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Smart Cities and Greener Futures: Evidence from a Quasi-Natural Experiment in China's Smart City Construction

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Abstract: As the digital economy becomes the new engine of economic growth, China has introduced a series of smart city policies aimed at promoting high-quality and sustainable urban development. This paper aims to evaluate the green development effects of China's "Smart City Pilot" policy and to explore the heterogeneity of policy effects across different types of cities. Using panel data from 283 prefecture-level cities in China from 2006 to 2020, this study examines the relationship between smart city construction policy and urban green development efficiency using the green total factor productivity (GTFP). We employ the Causal Forest and mediation effect models to estimate the impact of smart city pilot policy on GTFP and explore the underlying mechanisms. The main results are: (1) The smart city pilot policy significantly enhances urban GTFP, a finding consistent across diverse policy evaluation approaches. (2) The influence of the policy on green development varies among cities, and such heterogeneity is effectively captured by the Causal Forest. (3) This varied impact primarily stems from urban location factors and inherent characteristics. Notably, the policy effect in Eastern China outpaces that in other regions. The policy yields greater green benefits with financial development and medical capital rises, but excessive government public expenditure curtails its positive influence. (4) The mediation mechanisms through which the smart city pilot policy promotes green development exhibit certain differences between the "high-effect group" and the "low-effect group". The former predominantly leverages innovation-driven and agglomeration effects, while the latter chiefly relies on industrial structural advancement and rationalization.

Keywords: smart city construction; green total factor productivity; Causal Forest; heterogeneous treatment effects

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1. Introduction

Recent global climate change issues have become increasingly severe, with dire consequences for agriculture, socio-economics, and human well-being [1]. This trend threatens the sustainable development of human society. In 2022, extreme climate events such as the prolonged drought in East Africa, record rainfall in Pakistan, and record heatwaves in China and Europe affected millions of people and caused billions in economic losses. Tackling global climate challenges has become an urgent collective endeavor. As the largest developing country and energy consumer in the world, China has established robust targets to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. This aligns not only with China's pursuit of sustainable development domestically but also with its international duties and pledges to actively engage in global climate governance and construct a shared future for humanity.

With the new wave of the global technological revolution, emerging digital technologies like the Internet, big data, and cloud computing have played vital roles in economic growth [2], green innovation [3], government management [4], corporate governance, and environmental improvement [5]. The digital transformation injects new momentum into ecological priority, green low-carbon development, and achieving carbon peaking and neutrality on schedule [6–8]. Against this background, China's "14th Five-Year Plan for National Informatization" advocates for "digital-green collaborative development" and "promoting green development with digitalization, while driving digitalization with green development".

Cities, as the basic carriers of socio-economic development, are both the primary sources of carbon emissions and the central front in coordinated and enhanced pollution reduction and carbon mitigation efforts. The smart city is a novel urban development mode encompassing efficient production, modern public services, energy conservation, environmental protection, and economic growth—inherently aligning with green development. By integrating the internet, contemporary information technology, and urbanization, smart cities establish a new framework for modern urban development and may offer a potential solution to environmental challenges [9]. In late 2012, China formulated and progressively implemented the smart city pilot policy. Essentially, it relies on information technologies such as the Internet of Things, cloud computing, and big data, as well as an urban innovation ecosystem nurtured in a knowledge environment, to achieve a leapfrog in urban development patterns. The smart city pilot policy aims to build intelligent, innovative, green, and low-carbon areas as development goals. It is a sustainable policy that requires achieving a "win–win" between the information economy and the ecological environment. The "National Plan on New Urbanization (2014–2020)" announced in 2014 outlined the primary direction for smart city pilot construction and elevated smart city strategies to the national strategic level. In 2021, China's 14th Five-Year Plan (2021–2025) proposed accelerated deployment of smart cities and new infrastructures, promoting new technologies, and the establishment of a next-generation information infrastructure system. Currently, the construction of China's smart cities has achieved remarkable results. In terms of investment scale related to smart city construction, the market size of SC in 2022 was 20 times larger than in 2016, with market capacity reaching the trillion-dollar level. According to the "Global New Smart City (SMILE Index)" released by the China International Fair for Trade in Services (CIFTIS) in 2023, Beijing, Guangzhou, and Hong Kong were ranked among the top 10 in the global smart city rankings. China's prowess in the realm of smart cities was brought to the forefront. Meanwhile, the current implementation of smart city pilots faces certain problems, such as unbalanced development, unclear top-level design, slow adoption of digital technologies, and insufficient financial support. Some cities do not pay enough attention to their unique advantages and practical conditions in economic and ecological development but simply copy the best practices of demonstration cities. This greatly reduces the socioeconomic and environmental benefits that a smart city is supposed to achieve. These issues, to varying degrees, restrict the efficiency of smart city construction and pose obstacles to the promotion of green and sustainable urban development.

As the digital era emerges, an increasing number of developing countries have put the construction of smart cities on the agenda, seeing it as an important path to promoting high-quality, sustainable development. Aside from China, countries such as India, Brazil, and South Africa are also actively exploring smart city construction plans. How does one promote high-quality smart city construction? How does one better leverage smart city construction to promote green urban development? These have been important issues of concern for government administrators and research scholars. As a representative of developing countries, China is at the forefront in terms of the pilot duration and number of cities for smart city construction among developing countries. China's experience can provide important empirical data and case support to study the aforementioned issues. Against this background, this paper takes China's "smart city pilot" policy (hereafter SC policy) as the research object. Based on panel data from 283 prefecture-level cities in China from 2006 to 2020, we construct a green total factor productivity (GTFP) index and adopt machine learning causal inference methods to deeply discuss the effects and mechanisms of smart cities on green development.

This study offers three primary contributions. Firstly, we employ the Causal Forest method to assess the impact of the SC policy on GTFP, thereby expanding both theoretical and empirical research on green development. Secondly, this study offers a granular examination of regional variances in policy outcomes. This approach illuminates commonalities among cities with pronounced effects and facilitates a deeper understanding of their unique trajectories and patterns, enhancing the efficacy of subsequent policy adjustments. Thirdly, we identify the underlying mechanisms influencing GTFP through three mediating channels: innovational dynamics, industrial structure optimization, and factor aggregation. This analysis offers referential frameworks for promoting sustainable and green development worldwide in the digital age.

The structure of this paper is arranged as follows: Section 2 is the literature review. Section 3 is devoted to studying the underlying mechanism and giving research hypotheses. Section 4 outlines the methodologies and data employed. Section 5 showcases empirical findings alongside robustness tests. Sections 6 and 7 further explore the heterogeneity of treatment effects and mediation mechanisms, respectively. Finally, Section 8 provides targeted recommendations and concludes the paper.

2. Literature Review

The concept of a smart city (SC) traces back to IBM's "Smart Planet" initiative launched in 2008, representing the integration of digital cities and emerging information technologies like the Internet of Things [10]. As defined by Bonab et al. [11], an SC is an organic urban system that consciously pursues sustainable development by leveraging technology to synthesize data, resources, policies, and human capital. Ahvenniemi et al. [12] argued that technology should enable sustainability in SCs; cities that fail to incorporate sustainability cannot be considered truly "smart". SC development is deemed the urban growth model in the digital era and the trajectory of societal advancement [13]. With major countries incorporating SCs into national development strategies, research on the influence of SCs has proliferated.

By examining the repercussions of SC initiatives, scholars have explored economic, societal, and environmental impacts. Liu and Peng [14] indicated that SCs reduce energy consumption and pollution by shifting from linear to networked integration of natural resource utilization, clean manufacturing, and waste disposal, thereby achieving cost savings and quality improvement. Conversely, Green [15] cautioned against potential downsides, arguing that in SCs, civic engagement might become overly reliant on technology applications, which could marginalize citizens who are averse to or lack access to such platforms. Concerns over discrimination, infringements on personal liberties, and privacy also emerged in this context. The environmental impact of digital incorporation in city planning remains a contentious issue. Lange et al. [16] pointed out that our current digital pivot has increased energy consumption, implying that technology alone cannot uncouple economic growth from energy demands; more comprehensive sustainability strategies are needed. Salahuddin and Alam [17] found that in the long run, a 1% increase in internet users in OECD nations correlated with a 0.026% rise in per capita electricity consumption. Yet, digital technology might also bolster energy efficiency [7]. For example, Khuntia et al. [18] studied Indian manufacturers and found that operations-oriented IT investments effectively reduced enterprise energy use. However, Cai et al. [19] found no significant linkage between U.S. SCs and environmental or social sustainability. While Yigitcanlar and Kamruzzaman [20] asserted that SCs in the UK are not driving low-carbon sustainable development, others posited that SC policies reduce regional carbon dioxide and pollutant emissions [21,22]. Liu et al. [8] presented evidence that the SC policy decreased industrial SO_2 emissions in central and northeastern China while significantly reducing electricity consumption per GDP unit in eastern and western regions. The ongoing debate centers on whether SCs genuinely address environmental challenges and foster eco-friendly urban growth.

Researchers have also looked at the potential environmental impacts of different sectors of SCs, including housing [23], data centers [24], renewable energy, and energy use in transport [25]. Kylili and Fokaides [23] argued that zero-energy buildings, when synergized with urban energy networks, can be pivotal in fulfilling the European SC construction and emission reduction targets. Zhu et al. [24] examined emission reduction technologies across 20 notable data centers in global low-carbon smart cities. Their findings emphasized the need to optimize IT equipment and develop advanced cooling technologies to reduce energy usage in data centers. Anh Tuan et al. [25] analyzed the role and challenges of integrating renewable energy into SC grids by examining both technological and economic perspectives. Their analysis indicates that extensive renewable energy penetration is viable for SCs of all scales. Chu et al. [21] explored the impacts of SC initiatives on China's ecological environment, verifying that these projects significantly reduced industrial emissions by driving technological innovations and optimizing resource allocation in cities. Ruggieri et al. [26] assessed transportation decarbonization across six European SCs: London, Hamburg, Oslo, Milan, Florence, and Bologna. They found cities promoting electric vehicle adoption, notably Hamburg, Milan, and London, and witnessed substantial reductions in pollutants, including PM2.5, PM10, and NO2. However, some scholars have presented contrasting viewpoints; for instance, Dashkevych and Portnov [27] argued that the widespread adoption of internet technology and the number of universities in a city did not necessarily correlate with improved air quality.

