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Are smart cities green? The role of environmental and digital policies for Eco-innovation in China

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ABSTRACT

In this paper, we employ negative binomial and quasi-natural experimental methods (i.e., Difference-in-Differences and Propensity Score Matching), whereby we examine the joint impact of environmental and digital policies (for designing smart cities) upon the generation of eco-innovations in China. Using longitudinal data for the period 2006–2018, we examine the changes in *green patents* granted: (i) due to the implementation of various levels of *stringency* of *environmental policies* across all cities; and (ii) after the introduction of *smart city policies* in 2012 in China. The prior literature stresses the importance of environmental policies, yet less attention has been paid to digital policies required to drive eco-innovation and their spatial dimension in the context of a developing economy. Our results show that, when digital policies (artificial intelligence and internet of things) are implemented in cities that have adopted strict environmental policies, the production of green patents increases. We contribute to debates in the literature of policy mix for sustainability transitions in the context of a developing economy by illustrating the importance of both types of policy for eco-innovation, as they correct two market failures and, more importantly, address the systemic coordination problems that occur during the production of green patents.

1. Introduction

This paper argues that policies related to the implementation of digital technologies enhance eco-innovations over and above the impact of introducing environmental policy in smart cities in China. It contributes to debates in Development Studies by exploring the drivers of the spatial differences in eco-innovations, to the literatures on policy mix for sustainability transitions, and more broadly, to innovation economics by exploring the effect of digital policies in the context of developing economies. Indeed, recent reviews in *World Development* stress the need for empirical research on diverse environmental policies in generating economic opportunities in developing country contexts (Pegels & Altenburg, 2020).

Eco-innovation refers to innovations in products, processes, marketing practices, and organisational procedures, as well as systemic innovations in social and institutional structures, that lead to a reduced environmental impact (Kemp, 2009; OECD, 2009). An attractive feature of eco-innovation is that firms may reduce pollution without harming their competitiveness: the so-called 'win-win' hypothesis (Kesidou & Wu, 2020; Popp, 2005; Porter & Linde, 1995). Over the last decade, policy makers, academics and business leaders have been seeking to understand the drivers of eco-innovation in general (Cainelli & Mazzanti, 2013; Costantini, Crespi, & Palma, 2015; Horbach et al., 2012), and to identify the most effective policy tools for boosting eco-innovation in particular. With very few exceptions (Daniels et al., 2019; Fabrizi et al., 2018; Ulph & Ulph, 2013), most of the policy instruments that have been studied in the literature are environmental policies (Bergek & Berggren, 2014; Ghisetti & Pontoni, 2015), yet the sustainability transitions literature suggests that more than one type of policy is necessary in order to drive the economy towards eco-innovation (Cantner et al., 2016; Costantini et al., 2017; Edmondson et al., 2019; Uyarra et al., 2016). Also, with few exceptions, the spatial dimension of environmental policy, especially at the city level has been largely overlooked (Balland et al., 2018; Horbach, 2014; Montresor & Quatraro, 2019; Santoalha & Boschma, 2021). It is fundamental to understand the role of policy in supporting eco-innovation particularly in cities in developing and emerging economies as "growing first and cleaning up

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later" can augment environmental impact and risk locking-in their trajectory of development to "brown" technologies (see Pegels & Altenburg, 2020).

Therefore, this paper explores how cities in China that experience increasing urbanisation, environmental pollution and degradation, can be supported by the use of policies to build indigenous capacity for eco-innovation which can act as a mechanism for maintaining competitiveness and sustainability without jeopardising city growth. Here, we examine the role of digital policies in the production of green patents within the spatial context of smart cities, capturing digital technology implementation in the presence of environmental policies of various stringency levels.

Digital technologies include artificial intelligence (AI), the internet of things (IoT), blockchains, additive manufacturing, cloud computing, and augmented and virtual reality (Ciarli et al., 2021; Rindfleisch et al., 2017). Here, we focus on the application of AI and IoT in the context of smart city policies. We propose that generation of data and information by IoT and its intelligent analysis by AI can have profound effects on eco-innovation. AI is based on using big, rich and real-time data for a range of applications (Cockburn et al., 2018; Prem, 2019). It includes automation and augmentation techniques in improving operational and time efficiencies in manufacturing and services. IoT refers to an interconnected network, where physical devices are wirelessly connected via smart sensors used to collect and exchange data (Rejeb et al., 2022; Whitmore et al., 2015). AI implementation is still at pilot stage in a range of sectors, as it requires interconnectivity via IoT across actors, stakeholders and users. Bearing the costs of investments in digital infrastructure entails market failures, such as failures of coordination due to indivisibilities and economies of scale and knowledge externalities (Economist, 2020).

Digital policies as implemented in smart cities are a means of developing public digital infrastructure, generating rich, mass data on transport, air pollution, energy and resource use, waste management and citizens' opinions about environmental objectives, supporting sustainable growth and environmental sustainability (Albino et al., 2015). The spatial level of analysis is not only important because cities are responsible for up to 70 % of global GHG emissions (World Economic Forum, 2018) but also because it can offer a fruitful context for bringing about changes within the regulations, institutions and actors' behaviour, leading to transitions to greater sustainability. This gains additional importance if one considers that the previous literature on smart cities has yet to include a systematic exploration of the role of digital policies in eco-innovations. For instance, prior research shows that smart cities are developed using a techno-centric approach, oftentimes overlooking environmental sustainability (Liu & Peng, 2014; Shen et al., 2018). Also, research on whether digital technologies drive inclusive or environmental innovation is scarce in developing country contexts (Paunov & Pollo, 2016; Pegels & Altenburg, 2020).

The contribution of this paper is threefold. First, we extend debates related to environmental policies in development studies (Gupta et al., 2019; Pegels & Altenburg, 2020) by focusing on the *spatial dimension* of environmental regulation and its implementation in the context of cities in emerging economies. We demonstrate that more stringent levels of environmental policies across cities lead to higher production of green patents. This is important because it highlights the *systemic* nature of eco-innovations, as captured by the *spatial* differences in green patents. We establish that addressing grand challenges associated with climate change requires strong environmental policy intervention at the spatial level, which could steer cities towards the path of eco-innovation.

Second, we contribute to the eco-innovation literature (Demirel & Kesidou, 2011; Horbach et al., 2012; Constantini et al., 2017), by considering the effects of digital policies on the generation of eco-innovations in the context of cities in developing economies (Dang & Motohashi, 2015). This focus is original as there is an emerging literature exploring the role of digital technologies in enabling the adoption of sustainable practices (Beltrami et al., 2021; Rejeb et al., 2022). Digital policies embedded in smart cities can facilitate long-term sustainable development, as the combination of AI and IoT can provide the starting point for further innovations in the form of process, product or supply chain eco-innovations (e.g., smart manufacturing).

Third, we contribute to the policy mix literature on sustainability transitions (Edmondson et al., 2019; Flanagan et al., 2011; Rogge & Reichardt, 2016) by examining the joint impact of digital and environmental policies on eco-innovation in cities in China. The existing literature on policy-mix examines the role of narrow policy instruments, applicable to specific sectors, while our approach explores the role of policies with a cross-sectoral impact. We contend that digital policies complement environmental policies by reinforcing government monitoring, which facilitates the implementation of environmental regulations. Crucially, digital policies in the context of smart cities, enable stringent environmental policies to direct innovation activity towards eco-innovations that reduces environmental impact.

