BCP* equals one in and after 2015, and zero for years prior to 2015. However, Ningbo never enacted the BCP policy throughout the sample period. Thus, for firm-year observations in Ningbo, the indicator variable *BCP* remains zero across all years in our sample.

Overall, the staggered implementation of the BCP policy in China presents a quasi-natural experiment, offering an ideal setting for our analysis. This approach mitigates concerns of reverse causality, as the firm-specific level of green revenues is unlikely to affect the decision of national authorities (i.e., the Ministry of Industry and Information Technology and the National Development and Reform Commission) regarding the implementation of BCP. In addition, this setting disentangles the specific effect of the BCP policy from other concurrent regulations and macroeconomic factors that might otherwise bias our estimates. This is because the BCP policy was implemented over the period from 2014 to 2016, with 115 distinct cities adopting the policy in different years. This design is inherently unique, as it is unlikely that other policies would have the same scope across these unique cities or share the same implementation cities and timeline as the BCP. However, we acknowledge the limitations and potential biases associated with using a staggered DiD model. To address these concerns, we perform robustness checks on endogeneity issues and the DiD model, detailed in Sections 4.3 to 4.10.

3.2.5. Entropy balancing approach

To mitigate the potential concern that the changes in green revenues are attributed to firm characteristics between firm-year observations located in BCP cities (treatment group) and those located in non-BCP cities (control group) rather than digital transformation, we employ entropy balancing following previous studies (Beck et al., 2022; Cao et al., 2023). Entropy balancing is a matching technique that reweights control sample units to achieve covariate balance. We use entropy balancing for two primary reasons. First, it provides a high degree of covariate balance between the treatment and control groups (Beck et al., 2022). Unlike traditional matching methods such as nearest neighbor matching, entropy balancing employs a reweighting scheme to achieve this balance, ensuring that all observations in the sample are retained, thus preserving valuable information and observations. Second, this method directly adjusts weights based on sample moments, eliminating the need for iterative searches through propensity score models, which can introduce bias into the matching process (Hainmueller, 2012). This method accounts for random and systematic disparities in variable distributions between the treatment and control groups, strengthening the causal inferences drawn from DiD estimations and enabling more accurate and reliable estimation of treatment effects.

We thus entropy balance control and treatment groups, ensuring covariate balance across the two groups. Specifically, we employ this method to achieve a covariate balance between firm-year observations in cities that enacted the BCP during post-enactment years ($BCP = 1$) and their counterparts ($BCP = 0$) without relying on design choices that could influence the composition of the control sample. Appendix D provides an overview of the mean, variance, and skewness for the balancing dimensions between the treatment and control groups, both before (Panel A) and after balancing (Panel B). This table reveals that, after balancing, the standard deviation differences between covariates reduce to zero, and the variance ratios of the covariates converge to one, indicating successful covariate balance. To further verify that our results are not biased by the selection of matching techniques, we also employ an alternative matching method, propensity score matching, as a robustness check, which is detailed in Section 4.4.

4. Empirical results

4.1. Descriptive statistics

Panel A of Table 1 shows the descriptive statistics of the full sample. The mean value of corporate green revenues (*GR*) equals 3.4 %,

Table 1
Descriptive statistics.

Panel A: Descriptive statistics of full sample								
Variables	N	Mean	SD	Min	P25	Median	P75	Max
GR	31,716	0.034	0.148	0.000	0.000	0.000	0.000	1.000
DT	31,716	1.354	1.419	0.000	0.000	1.099	2.303	5.352
BCP	31,716	0.418	0.493	0.000	0.000	0.000	1.000	1.000
Size	31,716	22.163	1.279	19.308	21.235	21.977	22.883	26.452
SOE	31,716	0.376	0.484	0.000	0.000	0.000	1.000	1.000
Age	31,716	2.869	0.352	1.099	2.639	2.890	3.135	3.611
LEV	31,716	0.433	0.203	0.078	0.267	0.424	0.584	0.908
NWC	31,716	0.224	0.246	−0.420	0.053	0.222	0.399	0.814
Cash	31,716	0.162	0.125	0.005	0.073	0.126	0.214	0.717
Quick	31,716	1.749	1.616	0.127	0.738	1.201	2.088	9.149
BTM	31,716	0.618	0.241	0.137	0.432	0.613	0.796	1.246
ROA	31,716	0.036	0.066	−0.551	0.014	0.038	0.067	0.219
TobinsQ	31,716	1.980	1.078	0.802	1.256	1.631	2.316	7.322
Fixed	31,716	0.215	0.161	0.002	0.088	0.182	0.307	0.774
SA	31,716	−3.790	0.252	−4.522	−3.957	−3.793	−3.621	−2.970
Panel B: Univariate comparison								
Variables		*BCP* = 0 (N = 18,454)		*BCP* = 1 (N = 13,262)		Difference		
		Mean	Median	Mean	Median	*t*-statistic	Wilcoxon Z	
GR		0.031	0.000	0.039	0.000	−4.986***	−10.161***	
DT		1.082	0.693	1.733	1.609	−41.337***	−42.845***	
Size		22.040	21.874	22.334	22.120	−20.301***	−18.588***	
SOE		0.389	0.000	0.359	0.000	5.425***	5.434***	
Age		2.803	2.833	2.961	2.996	−40.534***	−38.567***	
LEV		0.437	0.429	0.426	0.417	4.817***	4.687***	
NWC		0.210	0.208	0.244	0.244	−12.138***	−11.884***	
Cash		0.164	0.124	0.160	0.130	2.519**	2.095**	
Quick		1.694	1.126	1.826	1.299	−7.182***	−15.696***	
BTM		0.624	0.625	0.610	0.594	5.081***	6.630***	
ROA		0.039	0.038	0.034	0.037	6.659***	3.257***	
TobinsQ		1.934	1.599	2.044	1.683	−9.010***	−6.630***	
Fixed		0.236	0.206	0.185	0.147	28.450***	31.233***	
SA		−3.749	−3.752	−3.848	−3.849	35.077***	34.246***	

Notes: This table shows the descriptive statistics. The variable definitions are shown in Appendix B.

accompanied by a standard deviation of 0.148. These results are consistent with previous studies (Klausmann et al., 2024; Kruse et al., 2020; Kruse et al., 2024). This implies that there is a significant variation in corporate green revenues among firm-year observations. The mean value and standard deviation of digital transformation (*DT*) are 1.354 and 1.419, indicating that digital transformation differs among diverse firms. The mean value of *BCP* (0.418) shows that 41.8 % of firm-year observations in our sample are subject to the BCP. Panel B exhibits the results of univariate comparisons. These results preliminarily indicate that corporate green revenues and firms' digital transformation in the presence of the BCP are significantly higher than those before the implementation of the BCP. However, we also find that firms' leverage ratio, cash holdings, market-to-book ratio, ROA, and fixed assets significantly decrease after the adoption of the BCP relative to counterparts.

4.2. Baseline results

Table 2 shows the results of the impacts of firms' digital transformation on green revenues in the presence of the BCP. Columns (1), (3), and (5) only include industry and year-fixed effects as the control variables to mitigate concerns about potential confounding effects from other covariates on our estimates (Gormley and Matsa, 2014). Other columns include all control variables and the region-fixed effects to control for the time-invariant regional heterogeneity. We consider different robust standard errors clustered at the industry, firm, or region level to assess the sensitivity of our estimates to the use of robust standard errors clustered at various levels. In robustness analyses and additional tests, we default to using robust standard errors clustered at the region level, as the treatment and control groups are determined by the city-level implementation of BCP.[6] Columns (7) and (8) present the baseline results derived from the entropy-balanced sample.

We find that the impact of firms' digital transformation on green revenues in the presence of the BCP is statistically significant. Columns (1) to (8) show that the coefficients on $DT \times BCP$ are all positive and significant at the 1 % and 5 % levels. However, the coefficients on *DT* are all negative and significant. The coefficients on *BCP* are insignificant across columns. These results indicate that firms' digital transformation has an adverse impact on corporate green revenues without macro-level (regional) monitoring and regulatory support. However, firms' digital transformation significantly enhances green revenues when such transformation occurs under the monitoring and regulatory support of the BCP. This contributes to the harmonization of environmental integrity, economic prosperity, and social equity (Bansal, 2005).

Our results are also economically significant. In the presence of the BCP, regulated firms' digital transformation increases green revenues by approximately 4.19 %[7] of the standard deviation relative to their counterparts. However, without the implementation of the BCP, a one standard deviation increase in firms' digital transformation is associated

[6] Our results and findings of robustness analyses and additional tests remain consistent and robust when clustering standard errors at the industry or firm level (untabulated).