To determine whether an SC does indeed promote green urban development, the treatment effects of China's SC policy need to be examined. While previous studies employed econometric methods like difference-in-differences to estimate the average treatment effect (ATE), they faltered in assessing heterogeneous treatment effects (HTEs). In recent years, merging traditional machine learning with causal inference has emerged as a new research avenue [28]. Hill [29] proposed using Bayesian Additive Regression Trees (BARTs) to identify causal effects in non-experimental settings. Nonlinear simulations showed BARTs produced more accurate average treatment effect estimates compared to propensity score matching, weighting, and regression adjustment. Johansson et al. [30] presented a counterfactual reasoning framework combining domain adaptation and representation learning. Louizos et al. [31] estimated a latent space capturing confounders and effects using variational autoencoders, learning individual causal effects from observational data. Wager and Athey [32] applied random forests to estimate treatment effects, discussing the consistency and asymptotic normality of the estimates (Causal Forest). Athey et al. [33] extended the Causal Forest to Generalized Random Forests, demonstrating applications to quantile regression forests and instrumental variable regression.

In summary, while numerous studies have explored the effects of SC evolution on urban environments from diverse dimensions, discussions on green development are still relatively lacking. In addition, China has a vast territory with certain imbalances in economic development across regions, leading to significant differences in city-specific characteristics. The current literature points out regional variations in policy implementation throughout China, necessitating a more detailed analysis of SC policy efficacy across various regions [34–36]. In causal inference, compared with traditional econometrics methods, the emerging Causal Forest approach demonstrates stronger real-world interpretability, more accurate predictive capability, and finer granularity, thus gaining increasing application. However, applications of machine learning for policy evaluation in Chinese cities remain scarce. Based on the Causal Forest, we examine the impact of China's SC policy on urban green development. This offers a nuanced understanding of both the overarching and regional consequences of the policy. Furthermore, we seek to identify the determinants underlying the heterogeneous effects of the policy, aiming to enhance sustainable urban development.

3. Mechanism Elaboration and Research Hypotheses

SCs represent an advanced stage in urban digitization. Their pilot initiatives primarily focus on utilizing information technology innovations to catalyze upgrades in urban governance models. SCs extensively implement next-generation technological architectures to empower integrated "industry–academia–research" development platforms. By sharing information, they effectively promote synergies between specialized production factors across domains, propel intelligent industrial clusters, and expand the ecological dimensions of clean industry. This contributes to molding green and sustainable urban paradigms. On one hand, SCs transform conventional municipal utilities into intelligent, digitalized counterparts. The comprehensive penetration and application of digital tech-based management platforms enable efficient data transfer, aiding enterprises in tapping into market demands with data insights. This enhances resource distribution and energy efficiency, facilitating an urban shift towards greener transformation [37,38]. On the other hand, SCs conduct green upgrades on large-scale energy-intensive infrastructure and proactively integrate and promote renewable energies. This realizes the efficient utilization of renewables like wind and solar power, transforming urban energy structures. For instance, SCs use Internet of Things (IoT) technologies to meticulously plan and manage electric vehicle charging facilities. This provides convenience for harnessing clean energies. From the above analysis, we suppose:

Hypothesis 1. *The "smart city pilot" policy helps promote the green development of the pilot cities.*

Disparities in locational endowments and development stages lead to considerable differences in development levels and industrial structures across cities. The overall levels of economic, financial, and human capital development in eastern cities are generally higher compared to central and western cities. Meanwhile, western regions have a higher dependence on natural resources in their economic structures. The heightened environmental pressures and energy consumption could also potentially constrain green and low-carbon transitions in these cities. According to the new economic geography proposed by Krugman [39], locational advantages amplify enterprise clustering, propelling urban economic growth. Cities with advanced financial development possess well-functioning market mechanisms that provide consistent capital inflows, ensuring effective policy implementation. Human capital determines the development potential and quality of cities. High-quality human capital more effectively leverages digital technologies to catalyze urban green innovation and diffusion [40]. Such cities generally harbor residents with a higher environmental quality preference and a proclivity for digital integration. The effective synergies between locational advantages, sophisticated finance, and abundant technological talent propel the deep integration of high-tech with the traditional physical economy. The advancement of SC policy reinforces the application of digital technologies across diverse urban domains like management, public services, and enterprise production. This facilitates the optimization and restructuring of entire industrial chains and corporate processes, thereby more readily bolstering green urban production [41].

In contrast, cities heavily reliant on resource-intensive industries like heavy manufacturing typically have relatively singular economic structures. Such structures are more prone to "resource curses". Digital technologies struggle to improve existing industrial structures, while financial underdevelopment deprives cities of environmental governance funds and might impede the effectiveness of SC policy [42]. Therefore, this paper proposes the following hypothesis regarding the sources of heterogeneous treatment effects (HTEs):

Hypothesis 2. *The treatment effects of the "smart city pilot" policy demonstrate heterogeneity across pilot regions. Differences in city-specific features like financial development, human capital, and industrial development are important factors causing HTEs.*

Innovation-driven green development is an important new approach to transitioning from pollution-intensive industries and enhancing both economic efficiency and environmental quality [43]. Referencing the "quadruple helix model" [44], the construction of SCs requires four key participants—government, academia, industry, and citizens—to be coupled together and jointly promote SC innovation. The government provides support for research, development, and introduction of new technologies through policy guidance, aggregates the participants in the quadruple helix model through industry–academia–research–integration, conducts collaborative cooperation on intelligent solutions for issues like environmental problems, and creates huge markets for advanced green terminal products [45,46]. In addition, SCs established intelligent information platforms to promote inter-industry correlative innovation spillovers of information and also provide the government with more precise dynamic management media. The central government clearly stated in its top-level design that people-oriented and ecological civilization are the guiding ideologies for the construction of SCs. This requires local governments to strengthen environmental regulation to generate the "Porter Hypothesis", which forces companies to develop low-pollution, low-consumption, and high-value-added advanced manufacturing technologies, thereby effectively reducing the unreasonable outputs of cities in the pollution field and optimizing energy consumption structures [9,47]. With the simultaneous rise of information technology and urban green technology innovation, the current situation of fossil energy consumption is alleviated, resource misallocation and waste are avoided, and waste recycling and reuse are achieved, which facilitates cities' green transformation. In view of this, this paper proposes the third hypothesis:

Hypothesis 3. *The implementation of the "smart city pilot" policy can improve urban green innovation capabilities, thus advancing green development.*

The digitization of the economy is now a pivotal driver of contemporary economic growth. The construction of SCs actively promotes the in-depth integration of next-generation, data-centric technologies into the traditional real economy, spawning innovative products, markets, and business models. This spurs effective market competition, prompting existing enterprises to place greater emphasis on technological innovation. The high-end manufacturing industry is leading the way in leveraging this conversion of old and new momentum to transform traditional industries towards high-intelligence industries. Inter-sectoral differences in technological levels lead to divergences in productivity growth, inducing industrial structure adjustments [48]. This exerts the "Baumol effect" on other traditional small and medium-sized industries, progressively limiting high-pollution, resource-intensive industries with low value addition. It also guides the transfer of resources and factors of production from low marginal efficiency industries to high marginal efficiency industries, thereby promoting the high-level transformation of the existing industrial structure and optimizing resource allocation across industries. Concurrently, the modern service sector is pioneering fresh business paradigms and forming clusters of upstream and downstream value chains in medium- and high-end industries. By consolidating resources, these clusters not only facilitate large-scale economic activities but also foster technological interchange and spillover across sectors. This inter-industry synergy leads to a more balanced industrial layout, elevates pollution management standards, and propels cities towards sustainable, green growth [49].

Hypothesis 4. *The "smart city pilot" policy can optimize urban industrial structures, thereby guiding greener urban development.*

To better advance the construction of SCs, both national and regional governments have proactively introduced sophisticated urbanization infrastructure and rolled out a suite of supporting policies, including financial subsidies, tax reductions and exemptions, preferential land use, etc. Such endeavors have created an attractive environment for investment, business, education, and healthcare, which is effectively luring top-tier talent and foreign direct investments, promoting the agglomeration of low-energy-consuming and high-value-added high-tech industries, and generating economies of scale. As pointed out by multiple scholars, the rising ubiquity of cutting-edge information technology in SCs aligns with Metcalfe's Law. Specifically, as the number of Internet users swells and network integrity heightens, the utility and value of the Internet amplify exponentially [50–52]. With the continual expansion in the application scope of information technology, its capacity to dissolve information gaps, enhance inter-industry communication, and foster technological diffusion becomes more pronounced. This invariably ameliorates urban industrial excesses and resource allocation issues, underpinning green urban progression. Simultaneously, substantial investments from both local and international sources are revitalizing urban production endeavors. As an advanced factor of production, information technology will be embedded in primary factors of production like capital, which will steer the economic landscape towards heightened efficiency and long-term sustainability. Following the above analysis, this paper proposes the fifth hypothesis:

Hypothesis 5. *The "smart city pilot" policy can facilitate the aggregation of material capital and information technology factors, thereby increasing green development.*

The theoretical mediation mechanisms of how SC policy improves GTFP are briefly summarized in Figure 1:

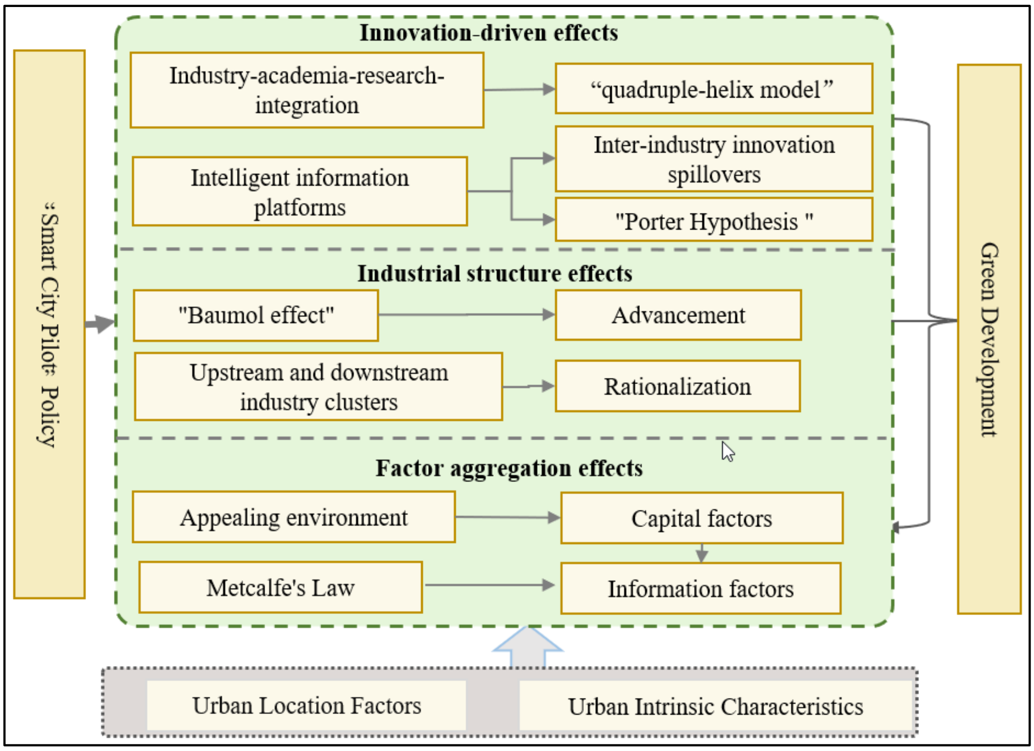

Figure 1. Theoretical mechanisms of how SC policy improves GTFP.