To pursue its aims, the paper analyses longitudinal data on 167 cities in China for the period 2006–2018. 32 cities implemented smart city applications after the introduction of the policy in China in 2012, while the remainder did not. The environmental policy instruments implemented across these cities are of varied stringency. The paper explores the causal impact of such policies upon green patents granted at the city level: (a) by examining both the changes in these cities over time, after implementing the smart city policies, and (b) by comparing the smart cities with cities that did not implement such policies. We do this by employing a negative binomial and quasi-natural experiment methods (i.e. Difference-in-Differences). This is a novel, robust methodological approach, which accounts for endogeneity. The focus is particularly on the differential impact of smart city policy over and above the impact of the environmental policy instruments by employing the Difference-in-Differences method. Finally, Propensity Score Matching (PSM) analysis,[1] which does not make assumptions of random treatment or exogeneity, confirms the robustness of our results.

2. Theory and hypotheses

2.1. Environmental policy for eco-innovation

The rationale for environmental policy is based on the notion of *negative environmental externalities*.[2] Environmental economists contend that environmental policy addresses this market failure by forcing firms to internalise the costs of their operations (Christainsen & Haveman, 1981; Gray, 1987). Whilst environmental economists tend to perceive environmental policies as a burden imposed upon firms, Porter and Linde (1995, p. 98) contested this orthodox view, arguing that "properly designed environmental standards can trigger innovation that may partially or more than fully offset the costs of complying with them." Subsequently, the debate in the field of environmental economics focused on whether technology standards[3] or flexible policies[4] are the most appropriate envi-

[1] The PSM method implies that both the smart cities and non-smart cities groups have no statistically significant inter-group difference based on the matching variables.

[2] Negative refers to the fact that industrial pollution imposes a burden upon society and the environment, whilst externality to the fact that firms do not compensate society for their harmful environmental impact.

[3] Technology standards refer to direct regulation that is mandatory and non-compliance is penalized.

[4] Flexible policies refer largely to price policies that provide incentives to firms so that their private choice coincides with society's low-carbon aim. Examples of flexible policies are tradable permits, Pigouvian taxes, deposit/refund systems, and subsidies.

ronmental policy tool for combating pollution, and reached a consensus that the latter are more cost-effective in terms not only of combating pollution but also of inducing the diffusion and/or development of green technology (Milliman & Prince, 1989). Such innovations could be profitable for firms due to efficiency gains (Rexhäuser & Rammer, 2014) or new market opportunities.

The eco-innovation literature, with a few exceptions (Coenen et al., 2012; Cooke, 2011, 2012; Horbach, 2014), has overlooked 'space' (Gibbs & O'Neill, 2017). Recently, the debate has shifted towards the geographical dimension of green innovation, whereby the *locus* of policy and eco-innovations is the city or region (Barbieri & Consoli, 2019). This body of literature acknowledges that "the new institutional fix for environmental problems may vary across space" (Gibbs, 2006, p. 207), whereby the latter refers to spaces within a nation or state. One strand of this literature explains the differences in green technology across space as a result of regional capability (Balland et al., 2018; Montresor & Quatraro, 2019) and regional spillovers (Antonioli et al., 2016; Corradini, 2019). Others emphasize the role of political support at the regional level in strengthening a region's capability, leading to even greater green specialisation (Santoalha & Boschma, 2021).

Here, we shift our attention towards the geographical dimension of environmental policy for eco-innovations. This is because transitioning to such radical or disruptive technology often requires the adoption of a systems co-evolutionary approach, driven by strong political support (Geels, 2002, 2006; Kemp, 2009). In line with this, Cooke (2012) contends that green regional innovation systems are frequently driven by regional policy-makers, who coordinate the transition to new sustainable regional paths. We argue that more attention needs to be paid to the *systemic* nature of eco-innovation, as captured by *spatial* differences in the production of green patents. Specifically, such system transformations, that address huge climate challenges, require strong policy intervention as the incumbent actors are slow or relatively reluctant to undertake these (Haddad et al., 2022; Schot & Steinmueller, 2018). In this paper, we hypothesise that the stringency of the environmental policy adopted at the city level plays a crucial role in steering their path towards eco-innovation.

Hypothesis 1 Cities with stricter environmental policies are generating more green patents compared to cities with lax environmental policies.

2.2. Digital policies for eco-innovation

Eco-innovation is characterised by *positive technological externalities* as firms might not fully appropriate the returns on their investments due to knowledge spilling over to other firms (Wang et al., 2017). This double externality calls for government regulation that is not limited to the domain of environmental policy. For instance, Costantini et al. (2017) consider innovation policies across OECD countries and show that a more comprehensive policy is more likely to generate new, energy-efficient inventions.

Positive technological externalities suggest that organisations in the same sector and in interconnected sectors, such as those connected vertically or with input–output relationships, experience strategic complementarity. This implies that the optimal strategy of one organisation, with regards to investment in eco-innovations, is positively affected by the respective strategies of other inter-connected organisations. This gives rise to problems related to *coordination*, as the mutual/group-level benefits depend on decisions taken unilaterally, with a tendency among the individual actors to underinvest.

Next, we discuss how digital policies address these coordination-related problems. We focus on the role of investments of public digital infrastructure such as AI and IoT for eco-innovations in the context of smart cities. AI can have profound effects on eco-innovation as it resembles the characteristics of general-purpose-technologies (GPT) with many applications, which can stimulate systemic sustainable transformations in the context of cities. IoT allows the collection and sharing of locally situated data. AI enables the sophisticated analysis of such data, which could generate insights that address local environmental problems. We argue that *investments in public digital infrastructure in cities* can facilitate the adoption and development of environmentally friendly technologies and generate positive technological externalities through the following mechanism, as discussed below.

The provision of a reliable public digital infrastructure in cities can lead to process eco-innovations, as smart production entails improved efficiencies around resource use and reduction of production times with beneficial energy savings (Alcayaga et al., 2019). In the context of smart cities, the embedded AI and IoT technology infrastructure, can facilitate firms to monitor resource use and waste/emissions management. This in turn, can stimulate process eco-innovations as firms in these cities are able to improve production or distribution efficiency in terms of energy or resources. Smart cities can embed the development of distributed energy grids, to integrate, aggregate and optimise the use of renewable energy, thereby expanding its use, improving energy efficiency, and reducing emissions. Smart meters and IoT devices can help to optimise meeting energy and water demand, facilitating their efficient use while reducing the need to build additional infrastructure, which could increase pollution (see Beltrami et al., 2021).

Overall, smart cities can form the loci for a favourable selection environment (Gibbs & O'Neill, 2017), whereby the provision of a public digital infrastructure for AI and IoT applications can enable firms to adopt process eco-innovations, thereby supporting the upgrading of the traditional sectors (Bag et al., 2021). In sum, the application of AI and IoT in cities can lead to systemic eco-innovations that solve complex problems, as embedded public digital technology infrastructure of interconnected systems in smart cities helps firms to make their production processes greener. The following hypothesis states our expectations of the role of digital policies in eco-innovations in smart cities in China.