[7] The coefficient on $DT \times BCP$ (0.0062) × 100 % / The standard deviation of *GR* (0.148) = 4.19 %

Table 2
Impacts of digital transformation on green revenues in the presence of BCP.

Variables	*Green Revenues (GR)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DT × *BCP*	0.0052***	0.0052***	0.0052**	0.0050**	0.0052**	0.0050**	0.0066***	0.0062**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DT	−0.0029***	−0.0032***	−0.0029*	−0.0031*	−0.0029*	−0.0031*	−0.0041**	−0.0038**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
BCP	−0.0052	−0.0042	−0.0052	−0.0075	−0.0052	−0.0075	−0.0056	−0.0056
	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Size		0.0031		0.0030		0.0030	0.0027	0.0021
		(0.003)		(0.002)		(0.003)	(0.003)	(0.003)
SOE		−0.0096		−0.0080		−0.0080	−0.0095	−0.0079
		(0.006)		(0.005)		(0.007)	(0.007)	(0.007)
Age		−0.0505***		−0.0489***		−0.0489***	−0.0515***	−0.0518***
		(0.018)		(0.015)		(0.013)	(0.012)	(0.013)
LEV		0.0488***		0.0461***		0.0461***	0.0471***	0.0473***
		(0.017)		(0.015)		(0.015)	(0.012)	(0.012)
NWC		0.0229		0.0218*		0.0218	0.0142	0.0124
		(0.017)		(0.013)		(0.015)	(0.014)	(0.014)
Cash		−0.0173		−0.0171		−0.0171	−0.0181	−0.0154
		(0.014)		(0.014)		(0.013)	(0.012)	(0.013)
Quick		−0.0006		−0.0010		−0.0010	0.0006	0.0004
		(0.001)		(0.001)		(0.002)	(0.002)	(0.002)
BTM		−0.0176**		−0.0169		−0.0169	−0.0105	−0.0068
		(0.008)		(0.011)		(0.011)	(0.013)	(0.014)
ROA		−0.0191		−0.0056		−0.0056	−0.0161	0.0037
		(0.030)		(0.018)		(0.018)	(0.015)	(0.017)
TobinsQ		−0.0049**		−0.0047***		−0.0047***	−0.0043**	−0.0036*
		(0.002)		(0.002)		(0.002)	(0.002)	(0.002)
Fixed		0.0164		0.0206		0.0206	0.0264	0.0296*
		(0.039)		(0.019)		(0.015)	(0.017)	(0.018)
SA		−0.0510**		−0.0505***		−0.0505***	−0.0604***	−0.0627***
		(0.021)		(0.017)		(0.016)	(0.017)	(0.019)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Matched Sample	No	No	No	No	No	No	Yes	Yes
Cluster	Industry	Industry	Firm	Firm	Region	Region	Region	Region
Observations	31,716	31,716	31,716	31,716	31,716	31,716	31,716	31,716
Adjusted R^2	0.146	0.153	0.146	0.191	0.146	0.191	0.170	0.217

Notes: This table presents the impact of digital transformation on corporate green revenues in the presence of the BCP. These results indicate that digital transformation significantly enhances corporate green revenues in the presence of the BCP. However, this effect is negative in the absence of the BCP. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the industry, firm, or region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

with a 15.86 %[8] decrease in their green revenues relative to the sample mean. These results support the *H1*. These findings align with the dynamic capability framework, which posits that firms strategically navigate changes in the business landscape by managing both internal and external competencies to establish and sustain their competitive advantages (Teece et al., 1997), such as generating revenues from green businesses.

For example, firms recognize the disruptive nature of technology and respond by continuously enhancing their digital capabilities, enabling them to discern emerging trends and strategically align their business approaches with new opportunities (Wang et al., 2023b). In addition, the implementation of the BCP is macro-level instrumental in facilitating digital transformation, which subsequently enhances organizational coordination and vertical integration (Zhang and Liu, 2023). This digital transformation process, under monitoring and regulatory support, allows firms to optimize their business models and operational structures, resulting in significant energy conservation and emission reductions (Wang et al., 2023c). By strategically adopting digital technologies under the BCP, firms can improve operational efficiency and achieve environmental sustainability. This approach aligns with the principles of sustainable development, promoting a balance between economic growth, environmental stewardship, and social well-being.

4.3. Parallel trend assumption

For a DiD model to be valid, a key underlying assumption is that the trends in green revenues for firms located in the regulated cities and their counterparts must be parallel prior to the adoption of the BCP. This means that while various observable and unobservable factors may cause differences in the levels of green revenues between these two groups, the change in these differences should remain constant over time in the absence of the BCP. This parallel trend assumption ensures that any observed changes in green revenues following the implementation of the BCP can be attributed to digital transformation rather than to other confounding factors. Without this assumption holding true, the estimates of the DiD model would be biased, leading to incorrect inferences about the impact of the digital transformation on green revenues.

Thus, we adopt a dynamic analysis following Beck et al. (2010) by replacing *BCP* with seven indicator variables representing each year relative to the BCP. Table 3 shows the results of this dynamic analysis. We find that the coefficients on *DT*×*BCP k* (k = *Pre3*, *Pre2*, and *Pre1*) are insignificant and indistinguishable from zero across columns. However, the coefficients on *DT*×*BCP k* (k = *Post1*, *Post2*, and *Post3*) are all positive and significant across columns. We also conduct an *F*-test to assess the joint significance of these coefficients, validating the dynamic

[8] The coefficient on *DT* (−0.0038) × The standard deviation of *DT* (1.419) × 100 % / The mean value of *GR* (0.034) = 15.86 %

Table 3
Dynamic analysis for parallel trend assumption.

Variables	Green Revenues (GR)		
	(1)	(2)	(3)
DT×BCP Pre 3 (β1)	−0.0007	−0.0007	−0.0007
	(0.003)	(0.003)	(0.003)
DT×BCP Pre 2 (β2)	0.0006	0.0006	0.0006
	(0.003)	(0.003)	(0.004)
DT×BCP Pre 1 (β3)	−0.0006	−0.0006	−0.0006
	(0.003)	(0.004)	(0.004)
DT×BCP Post 1 (β4)	0.0049**	0.0049*	0.0049*
	(0.002)	(0.003)	(0.003)
DT×BCP Post 2 (β5)	0.0055***	0.0055**	0.0055**
	(0.002)	(0.002)	(0.003)
DT×BCP Post 3 (β6)	0.0050***	0.0050**	0.0050**
	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes
Cluster	Industry	Firm	Region
F-test: β1 + β2 + β3 = 0 (*p*-value)	0.934	0.943	0.950
F-test: β4 + β5 + β6 = 0 (*p*-value)	0.003***	0.017**	0.032**
Observations	31,716	31,716	31,716
Adjusted R^2	0.217	0.217	0.217

Notes: This table shows the results of the test for parallel trend assumption using dynamic analysis. This result indicates that the impact of firms' digital transformation on green revenues is insignificant in the absence of the BCP. However, this impact is significant after the implementation of the BCP. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the industry, firm, or region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

analysis. The results indicate that the joint significances for the pre-implementation years are insignificant, whereas those for the post-implementation years are significant at the 1 % and 5 % levels across all columns. Panels A, B, and C of Fig. 2 visualize the results of the parallel trend tests, plotted with the 95 % confidence intervals, based on the regression models used in Columns (1), (2), and (3) of Table 3, respectively. We find that the impact of digital transformation on corporate green revenues is insignificant before the implementation of the BCP. This impact, however, increases significantly after the initiation of the BCP. This figure also shows a gradual increase in treated firms' green revenues after the implementation of the BCP. These results indicate that firms' digital transformation significantly increases corporate green revenues only after the implementation of the BCP.

4.4. Alternative matching techniques

This section employs an alternative matching technique to ensure that our estimates are not sensitive to the selection of matching techniques. We use the propensity score matching approach to mitigate selection bias due to non-random mutual selection and other functional misspecification following previous studies (Fenizia and Saggio, 2024; Yang et al., 2021). This approach matches firm-year observations in cities that implemented the BCP during post-implementation years with their counterparts, ensuring greater comparability in terms of observable firm characteristics. This reinforces the causal inferences obtained from the DiD estimation, as it controls for variations in observable firm characteristics, thereby ensuring a more accurate estimation of treatment effects.