4. Methodology and Data

4.1. Model Design

4.1.1. EBM Model and GTFP

The fundamental principle of green development necessitates achieving enhanced economic growth while emitting fewer pollutants. This is quantified using the indicator for "green productivity". Such productivity is further categorized into single-factor productivity and total-factor productivity. The former typically includes only two factors: pollutant emissions and urban GDP, assessing green development by their ratio. However, it does not incorporate the impact of other input and output elements in production activities [53].

In contrast, green total factor productivity (GTFP) comprehensively considers various inputs and outputs in the social production system and provides more comprehensive and reasonable results [54]. Thus, GTFP becomes the preferred indicator for measuring green development.

The measurement methods for GTFP mainly include the Solow Residual [55], Growth Accounting [56], Stochastic Frontier Analysis (SFA) [57], and the DEA method, etc. Among them, the DEA has gained widespread use due to its advantages, such as not requiring a specific production function form and accommodating multiple inputs and outputs. The GTFP measurement in this paper is constructed within the DEA framework. Generally, there are two basic approaches to efficiency in the conventional DEA model: radial and non-radial. However, both the radial measure, such as CCR, and the non-radial measure, such as SBM, have some limitations. The main limitation of the radial model is that it ignores non-radial slacks during efficiency score evaluations [58]. For non-radial models, due to slacks not necessarily proportional to the inputs or outputs, their derived results may not align proportionally with the original input or output data [59].

This paper measures GTFP using the EBM (Epsilon-Based Measure) model proposed by Tone and Tsutsui [60], which is a hybrid model that contains both radial and non-radial distance functions, effectively overcoming the weakness of models based on a single distance function. The EBM model has *H+1* decision-making units (DMUs), each containing multiple inputs, desirable outputs, and undesirable outputs in the production system. Using a linear programming model, it calculates the global optimum efficiency score, denoted as Ψ and referred to as GTFP in this study. For the DMU_0, the objective function and constraints of the EBM model are given as follows in Equation (1).

$$\Psi = min\frac{\theta-\varepsilon_x\sum_{u=1}^{m}\frac{\omega_u^- s_u^-}{x_{u0}}}{\phi+\varepsilon_{y_G}\sum_{j=1}^{n}\frac{\omega_j^+ s_j^+}{y_{Gj0}}+\varepsilon_{y_B}\sum_{z=1}^{l}\frac{\omega_z^- s_z^-}{y_{Bz0}}}$$
$$s.t.\begin{cases} X_u\delta + s_u^- = \theta x_{u0}, u = 1,2,\cdots,m \\ Y_{Gj}\delta - s_j^+ = \phi y_{Gj0}, j = 1,2,\cdots,n \\ Y_{Bz}\delta + s_z^+ = \phi y_{Bz0}, z = 1,2,\cdots,l \\ \delta \geq 0, s_u^-, s_j^+, s_z^- \geq 0 \end{cases} \quad (1)$$

Here, X_u, Y_{Gj}, and Y_{Bz} respectively represent the *H*-dimensional vector sets of the *u*th input, the *j*th desirable output, and the *z*th undesirable output for the remaining DMU_h (h = 1, 2, . . . , H). δ is an *H*-dimensional parameter vector set. The terms ω_u^-, ω_j^+, and ω_z^- and s_u^-, s_j^+, ands_z^-, respectively, denote the weights and slack variables for the *u*th input, *j*th desirable output, and *z*th undesirable output. ε is a crucial parameter within the model, ranging between 0 and 1, indicating the significance of the non-radial part in the efficiency score measurement. ε needs to be determined based on the given data before establishing the EBM model. For a detailed computation method, please refer to Tone and Tsutsui [60] due to space limitations.

4.1.2. Causal Forest and Policy Treatment Effect Estimation

Within traditional econometrics, methods such as difference-in-differences (DID) and regression discontinuity design (RDD) are commonly used to evaluate the average treatment effect (ATE) of policies. The specific form of these regression models needs to be specified in advance, and their matching effectiveness will significantly decrease in situations with excessive covariates [61,62]. They may suffer from endogeneity issues like omitted variables, measurement errors, and simultaneous causality, undermining the consistency of parameter estimates. Moreover, due to differences in resource endowments across cities, there can be heterogeneity in policy treatment effects. Traditional econometric models have difficulty capturing heterogeneous treatment effects (HTEs).

Unlike traditional policy evaluation methods, data-driven machine learning models do not require predefined model forms. They possess higher predictive accuracy when handling high-dimensional, complex, and nonlinear data structures and more flexibly capture the interactions among variables. However, as the actual policy treatment effect is latent and unobservable, it cannot be directly validated against the ground truth. Hence, conventional machine learning approaches cannot directly identify causality or estimate the adjustment coefficient β for Neyman-Rubin's ATE [28]. To address this, Athey and other scholars combined the traditional Random Forest framework with Rubin's causal inference and proposed a model named Causal Forest [32,33,63].

Incorporating the Potential Outcomes Framework [64], the causal effect of SC policy on green development is evaluated based on $\tau = E[Y_i(1) - Y_i(0)]$. Here, potential variables $Y_i(1)$ and $Y_i(0)$ represent the level of green development when the policy is implemented and not implemented, respectively, in the ith sample. Assuming observational data are independently and identically distributed and satisfy the overlap assumption (i.e., after controlling for covariates, the allocation of pilot cities is as good as random assignment), $e(x) = P[W_i|X_i = x]$ is the propensity score, representing the probability of assigning a city to the pilot group based on its characteristics. $m(x) = E[Y_i|X_i = x]$ denotes the expected effect of the SC policy. Assume that $\hat{m}$ and $\hat{e}$ are $o\left(n^{-1/4}\right)$-consistent in root-mean-squared error. Here, W_i is the policy treatment variable, indicating the treatment assignment (set as 0 or 1) for i-observation, i.e., whether it belongs to a pilot city, while X represents the covariate set of training data. According to Athey et al. [33] and Nie and Wager [65], the objective function used by the causal tree is "R-learner" (Equation (2)), used to estimate individual treatment effects (ITEs), i.e., $\tau(\cdot)$. Here, $\gamma_n(\tau(\cdot))$ is a regularizer that controls the complexity of the learned $\tau(\cdot)$ function.

$$\hat{\tau}(\cdot) = argmin_\tau \left\{ \sum_{i=1}^{n} \left(\left(Y_i - \hat{m}^{(-i)}(X_i) \right) - \tau(X_i) \left(W_i - \hat{e}^{(-i)}(X_i) \right) \right)^2 + \gamma_n(\tau(\cdot)) \right\} \quad (2)$$

where $(-i)$-superscripts denote "out-of-bag" predictions, which are estimates derived without including the ith sample in the training set. Athey et al. [33] pointed out that $W_i - \hat{e}^{(-i)}(X_i)$ equates to orthogonalized estimators, i.e., after removing the impact of X_i from W_i, it consistently estimates the conditional average treatment effects (CATEs).

The Causal Forest grows a set of B causal trees, each assigned distinct sub-samples and partitioned recursively using the "R-learner". This approach integrates the adaptive kernel from traditional Random Forests, aggregating results from each tree through a weighted summary to derive the ATE estimate.

$$\begin{gathered} \hat{\tau} = \frac{\sum_{i=1}^{n} \alpha_i(x)\left(Y_i - \hat{m}^{(-i)}(X_i)\right)\left(W_i - \hat{e}^{(-i)}(X_i)\right)}{\sum_{i=1}^{n} \alpha_i(x)\left(W_i - \hat{e}^{(-i)}(X_i)\right)^2} \\ \alpha_i(x) = \frac{1}{B}\sum_{b=1}^{B} \frac{1(\{X_i \in L_b(x), i \in S_b\})}{|\{i : X_i \in L_b(x), i \in S_b\}|}, \hat{m}(x) = \sum_{i=1}^{n} \alpha_i(x) Y_i, \end{gathered} \quad (3)$$

In Equation (3), $L_b(x)$ is the set of training examples falling in the same "leaf" as the test point x, and S_b relates to the sub-sample associated with the tree. $\alpha_i(x)$ is a data-adaptive kernel, akin to the weights in nearest neighbor matching. It captures the frequency with which the ith training example falls into the same leaf as x.

Concretely, two separate regression forests are first fitted to estimate $\hat{m}(\cdot)$ and $\hat{e}(\cdot)$. These two first-stage forests, combined with Equation (3), are used to grow a Causal Forest for "out-of-bag" predictions. As for tuning parameter selection, we employ cross-validation to select those that minimize the objective function. To smooth discontinuities, the model ensembles multiple base trees into a forest using subsampling. This approach, contrasting with the bagging in Random Forest, results in estimates with better statistical properties. Subsampling dedicates half of the samples to determining Causal Forest partitions and the other half to deriving the average treatment effect estimates. The same data is not used for both partitioning and predicting, ensuring that all base trees remain honest (uniformly referred to as "honesty estimation" in the subsequent paper). Athey and Wager [66] showed that using subsampling to average honesty trees for forest construction ensures that, as the number of samples approaches infinity, estimates possess unbiased and asymptotically normal statistical properties. This forms a theoretical basis for constructing confidence intervals for the ATE.

In evaluating policy effects, Athey et al. [33] also introduced clustering methods under the Causal Forest, which cluster groups with similar characteristics, controlling for intergroup variability effects. It addresses the pitfalls of data-driven machine learning algorithms, particularly the issue of "overfitting". Taking city-level clustering as an instance, the ATE estimation is illustrated in Equation (4):

$$\begin{gathered}\overline{\tau} = \frac{1}{J}\sum_{j=1}^{J}\hat{\tau}_j, \hat{\tau}_j = \frac{1}{n_j}\sum_{\{i:A_i=j\}}\hat{\Gamma}_i, \hat{\sigma}^2 = \frac{1}{J(J-1)}\sum_{j=1}^{J}(\hat{\tau}_j - \overline{\tau}), \\ \hat{\Gamma}_i = \hat{\tau}^{(-i)}(X_i) + \frac{W_i - \hat{e}^{(-i)}(X_i)}{\hat{e}^{(-i)}(X_i)\left(1-\hat{e}^{(-i)}(X_i)\right)}\left(Y_i - \hat{m}^{(-i)}(X_i) - \left(W_i - \hat{e}^{(-i)}(X_i)\right)\hat{\tau}^{(-i)}(X_i)\right)\end{gathered} \tag{4}$$

where J represents the number of clustered groups (cities). The standard error estimate $\hat{\sigma}^2$ reflects the dispersion of individual treatment effects.