Hypothesis 2 Smart cities constructed based on digital policies are generating more green patents compared to non-smart cities.

2.3. Policy mix for eco-innovations: environmental and digital policies

A further aim of this study is to explore the impact of digital policies on eco-innovation in the presence of environmental policies, which allows us to test whether the two complement each other, leading to superior outcomes compared to those potentially achievable by either of these policies used independently. For this purpose, we build on the literature of policy mix, which refers to the role of specific combinations of environmental policy instruments and their interactions in facilitating eco-innovations and sustainability transition (Edmondson et al., 2019; Rogge & Reichardt, 2016; Rogge & Schleich, 2018; Uyarra et al., 2016). This literature has focused on specific demand-pull and technology-push environmental policy instruments and identifying the most "effective" combination within specific contexts (regions, countries) and for specific types of environmental technology (e.g., green energy) (Constantini et al., 2017; Magro & Wilson, 2019). The role of *broader policies* supporting general purpose technologies with a cross-sectoral impact has been largely overlooked, so it is explored here.

We build on the arguments found within Eco-innovation Studies, which suggest that policies are enacted by a variety of actors and systems, which challenges the notion of an "optimal" policy mix in a general sense (e.g., Flanagan et al., 2011; Kern et al., 2017). For instance, Fabrizi et al. (2018) show that participation in green research networks facilitates knowledge combination across countries and complements the impact of EU environmental policies on the generation of new green knowledge (patents) at the national level.

Mixing environmental and digital policies in smart cities can alleviate reinforcing market failures associated with eco-innovations, namely, negative environmental externalities and systemic coordination failures. Indeed, the effectiveness of policy mix, is influenced by the comprehensiveness and consistency of the combined policies which should also be void of contradictory elements: when aimed at the same overall purpose (here sustainability transitions) the combined policies need to address complementing and not similar goals (Flanagan et al., 2011; Constantini et al., 2017). Even when the combined policy instruments are theoretically complementing, in practice, they may prove to have no significant or synergistic effect, or to have a different impact across different contexts (e.g. Rogge & Reichardt, 2016; Constantini et al., 2017). We posit that digital policies complement environmental policies by strengthening government monitoring and in turn they facilitate the implementation of environmental regulations. In doing so, digital and environmental policies jointly encourage firms in smart cities to invest in eco-innovations and to ultimately achieve the dual target of economic competitiveness and sustainability as follows.

First, digital policies embedded in smart cities can enable environmental regulators to measure and monitor pollution levels more accurately and efficiently. For instance, Brauer's et al. (2019) study in India shows that dense sensor networks cost less than establishing networks of ground monitoring stations[5] for ambient air pollution. Smart cities can use an interconnected network of sensors (IoT) to measure atmospheric pollution.

Second, once AI technologies receive the information from the interconnected sensors in smart cities, they can perform precise data analysis - optimisation, predictive, prescriptive studies- that facilitate regulators in their decision making. For instance, AI applications can be programmed to send alerts to environmental regulators when pollution levels exceed the guideline limits. Liu's et al. (2021) study in Beijing shows that AI applications (i.e. combined weight prediction model) provide more accurate analysis of data and improves the forecasting levels of Nitrogen dioxide (NO_2).

Third, regulatory bodies using AI knowledge (generated based on data from IoT) can make faster and better decisions when implementing environmental policies, which in turn steer the behaviour of firms towards eco-innovation. Typically, non-compliance to environmental polices is due to the lack of monitoring and enforcement. For example, Gupta et al. (2019) using a sample of 117 water polluting plants and 109 air polluting plants in India found that the probability of inspection increases plant-level compliance. Digital technologies embedded in smart cities allow environmental regulators to detect air, water, or waste polluters, and impose penalties to non-compliant firms. Firms seeking to avoid the costs of environmental fines and penalties will be "pushed" to invest on green technologies stimulating green patents (Popp, 2005).

Based on the above discussion, we posit that the probability of generating eco-innovations is higher in smart cities with stricter environmental regulations, whereby regulators are able to monitor and enforce environmental policies and firms have a higher incentive to implement environmentally sustainable practices. Digital and environmental policies can create a reinforcing cycle that spawns further innovation, thereby enlarging the scope of eco-innovation for organisations within the system at the context of cities. Therefore, we expect that digital policies will complement the impact of environmental policies.

Hypothesis 3. Cities with digital policies and strict environmental policies are generating more green patents compared to cities with a single policy [either digital or strict environmental policy].

3. Data and methodology

3.1. Digital policies and smart cities

Smart cities are an example of a combination of AI and IoT applications to specific geographical contexts and are used here as a way to capture the implementation of digital policies. Smart cities have been defined in numerous ways, reflecting their different dimensions (Albino et al., 2015; Komninos, 2002; Wu et al., 2018). They refer to automated, assisted intelligence that uses large, unstructured, real-time datasets in various domains, such as smart urban mobility systems, smart urban energy systems, and smart homesystems (Yigitcanlar et al., 2019). At the core of the smart city lies the technical infrastructure, with sensory devices and software, which enables the capturing of data about people and their use of services and resources (such as energy consumption, mobility, and transport), the streaming of data to interconnected platforms, the sharing of data among the stakeholders and, finally, the use of data analytics (modelling, forecasting, optimisation) on which to base better operational decisions (Harrison et al., 2010). These wider applications of AI and IoT have the potential to stimulate eco-innovations within systems and to upgrade existing technologies and processes.

3.2. Data

We create an original dataset by merging three different datasets as follows. *Firstly,* we capture the impact of digital policies by focusing on smart-city policies in China. China has undergone rapid industrialisation, urbanisation and economic growth, and has increasingly invested in smart-city policies. The country is a late-adopter of digital policies, which allows it to benefit from the experience of other cities and steer the construction of smart city policies to support the long-term potential for sustainable growth by building indigenous innovation and a capacity for eco-innovations. China launched a smart city pilot policy in 2012, so we use city-level panel data on 167 cities for the period 2006–2018.[6] This dataset includes a combination of 32 cities that transitioned to smart cities post-2012 and 135 that did not. This allows us to undertake a systematic exploration of the role of digital policies in eco-innovation by examining the changes within the cities that transitioned to smart-cities over time and to compare them with other cities where digital policies have not been used. We not only apply the Difference-in-Differences (DiD) approach, based on the overall Chinese city-level data, but also employ the Propensity Score Matching method (PSM) to select the control group. Furthermore, these cities vary in terms of the stringency of their environmental

[5] The cost of an individual station is estimated $135,000 U.S. Dollars (Brauer et al., 2019).

[6] We exclude pilot cities, as digital policies were piloted only in smaller districts, such as in the case of Zhangzhou, where smart policies were implemented only in the district of Pinglu. There are 135 non-smart cities and 32 smart cities. The latter launched a pilot policy of smart city construction in 2012, and include: Shijiazhuang, Qinghuangdao, Handan, Langfang, Tdigitalyuan, Changzhi, Wuhdigital, Liaoyuan, Wuxi, Changzhou, Zhenjiang, Tdigitalzhou, Wenzhou, Jinhua, Wuhu, Bengbu, Hudigitalnan, TongLing, Nanping, Pingxiang, Dongying, Weihdigital, Dezhou, Zhengzhou, Hebi, Luohe, Wuhan, Ya'an, Liupanshui, Lhasa, Hsienyang, and Wuzhong.

policy implementation, which offers ample variation to explore whether such policies are reinforced by digital policies.