Aligning with previous studies (Wu and Wang, 2022; Yang et al., 2021), we employ the nearest neighbors matching. We use the nearest neighbors (1:6) of the propensity score as the matching ratio and caliper width. Fig. 3 shows that the standardized bias across each covariate is significantly reduced after matching. We also find the standardized bias of each covariate is lower than 10 % after matching. These results indicate that the propensity score matching significantly mitigates differences in observable firm characteristics. Thus, the observed changes in firms' green revenues can be attributed to corporate digital transformation in the presence of the BCP. Table 4 shows that the coefficients on *DT×BCP* are all positive and significant. The coefficients on *DT* are all negative and significant. The coefficients on *BCP* are insignificant. These results are consistent with our baseline results, indicating that our baseline results are robust after using the propensity score matching approach to balance treatment and control groups.

4.5. Alternative specification

We further examine the impact of firms' digital transformation on green revenues following the implementation of the BCP based on alternative specifications of corporate digital transformation. This approach allows us to test whether our results are sensitive to different specifications of corporate digital transformation by employing alternative specifications, providing a more robust analysis. By incorporating an additional layer of comparison, this method helps us to control for potential confounding factors and enhances the validity of our findings (Beraja et al., 2023).

Following Xuan (2009) and Beraja et al. (2023), we adopt the following model to investigate the impact of implementation of the BCP on changes in green revenues of firms with greater digital transformation relative to their counterparts:

$$\mathrm{GR}_{i,t} = \alpha + \beta_1 \mathrm{DT\ Dummy}_{i,t} \times \mathrm{BCP}_{i,t} + \beta_2 \mathrm{DT\ Dummy}_{i,t} + \beta_3 \mathrm{BCP}_{i,t} + \theta \mathrm{X}_{i,t} + \gamma_j + \delta_r + \mu_t + \varepsilon_{i,t} \tag{2}$$

Where $DT\ Dummy_{i,t}$ denotes two measures of the level of firms' digital transformation (*DT Dummy1* and *DT Dummy2*). $DT\ Dummy1_{i,t}$ is an indicator variable that equals one if firms' level of *DT* in a given year is above the sample median, and zero otherwise. $DT\ Dummy2_{i,t}$ is an indicator variable that equals one if firms' level of *DT* in a given year is within the top tercile, and zero otherwise. Other variables are the same as those incorporated in Model (1). We, therefore, are interested in β_1, the coefficient on $DT\ Dummy_{i,t} \times BCP_{i,t}$, which captures the impact of the implementation of the BCP on green revenues of firms with greater digital transformation relative to their counterparts.

Table 5 exhibits the results of this impact based on alternative specifications of corporate digital transformation. The coefficients on *DT Dummy*1×*BCP* (*DT Dummy*2 × *BCP*) are all positive and significant at the 1 % and 5 % levels across columns. However, the coefficients on *DT Dummy*1 (*DT Dummy*2) are all negative and significant at the 1 % and 5 % levels across columns. These results are consistent with baseline results contingent upon Model (1), implying that our estimates and findings are robust and not sensitive to different specifications.

4.6. Other confounding events: placebo tests

Another challenge to the validity of our DiD model is the potential that simultaneous regulations or developments may systematically correlate with both the city-level implementation of the BCP and changes in firms' green revenues. In addition, unobserved confounding factors influencing both the treatment and control groups in ways similar to the BCP implementation could undermine the credibility of our estimates. Therefore, it is crucial to ensure that the observed causal effects on firms' green revenues are genuinely attributable to digital transformation rather than being driven by other confounding policies, spurious correlations, or random external influences.

To address the potential endogeneity issue arising from concurrent regulations, policies, or random factors that may correlate with digital transformation and firms' green revenues, we conduct a placebo test. In line with the methods used in prior studies (e.g., Defusco, 2018; Wang et al., 2022; Cao et al., 2023; He et al., 2024), we randomly generate fictitious regulations related to digital transformation, with

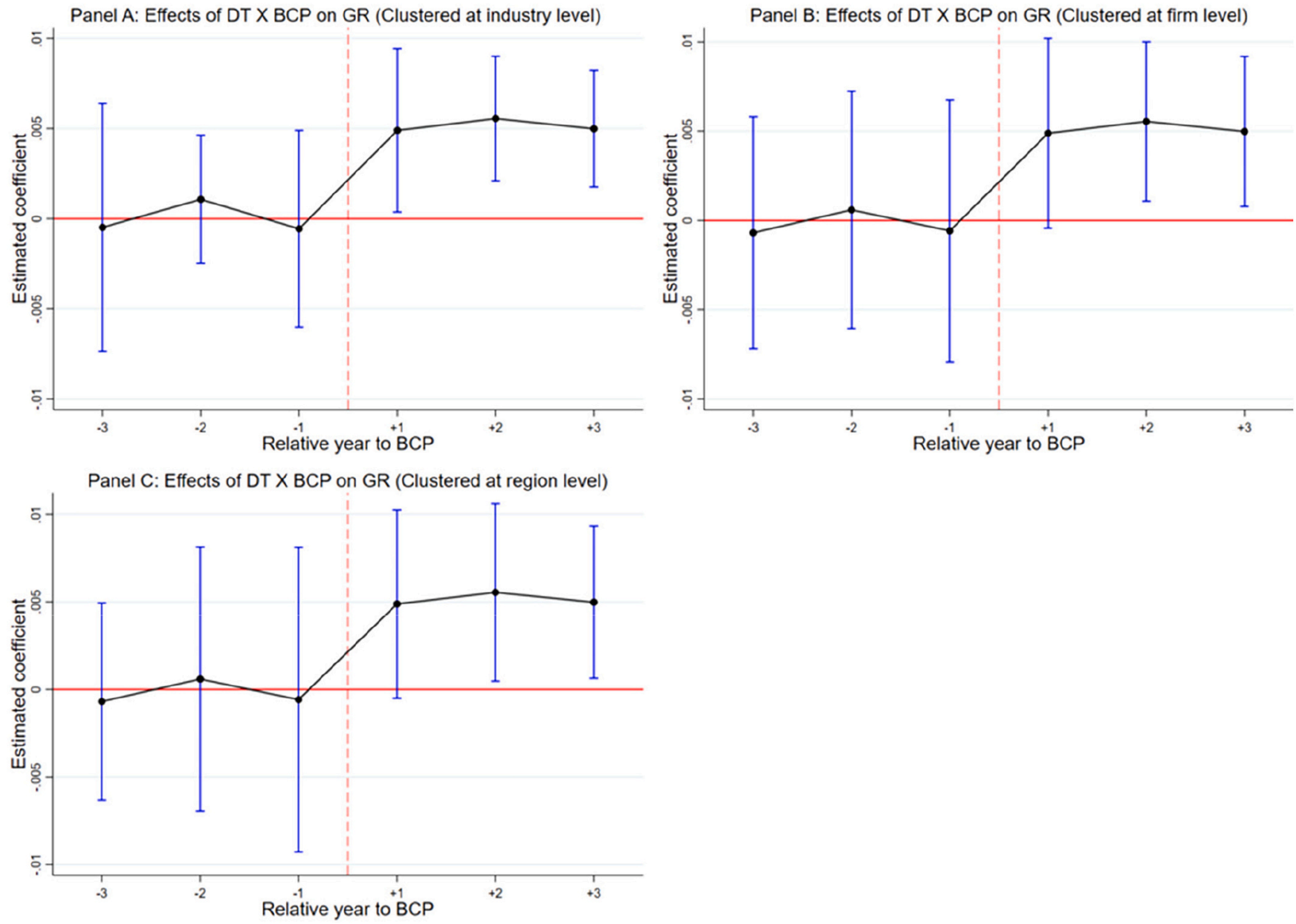

Fig. 2. Parallel trend tests.
Notes: This figure visualizes the dynamic analysis of parallel trend tests. Panels A, B, and C present the results of the parallel trend tests, plotted with the 95 % confidence intervals, corresponding to the regression models used in Columns (1), (2), and (3) of Table 3. Panels A, B, and C show the dynamic analysis results based on the regression models using robust standard errors clustered at the industry, firm, and region levels, respectively. These findings confirm the presence of a parallel trend prior to the implementation of the BCP policy. The coefficients for the pre-implementation years are insignificant and statistically indistinguishable from zero across all panels. However, the post-implementation coefficients are positive and significant across all panels. The specific coefficient values and significant levels are detailed in Table 3. These results indicate a gradual and significant increase in the impact of firms' digital transformation on green revenues after the implementation of the BCP. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pseudo-treatment groups and pseudo-event years, that could potentially influence firms' green revenues. We repeat this process 1000 times to obtain 1000 pseudo-estimated coefficients based on these fictitious regulations related to digital transformation, simulating their potential impact on firms' green revenues. This approach enables us to assess the robustness of our estimates by comparing them against a distribution of pseudo-estimated coefficients derived from scenarios where no actual policy intervention occurred. By ensuring that our findings are not replicated under these placebo conditions, we can bolster the credibility of our results and mitigate concerns regarding potential confounding factors.