The Causal Forest method demonstrates greater real-world interpretability and finer granularity in the assessment of policy effects. It not only enables the estimation of average treatment effects but also allows for the estimation of individual treatment effects for each city sample. This enables a more granular evaluation of the policy effects of SC policy from a finer perspective. The most intuitive advantages of using the Causal Forest in this paper are: Firstly, as an adaptive nearest neighbor method, the Causal Forest determines the importance of features and further weights based on data, mitigating the challenges posed by the "dimensionality curse" and reducing the bias of manually selecting covariates. It effectively improves the individual selection bias in randomized controlled trials compared with traditional policy effect evaluation methods, resulting in more objective treatment effect outcomes [63]. Secondly, it allows for a more nuanced identification and depiction of the heterogeneous effects of SC policy on green development across different cities. Under this analytical framework, empirical designs and tests can be conducted to deeply explore the manifestation of policy heterogeneity and its underlying driving factors.

4.1.3. Empirical Research Process

The aforementioned research methods (EBM and Causal Forest models) provide technical support for the empirical analysis in this paper. On this basis, combined with the research hypotheses, Figure 2 shows the research process of the empirical analysis.

Firstly, we select and preprocess the data for the empirical discussion and explain the quantitative measurements of the key variables—urban green development level and the SC policy. Next, we construct a Causal Forest for the impact of SC policy on urban green development and conduct empirical analysis. After that, we focus on the possible heterogeneous effects of policy across different types of cities and explore the driving factors behind them. Finally, we conduct mechanism tests by dividing the policy treatment effects into high and low groups. Through comparative analysis, we can more specifically identify the issue of "which paths are more important" in the process of smart city pilots empowering green development. The above empirical analysis process aligns with the research purpose, that is, the impact of SC policy on green urban development and its heterogeneous characteristics. The results of the empirical analysis in the following text also achieve this goal very well.

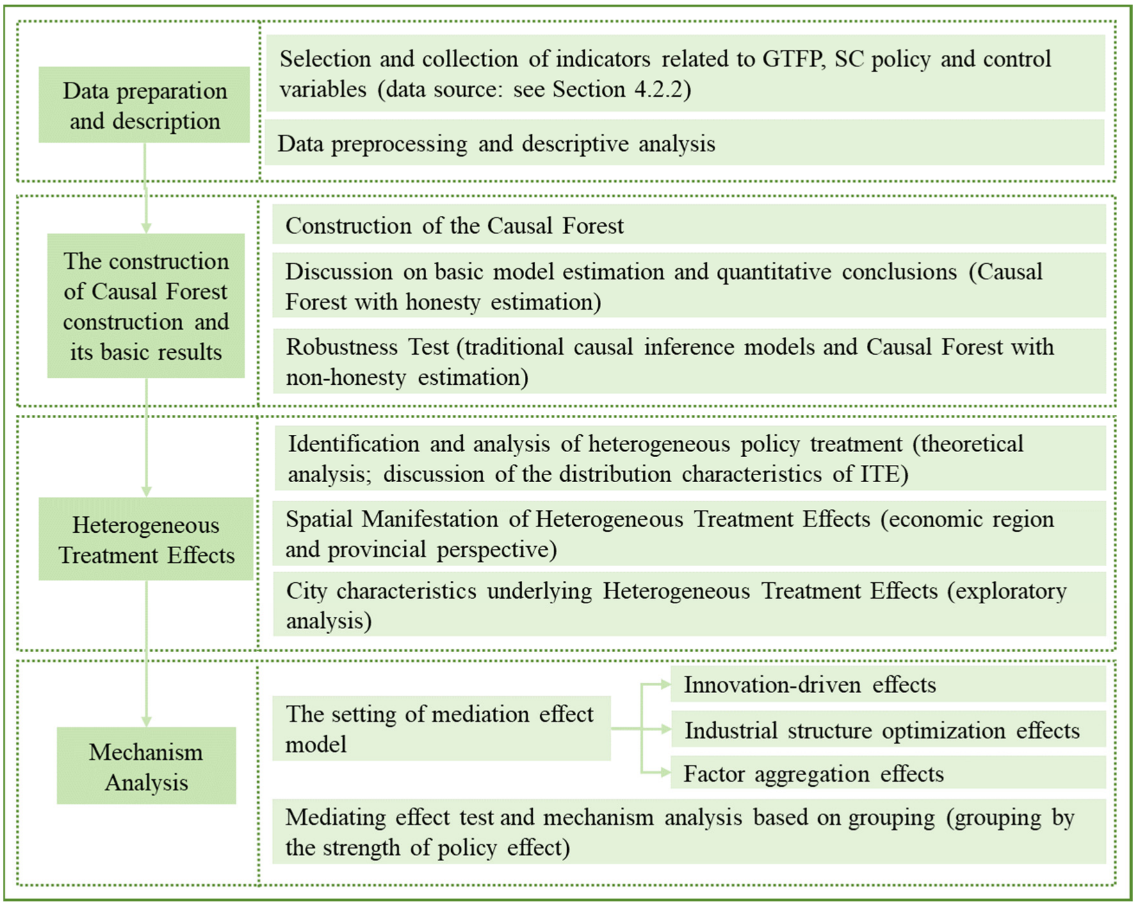

Figure 2. The research process of the empirical analysis.

4.2. Variable Selection and Descriptive Analysis

4.2.1. Explanatory Variable

The dependent variable in this paper is green total factor productivity (GTFP). According to the EBM model framework, the vector space includes urban input, desirable output, and undesirable output. Inputs are considered from four perspectives: labor, land, capital, and energy. The labor input is measured by the total employment of the whole society, which is the sum of the urban year-end employment by unit and the urban year-end employment in the private and individual sectors. The land input is gauged using the built-up area of the city. Following the method proposed by Zhang et al. [67], the perpetual inventory method is applied to estimate the actual capital stock of prefecture-level cities in period t to represent capital input (K_t). This is adjusted for inflation with 2006 as the base year, using the formula $K_t = I_t + (1-r)K_{t-1}$, where I_t represents the fixed asset investment of the prefecture-level city in period t and r stands for the fixed asset depreciation rate, uniformly set at 9.6%. It is assumed that the initial capital stock is 10% of the fixed asset investment.

Given that the "China City Statistical Yearbook" does not provide data on urban energy, this paper refers to Wu et al. [68] to infer urban energy consumption based on nighttime light data (DMSP/OLS) to characterize energy inputs. The desirable output is denoted by the real GDP, which has been deflated based on the year 2006. The undesirable outputs encompass the emissions of industrial sulfur dioxide, wastewater, and smoke and dust at the prefecture-level cities.

4.2.2. Core Explanatory Variables and Control Variables

The core explanatory variable is the dummy variable "smart city pilot" policy, denoted by $W = treat \times post$. The variable "*treat*" identifies regions with the policy: *treat* = 1 for the treatment group (pilot cities) and *treat = 0* for the control group. The variable "*post*" is a time dummy variable, 1 for the policy's implementation year and subsequent years, and 0 otherwise. China's Ministry of Housing and Urban–Rural Development (MOHURD) announced and implemented the SC policy on 5 December 2012. The first batch of pilots encompassed 90 areas: 37 prefecture-level cities, 50 districts (or counties), and 3 towns. In August 2013, the MOHURD released the second batch of the National SC Pilot List for 2013, designating an additional 103 pilots (districts, counties, and towns). Given that our research object is prefecture-level cities, county-level areas are omitted, resulting in 103 pilot cities.

The study also considers several control variables. Urban population characteristics are measured by population density. Financial development is gauged by the number of financial practitioners per 10,000 residents. Human capital within cities encompasses two primary aspects: medical and educational capital. Medical capital is represented by the average bed count per 10,000 residents. It is computed by dividing the total number of beds by the city's population and then normalizing to a base of 10,000 residents. Educational capital is represented by the proportion of teachers per 10,000 residents. This is calculated as 10,000× number of full-time teachers in (primary schools + ordinary high schools + regular higher education institutions + secondary vocational schools)/total population. Industrial capacity is measured by the number of industrial enterprises above the designated size in cities. Government expenditure is indicated by the proportion of local fiscal budget expenditure to GDP. Fiscal revenue is measured by the proportion of local government fiscal revenue to GDP. These variables will be incorporated into the Causal Forest as control variables. Significantly influential variables will then be isolated as moderating variables to further analyze how the policy treatment effect changes with different observed characteristics. The specific description of the variables involved is present in Table 1.

Table 1. Descriptive statistics results.

VarName	Obs	Mean	P5	Median	P95	SD	CV
GTFP	4245	29.567	10.531	26.877	59.724	15.598	0.528
Pop	4245	464.662	61.376	332.533	1162.419	536.329	1.154
Fin	4245	1.359	0.698	1.217	2.543	0.664	0.488
Med	4245	40.703	19.675	39.795	64.658	13.840	0.340
Edu	4245	97.275	72.952	95.796	127.863	16.714	0.172
Ind	4245	1286.126	112.000	673.000	4962.000	1722.805	1.340
Gov	4245	18.389	8.126	15.781	37.383	10.246	0.557
Rev	4245	7.177	3.482	6.763	12.151	2.798	0.390

Notes: P5 and P95 are the fifth and ninety-fifth quantiles, respectively. SD is the standard deviation of each variable. CV is the coefficient of variation. The value of GTFP has been magnified by 100 times.

The research data are from the "China City Statistical Yearbook", "China Statistical Yearbook for Regional Economy", "China Energy Statistical Yearbook", "China Statistical Yearbook on Environment", local statistical bureaus, the Harvard University official website, etc. To ensure data integrity and consistency, the research samples do not include the Hong Kong, Macao, and Taiwan regions, the Tibet Autonomous Region, or cities with severely missing data. Finally, relevant indicators of 283 prefecture-level cities in China from 2006 to 2020 are selected as empirical research data.

5. Analysis of Empirical Results

5.1. Basic Estimation Results

Before constructing the Causal Forest, it is necessary to conduct some preliminary tests to examine if potential confounding variables might affect the results, that is, to assess whether the data satisfies the overlap assumption. Confounding variables are variables that correlate with both the independent and dependent variables and may confound or distort the relationship between them. The overlap assumption requires that there is some overlap between the treatment and control groups such that for each value of the covariates, there should be a nonzero probability of receiving treatment and control. One widely used approach to address the selection bias caused by confounding is propensity score matching. By examining the propensity score distributions in both the treatment and control groups, we assess whether the data align with the Causal Forest's overlap assumption.