Secondly, we measure eco-innovations at the city level for all 167 cities for the period 2006–2018 using data on green patents granted by the China National Intellectual Property Administration (CNIPA). China formally enacted the Patent Law in 1984, which came into effect in 1985. Until the end of the 1990 s, the number of patent applications by local residents and organisations grew modestly, with an average annual growth rate of 11 %. However, since the turn of the century, this figure has surged dramatically, with an average growth rate of 30 %, to reach 4,380,468 in 2019, according to the World Intellectual Property Organization (WIPO). CNIPA provides detailed information on patents (Dang & Motohashi, 2015), including their application number, application date, IPC classification, the applicant's name and address, the inventor's name and the patent attorney's name and address. *Thirdly,* city-level variables were obtained from the China Urban Statistical Yearbook and China Environmental Statistical Yearbook, as detailed in Table 1.

3.3. Variables

3.3.1. Eco-innovation (green patents granted)

Eco-innovation is measured by patent data, in line with previous studies (Brunnermeier & Cohen, 2003; Johnstone et al., 2010; Lanjouw & Mody, 1996; Oltra et al., 2010; Popp, 2002). Green patents refer to inventions, utility models and design patents that use green technologies. To identify green patents granted (*gpc*), we use a detailed patent search strategy, developed by the OECD (Haščič & Migotto, 2015), combined with the "IPC Green Inventory" provided by the World Intellectual Property Organization.[7] We acknowledge the limitations of using the number of green patents to measure eco-innovation, as patents are highly sector-specific and may not reflect the outcomes of investments in innovation activities aimed at sustainability (see Constantini et al., 2017).

3.3.2. Digital polices (Smart-city treatment variable)

To capture the impact of digital policies on changes in eco-innovations within smart cities, we use the variable: $Smart-city_i \times post_t$, where $Smart-city_i$ equals 1 if a city is a smart city, and otherwise equals 0. $post_t$ is a time dummy variable, which equals 1 in 2012 and after, and 0 before 2012. Smart city implementation utilises digital technologies to gather and analyse relevant data to inform government and business decisions and actions (Albino et al., 2015; Komninos, 2002; Wu et al., 2018; Yigitcanlar et al., 2019). The broader aspects of China's pilot smart cities are detailed in Appendix B.

3.3.3. Environmental policy variables

In line with previous studies, we use two indicators to measure the stringency of the environmental regulations. First, we proxy[8] the stringency of environmental policy with the sulfur dioxide removal rate (*soqccs*) (see Table 1 row 2). This indicator measures the reduction in pollutant emissions, whereby a larger percentage of sulfur dioxide removed from the atmosphere reflects a stringent environmental regulation (Feng et al., 2019). Second, we proxy the stringency of environmental policy with sewage discharge income (*spwsr*) (see Table 1 row 3). This indicator captures the industrial pollution control compliance rate, whereby a higher rate points to a stricter environmental policy (Yang et al., 2018).[9]

3.3.4. Control variables

We control for a series of city-level factors that might affect eco-innovation. First, we control for inward foreign direct investment (FDI) weighted by GDP (*fgdp*), as FDI is an important driver of technological innovation. Second, we use the city population (*pop*) and GDP per capital (*agdp*), to control for the size of the city and its growth potential. Third, the variations across the cities in terms of their industrial structure are captured by the output value of manufacturing sectors, weighted by GDP (*sgdp*). Fourth, government support is measured by government expenditure, weighted by GDP (*gov*) (in the negative binomial analysis we use government science and technology expenditure, weighted by GDP, *govsci*). Fifth, we use the sum of savings and loans, weighted by GDP (*allfin*), to reflect the financial development of cities and use investment in pollution control (*iiepc*) to capture the environmental performance of cities. Finally, we expect cities with a higher urbanisation rate (urban population divided by total population, *urban*) to have higher capital investment and a large pool of skilled human resources.

Table 1 presents descriptive statistics for all of the variables. The correlation coefficients are at low acceptable levels, with the variance inflation factors (VIF) ranging from 1.13 to 2.89, well below the threshold level of 10.

3.4. Empirical models

We test hypotheses 1–3, by employing two empirical approaches: a negative binomial and a Difference-in-Differences estimation method.

3.4.1. Negative binomial approach

We use a version of the Negative Binomial method (Cameron & Trivedi, 2013; Fabrizi et al., 2018) to estimate Eq. (1), that allows for correlated fixed effects:

$$gpc_{it} = \beta_0 \ln ER_{it-1} + \beta_1 Smart - city + \beta_2 \ln ER_{it-1} * Smart - city + \beta_3 \ln govsci_{it-1} + \beta_4 pop_{it} + F_i + T_t + \varepsilon_{it} \quad (1)$$

where gpc_{it} is the number of green patents granted in city i in year t, the main explanatory variables are *ER* (Environmental Regulations: *soqccs* and *spwsr*) (H1) and the *Smart-city* dummy (H2). The interaction effect of ER_{it-1}*Smart-city* tests (H3). The variable *govsci* measures the government's science and technology expenditure as a percentage of GDP, *pop* captures the size of population, F_i *is* the city-fixed-effect, T_t is the year-fixed-effect, and ε_{it} is the error term.

We address any unobserved heterogeneity by using the "pre-sample mean scaling" (PSM) method (2002; Blundell et al., 1995). As stated by Bloom et al. (2013), the pre-sample averages can then be used as an initial condition to proxy for unobserved heterogeneity under the assumption that the first moments of all the observables are stationary. Although there will be some finite sample bias, Monte Carlo evidence shows that "this pre-sample mean scaling estimator performs well compared to alternative econometric estimators (like quasi-differenced Generalized Method of Moments estimator) for dynamic panel data models with weakly endogenous variables" (Bloom et al., 2013, p. 1367). In order to reduce problems with endogeneity, following Wang and Hagedoorn (2014) and Costantini et al. (2015), we use one-year lagged values of all regressors (except for population size).

3.4.2. Difference-in-Differences (DiD) approach

Firstly, we apply DiD in a natural experiment setting based on the overall Chinese city-level data. This method allows us to test the causal effect of digital policies on eco-innovation, as captured by smart city construction (H2). The DiD approach is frequently used in applied economics to check for causal effects. In our set-

[7] https://www.wipo.int/classifications/ipc/en/green_inventory/.

[8] Our measures are *proxies* that seek to capture the stringency of environmental policy.

[9] Due to the data availability, environmental regulation variables are based on provincial-level data.

Table 1
Descriptive statistics.