Fig. 4 visualizes the results of the placebo test. This shows that pseudo-estimated coefficients are concentrated around zero, exhibiting a normal distribution. The actual coefficient on $DT \times BCP$ (0.0062) stands as an outlier, deviating significantly from this distribution derived from fictitious concurrent regulations related to digital transformation that may influence firms' green revenues. This result shows that our baseline results are robust and not likely to be driven by other concurrent regulations and random factors that may bias our estimates.

4.7. Omitted variable bias test

Another potential source of endogeneity is omitted variable bias, which may impact our estimates. If firms' characteristics are simultaneously correlated with the firms' digital transformation and green revenues, the omission of this characteristic could cause the firms' digital transformation to be correlated with the error term. This correlation would result in endogeneity and bias in our estimates. To address this issue, we test the potential endogeneity concern related to omitted variable bias using the method of Oster (2019). Following Cao et al. (2023), we employ Oster (2019) on the bound estimate to evaluate the sensitivity of coefficient estimates, comparing changes in R^2 between regressions with and without control variables. We adopt selection proportionality (δ) and R_{max} to denote the maximum R^2 for regressions when omitted variables are included in the analysis.

We estimate two omitted variable bias tests to investigate the robustness of the baseline results following Oster (2019). First, we set δ to one, and R_{max} to 1.2 times the adjusted R^2. Consequently, our results are unlikely to be influenced by omitted variable bias if β^* (i.e., $\beta^* = \beta^*(R_{max}, \delta)$) falls within the 95 % confidence interval of our treatment variables. Second, we set β^* to zero and R_{max} to 1.2 times the adjusted

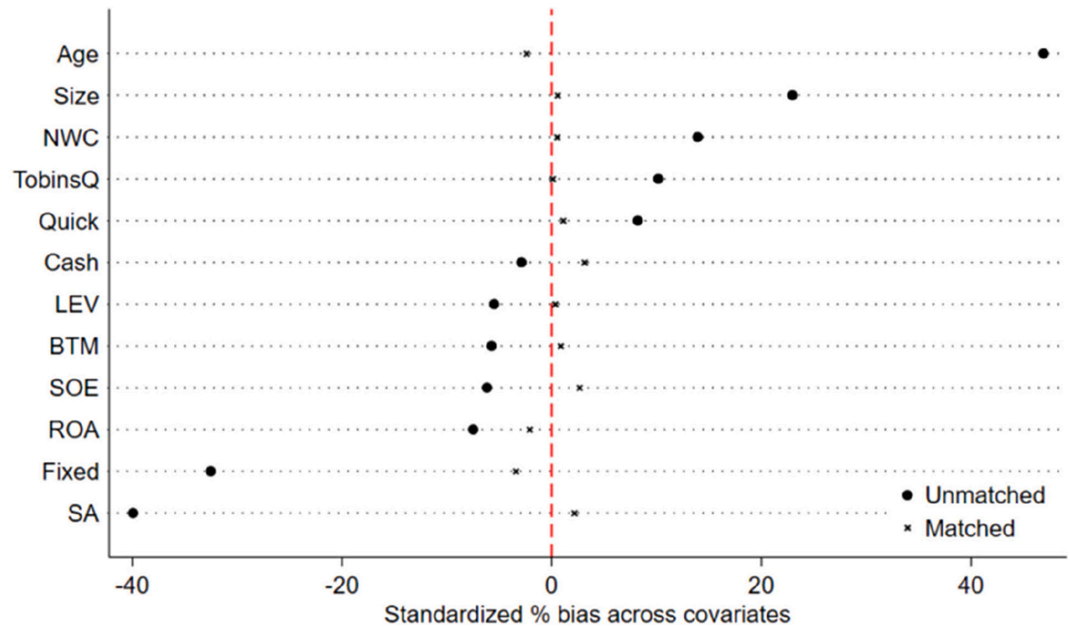

Fig. 3. Propensity scores matching results.
Notes: This figure presents the standardized bias across covariates between treatment and control groups before and after implementing propensity score matching.

Table 4
The results of using a propensity-score-matched sample.

Variables	*Green Revenues (GR)*		
	(1)	(2)	(3)
DT × *BCP*	0.0052**	0.0052**	0.0051**
	(0.002)	(0.002)	(0.002)
DT (β2)	−0.0028*	−0.0030*	−0.0030*
	(0.002)	(0.002)	(0.002)
BCP (β3)	−0.0043	−0.0035	−0.0059
	(0.006)	(0.006)	(0.005)
Controls	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	No	Yes
Propensity Score Matched	Yes	Yes	Yes
Cluster	Region	Region	Region
Observations	28,996	28,996	28,996
Adjusted R^2	0.150	0.155	0.191

Notes: This table shows the impact of digital transformation on corporate green revenues after BCP after adopting the propensity-score-matched approach to ensure our results are not driven by sample-selection bias. This shows the results of the impacts of digital transformation on corporate green revenues after matching treatment and control groups. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

R^2. Therefore, our results are unlikely to be influenced by omitted variable bias if δ is larger than one or less than minus one. Table 6 shows that β^* for the effect of $DT \times BCP$ on green revenues (0.0073) is within the 95 % confidence interval. In addition, δ for the effects of $DT \times BCP$ on green revenues (2.3662) is larger than one. These results indicate that our baseline results are robust and not driven by omitted variable bias.

4.8. *Controlling city-level variables and time-variant unobservable regional heterogeneity*

In this section, we incorporate city-level control variables and an interaction term between region and year-fixed effects to mitigate concerns about the potential influence of city-specific characteristics and time-variant unobservable heterogeneity across different cities on our estimates. In Columns (1) and (2) of Table 7, we control for additional city-level characteristics alongside the variables already included in Model (1). Detailed definitions of these city characteristics are provided in Appendix B. Column (3) incorporates the interaction term between region and year-fixed effects to control for time-variant unobservable heterogeneity across diverse cities. City-specific characteristics are omitted from this column, as they are automatically dropped due to multicollinearity when the interaction term between region and year-fixed effects is incorporated in the regression. We find that the coefficients on $DT \times BCP$ remain consistent across all columns, indicating that our baseline results are robust and not driven by the potential influence of city-specific characteristics and time-variant unobservable heterogeneity across cities.

4.9. *Alternative estimation method*

Previous studies (Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020, 2023) have highlighted that estimates from staggered DiD models with two-way fixed effects (TWFE) may be biased when multiple policy shock time points exist. Considering the potential bias since heterogeneity in treatment effects and variation in treatment timing, we re-estimate our results using an alternative method following prior research (He and Wang, 2024; Jia et al., 2024; Tan et al., 2024). Specifically, we apply the approach developed by de Chaisemartin and D'Haultfœuille (2020). Fig. 5 presents these results, plotted with 95 % confidence intervals. We observe that the parallel trend before the implementation of the BCP policy is upheld. Although differences in the coefficients appear post-BCP, the overall upward trend remains consistent. Our analysis reveals that the *t*-statistic for the Average Treatment Effect on the Treated (ATT) is 2.650, indicating a positive and significant effect at the 1 % level. In addition, the joint significance test for the pre-implementation years is insignificant (*p*-value = 0.243), while the joint significance for the post-implementation years is significant at the 1 % level (*p*-value = 0.000). These findings suggest that our results are robust under different estimation methods, further strengthening the validity of our results. In addition, for further robustness checks related to the staggered DiD model, we apply the Goodman-Bacon decomposition to assess the weight of biased components in the total effect, as discussed in Section 4.10.

Table 5
The tests of alternative specifications.