Based on the propensity score distribution in Figure 3, there is a significant overlap between the treatment and control groups, with no obvious cliffs or discontinuities. This alignment fits the Causal Forest's overlap assumption, ensuring the validity and reliability of subsequent model building. The high degree of overlap implies that within the range of variable values, the probabilities are similar for both groups. The treatment and control groups share mutual attributes and characteristics. Thus, this reduces the interference of potential confounding factors on the treatment effect, allowing a more confident assignment of the treatment effect to policy variables rather than the confounded effects of other covariates. The high overlap also enables the Causal Forest to utilize more effective information. For each set of observed covariates, matches are present in both groups, facilitating direct comparisons between treated and untreated individuals. This direct comparison enhances the precision and reliability of the causal effect estimation.

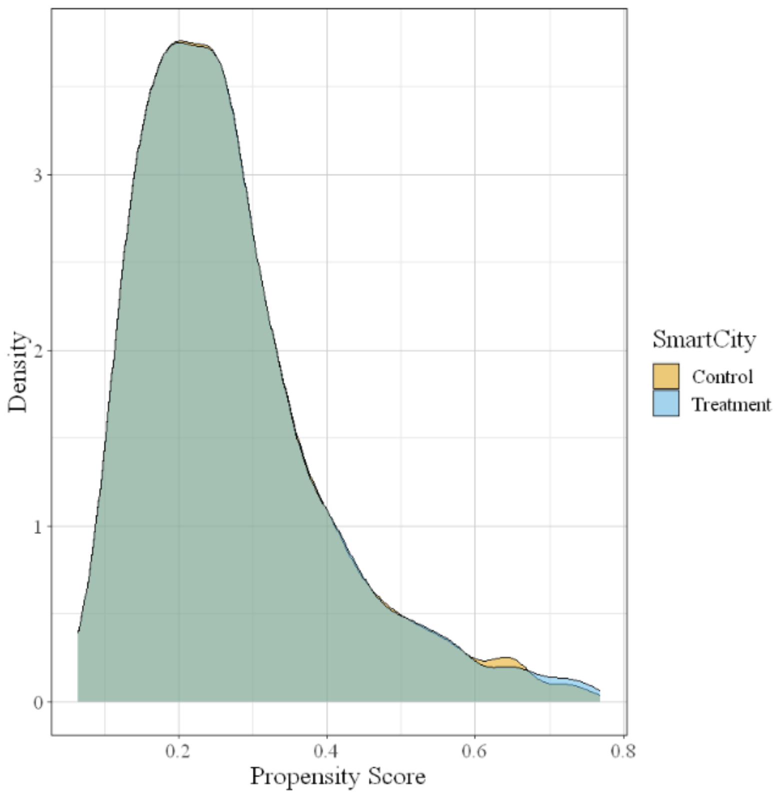

Figure 3. Distribution of propensity scores for treatment and control groups.

The Causal Forest is part of ensemble learning methods wherein the number of base classifiers (causal trees) significantly influences model performance. When the forest contains a limited number of causal trees, it often results in larger estimation errors and risks underfitting. This paper initially explores the impact of setting different numbers of causal trees. Subsequently, these trees are clustered at the prefecture-city level to examine the variations in the estimated ATE. The Causal Forest is constructed using the R package "grf" (R version 3.6.3; grf version 2.2.1). Unless specified otherwise, default values are employed for the related hyperparameters.

The constructed Causal Forest model reports the variable importance of each covariate, i.e., the proportion of times these variables serve as splitting criteria in the branching nodes of the Causal Forest relative to the total number of splits. All control variables exhibit importance exceeding 0.05, indicating relatively robust explanatory capability for the outcome and ensuring the accuracy of the treatment effect estimation. Table 2 shows the "out-of-bag" ATE estimates based on the Causal Forest with honesty estimation.

Table 2. ATE estimates of the SC policy on the GTFP.

Items	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP	(5) GTFP
ATE	3.070 *** (0.454)	3.096 *** (0.454)	3.060 *** (0.455)	3.063 *** (0.975)	3.035 *** (0.453)
95% CI	[2.181, 3.960]	[2.205, 3.986]	[2.167, 3.952]	[1.151, 4.975]	[2.148, 3.922]
Clusters	No	No	No	Yes	No
N trees	500	1000	2000	2000	2000
N Obs.			4245		
Model:			Causal Forest		

Notes: *** represent statistical significance at the 1% level. Column (5) represents a Causal Forest where the data ratio for constructing partitions is set to 0.8, and it is employed for subsequent robustness analysis in this study.

From columns (1)–(3) in Table 2, it is observed that as the number of causal trees grows, the ATE of the SC policy on the GTFP in prefecture-level cities remains relatively stable, hovering around 3.06. Concurrently, the standard error remains consistent. This consistency indicates that the selected number of base causal trees satisfies precision requirements. A comparison between columns (3) and (4) reveals that while the ATE remains largely unchanged post-clustering, there is a notable increase in the standard error. It is likely attributed to treatment effects across different years varying significantly between prefecture-level cities, and clustering ignores such time differences in the policy treatment effect, thus reducing estimate precision. The results imply that the SC policy has a significantly positive effect on improving GTFP, with a 95% confidence interval for the treatment effect of [3.06 − 0.89, 3.06 + 0.89].

5.2. Robustness Test

To ensure the robustness of the conclusions regarding the green development effects in SCs, this study also applies traditional causal inference analytical methods. These include ordinary least squares (OLS), difference-in-differences (DID), and propensity score matching followed by difference-in-differences (PSM-DID). Additionally, we employ the Causal Forest with non-honesty estimation for robustness analysis.

The DID model offers an advantage over OLS as it accounts for unobservable individual factors. Incorporating propensity score matching into DID assists in mitigating potential sample selection biases, further diminishing imbalances in covariates between the treated and control groups. Theoretically, results from the PSM-DID model should be more precise than those obtained from both OLS and DID. The Causal Forest approach with non-honesty estimation establishes a data ratio for constructing partitions and estimating ATE at a split of 0.8:0.2.

$$GTFP_{it} = \beta_0 + \beta_1 treat_i \times post_t + \rho X_{it} + \delta_i + \mu_t + \varepsilon_{it} \quad (5)$$

In Equation (5), $treat_i$ signifies the group dummy variable, $post_t$ represents the time dummy variable, and the interaction term $treat_i \times post_t$ indicates the net effect of the policy's implementation. The variable X_{it} is a series of control variables, while δ_i and μ_t correspond to city and time-fixed effects, respectively. ε_{it} refers to the random disturbance.

The regression results are shown in Columns (1)–(3) in Table 3 and Column (5) in Table 2, respectively. In these models, the coefficients of the dummy variables for SC policy are consistently positive and significant. This indicates that SC construction has notably promoted the urban green transformation process. The conclusions drawn from Table 2 demonstrate robustness. Analyzing the estimated ATE, there is no significant difference between the ATE values sourced from the Causal Forest models with non-honesty and honesty estimations, while the estimates from traditional causal inference models are marginally below those of the Causal Forest. Traditional linear regression models are not particularly adept at identifying endogeneity arising from simultaneous causality. Although theoretically, instrumental variable estimation alleviates the endogeneity issue, the exogeneity condition of instrumental variables is highly subjective and difficult to verify from the data. Mullainathan and Spiess [28] pointed out that machine learning algorithms can be applied to the first-stage regression estimation of instrumental variables. This enhances the estimation ability of the instrumental variables on the dependent variable, thus ameliorating the weak instrumental problem. Therefore, this paper argues that traditional linear causal inference models underestimate the green development effects of policies.

Table 3. Robustness tests.

Items	(1) GTFP	(2) GTFP	(3) GTFP
treat × *post*	1.810 ***	2.526 ***	2.686 ***
	(0.508)	(0.430)	(0.430)
Control variables	Yes	Yes	Yes
_cons	20.422 ***	9.477 ***	0.276
	(1.335)	(0.864)	(1.717)
Model	OLS	DID	PSM-DID
Time FE	No	Yes	Yes
City FE	No	Yes	Yes
N Obs.	4245	4245	4240
R^2	0.357	0.274	0.282

Notes: *** represent statistical significance at the 1% level. Columns (1)–(3) report estimates of the ATE for OLS, DID, and PSM-DID, respectively.

6. Analysis of Heterogeneous Treatment Effects

6.1. Heterogeneity Test Based on the Causal Forest

China is a vast country with considerable developmental disparities between regions. For instance, eastern cities have notably higher levels of economic and financial growth, government efficiency, technology, and human capital compared with central and western cities. Additionally, there are substantial differences in economic structures, energy consumption, and resource dependency across different regions. The western regions, typified by Ningxia, Inner Mongolia, Xinjiang, and Shanxi, consistently rank high nationally in per capita energy consumption. Such differences lead to varying constraints and motivations for green development across city regions. The above disparities can affect the implementation and outcomes of SC policy across areas, leading to potential heterogeneities in the promoting effects of SC development on urban green growth.

Compared with traditional linear regression models, which focus on the ATE of policies, the Causal Forest offers finer granularity. Not only does it estimate ATE, but it also evaluates the treatment effect on each pilot city (i.e., the individual treatment effects, ITEs). Based on the estimation results of the Causal Forest in Section 5.1, we visualize the distribution of the individual treatment effects of the SC policy on urban green total factor productivity through histograms, as shown in Figure 4. The policy effects across these cities follow a bell-shaped distribution with a mean of 3.06 and a standard deviation of 2.33. These treatment effects are dispersed, spanning from −5 to 12. Specifically, within a 90% confidence interval, they concentrate between −0.54 and 11.35.

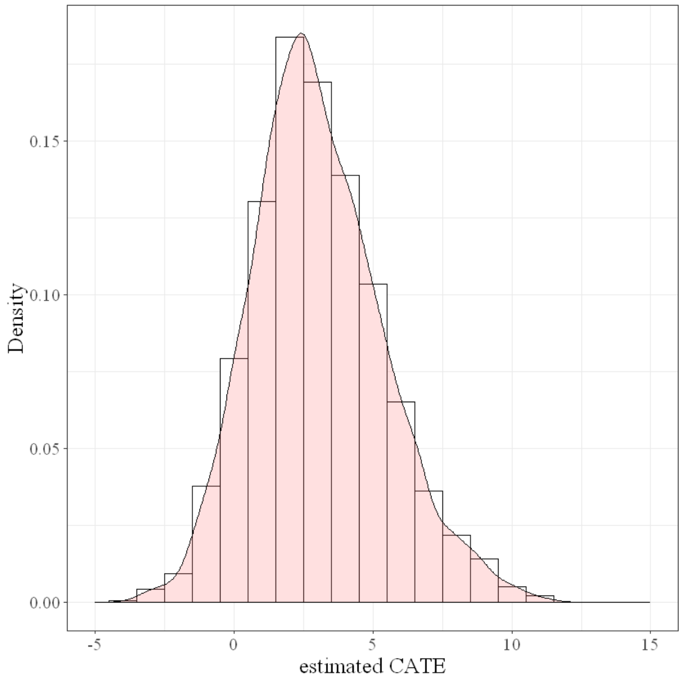

Figure 4. Distribution of the ITE of the SC policy on GTFP. The horizontal axis represents the estimated city CATE, and the vertical axis represents the corresponding density.