Variables	Code	Mean	Std. Dev.	Data source
Green Patents Granted (log)	*gpc*	3.369	1.557	China National Intellectual Property Administration (CNIPA)
Sulfur Dioxide Removal Rate	*soqccs*	0.457	0.254	China Environmental Statistical Yearbook
Sewage Discharge Income(log)	*spwsr*	11.100	0.714	China Environmental Statistical Yearbook
FDI/GDP	*fgdp*	0.019	0.018	China Urban Statistical Yearbook
Population (log)	*pop*	8.150	0.651	China Urban Statistical Yearbook
GDP per Capita (log)	*agdp*	10.339	0.661	China Urban Statistical Yearbook
Output Value of Manufacturing Sectors/GDP	*sgdp*	0.489	0.106	China Urban Statistical Yearbook
Government Expenditure/GDP	*gov*	0.172	0.095	China Urban Statistical Yearbook
Government Science and Technology Expenditure/GDP	*govsci*	0.002	0.002	China Urban Statistical Yearbook
(Savings + Loans)/GDP	*allfin*	1.409	0.564	China Urban Statistical Yearbook
Investment in Pollution Control (log)	*iiepc*	9.881	0.885	China Environmental Statistical Yearbook
Urbanisation rate	*urb*	0.340	0.166	China Urban Statistical Yearbook

ting, as the digital policy change does not affect each individual city, we can use DiD to estimate the effects of the smart-city policy. The key notion underlying this method is that, if the treated and the non-treated groups are exposed to the same exogenous time trends, then an estimate of the "effect" of the treatment during the pre-treatment period (when we know that the treatment has had no effect) can be used to eradicate the effect of any confounding factors when comparing the post-treatment outcomes for both the treated and non-treated groups. DiD is effective empirically when it is impossible to control the confounding variables and instruments are unavailable, while pre-treatment information is available.

Secondly, we employ the Propensity Score Matching method (PSM) to select the control group. The propensity scores are calculated according to observed characteristics influencing the policy operation, for the purpose of controlling selection bias (Lechner, 2002; Rosenbaum & Rubin, 1984). The empirical model in Eq. (2) is as follows:

$$gpc_{it+1} = \beta Smart - city_i \times post_t + \delta^T Control_{it} + F_i + T_t + \varepsilon_{it} \tag{2}$$

Where i and t indicate the city and time respectively, the dependent variable, gpc_{it}, represents the number of green patents granted. $Smart - city_i \times post_t$ is the key independent variable used to test H2.

Thirdly, we employ the DDD (Difference-in-Differences-in-Differences) method to test the policy mix effect (H3): whether digital policies (i.e., smart cities) and stringent environmental policies are jointly generating more green patents compared to a single policy.

$$gpc_{it+1} = \beta Smart - city_i \times post_t \times lnER_{it} + \delta^T Control_{it} + F_i + T_t + \varepsilon_{it} \tag{3}$$

We include in Eq. (3) the interaction term $Smart - city_i \times post_t \times ER_{it}$. Where F_i indicates the city fixed effect, T_t indicates the year fixed effect, and ε_{it} is the error term.

4. Empirical results

4.1. Negative binomial regression results

The results of the Negative Binomial regression are shown in Table 2. This estimation method appears to fit the data well, as shown by the results of the Wald test. Specifically, the parameter of the over-dispersion *lnalpha* is always significant, leading us to reject the null hypothesis regarding the absence of dispersion. In all specifications, the pre-sample variable has a highly significant coefficient, thereby confirming the presence of unobservable heterogeneity across the cities.

We use the sulfur dioxide removal rate (*soqccs*) and sewage discharge income (*spwsr*) to measure the stringency of the environmental regulations across the cities. The empirical results in column (1) and (2), with coefficients of 0.166 and 0.066, are all statistically significant at the 1 % level, and provide support for H1. Cities with stricter environmental policies are generating more green patents compared to cities with lax environmental policies.

In column (3), we introduce a smart city dummy variable that takes the value of 1 for smart cities, and 0 otherwise. The smart city coefficient is 0.397, with statistical significance at the 1 % level, which supports H2. Digital policies in smart cities can generate more green patents compared to non-smart cities.

In columns (4) and (5), we further include the interaction term between the smart city dummy and environmental policy variables, with coefficients of 0.322 and 0.045 at a 1 % significance level. The results support H3.

4.2. The Difference-in-Differences regression results

4.2.1. Basic regression results

The DiD regression results are presented in Table 3. Columns (1) and (2) first introduce the $Smart - city \times post$ term and the control variables, by using the DiD and PSM-DiD method. Columns (3) and (4) control for year and city fixed effects. The results show that the construction of smart cities has a significant positive impact on eco-innovation, with coefficients of 0.162 and 0.21 respectively, and both are significant at the 5 % level, thus supporting H2. The balance test results are presented in Table A1 in the Appendix.

4.2.2. Parallel trend analysis and yearly effect

We test the parallel trend assumption between the treatment and control groups, which should have similar growth trends in green patents prior to the digital policy implementation. Figure 1 presents the growth trend in the number of green patents between the treatment and control groups. The growth trends of the two groups are roughly parallel before 2012 and diverge after 2012, when smart-city policy was introduced.

Following Hering and Poncet (2014), we conduct a parallel trend test, and the results are shown in Table 4 and Figure 2. We use time dummy variables to explore whether or not the number of green patents between the two groups display different trends prior to the policy's implementation. The year dummy variables include: one year before the policy implementation (pre_{t-1}), two years before the policy implementation (pre_{t-2}), and three years before the policy implementation (pre_{t-3}). We also introduce the year dummies following the policy implementation to examine whether or not the eco-innovation effect of smart city construction is continuous, including one year after the policy implementation ($post_{t+1}$), two years after the policy implementation ($post_{t+2}$), and three years after the policy implementation ($post_{t+3}$).

Table 4 shows that all coefficients of the $Smart - city \times pre_{t-\mathrm{n}}(\mathrm{n} = 1, 2, 3)$ are statistically insignificant, which indicates that the parallel trend assumption is satisfied. This shows that cities in

Table 2
Negative binomial regressions results.

Dependent variable: Green patents granted (gpc)	(1)	(2)	(3)	(4)	(5)
ln(pre-sample fixed effect)	0.634***	0.625***	0.626***	0.618***	0.614***
	(0.055)	(0.054)	(0.047)	(0.056)	(0.055)
$\ln(soqccs)_{t-1}$ **H1**	0.166***			0.215***	
	(0.045)			(0.053)	
$\ln(spwsr)_{t-1}$ **H1**		0.066***			0.072***
		(0.011)			(0.012)
smart city **H2**			0.397***		
			(0.126)		
$\ln(soqccs)_{t-1}$*smart city **H3**				0.322**	
				(0.128)	
$\ln(spwsr)_{t-1}$*smart city **H3**					0.045***
					(0.017)
$\ln(govsci)_{t-1}$	0.688***	0.632***	0.562***	0.672***	0.602***
	(0.084)	(0.085)	(0.073)	(0.084)	(0.087)
pop_t	0.602***	0.455***	0.551***	0.592***	0.465***
	(0.115)	(0.116)	(0.096)	(0.111)	(0.118)
Constant	−3.651***	−2.079**	−3.349***	−3.528***	−2.132**
	(0.831)	(0.879)	(0.716)	(0.806)	(0.898)
ln(alpha)	−0.497***	−0.543***	−0.497***	−0.516***	−0.565***
	(0.088)	(0.093)	(0.072)	(0.087)	(0.092)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	−4534.83	−4568.42	−6300.67	−4525.95	−4558.74
Wald chi2	1374.19	1551.19	1430.17	1410.86	1521.19
Pseudo-R-squared	0.165	0.170	0.166	0.167	0.173

Note: The standard error is given in parentheses. The standard errors are clustered at the city-level.
***, ** and * represent a significance level of 1%, 5%, and 10%, respectively.
Time period is from 2012 to 2018.
Environmental regulation is measured using two variables: the *Sulfur Dioxide Removal Rate (soqccs)* and *Sewage discharge income (spwsr)*.
The Artificial intelligence policy is measured using the *Smart city* variable, which takes the value of = 1 if the city is smart, and = 0 otherwise.