Variables	Green Revenues (GR)					
	(1)	(2)	(3)	(4)	(5)	(6)
DT Dummy1 × BCP	0.0165***	0.0162***	0.0139***			
	(0.006)	(0.006)	(0.005)			
DT Dummy1	−0.0097**	−0.0096**	−0.0074**			
	(0.004)	(0.004)	(0.004)			
DT Dummy2 × BCP				0.0149**	0.0147**	0.0138**
				(0.007)	(0.007)	(0.006)
DT Dummy2				−0.0113**	−0.0113**	−0.0105**
				(0.005)	(0.005)	(0.005)
BCP	−0.0036	−0.0034	−0.0030	−0.0005	−0.0005	−0.0011
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Controls	No	Yes	Yes	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	No	No	Yes
Matched Sample	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Region	Region	Region	Region	Region	Region
Observations	31,716	31,716	31,716	31,716	31,716	31,716
Adjusted R^2	0.164	0.169	0.217	0.164	0.169	0.217

Notes: This table presents the results of the impact of firms' digital transformation on green revenues in the presence of the BCP based on the alternative specifications. These results are consistent with our baseline results, implying that our results are robust and not sensitive to different specifications. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

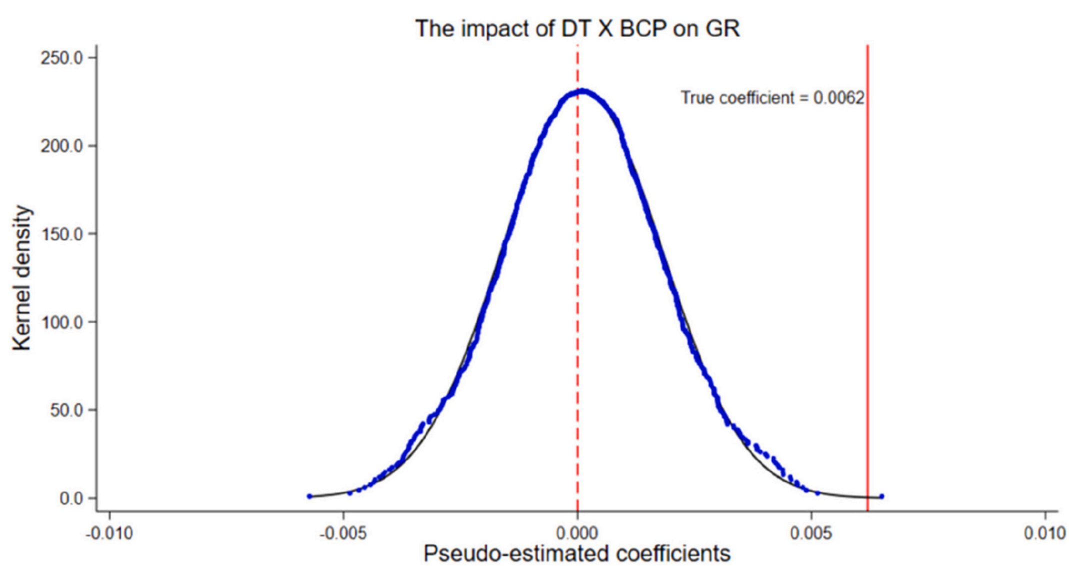

Fig. 4. Placebo tests.
Notes: This figure shows the placebo tests of the impact of firms' digital transformation on green revenues in the presence of the BCP. We perform 1000 times placebo tests to obtain pseudo-estimated coefficients. These pseudo-estimated coefficients cluster around zero, exhibiting a normal distribution. The solid line is the true coefficient on the impact of firms' digital transformation on green revenues in the presence of the BCP using robust standard errors clustered at the region level. We find that the true coefficient stands as outliers, deviating significantly from this normal distribution. This confirms that our results are robust and not likely to be driven by other concurrent regulations and confounding factors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.10. Goodman-Bacon decomposition

A key concern regarding potential bias in the estimation of TWFE within the staggered DiD framework arises when treatment effects vary over time. In such cases, staggered DiD estimates may yield treatment effect results that are opposite to the true ATT (Baker et al., 2022; Goodman-Bacon, 2021). The staggered DiD estimate is, in essence, a weighted average of multiple conventional 2 × 2 DiD estimates. The weighting is based on the size of each subsample (i.e., the sample from each 2 × 2 DiD) and the relative proportions of the treatment group compared to the control group. However, in certain 2 × 2 comparisons, already-treated units may be used as controls, potentially leading to a "bad comparison" issue (Goodman-Bacon, 2021).

In line with previous studies (He and Wang, 2024; Tan et al., 2024), we utilize the method introduced by Goodman-Bacon (2021) to decompose the DiD estimate. The overall average treatment effect in the DiD framework comprises four components, with the decomposition results displayed in Fig. 6. Our analysis reveals that the estimates are primarily driven by the comparison between the Treatment and Never Treated groups, which carries a weight of 0.755. However, the biased component arising from Later Group Treatment vs. Earlier Group Comparison holds a weight of only 0.052, indicating that the "bad comparison" issue accounts for a mere 5.2 % of the total effect. As a result, our staggered DiD model is robust and unlikely to be influenced

Table 6
Omitted variable bias tests.

	Green Revenues (GR)	
	(1)	(2)
Standard	Estimated value	Omitted variables bias
$\beta^*(R_{max}, \delta) \in [0.0004, 0.0095]$	$\beta^*(R_{max}, \delta) = 0.0073$	Unlikely
$\delta > 1$ or $\delta < -1$	$\delta = 2.3662$	Unlikely

Notes: This table shows the results of Oster's (2019) bound estimate to ensure our results are not driven by omitted variable bias. We test the sensitivity of estimated coefficients and the change in R^2 between regression models with and without control variables. We employ the selection proportionality parameter δ and maximum goodness-of-fit R_{max}. We use the model proposed by Oster (2019), denoted as $\beta^* = \beta^*(R_{max}, \delta)$, which yields consistent estimates of the actual coefficients. These results show that our baseline results are robust and not driven by omitted variable bias.

Table 7
The results of controlling city-level variables and other fixed effects.

Variables	Green Revenues (GR)		
	(1)	(2)	(3)
DT × *BCP*	0.0062**	0.0053**	0.0058**
	(0.003)	(0.003)	(0.003)
Population	0.0109	0.0137	
	(0.010)	(0.011)	
Retail	−0.0023	−0.0080	
	(0.007)	(0.007)	
STExp	0.0052*	−0.0022	
	(0.003)	(0.003)	
EduExp	−0.0020	0.0130	
	(0.006)	(0.008)	
HighEduTeachers	−0.0034	−0.0191	
	(0.004)	(0.013)	
Hospital	−0.0077	−0.0033	
	(0.007)	(0.006)	
Other Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	Yes
Region FE × Year FE	No	No	Yes
Matched Sample	Yes	Yes	Yes
Cluster	Region	Region	Region
Observations	24,993	24,993	24,271
Adjusted R^2	0.168	0.210	0.166

Notes: This table shows the impact of digital transformation on corporate green revenues in the presence of the BCP policy after controlling for city-level variables. Columns (1) and (2) show the results after incorporating city-level control variables. Column (3) presents the results of controlling for the interaction term of region and year-fixed effects. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

by the "bad comparison" problem.

5. Mechanisms analyses

5.1. Environmental regulatory intensity

In this section, we examine the underlying mechanism of environmental regulatory intensity. Institutional theory suggests that organizations operate within a hierarchical framework comprising macro- and micro-level institutional environments (Gao et al., 2017). Regional institutional development significantly shapes firms' sustainability strategies as part of these macro-level mechanisms (Pan et al., 2018). Wang et al. (2023a) document that digital transformation holds significant potential to enhance sustainability performance through business process optimization. Moreover, advancements in technological processes enable firms to foster green innovation, thereby improving business efficiency and promoting sustainable value creation (Bos-Brouwers, 2010).

For example, digital technologies, such as Internet-of-Things sensors and big data analytics, facilitate real-time monitoring of environmental metrics. This capability allows regulators to collect accurate and timely data on pollution levels, resource usage, and compliance with environmental standards (Bendig et al., 2023). Digital transformation also promotes the adoption of cutting-edge technologies and best practices in environmental management (Goldfarb and Tucker, 2019). Therefore, regions that integrate digital tools are more likely to implement sophisticated solutions for pollution control, waste management, or resource conservation, thus establishing more stringent regulatory standards. We conjecture that the impact of firms' digital transformation on green revenues following the BCP is more pronounced among firms located in regions with higher environmental regulatory intensity.

Drawing on textual analysis, we construct a region-year-level dataset of environmental regulatory intensity (*ERI*) by gathering data on the frequency of keywords related to environmental regulations from the annual government working reports of various cities. Thus, we quantify the environmental regulatory intensity and track its variations over time and across different regions, providing a comprehensive measure of environmental regulatory efforts at the regional level.