Figure 4 shows that the effects of the pilot policy implementation are markedly heterogeneous across different cities. However, it remains ambiguous whether this heterogeneity is due to intrinsic differences in city characteristics or caused by factors like sample selection and randomness in estimation. Drawing from Athey and Wager [66], two approaches are employed to ascertain the genuineness of this observed heterogeneity. The first approach divides the out-of-bag CATE estimates by the median into "high" and "low" groups and uses a doubly robust approach to estimate the ATE within each group. Comparing the differences in the averages provides a qualitative assessment of the strength of the heterogeneity. The second approach, based on the "best linear predictor" proposed by Chernozhukov et al. [69], breaks down the average treatment effect estimate $\hat{\tau}^{(-i)}(X_i)$ into C_i and D_i components. Here, $C_i = \overline{\tau}\left(W_i - \hat{e}^{(-i)}(X_i)\right)$ and $D_i = (\hat{\tau}^{(-i)}(X_i) - \overline{\tau})\ (W_i - \hat{e}^{(-i)}(X_i))$, where $\overline{\tau}$ is the sample average treatment effect. The regression is then formulated as $(Y_i - \hat{m}^{(-i)}(X_i) = \beta_1 C_i + \beta_2 D_i$. A significantly positive β_2 coefficient denotes real heterogeneity within the sample. Table 4 reports the results of the heterogeneity tests.

Table 4. Heterogeneity tests.

Items	Estimate	Std. Error	T-Value
mean.forest.prediction	0.898 ***	0.155	5.802
differential.forest.prediction	3.071 ***	0.211	14.532
95% CI for difference in ATE:		[7.142, 9.770]	

Note: *** represent statistical significance at the 1% level.

From the analysis, it is evident that the ATE difference estimated by the first method is significantly above 0. Similarly, the key parameter β_2 from the second method is also significantly greater than 0. Results from both tests confirm the existence of genuine heterogeneity in policy effects at the prefectural city level. Moreover, the Causal Forest effectively captures this heterogeneity.

6.2. Spatial Manifestation of Heterogeneous Treatment Effects

6.2.1. Spatial HTEs: Economic Region Perspective

Section 6.1 reveals that the pilot policy exhibits heterogeneous effects on green development across different cities. Building on this, this section delves into the spatial performance of this heterogeneity. Firstly, we conduct an analysis of variance (ANOVA) of the pilot policy's effects on green development across cities in different economic regions (Eastern, Central, Western, and Northeast China). The geographical divisions of four regions are based on the "China Statistical Yearbook". As shown in Table 5, the heterogeneous effects of the pilot policy are pronounced across regions: the within-region variation is 78.22, contrasting with a between-region variation of 16.87, which accounts for 17.7% of the total variation. The corresponding F-statistic is significant, revealing that the location factor is an important cause of the HTE.

Table 5. Variance decomposition: city CATE under economic region grouping.

Variation	SS	df	MS	F	*p*-Value
Between-Region	16.872	3	5.624	7.12	0.0002
Within-Region	78.225	99	0.790		
Total	95.096	102	0.932		

Expanding on this, Table 6 presents the results of Kruskal–Wallis tests for pairwise comparisons of the policy effects across Eastern, Central, Western, and Northeast China cities. It shows that the regional differences in policy effects are primarily manifested between Eastern China and non-Eastern China. However, Central, Western, and Northeast China display less pronounced regional disparities in the policy's green development effects.

Table 6. Kruskal–Wallis tests: pairwise comparisons by economic regions.

Null Hypothesis (H_0)	Critical Values	Rank Means Difference
CATE (Eastern) = CATE (Central)	20.90	26.12 ***
CATE (Eastern) = CATE (Western)	20.30	30.99 ***
CATE (Eastern) = CATE (Northeast)	33.71	34.12 ***
CATE (Central) = CATE (Western)	18.76	4.87
CATE (Central) = CATE (Northeast)	32.80	8.00
CATE (Western) = CATE (Northeast)	32.42	3.13

Notes: *** represent statistical significance at the 1% level. The parameter "Rank Means Difference" indicates the mean rank difference between two groups. If it surpasses the "critical value", the difference is statistically significant.

Table 7, incorporating the Causal Forest, further assesses policy effects in Eastern, Central, Western, and Northeast China. The findings consistently demonstrate that the policy's dividend effect is notably stronger in Eastern China compared to the other regions.

Table 7. Policy effects in the Eastern, Central, Western, and Northeastern regions.

Items	Eastern	Central	Western	Northeastern
CATE	3.942 ***	2.718 ***	2.515 ***	1.322
95% CI	[2.535, 5.349]	[1.774, 3.662]	[1.567, 3.463]	[−0.410, 3.074]
Clusters	No	No	No	No
N trees	1000	1000	1000	1000
Model	Causal Forest	Causal Forest	Causal Forest	Causal Forest
N Obs.	1290	1200	1245	510

Note: *** represent statistical significance at the 1% level.

Eastern China stands out as a focal point for the socio-economic landscape, enjoying pronounced locational advantages in transportation, trade, resource endowments, and socio-economic dynamism. Its developed economic foundations, robust infrastructure, and advanced market environments enable Eastern cities to excel in nurturing and harnessing digital transformation.

Figure 5 shows the digital economic performance between Eastern and non-Eastern China. Specifically, Eastern China's digitalization significantly surpasses that of its counterparts. With optimal conditions for digitalization and advanced technologies, combined with a sturdy economic foundation, Eastern cities effectively implement and deepen the SC policy. This enables swifter policy transmission and more pronounced dividend effects. Conversely, Northeast China, for instance, has a relatively singular industrial structure that greatly leans towards heavy industry. Such economic patterns often face the "resource curse", limiting the in-depth integration of advanced technologies. As a result, policy implementations find it challenging to make impactful changes to existing structures, affecting the potential success of SC initiatives.

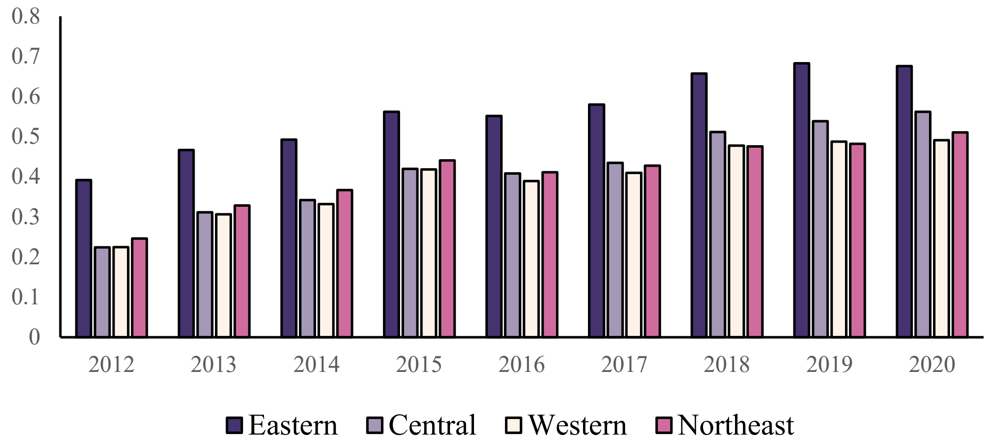

Figure 5. Digital economic development in different regions, 2012–2020. Note: The regional digital economic development is measured using the entropy method, considering multiple digital indicators.

6.2.2. Spatial HTE: Provincial Perspective

We also explore the spatial HTE across pilot cities from a provincial perspective, with Table 8 detailing the ANOVA results for city CATE. Notably, between-group variation appears greater here than in Table 5. The between-province variation is 36.24, while the within-province variation is 58.84, with the former accounting for 38% of the total variation. In comparison to economic region divisions (Table 5), this reveals more significant between-group differences and a more pronounced within-group clustering effect.

Table 8. Variance decomposition: city CATE under provincial grouping.

Variation	SS	df	MS	F	*p*-Value
Between-Province	36.248	27	1.343	1.71	0.0361
Within-Province	58.848	75	0.785		
Total	95.096	102	0.932		

Clustering pilot cities at the provincial level, we estimated the policy effects for each province and presented a descending order ranking in Table 9.

In Section 6.2.1, we observed pronounced policy effects in Eastern China. Most of these provinces appear in the upper half of Table 9. Specifically, the top 10 provinces (or municipalities) with the highest treatment effects are, in order: Hainan, Zhejiang, Beijing, Shanghai, Liaoning, Jiangsu, Guangdong, Tianjin, Chongqing, and Guizhou. In contrast, the five provinces with the lowest treatment effects are Yunnan, Guangxi, Henan, Shaanxi, and Gansu.

Table 9. The rank of provincial CATE.

PR	CATE	Reg.	PR	CATE	Reg.	PR	CATE	Reg.
Hainan	6.714	E	Xinjiang	5.125	W	Qinghai	4.257	W
Zhejiang	6.663	E	Shanxi	5.001	C	Hubei	4.233	C
Beijing	6.459	E	Ningxia	4.693	W	Anhui	4.214	C
Shanghai	6.052	E	Heilongjiang	4.689	NE	Jiangxi	4.213	C
Liaoning	5.700	NE	Inner Mongolia	4.685	W	Sichuan	4.082	W
Jiangsu	5.585	E	Fujian	4.629	E	Yunnan	4.074	W
Guangdong	5.433	E	Shandong	4.574	E	Guangxi	3.976	W
Tianjin	5.284	E	Hebei	4.502	E	Henan	3.952	C
Chongqing	5.281	W	Hunan	4.296	C	Shaanxi	3.941	W
Guizhou	5.196	W	Jilin	4.271	NE	Gansu	3.405	W

Note: E, C, W, and NE represent the Eastern, Central, Western, and Northeast regions of China, respectively.

The high-effect provinces include some economically developed Eastern provinces (or municipalities) like Beijing, Shanghai, Guangdong, and Zhejiang. With relatively advanced high-tech industries and financial sectors, these Eastern provinces possess inherent advantages in industrial structure and technical talent, facilitating prompt implementation of SC policy and enabling them to quickly become important drivers of GTFP growth.