Table 3
Difference-in-Differences & Propensity Score Matching regression results.

Method	(1) DiD	(2) PSM-DiD	(3) DiD	(4) PSM-DiD
Dependent Variable: Green patents granted (gpc)				
$Smart-city \times post$ **H2**	−0.085	−0.098	0.162***	0.210**
	(0.071)	(0.123)	(0.05)	(0.096)
Control variables	Yes	Yes	Yes	Yes
City Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes
Observations	1050	378	1050	378
R^2	0.669	0.385	0.866	0.785

Note: The standard error is given in parentheses. The standard errors are clustered at the city-level.
***, ** and * represent the significance level of 1%, 5%, and 10%, respectively.
The PSM matching balance test is shown in Appendix Table A1.

our treatment and control samples had similar eco-innovation growth trends before the introduction of smart city policy. The coefficients of the $Smart-city \times post_{t+n}$ are positive and statistically significant. This suggests that the effect of smart city construction holds in the short (t + 1) and long term [(t + 2)(t + 3)].

4.2.3. Anticipation effect

Many cities will apply for the smart city pilots. This indicates the possibility of an anticipation effect in which potential participants begin to adjust their innovative strategies even before the formal digital policies implementation. We conduct an anticipation effect test, we run $smart-city$ treatment variable before the policy implementation period (2006–2011). The result is displayed in column (1) of Table 5. The coefficient of the $smart-city$ is statistically insignificant, which suggest that the anticipation effect is insignificant.

4.2.4. Placebo test

Following Hung and Wang (2014), we conduct analysis akin to a placebo test. First, we set up a hypothetical policy time for the placebo test. We assume that the smart city policy was implemented in 2008 ($post_{2008}$) and 2009 ($post_{2009}$) respectively. The results are presented in columns (2) and (3) of Table 5. The coefficients of the $Smart-city \times post_n$(n = 2008, 2009) are insignificant, which is inconsistent with the basic regression results and confirms the eco-innovation effect of smart city construction.

Second, we also set a hypothetical treatment group to conduct the placebo test. We select a hypothetical treatment group, with the same number of cities as in the original treatment group. This process is repeated 500 times. Figure 3 presents the kernel density plot of the $Smart-city \times post$ coefficients for these 500 repetitions. The estimated coefficient of $Smart-city \times post$ is −0.140, with a standard deviation 0.224, which is far from the basic regression coefficient of 0.21 (see Fig A1).

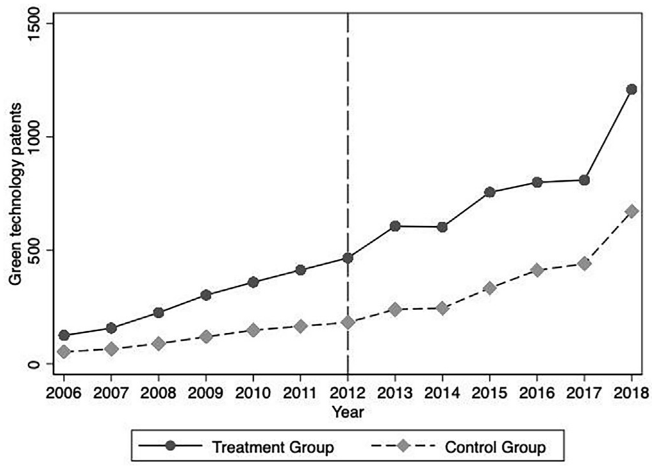

Fig. 1. Growth trend of green patents. Note: The horizontal axis represents one year prior to the policy implementation (pre_{t-1}), two years prior to the policy implementation (pre_{t-2}), three years prior to the policy implementation (pre_{t-3}), one year after the policy implementation ($post_{t+1}$), two years after the policy implementation ($post_{t+2}$) and three years after the policy implementation ($post_{t+3}$).

Table 4
Parallel trend and yearly effects.

	Green patents granted (gpc)
$Smart - city \times pre_{t-3}$	0.055
	(0.195)
$Smart - city \times pre_{t-2}$	0.085
	(0.167)
$Smart - city \times pre_{t-1}$	0.027
	(0.151)
$Smart - city \times post_{t+1}$	0.344***
	(0.171)
$Smart - city \times post_{t+2}$	0.125***
	(0.052)
$Smart - city \times post_{t+3}$	0.287**
	(0.083)
Control variables	Yes
City Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	411
R^2	0.804

Note: The standard error is given in parentheses. The standard errors are clustered at the city-level.
***, ** and * represent the significance level of 1%, 5%, and 10%, respectively.

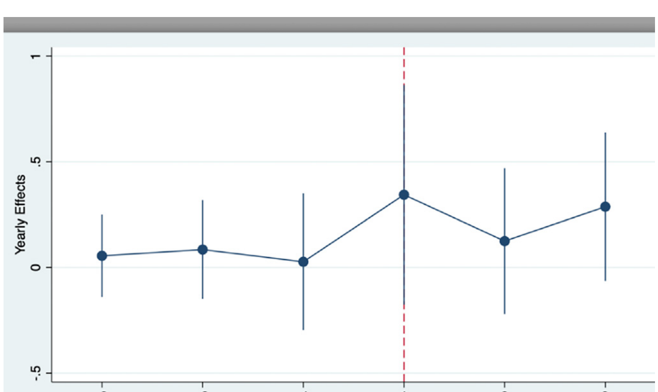

Fig. 2. Parallel trend graph.

4.2.5. Robustness tests

A series of environmental protection policies (laws and regulations) were introduced in 2013.[10] In order to explore whether or not the impact of the introduction of digital policies is still observable, given the impact of these environmental protection policies, we include a year dummy variable ($policy_{2013}$) in column (4) of Table 5. The results show that the coefficient of the interaction term $Smart - city \times post$ is positive and significant, which is consistent with the results shown in the basic regression results (see Table 3).

4.2.6. Policy mix effect – Digital Policies and Stringent Environmental regulation

We employ the DDD (Difference-in-Differences-in-Differences) method to test the policy mix effect. Specifically, we estimate the equation, based on the DiD empirical model (including the interaction term between the *Smart-city *post*), but this time with the inclusion of the interaction term with Environmental Regulation (*Smart-city *post*ER),* hereafter short for the policy mix variable. *Policy mix _psm* (is based on a PSM city-level sample), which means that the control group was selected using the PSM method. The PSM method implies that both the smart cities and non-smart cities groups have no statistically significant inter-group difference based on the matching variables. However, within the smart cities (or the non-smart cities) groups, there still exist differences regarding the environmental regulations. We report the *Policy mix _whole* result for the robustness check. *Policy mix _whole* is based on the whole Chinese city-level sample, which means that the control group includes all non-smart cities.

The regression results are shown in Table 6. The coefficients of the interaction terms are both significantly positive. The coefficients 0.364 (column 1), 0.180 (column 2), 0.019 (column 3), and 0.013 (column 4), are all statistically significant at the 1 % level, which provides further support for H3. Digital and environmental policies are jointly generating more green patents compared to the impact of each separate policy in isolation.