We follow the methods introduced by previous studies (Ackermann et al., 2023; Cao et al., 2023) to assess our mechanism tests. Table 8 shows the results of the tests of the mechanism of environmental regulatory intensity. Column (1) reports the results of the impact of the implementation of the BCP policy on cities' environmental regulatory intensity using city-year observations. We find that the implementation of the BCP policy significantly enhances cities' environmental regulatory intensity. If firms' digital transformation significantly increases green revenues after the implementation of the BCP policy through changes in cities' environmental regulatory intensity (ΔERI), we can observe a more pronounced effect among firms located in cities with greater increases in environmental regulatory intensity. We define firms located in cities with high (low) increases in environmental regulatory intensity when ΔERI falls within the top (bottom) tercile. $High\Delta ERI$ ($Low\Delta ERI$) equals one when firms are located in cities with high (low) changes in environmental regulatory intensity, and zero otherwise. Column (2) presents that the coefficient on $DT \times BCP \times High\Delta ERI$ (0.0049) is positive and significant at the 1 % level. We also find that the coefficient for firms located in cities with higher changes in environmental regulatory intensity ($DT \times BCP \times High\Delta ERI$) is larger than the coefficient for firms located in cities with lower changes in environmental regulatory intensity ($DT \times BCP \times Low\Delta ERI$). This indicates that digital transformation significantly enhances corporate green revenues in the presence of the BCP through changes in environmental regulatory intensity, supporting *H2*.

5.2. Environmental protection practices

We further examine another underlying mechanism regarding firms' environmental protection practices. Digital transformation enhances firms' competitiveness, business process efficiency, and reduces information costs (Sui et al., 2024). However, emerging sustainability concerns compel firms to expand their business goals beyond traditional economic objectives, necessitating contributions to climate change mitigation through sustainability actions. Thus, firms structure their operations to be both economically feasible and environmentally friendly (Erbetta et al., 2022). To achieve these complex objectives, firms need to strategically allocate resources to sustain economic profitability while adapting to evolving environmental requirements, such as engaging in environmental protection practices. Cai et al. (2023) document that firms with substantial digital transformation are more inclined to enhance both their operational efficiency and environmental protection practices. Consequently, firms with more environmental

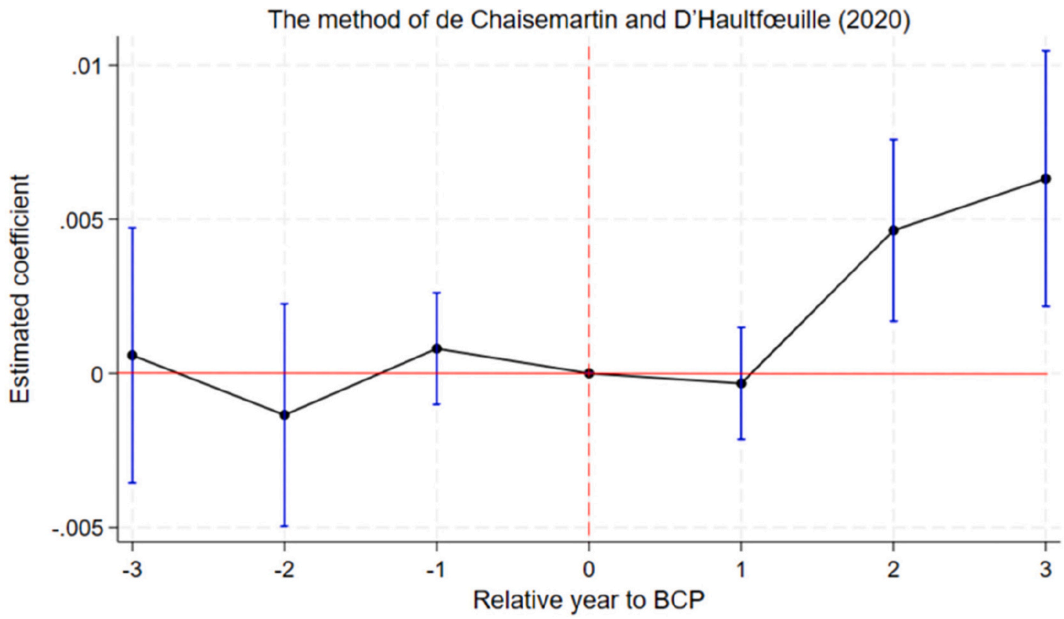

Fig. 5. Alternative estimation methods.
Notes: This figure illustrates the estimated coefficients and 95 % confidence intervals from an event-study model using the method of de Chaisemartin and D'Haultfœuille (2020) that estimate the dynamic effect of digital transformation on firms' green revenues. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

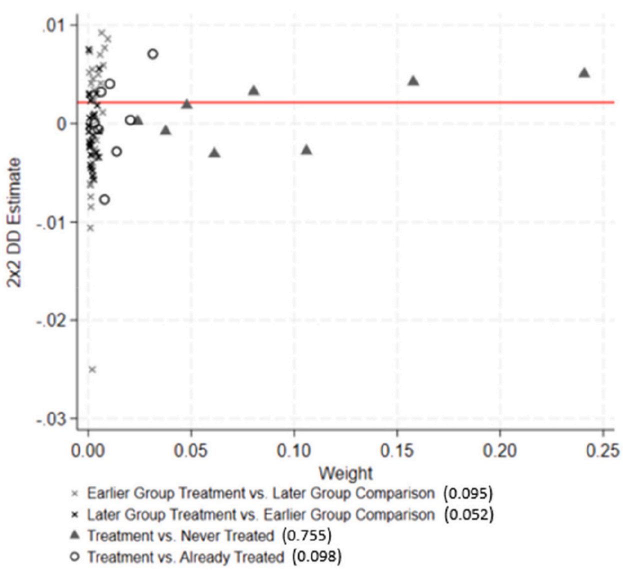

Fig. 6. Goodman-Bacon decomposition.
Notes: This figure shows the results of Goodman-Bacon decomposition. The average treatment effect results of DiD model includes four components, namely Earlier Group Treatment vs. Later Group Comparison, Later Group Treatment vs. Earlier Group Comparison, Treatment vs. Never Treated, and Treatment vs. Already Treated, respectively. The estimates are primarily influenced by the comparison between the Treatment and Never Treated groups, with a weight of 0.755. The biased component arising from Later Group Treatment vs. Earlier Group Comparison carries a weight of 0.052, implying that the "bad comparison" issue accounts for a mere 5.2 % of the total effect.

Table 8
Mechanism of environmental regulatory intensity.

Variables	*City Environmental Intensity (ERI)*	*Green Revenues (GR)*
	(1)	(2)
DT×BCP × High ΔERI		0.0049***
		(0.002)
DT×BCP × Low ΔERI		0.0039***
		(0.001)
DT		−0.0016
		(0.002)
BCP	0.0787**	0.0004
	(0.039)	(0.005)
Firm-level Controls	No	Yes
City-level Controls	Yes	No
Industry FE	No	Yes
Year FE	Yes	Yes
Region FE	No	Yes
Matched Sample	Yes	Yes
Cluster	Region	Region
Observations	3162	31,716
Adjusted R^2	0.115	0.217

Notes: This table shows the results of the mechanism analysis of environmental regulatory intensity. We define firms located in cities with higher (lower) environmental regulatory intensity when changes in *ERI* fall within the top (bottom) tercile. Column (1) reports the results of the impact of the BCP policy on cities' environmental regulatory intensity using city-year observations. Column (2) shows the results of the impact of firms' digital transformation on green revenues following the BCP among firms located in cities with higher and lower environmental regulatory intensity. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

practices are more likely to achieve and sustain better economic performance while reducing their environmental impact (Dahlmann et al., 2019). By improving their environmental practices, these firms accumulate capabilities that enable them to develop and implement green business strategies. We, therefore, conjecture that the impact of firms' digital transformation on green revenues is more pronounced among firms with more environmental protection practices.

We adopt the frequency of key terms related to environmental protection (*EPP*) disclosed in firms' annual reports to proxy firms' environmental protection practices. We follow the methods of previous studies (Ackermann et al., 2023; Cao et al., 2023) to test our mechanism. Table 9 presents the results of the mechanism of firms' environmental protection practices. Column (1) shows that the implementation of the

Table 9
Mechanism of environmental protection practices.