Also noteworthy among the high-effectiveness provinces are Chongqing and Guizhou. Although located in Western China, Chongqing enjoys unique geographical and economic strengths. It is an important transportation hub connecting Western and Eastern China and a vital node on the Yangtze River Economic Belt and the "Belt and Road" Initiative, endowing it with a diversified industrial structure and a developed electronic information industry. Guizhou features geological stability, a mild climate, and abundant energy resources, making it suitable for housing large data centers. In recent years, Guizhou has actively nurtured big data industry bases, achieving in-depth integration of digitalization with local comparative advantages and generating strong "catch-up" effects for green growth.

Conversely, provinces with low treatment effects are generally economically lagging. Their economic structures predominantly revolve around agriculture and resource-based industries, with relatively small high-tech industries and service sectors. Such features constrain the emergence and growth of new green industries and models, leading to certain lags in SC development.

6.3. City Characteristics Underlying Heterogeneous Treatment Effects

In this section, we delve into how covariates influence the heterogeneous effects of the pilot policy to explore the key factors driving this heterogeneity. Following Wager and Athey (2019), we remove the top and bottom 5% of observations for each covariate to eliminate effects from extreme values. Keeping other variables constant, we categorize the out-of-bag CATE estimates into high and low groups. Subsequently, we conduct T-tests to examine the difference in means between these groups.

The T-test results in Table 10 show that all control variables are statistically significant, indicating that differences in these city characteristics cause heterogeneous green effects of SC policy. The "Variable Importance" column displays the relative importance of input variables in the Causal Forest model structure. During the growth of the Causal Forest in Section 5.1, medical capital, financial level, and government expenditure emerged as the most important three variables, jointly contributing to 60% of the weight. This denotes that HTE is largely driven by these three factors. Figure 6 further elucidates the trajectory of CATE against changes in urban characteristics, visually illustrating the correlation between these features and policy treatment effects.

Table 10. Tests of city characteristics driving HTE.

Variables	Variable Importance	T-Test	CATE. High	CATE. Low
Med	0.240	6.798 ***	3.208	1.696
Gov	0.186	−15.375 ***	1.957	4.776
Fin	0.174	5.288 ***	3.000	1.024
Pop	0.141	4.949 ***	2.154	1.371
Ind	0.088	−2.076 **	1.646	1.822
Edu	0.085	7.010 ***	2.983	1.608
Rev	0.085	5.551 ***	2.206	1.683

Notes: ***, and ** represent statistical significance at the 1%, and 5% levels, respectively. "Variable Importance" refers to the variable weights in the Causal Forest.

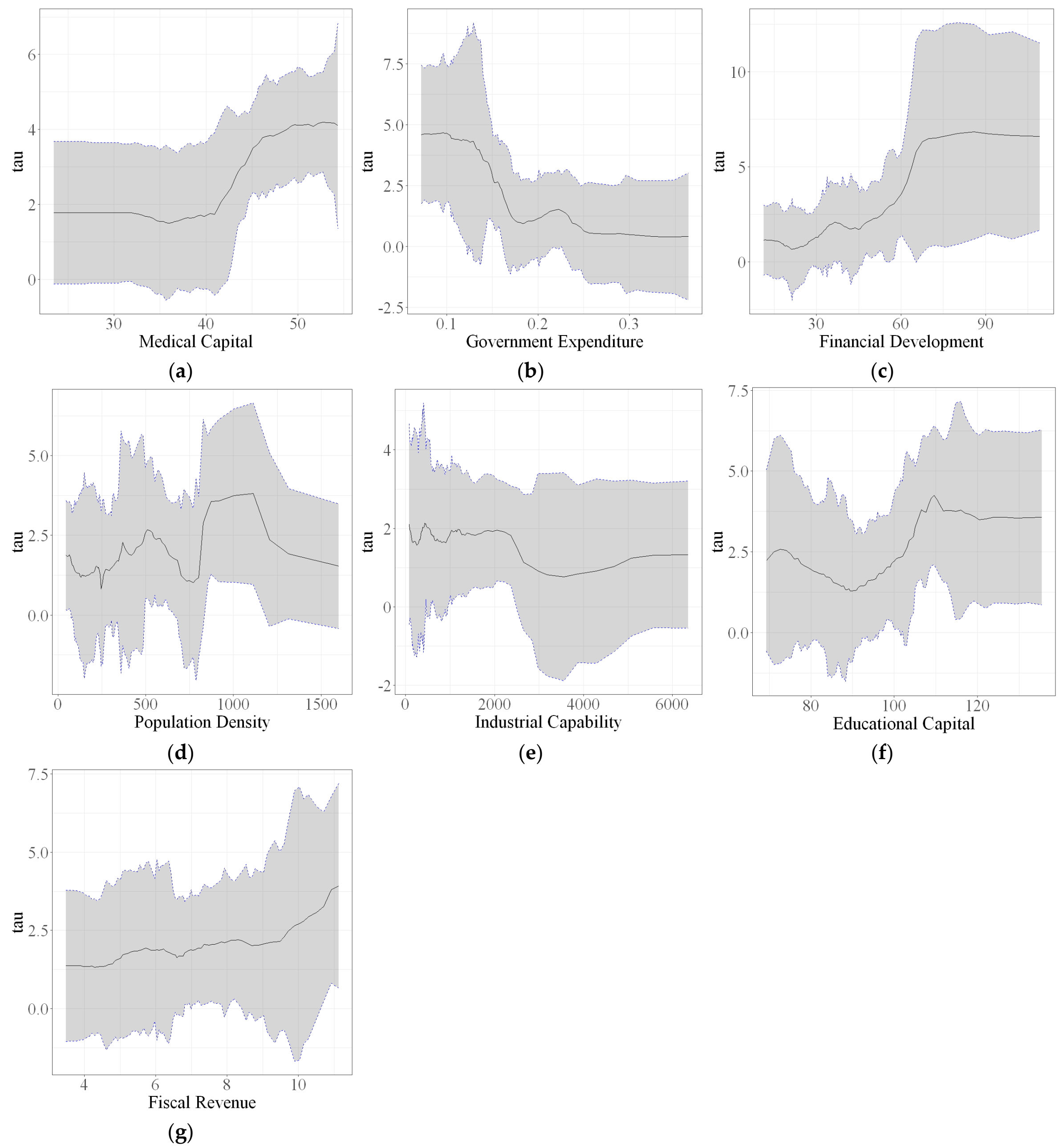

Figure 6. Driving factors behind HTE. The changes in HTE with regards to (**a**) medical capital, (**b**) government expenditure, (**c**) financial development, (**d**) population density, (**e**) industrial capability, (**f**) educational capital, and (**g**) fiscal revenue.

Figure 6 shows that SC policy generates stronger green development effects by increasing human capital (educational and medical capital), financial development, population density, and fiscal revenue. The positive impacts of human capital and finance on city green development stem from cities with advanced financial systems that have well-functioning market mechanisms, ensuring stable and sufficient capital support for policy implementations. The caliber of a city's human capital, as affected by the standards of its education and medical treatment, influences the quality and potential of its labor force. In more educationally and medically advanced cities, there is a better cultivating environment for digitized, highly skilled talents. Moreover, these citizens readily embrace technological advancements and demonstrate heightened environmental awareness and demands. The positive effect of population density demonstrates the agglomeration economy facilitating policy delivery. The positive effect of fiscal revenue reflects the influence of regional economic development in promoting green development policy effects.

In contrast, reasonable government expenditure strongly facilitates urban green transition, but beyond a threshold, further expenditure will diminish the promotional effect. This may be because large-scale spending amplifies the financial market's dependence on the public sector, which in turn reduces investments in private green innovations. As a consequence of this shift, there might be a crowding out of financial market roles, resulting in inefficiencies. Such heightened dependence can sometimes conflict with market efficiency or the optimal allocation of resources. In some cases, the government might prioritize long-term strategic projects over short-term green transition endeavors. In addition, cities with an over-reliance on the secondary sector see diminishing returns in green benefits from SC policy.

7. Mechanism Analysis

Drawing from the theoretical analysis and hypotheses detailed in Section 3, digital transformation principally fosters green development by bolstering green technology innovation, promoting industrial structure upgrading, and optimizing the aggregation of production factors. This section further identifies and verifies these three mediation paths through a stepwise mediation model based on Equation (5), with the general logic of testing shown in Equation (6).

$$\begin{gathered} Y = \hat{c}X + \hat{\lambda}Z + e_1 \\ M = \hat{a}X + \hat{\lambda}Z + e_2 \\ Y = \hat{c}'X + \hat{b}M + \lambda' Z + e_3 \end{gathered} \tag{6}$$

$$z_{sobel} = \hat{a}\hat{b} / \sqrt{S_{\hat{a}}^2 \hat{b}^2 + S_{\hat{b}}^2 \hat{a}^2} \tag{7}$$

In Equation (6), Y, X, Z, and M represent the $GTFP_{it}$, $treat_i \times post_t$, control variables, and mediating variables, respectively. The verification process starts by assessing the significance of coefficient $\hat{c}$. If it proves significant, proceed by testing the significance of $\hat{a}$, $\hat{b}$, and $\hat{c}'$ in three cases. When all three ($\hat{a}$, $\hat{b}$, and $\hat{c}'$) are significant, it indicates partial mediation. However, if only $\hat{a}$ and $\hat{b}$ are significant while $\hat{c}'$ is not, full mediation is implied. When at least one of $\hat{a}$ and $\hat{b}$ is not significant, evaluate using the z-statistic Sobel test, symbolized as z_{sobel} (as seen in Equation (7)), where $S_{\hat{a}}^2$ and $S_{\hat{b}}^2$ are the estimated standard errors of a and b, respectively. If $| z_{sobel} | > 1.96$, it is determined that M has a mediation effect.

The specific operation is to divide the pilot cities into a "high-effect group" and a "low-effect group" according to the mean value of city-level CATE calculated in Section 6.2. Subsequently, construct mediation models for the two groups, respectively, to verify the three aforementioned mediation paths.

7.1. Innovation-Driven Effects

This section evaluates green innovation in cities by replacing the dependent variable in Equation (5) with the total number of green patent and invention applications per 10,000 people. The data is sourced from the China National Intellectual Property Administration.

Panel A in Table 11 shows that the regression coefficients for both green patents and inventions are positively significant at the 1% level within the "high-effect group". Here, green patents display a partial mediation effect, while green inventions demonstrate a full mediation effect. This indicates that expanding the construction of SCs indeed enhances a city's capacity for green technological innovation, thereby expediting the green, sustainable development of prefecture-level cities.

Table 11. Mediation effect tests of the innovation-driven effects.