5. Conclusion

The prior literature has stressed the importance of environmental regulation for eco-innovation, yet little attention has been paid to the different types of policies required to drive eco-innovation and their spatial dimension. Even less attention has been paid to the implications of digital policies for eco-innovation. In this paper, we apply a negative binomial regression and quasi-natural experimental methods (i.e., Difference-in-Differences and Propensity Score Matching). We examine the joint impact of digital policies, regarding the design of smart cities in China, and environmental policies, on the production of green patents. We contribute to debates in development studies focusing on eco-innovation by

[10] Technical Policy of Pollution Prevention and Control in Cement Industry; Technical Policy of Pollution Prevention and Control in Iron and Steel Industry; Technical Policy of Pollution Prevention and Control in Sulphuric Acid Industry; Technical Policy of Volatile Organic Compounds (VOCs) Pollution Control; Regulations on Urban Drainage and Sewage Treatment; Action Plan for the Prevention and Control of Air Pollution; Regulations on the Prevention and Control of Pollution from Livestock and Poultry Scale Breeding; Guidelines on Accelerating the Development of Green Cycle and Low Carbon Transportation; Opinions on Speeding up the Development of Energy Conservation and Environmental Protection Industry; Guidelines on Resolving Serious Overcapacity Contradictions; National Desertification Prevention and Control Plan; Notice on Further Strengthening the Management of Strict Environmental Impact Assessment for the Protection of Aquatic Biological Resources; Suggestions on Promoting the Operation of Coal Industry; Regulations on the Adjustment and Management of National Nature Reserves; Guidelines on Pilot Work of Compulsory Liability Insurance for Environmental Pollution; Notice on Enhancing Information Disclosure of Environmental Regulation of Pollution Sources; Notice on the Key Work Arrangements of Environmental Information Disclosure; and Guidelines on Strengthening Emergency Management of Heavily Polluted Weather.

Table 5
Placebo test and robustness test.

Dependent Variable:	Anticipation effect	Placebo test			Robustness test
Green patents granted (gpc)	(1)	(2)	(3)		(4)
Smart – city	0.186 (0.145)				
Smart – city × $post_{2008}$		0.127 (0.089)		*Smart – city* × *post*	0.122* (0.736)
Smart – city × $post_{2009}$			0.138 (0.086)	$policy_{2013}$	−2.217*** (0.190)
Control variables	Yes	Yes	Yes		Yes
City Fixed Effects	Yes	Yes	Yes		Yes
Year Fixed Effects	Yes	Yes	Yes		No
Observations	630	630	630		1050
R^2	0.848	0.849	0.851		0.785

Note: The standard error is given in parentheses. The standard errors are clustered at the city-level.
***, ** and * represent the significance level of 1%, 5%, and 10%, respectively.

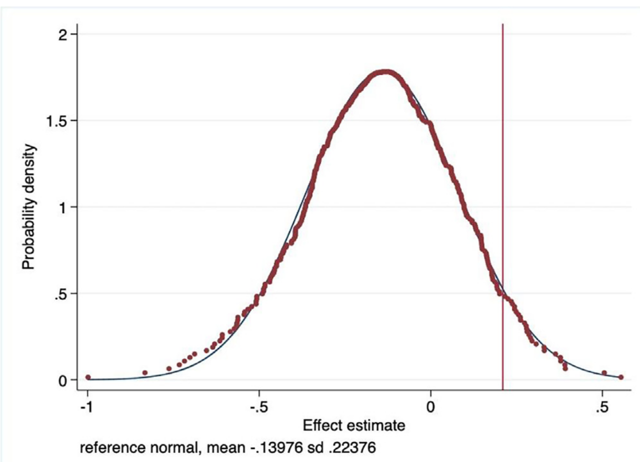

Fig. 3. Kernel density plot of the placebo test coefficient (the virtual treatment group).

introducing insights from recent studies into the policy mix for sustainability across cities, focusing on the role of digital policies. Also, this study uses a novel methodological approach, which makes it possible to examine the quasi-exogenous impact of digital policies on eco-innovation.

Our results demonstrate that digital policies stimulate green patents. Notably, when digital policies are implemented in cities which have strict environmental policies, the production of green patents increases. This suggests that, when these two policies act jointly, there are strong systemic synergies and a deeper, more extensive level of impact on eco-innovation compared to the impact exerted by environmental policies alone. We argue that this is due to digital policies acting to alleviating problems of systemic coordination, which leads to improved outcomes at a systemic level – the city level, in this case. This is a substantial contribution, as environmental policies alone, on occasion, have been linked to low or superficial investment in sustainable solutions (Frondel et al., 2007). Indeed, our results may have important policy implications, as research shows that policy instruments constructed around monetary incentives can often lead to outcomes whose likelihood reduces over time, producing limited results in terms of fostering transitions at the system level (e.g., Lamperti et al., 2020).

Our research, deriving from a leading developing economy, supports the view that smart city construction can provide the public digital infrastructure that nurtures coordination amongst new technology industries, generating positive technological externalities, and building indigenous capacity for eco-innovations. We furthermore contribute to the literature on policy mix, as existing studies tended to focus on the impact of narrow policy tools on sustainability outcomes within specific sectors. We shed further light on the combination of policies, acting at a broader level, that can influence sustainability transitions. Our findings show that digital policies, such as public digital infrastructure investments in AI and IoT, make a substantial contribution to eco-innovations of smart cities in China, by both boosting the performance of these cities over time and in comparison to non-smart cities. Furthermore, parallel trend analysis highlights a long-term impact of

Table 6
The effect of policy mix (digital and environmental policy) upon eco-innovation.

	Environmental regulation			
	Sulfur Dioxide Removal Rate (soqccs)		Sewage discharge income (spwsr)	
Policy mix_psm **H3**	0.364*** (0.141)		0.019** (0.009)	
Policy mix_whole		0.180* (0.105)		0.013** (0.005)
Control variable	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observation	378	1050	378	1050
R^2	0.787	0.811	0.785	0.672

Note: The standard error is given in parentheses. The standard errors are clustered at the city-level.
***, ** and * represent the significance level of 1%, 5%, and 10%, respectively.
Policy mix_psm is based on the PSM city-level sample.
Policy mix_whole is based on the overall Chinese city-level sample.

digital and environmental policies on eco-innovations reflecting sustained implications of such policies at the city level, steering their development path towards sustainability. Our results suggest that cities can form the loci for sustainable transitions, which is highly desirable in countries such as China, where smart city policies focus on areas of high industrialisation, urbanisation and growth, raising strong concerns regarding environmental sustainability and sustaining competitiveness.

We should note that the results of our research, mainly reflect industrial applications of digital and environmental policies and their impact. As a consequence, outcomes from broader indicators for sustainability used in other studies on smart cities (Liu & Peng, 2014), which identify a disconnection between smart and sustainability in various countries (Albino et al., 2015; Hu, 2019) and in China (Shen et al., 2018) are not immediately comparable. Smart cities may involve broader changes, such as changes in institutions, such as smart governance, or circular economy (Shen et al., 2018), and they can influence the behaviour of individuals and of other actors (e.g. consumers or supply chains) (Geels, 2006), in a way that could potentially broaden and deepen the foundations supporting a green trajectory in developing economies (Pegels & Altenburg, 2020).