Variables	*Environmental protection practices (EPP)*	*Green Revenues (GR)*
	(1)	(2)
DT×BCP × High ΔEPP		0.0092***
		(0.003)
DT×BCP × Low ΔEPP		0.0052*
		(0.003)
DT	0.0002	−0.0041*
	(0.002)	(0.002)
BCP	0.0470**	−0.0061
	(0.021)	(0.007)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Region FE	Yes	Yes
Matched Sample	Yes	Yes
Cluster	Region	Region
Observations	23,173	23,173
Adjusted R^2	0.302	0.240

Notes: This table exhibits the results of the mechanism analysis of firms' environmental protection practices. We define firms that have more (less) environmental protection when changes in *EPP* fall within the top (bottom) tercile. Column (1) shows the results of the impact of the implementation of the BCP policy on firms' environmental protection practices. Column (2) exhibits the results of the impact of firms' digital transformation on green revenues following the BCP among firms with more and less environmental protection practices. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

BCP policy significantly increases environmental protection practices. If firms' digital transformation significantly increases green revenues after the implementation of the BCP policy through changes in firms' environmental protection practices (Δ*EPP*), we can observe a more pronounced effect among firms with higher increases in environmental protection practices. We define firms with high (low) increases in environmental protection practices when Δ*EPP* falls within the top (bottom) tercile. *High*Δ*EPP* (*Low*Δ*EPP*) equals one when firms with high (low) increased in environmental practices, and zero otherwise. Column (2) presents that the coefficient on *DT*×*BCP*×*High*Δ*EPP* (0.0092) is positive and significant at the 1 % level. We also find that the coefficient for firms with higher increases in environmental protection practices (*DT* × *BCP* × *High*Δ*EPP*) is larger than the coefficient for firms with lower increases in environmental protection practices (*DT* × *BCP* × *Low*Δ*EPP*). This indicates that digital transformation significantly enhances corporate green revenues in the presence of the BCP through changes in environmental protection practices, supporting *H3*.

6. Cross-sectional analyses

6.1. Investment efficiency

In this section, we examine the heterogeneity analysis of firms' investment efficiency. Optimal investments occur in perfect financial markets where all assets are allocated to projects with positive net present value (Baik et al., 2024). However, overinvested firms have inefficient investment strategies by excessively allocating their assets to projects with either positive or negative net present values (Cheng et al., 2013). Underinvested firms operate below the optimal level due to insufficient investment in positive net present-value projects (Strobl, 2014). Firms facing overinvestment issues frequently possess surplus resources that are not utilized effectively. Digital transformation can facilitate the optimization of resource allocation in these firms, thereby enhancing efficiency and minimizing waste (Wang et al., 2024). This improved allocation can result in increased green revenues by ensuring that resources are deployed toward more sustainable and economically viable projects. Thus, we predict that the impact of firms' digital transformation on green revenues following the BCP is more pronounced among firms facing overinvestment.

We employ the investment efficiency model from Biddle et al. (2009) to measure firms' investment inefficiency:

$$\mathrm{Investment}_{i,t+1} = \alpha + \beta \mathrm{Growth}_{i,t} + \varepsilon_{i,t+1} \tag{3}$$

where $Investment_{i,t+1}$ denotes the total investment of firm i in year $t+1$. $Growth_{i,t}$ represents the percentage change in sales from year t-1 to year t. $\varepsilon_{i,t+1}$ captures the investment inefficiency (i.e., over-investment or under-investment). We adopt the residuals $\varepsilon_{i,t+1}$, which proxy deviations from expected investment to capture firms' investment inefficiency. *Overinv* is set to one when $\varepsilon_{i,t+1}$ is greater than zero, and zero otherwise. Firms are classified as facing overinvestment when *Overinv* equals one, and as facing underinvestment when *Overinv* equals zero.

Table 10 shows the results of the heterogeneity analysis of firms' investment efficiency. We find that the coefficient on *DT*×*BCP* for firms facing overinvestment is more pronounced and significant than that for firms facing underinvestment. This result indicates that the impact of firms' digital transformation on green revenues in the presence of the BCP is more pronounced and significant among overinvested firms.

6.2. Green capability

We further investigate the heterogeneity of firms' green capabilities. Tang et al. (2023) find that digital transformation has the potential to promote firms' green innovation by optimizing resource allocation, fostering innovation, and leveraging network effects. Firms prioritizing green innovations are frequently embedded within a broader innovation ecosystem (Huang et al., 2024). Digital transformation can facilitate and enhance collaboration within this ecosystem, thereby promoting the development of new sustainable products and services. For example, digital transformation enables more effective data analytics and real-time monitoring, improving efficiency and fostering sustainable innovation and economic development (Goldfarb and Tucker, 2019). We thus predict that the impact of firms' digital transformation on green revenues following the BCP is more pronounced among firms with greater green capabilities.

Table 10
Cross-sectional analysis of firms' investment efficiency.

Variables	*Green Revenues (GR)*	
	(1)	(2)
	Overinvested (*Overinv* = 1)	Underinvested (*Overinv* = 0)
DT×BCP (β1)	0.0069**	0.0038
	(0.003)	(0.003)
DT	−0.0054*	−0.0020
	(0.003)	(0.002)
BCP	0.0059	−0.0053
	(0.012)	(0.007)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Region FE	Yes	Yes
Matched Sample	Yes	Yes
Cluster	Region	Region
Observations	10,046	17,546
Adjusted R^2	0.221	0.257

Notes: This table reports the results of a cross-sectional analysis of firms' investment efficiency. These results indicate that the impact of firms' digital transformation on green revenues following the BCP is more pronounced in firms facing overinvestment. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 11
Cross-sectional analysis of firms' green capability.

Variables	*Green Revenues* (*GR*)	
	(1)	(2)
	High patent application (High *GP*)	Low patent application (Low *GP*)
DT×*BCP* (β1)	0.0090**	0.0022
	(0.005)	(0.003)
DT	−0.0036	−0.0012
	(0.004)	(0.002)
BCP	−0.0003	−0.0040
	(0.017)	(0.006)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Region FE	Yes	Yes
Matched Sample	Yes	Yes
Cluster	Region	Region
Observations	9120	13,903
Adjusted R^2	0.277	0.245

Notes: This table shows the results of a cross-sectional analysis of firms' green capabilities. We define firms with greater (less) green capabilities when *GP* is above (below) the sample median. These results imply that the impact of firms' digital transformation on green revenues in the presence of the BCP is more pronounced in firms with greater green capabilities. The variable definitions are shown in Appendix B. Standard errors are reported in parentheses and clustered at the region level. *, **, and *** denote statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Amore and Bennedsen (2016) argue that patent applications offer detailed insights into the key features of underlying inventions, serving as valuable tools for classifying innovations and assessing the technological strategies of firms. Using the number of innovation patent applications as a proxy for firms' green innovation is justified by the rationale that these applications serve as concrete indicators of firms' commitment to environmentally sustainable practices and their investment in eco-friendly technologies (Kim and Valentine, 2021). We, therefore, follow Kim and Valentine (2021) and Sunder et al. (2017) to employ the logarithmic value of one plus the number of applications (*GP*) of green innovation patents as proxies of firms' green capabilities. The number of green innovation patent applications captures the quantity of firms' green innovations. We define firms as having high (low) green capabilities when *GP* is above (below) the sample median.

Table 11 shows the results of this heterogeneity analysis of firms' green capabilities. We find that the coefficient on *DT*×*BCP* for firms with more green innovation patents is more significant and pronounced than that for firms with fewer green innovation patents. We thus document that the impact of firms' digital transformation on green revenues in the presence of the BCP is more pronounced in firms with greater green capabilities, supporting our conjecture.

7. Conclusion

Green revenues emerge as a prospective solution to reconcile the conflicting economic motives and environmental problems. In this matter, we acknowledge the advancement of digital technology to raise an important but unaddressed query on whether and how digital transformation increases green revenue. Based on the data of Chinese A-share listed firms from 2009 to 2021, we investigate the impact of digital transformation on green revenue within the BCP context. Grounded on the resource-based view and dynamic capability framework, we demonstrate that digital transformation enhances corporate green revenues in the presence of the BCP. In addition, we identify heightened environmental regulatory intensity and enhanced environmental protection practices as the underlying mechanisms. Further analyses reveal that this effect is more pronounced among firms with overinvestment tendencies and those with higher green capabilities. Our study contributes to the literature as the first attempt to investigate the pivotal role of digital transformation within the micro and macroeconomic setting in enhancing green revenue. In addition, our contribution extends to embracing comprehensive and simultaneous mechanisms between firms' strategic action, regulatory setting, and government spending within the business sustainability framework.

Based on the findings, we draw the following strategic and policy implications to align profit-seeking activities with the pathway to net-zero targets. There is a need for mechanisms that enable comprehensive, simultaneous, and efficient collaboration among multiple stakeholders. Our study highlights that digital transformation at the firm level can enhance green revenue, contingent upon digital infrastructure, intensive regulations, and environmental commitment. In addition, our study suggests that digital transformation is particularly effective in over-investing firms. However, addressing this investment inefficiency is crucial, as it could undermine the effectiveness of digital transformation initiatives (Xu et al., 2023). Therefore, governments and regulators should facilitate and incentivize digital transformation projects and green innovation.

CRediT authorship contribution statement

June Cao: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Zijie Huang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ari Budi Kristanto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Conceptualization.