Panel A—("High-Effect Group")					
Items	**(1) GTFP**	**(2) Patent**	**(3) GTFP**	**(4) Invention**	**(5) GTFP**
treat × *post*	3.436 *** (0.573)	1.089 *** (0.117)	2.779 *** (0.577)	0.315 *** (0.066)	0.328 (0.551)
Patent			0.604 *** (0.086)		
Invention					0.268 * (0.146)
Results			Partial		Full
Panel B—("Low-Effect Group")					
Items	**(1) GTFP**	**(2) Patent**	**(3) GTFP**	**(4) Invention**	**(5) GTFP**
treat × post	1.220 * (0.643)	−0.457 *** (0.109)	−0.485 (0.598)	−0.209 *** (0.058)	−0.411 (0.597)
Patent			0.078 (0.100)		
Invention					0.522 *** (0.186)
Results			None		Partial

Note: ***, and * represent statistical significance at the 1%, and 10% levels, respectively.

Conversely, within the "low-effect group", the green patent metric did not clear the mediation test, and green inventions even showed a significant decline. One potential explanation might be that the SC construction in the "high-effect group" optimized the supporting environment of the cities, attracting a substantial number of high-tech professionals and leading to a talent drain from the "low-effect group" cities. As a result, Hypothesis 3 is solely confirmed in the "high-effect group".

7.2. Industrial Structure Optimization Effects

This section delves into the factors that propel urban green development, considering the perspectives of industrial structure advancement and rationalization. Industrial structure advancement refers to the trend and process wherein the general quality and efficacy of industrial structure transition from rudimentary to advanced levels. Following Li and Zhang [49], the labor productivity variation index is used to measure this advancement. The calculation formula is $Efficiency_{it} = \sum_{m=1}^{3} m \times \ln\left(lp_{i,t,m}\right)$, where $lp_{i,t,m}$ represents the labor productivity, that is, the added value of each industry divided by the local employed population. On the other hand, the rationalization of the industrial structure refers to the continuous enhancement of inter-industrial coordination and interconnectedness. The rationalization of industrial structure is perceived as a prerequisite and foundation for advancement, and advancement without rationalization easily leads to an "inflated" industrial structure. The Theil index, an inverse indicator of rationalization, has been deployed for its measurement—a lower value signifies a more reasonable urban industrial structure. Table 12 displays the mediation effect test results of the industrial structure optimization effects.

Table 12. Mediation effect tests of the industrial structure optimization effect.

Panel A—("High-Effect Group")				
Items	**(5) Efficiency**	**(6) GTFP**	**(3) Theil**	**(4) GTFP**
treat × *post*	−0.153 * (0.091)	0.491 (0.529)	−0.048 (0.750)	0.935 (0.583)
Efficiency		1.219 *** (0.101)		
Theil				−0.094 *** (0.020)
Results		Full		None
Panel B—("Low-Effect Group")				
Items	**(5) Efficiency**	**(6) GTFP**	**(3) Theil**	**(4) GTFP**
treat × *post*	0.489 *** (0.103)	−1.244 ** (0.556)	−2.736 *** (0.879)	−0.786 (0.567)
Efficiency		1.208 *** (0.096)		
Theil				−0.048 *** (0.012)
Results		Partial		Full

Note: ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The results show that the SC construction significantly optimized the industrial structure of the "low-effect group", thereby further increasing GTFP. Industrial structure advancement showed a full mediation effect, while rationalization demonstrated a partial one. In contrast, for the "high-effect group", there is no tangible evidence to show that SC construction optimizes the industrial structure, which may be attributed to these cities already possessing a well-structured and mature industrial framework, whereas cities within the "low-effect group" appear to have greater room for optimization. Consequently, Hypothesis 4 is verified solely in the "low-effect group".

7.3. Factor Aggregation Effects

From the perspective of production factors, this section examines and elaborates on the mechanisms by which policy implementation fosters green development through the aggregation of diverse factors. According to the Solow growth model, both capital accumulation and technological progress make significant contributions to economic growth. The SC policy advances high-tech industries, including big data and cloud computing, enhancing information transmission efficiency. Therefore, from the perspectives of information technology factors (*Info*) and material capital factors (*Capital*), this paper assesses the impact of factor agglomeration on green urban progress. The former is quantified by the number of employees in the information transmission, computer services, and software industries per 10,000 people, while the latter echoes the amount of annual fixed asset investment.

Table 13 shows that for the "high-effect group", the SC policy significantly enhanced the efficiency in allocating resources for both information technology and material capital factors. The accelerated mobility of factors further promoted urban green transformation. Capital factors have a full mediation effect, while information factors have a partial mediation effect. Conversely, in the "low-effect group", there is no evidence that the policy facilitated the aggregation of either material or information factors. Therefore, Hypothesis 5 is only validated for the "high-effect group".

Table 13. Mediation effect tests of the factor aggregation effects.

Panel A—("High-Effect Group")				
Items	**(1) Capital**	**(2) GTFP**	**(3) Info**	**(4) GTFP**
treat × *post*	0.652 *** (0.082)	−0.608 (0.530)	3.840 *** (0.939)	4.219 *** (0.577)
Capital		1.671 *** (0.112)		
Info				0.026 *** (0.011)
Results		Full		Partial
Panel B—("Low-Effect Group")				
Items	**(1) Capital**	**(2) GTFP**	**(3) Info**	**(4) GTFP**
treat × *post*	0.018 (0.073)	−0.603 (0.555)	0.284 (0.919)	3.868 *** (0.620)
Capital		1.889 *** (0.136)		
Info				0.047 *** (0.012)
Results		None		None

Note: *** represent statistical significance at the 1% level. All models include Time FE, City FE, and control variables. Due to space limitations, the N. Obs, R-squared, and other items are not reported. In Panel B, total fixed assets (*Capital*) are scaled by 100 billion.

8. Conclusions and Implications

The construction of smart cities is pivotal for achieving the United Nations' 2030 Sustainable Development Agenda and promoting ecological civilization to a higher level. The emerging Causal Forest approach demonstrates stronger real-world interpretability and finer granularity in assessing policy effects compared to traditional econometric policy evaluation models. This is intuitively reflected in the fact that it can not only scientifically assess the real-world impact of policies but also capture the heterogeneity of these impacts. This paper regards the "smart city pilot" policy as a quasi-natural experiment. Using a dataset encompassing 283 prefecture-level cities in China from 2006 to 2020, we evaluate the impact effect of SC construction on green development and its heterogeneity across various types of cities employing the Causal Forest and mediation effect models. This paper also delves into the urban characteristic factors that affect the differentiated effect. The corresponding research conclusions are of great value for more refined guidance for different regions to carry out SC construction in a differentiated way over time, intensity, and differentiation according to urban characteristics. In addition, this paper adopts sub-group mechanism analysis rather than the full-sample mechanism analysis used in most of the literature. The corresponding conclusions are helpful to more clearly understand the issue of "which mediation paths are more important in enhancing urban green development". The main findings include:

1. As an early attempt at new infrastructure construction, the Causal Forest estimates show that China's SC policy has significantly promoted urban GTFP. The 95% confidence interval of the ATE is [3.06 − 0.89, 3.06 + 0.89]. After a series of robustness tests, this conclusion remains robust.
2. The SC policy has a heterogeneous impact on promoting green development across different cities, which is captured effectively through the Causal Forest. Location factors constitute a major source of policy heterogeneity. From the perspective of

economic regions, the policy benefits are more pronounced in Eastern China than in other regions. At the provincial level, the top 10 provinces ranked by highest policy treatment effect are Hainan, Zhejiang, Beijing, Shanghai, Liaoning, Jiangsu, Guangdong, Tianjin, Chongqing, and Guizhou. The five provinces with the lowest treatment effects are Yunnan, Guangxi, Henan, Shaanxi, and Gansu.

3. Differences in city characteristics also significantly impact the HTE of SC policy. Financial development, medical capital, and governmental expenditure emerge as the primary drivers of this heterogeneity. Specifically, regions with more developed finance and medical capital have a higher CATE. Within reasonable ranges, government public expenditure is also associated with higher CATE, but beyond a threshold, further expenditure lowers CATE.
4. Dividing all pilot cities into high and low groups based on CATE, mediation analysis infers that the "high-effect group" principally exerted innovation-driven and factor aggregation effects, while the "low-effect group" mainly exerted industrial structural effects. Relevant policies have enhanced the green technology innovation capability of cities, significantly increased the number of green patents and green inventions, promoted the upgrading of industrial structures to be more advanced and rational, and facilitated the aggregation of material capital and information technology factors, thereby improving GTFP.

The quantitative research findings presented in this paper hold significant implications for the Chinese government's strategies to promote urban green development through the construction of SCs. These implications are primarily reflected in the following aspects: Firstly, improve top-level design for SC construction and gradually expand the scope of pilot cities. Currently, China is at a crucial stage of economic restructuring and green transformation. The government should continuously strengthen and refine policy support for SC construction pilots, fully unleashing the benefits of SC development to facilitate urban green development. Given the heterogeneous effect of SC construction on green development across different types of cities, it would be strategic to begin in eastern cities, which have higher levels of financial resources, human capital, and fiscal revenue. This initial focus will maximize the green boosting effect of SC policy before gradually extending the policy to other cities in the central and western regions.

Secondly, tailored approaches for different cities and multifaceted coordination. The timing, policy intensity, and support for SC construction should be appropriately adjusted according to the economic endowment and development characteristics of different cities. This would effectively promote the implementation pace and effectiveness of SC policy. While carrying out SC construction, cities should simultaneously enhance their financial services and human capital levels and optimize industrial structures, leveraging the agglomeration effect of urban areas and thus enhancing the green development effect of SC construction.

Thirdly, considering the actual mechanisms of SCs in boosting green development, more attention needs to be paid to the "innovation-driven effects" and "factor aggregation effects" channels. That is, in the exploration and construction of SC, strengthen the functions of SC systems in leading green innovation and factor aggregation. Different types of cities can tailor their efforts to their development characteristics and relative advantages, focusing on both facilitating the "innovation-driven effects" and the "factor agglomeration effects" to boost green and high-quality development.

This study still has some limitations. As an important representative of developing countries, China's experience is of great reference and significance for developing countries with similar conditions. However, in developed countries with less environmental pressure and different institutional systems for SC development, our conclusions may lack direct applicability. What degree of green effects do the SC policies exert in developed countries? Is there a significant difference in the influence effect and influence path of SC construction on urban green development between developed and developing countries? These questions need further exploration. Additionally, the study primarily addresses the city-level effects of SC construction on green development. Future research could delve into more specific microscopic scenarios, such as household green activities, corporate green production, and government green transformation, to further explore the effects and microscopic mechanisms of SC construction on urban green activities. This will also be one of the directions for the author's follow-up research.

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