In policy terms, our empirical analysis yields important insights for policy makers in developing economies. A commitment to net-zero emissions in China by 2060 was recently announced, accompanied by press releases (e.g., Mallapaty, 2020; Rogelj et al., 2021) that highlight the need to set specific targets, measures and goals as well as define a specific scope for their application. We believe that this paper constitutes an effort in that direction, as it shows how digital policies at the city level stimulate eco-innovation and offer a context for sustainability transition. Specifically, firstly, our research reinforces the role of strict environmental policies at the city level in eco-innovation. Second, we show that digital policies, in the form of smart city construction, play an important role in promoting eco-innovation in the context of developing economies due to its potential to have an impact at the systems-level. We, thus, shed light on the important role of policy in supporting digital infrastructure for sustainability transition in cities. Policy makers must continue to promote the development of public digital infrastructure (such AI and IoT) as well as the related technical expertise for their use and application in order to further support actors in smart cities to overcome any barriers linked to implementing IoT technologies and developing relevant capabilities. The availability of relevant technologies and devices and their cost will play an important role in rolling out such policies to other priority cities. Policy makers at the local (city) level may feel encouraged to bring together industry consortia, academic institutions and technology/product/operation service providers to build jointly high-quality interconnections among these actors to unleash the potential of digital technologies in stimulating the traditional sectors to embrace green transition.

Furthermore, policy makers can direct future digital policies towards developing and diffusing the implementation of more sophisticated AI technologies. IoT and big data offer the inputs that enable AI implementation. Sophisticated AI (such as machine learning) can provide an invention-of-a-method-of-invention (IMI) that can lead to disruptive – path breaking product eco-innovations, as it offers the potential to transform how knowledge is produced. By creating more advanced search tools and increasing our understanding of the patterns of the actors' behaviour, sophisticated AI expands our existing knowledge, makes the existing search processes more efficient, and provides the means for exploring new research questions that are beyond human perception and cognition (Cockburn et al., 2018). The diffusion of IMI across wider domains could increase the productivity of R&D, offering rich technological opportunities that will lead to disruptive, systemic innovations with a transformational impact. This is particularly helpful for addressing environmental problems, due to their wicked, uncertain, systemic, and complex nature (De Marchi, 2012; Ghisetti et al., 2015). It is expected that, within smart cities, subsequent to further government support and sharing of AI, various organisations, entrepreneurs, and the public sector will envisage and pursue such opportunities and environmental sustainability goals.

CRediT authorship contribution statement

Despoina Filiou: Conceptualization, Validation, Visualization, Writing – review & editing. **Effie Kesidou:** Conceptualization, Methodology, Project administration, Supervision, Validation, Visualization, Writing – review & editing. **Lichao Wu:** Data curation, Formal analysis, Methodology, Investigation, Software, Validation, Visualization, Writing – review & editing.

Data availability

The data that has been used is confidential.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Balance test.

Variables	Treatment Group	Control Group	Difference	T Value	P Value
FDI/GDP	0.023	0.021	0.104	0.34	0.732
Population	8.225	8.173	0.08	0.28	0.780
GDP per capita	10.656	10.596	0.124	0.47	0.640
Output Value of Manufacturing Sectors/GDP	0.567	0.569	−0.015	−0.07	0.947
Government Expenditure/GDP	0.133	0.139	−0.102	−0.47	0.644
(Savings + Loans)/GDP	1.454	1.435	0.031	0.13	0.893
Investment in pollution control	10.336	10.274	0.100	0.330	0.740
Urbanisation rate	0.359	0.367	−0.051	−0.20	0.841

Note: We perform propensity score matching based on the previous year of policy implementation, i.e. 2011; we use the logit model to estimate the propensity scores and apply the nearest neighbour matching method. The balance test results above show no significant difference regarding the mean values of the covariates between the treatment and control groups Additionally, none of the T values are significant, which supports the PSM matching results.

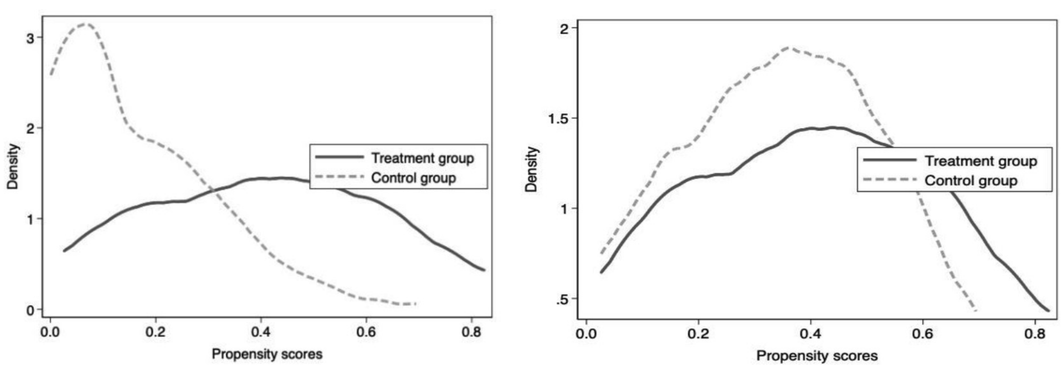

Fig. A1. Kernel density plot prior to and after the propensity score matching. Note: This shows the kernel density plots of the propensity score prior to and after the matching, respectively. It can be seen that there is a close match between the kernel density of the treatment and control groups, respectively, which further verifies the good matching results of PSM.

Appendix B

Aspects of Chinese smart pilot city construction.

First level index	Second level index	Third level index
Security system and infrastructure	Security system	Smart city development plan outline and implementation plan
		Institution
		Policies and regulations
		Funding planning and sustdigitalnment
		Operation management
	Network Infrastructure	Wireless network
		Broadband network(ADSL)
		Next generation radio and television network (NGB)
	Public platform and database	Urban public basic database
		Urban public information platform
		Information security
Smart construction and livability issues	Urban construction management	Town and country planning
		Digital city management
		Construction market management
		Estate management

(*continued on next page*)

(*continued*)

First level index	Second level index	Third level index
		Landscaping
		Historic preservation
		Building energy efficiency
		Green building
	Urban function improvement	Water supply
		Drdigitalnage system
		Water saving techniques
		Gas system
		Waste sorting collecting and sorting treatment
		Heating system
		Lighting system
		Underground pipeline and space comprehensive management
Smart management and service	Government service	Decision support
		Information disclosure
		Online administration
		Government service system
	Basic public services	Basic public education
		Labour and employment service
		Social insurance
		Social services
		Health Care
		Public culture and sports
		Disability Services
		Basic housing security
	Special application	Smart Transportation
		Smart energy
		Smart environmental protection
		Smart territory
		Smart emergency
		Smart security
		Smart logistics
		Smart community
		Smart home
		Smart payment
		Smart finance
Smart industry and economy	Industrial planning	Industrial planning
		Innovation input
	Industrial upgrading	Industrial factor agglomeration
		Transformation of traditional industries
	Emerging industries	New and high-tech industry
		Modern service industry
		Other emerging industries

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