Appendix A. The implementation of BCP in diverse cities

Implementation years	Cities
2014	Aba, Ale, Anqing, Beijing, Benxi, Changsha, Chengdu, Dalian, Daqing, Fuzhou, Guangzhou, Guiyang, Harbin, Jiangsu, Jinhua, Kunshan, Linyi, Luoyang, Nanchan, Nanjing, Pangzhihua, Qingdao, Quanzhou, Shanghai, Shangrao, Shijiazhuan, Shenzhen, Tianjin, Weihai, Wuhan, Wuhu, Wuzhong, Xiangtan, Xiamen, Yanbian, Yingchuan, Zhengzhou, Zhenjiang, Zhuzhou, Zibo, and Zhongshan
2015	Anshan, Baishan, Chongqing, Dazhou, Dezhou, Dongguan, Dongyin, Gangzhou, Guyuan, Hefei, Huhhot, Huangshi, Jiaxing, Jining, Karamay, Lanzhou, Meizhou, Mianyang, Neijiang, Ordos, Panjin, Putian, Shantou, Shiyan, Suizhou, Taiyuan, Tonglin, Xiangyang, Xinyu, Xinxiang, Yibing, Yichan, Yangzhou, Yongcheng, Yueyang, Yuxi, Zhangye, Zhongwei
2016	Baotou, Ezhou, Haikou, Hangzhou, Hengyang, Huangshan, Jiaozuo, Ji'an, Jinzhong, Jiuquan, Linzhi, Lhasa, Luzhou, Maanshan, Mudanjiang, Nanchong, Nanyang, Nantong, Shangqiu, Shenyang, Taizhou, Tianshui, Tongliao, Weinan, Wenshan, Wuhai, Wuwei, Wuxi, Xining, Ya'an, Yangquan, Yantai, Yiyang, Yulin, Zaozhuan, and Zunyi

Appendix B. Definition of variables

Variable	Definition
Outcome and treatment variables	
GR	The ratio of corporate green revenues to total revenues
DT	Logarithmic value of one plus the number of key terms pertinent to corporate digital transformation disclosed in firms' annual reports
DT Dummy1	The indicator variable equals one if a firm's level of DT in a given year is above the median, and zero otherwise
DT Dummy2	The indicator variable equals one if a firm's level of DT in a given year is within the top tercile, and zero otherwise
BCP	The indicator variable equals one if a firm is headquartered in a city implementing the BCP in the post-adoption year, and zero otherwise
Mechanism and cross-sectional variables	
ERI	Logarithmic value of one plus the number of key terms pertinent to environmental regulations disclosed in annual working reports of government
EPP	Logarithmic value of one plus the number of key terms pertinent to firms' environmental protection practices disclosed in annual reports
Inv	The firms' investment efficiency calculated by the model of Biddle et al. (2009)
Overinv	The indicator variable equals one if a firm is facing overinvestment in a given year, and zero otherwise
GP	Logarithmic value of one plus the number of applications of green innovation patent
Firm-level control variables	
Size	Logarithmic value of total assets
SOE	The structure of the firms' ownership equals one when firm *i* is a state-owned enterprise in year *t*, and zero otherwise
Age	Logarithmic value of one plus firms' age
LEV	Debt-to-asset ratio
NWC	Net working capital scaled by total assets
Cash	Cash and cash equivalent scaled by total assets
Quick	The value of firms' quick ratio
BTM	Firms' book-to-market ratio
ROA	The value of return on assets
TobinsQ	Tobin's Q value of firm
Fixed	Total fixed assets scaled by total assets
SA	SA index developed by Hadlock and Pierce (2010) for financial constraints
City-level control variables	
Population	Logarithmic value of one plus population of city
Retail	Logarithmic value of one plus total retail sales of consumer goods
STExp	Logarithmic value of one plus expenditure on science and technology
EduExp	Logarithmic value of one plus expenditure on education
HighEduTeachers	Logarithmic value of one plus the number of full-time teachers in regular higher education institutions in city
Hospital	Logarithmic value of one plus the number of hospitals in city

Appendix C. Key terms of firms' digital transformation

Classification	Key terms
Transformation of Artificial Intelligence	Artificial Intelligence, Autonomous Driving, Biometric Technology, Business Intelligence, Deep Learning, Facial Recognition, Identity Verification, Image Understanding, Intelligent Data Analysis, Intelligent Robots, Investment Decision Support Systems, Machine Learning, Natural Language Processing, Semantic Search, and Voice Recognition
Transformation of Big Data	Augmented Reality, Big Data, Credit Reporting, Data Mining, Data Visualization, Heterogeneous Data, Mixed Reality, Text Mining, and Virtual Reality
Transformation of Blockchain	Blockchain, Digital Currency, Differential Privacy Technology, Distributed Computing, and Smart Financial Contracts
Transformation of Cloud Computing	Cloud Computing, Converged Architecture, Edge Computing, EB-Level Storage, Green Computing, Graph Computing, In-Memory Computing, Internet of Things, Multi-Party Secure Computation, Petabyte-Level Storage, Physical Information Systems, Stream Computing, Trillion-Level Concurrency, and Brain-Like Computing
Transformation of Digital Technology	Digital Financial Services, Digital Marketing, *E*-Commerce, Fintech, Industrial Internet, Internet Healthcare, Internet Finance, Mobile Internet, Mobile Payment, NFC Payment, Open Banking, Online Connectivity, Quant Finance, Smart Agriculture, Smart Contracts, Smart Customer Service, Smart Energy, Smart Environmental Protection, Smart Financial Advisory, Smart Grid, Smart Healthcare, Smart Home, Smart Marketing, Smart Tourism, Smart Transportation, Third-Party Payment, Wearable Technology, and Unmanned Retail

Appendix D. The results of the entropy balancing approach

Panel A: Before balancing								
	Treatment group ($N = 13{,}262$)			Control group ($N = 18{,}454$)			Std.	Var.
	mean	variance	skewness	mean	variance	skewness	Diff.	Ratio
Size	22.330	1.776	0.803	22.040	1.500	0.716	0.108	1.184
SOE	0.359	0.230	0.590	0.389	0.238	0.455	−0.008	0.967
Age	2.961	0.091	−0.572	2.803	0.138	−1.049	−0.070	0.660
LEV	0.426	0.040	0.260	0.437	0.042	0.190	−0.005	0.947
NWC	0.244	0.055	−0.070	0.210	0.064	−0.020	−0.019	0.854
Cash	0.160	0.014	1.299	0.164	0.017	1.512	−0.014	0.797
Quick	1.826	2.494	2.031	1.694	2.690	2.201	−0.061	0.927
BTM	0.610	0.063	0.246	0.624	0.054	0.045	0.019	1.174
ROA	0.034	0.005	−2.777	0.039	0.004	−2.224	0.009	1.317
TobinsQ	2.044	1.318	1.849	1.934	1.045	1.992	0.126	1.261
Fixed	0.185	0.024	1.144	0.236	0.027	0.793	−0.009	0.895

(*continued on next page*)

(*continued*)

Panel A: Before balancing								
	Treatment group (N = 13,262)			Control group (N = 18,454)			Std.	Var.
	mean	variance	skewness	mean	variance	skewness	Diff.	Ratio
SA	−3.848	0.061	0.084	−3.749	0.061	0.011	−0.001	0.996
Panel B: After balancing								
	Treatment group (N = 13,262)			Control group (N = 18,454)			Std.	Var.
	mean	variance	skewness	mean	variance	skewness	Diff.	Ratio
Size	22.330	1.776	0.803	22.330	1.777	0.804	0.000	1.000
SOE	0.359	0.230	0.590	0.359	0.230	0.590	0.000	1.000
Age	2.961	0.091	−0.572	2.961	0.091	−0.587	0.000	1.000
LEV	0.426	0.040	0.260	0.426	0.040	0.260	0.000	1.000
NWC	0.244	0.055	−0.070	0.244	0.055	−0.070	0.000	1.000
Cash	0.160	0.014	1.299	0.160	0.014	1.299	0.000	1.000
Quick	1.826	2.494	2.031	1.826	2.495	2.031	0.000	1.000
BTM	0.610	0.063	0.246	0.610	0.063	0.246	0.000	1.000
ROA	0.034	0.005	−2.777	0.034	0.005	−2.777	0.000	1.000
TobinsQ	2.044	1.318	1.849	2.044	1.318	1.849	0.000	1.000
Fixed	0.185	0.024	1.144	0.185	0.024	1.144	0.000	1.000
SA	−3.848	0.061	0.084	−3.848	0.061	0.086	0.000	1.000

Appendix E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108312.

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