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HOW DOES CITY GROUP RISK-TAKING AFFECT CLIMATE-FRIENDLY TECHNOLOGY INNOVATION IN CITIES? EVIDENCE FROM CHINA

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Abstract. Climate-friendly technology innovation, which always comes with risk, is becoming an essential tool for Chinese cities to cope with climate change. As a macro variable, how does city group risk-taking affect climate-friendly innovation in cities? This study conducts a qualitative analysis on the basis of the theory of planned behaviour. Then, Chinese city data from 2008 to 2020 are employed to study the impact of city group risk-taking on climate-friendly technology innovation with city and year two-way fixed effects models. The results show: first, city group risk-taking promotes climate-friendly technology innovation in cities; for every one standard deviation increase in the level of city group risk-taking, the level of climate-friendly technology innovation in cities increases by 0.1294 standard deviations. Second, city group risk-taking improves a city's market vitality and promotes the city's governmental technology investments, both of which are conducive to climate-friendly technology innovation in cities. Third, the role of city group risk-taking in promoting climate-friendly technological innovation in cities is heterogeneous and is greater in cities with high enthusiasm for financial technology innovation, in cities with high population density and in cities with high environmental penalties.

Keywords: group risk-taking, market vitality, government technology investment, climate-friendly technology innovation.

JEL Classification: O33, E71, E29.

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1. Introduction

Climate change is the most significant global challenge in human history. It will lead to more extreme weather patterns with severe adverse consequences for human well-being and ecosystems on multiple fronts (Otte, 2021; Nguyen et al., 2024). Climate-friendly technology innovation (CFTI) is the most critical measure for combatting climate change (Nguyen et al., 2024). City group risk-taking (CGRT) is a macro variable that measures the extent to which all individuals in a city dare to practice risky behaviours. CFTI is always accompanied by risk, and high CGRT means that individuals in a city dare to take the risk of CFTI to combat climate change. However, how CGRT affects CFTI in Chinese cities is a topic that has yet to be studied. The answer to the topic is important for several reasons. First, China is the second largest economy in the world, and its cities play a central role in addressing climate change. With China's rapid economic development, CGRT has increased. Against this backdrop, the answer to the topic will help China actively address climate change, thereby benefiting all of humanity. Second, reducing carbon emissions, realising green and low-carbon development and promoting economic growth are two major tasks facing the majority of developing countries. CGRT shows that firms within cities dare to take risks, which contributes to economic growth at the macro level. If CGRT can promote CFTI, increasing CGRT can help the vast number of developing countries realise the two important tasks at the same time without the need to oppose the two. For this reason, this study examines the relationship between CGRT and CFTI on the basis of the theory of planned behaviour (TPB).

CFTI is the dependent variable in this study. Climate-friendly technologies are those that mitigate or adapt to climate change (Carattini et al., 2019, 2020; Fischer et al., 2012; Nguyen et al., 2024; Otte, 2021). The European Patent Office (EPO) and the United States Patent Office (USPTO) have jointly published the Cooperative Patent Classification (CPC), in which the Y02 classification is defined as technologies for mitigating or adapting to climate change. For this reason, we collect the number of patent applications and the number of granted patents under the Y02 classification in each city from 2008 to 2020 from Suzhou Industrial Park Benepe Information Technology Co. (https://www.zhihuiya.com/), which is derived from the China National Intellectual Property Administration (https://www.cnipa.gov.cn), but allows for a more convenient data query. We then calculate the number of climate-friendly patents granted per capita and the number of climate-friendly patent applications per capita by referring to Lu et al. (2021), Li and Yang (2018) to obtain *CFTI* and *rCFTI*, which are used as proxy variables for CFTI. *CGRT* is the independent variable in this study. Individuals choose between consumption and savings on the basis of their risk-taking ability, and individuals who dare to take risks tend to consume more (Yang & Ran, 2023). In contrast, risk-averse individuals choose to increase precautionary savings and reduce consumption (Zhang & Wu, 2016). Therefore, we obtain *CGRT* as follows: (total city retail sales of consumer goods)/ (total city retail sales of consumer goods + city savings deposits), which serves as a proxy variable for CGRT. Furthermore, entrepreneurship is a high-risk behaviour (Astebro et al., 2014). Therefore, entrepreneurship can be implemented by actively taking risks (Djankov et al., 2006). Since 2008, digital technology entrepreneurship involving artificial intelligence (AI), blockchain, cloud computing, big data, and the Internet of Things (IoT) has been the main form of entrepreneurship in cities. To this end, we refer to Li and Zhang (2007), Zahra and Bogner (2000) and count the number of AI, blockchain, cloud computing, big data, and IoT startups with a founding time of 8 years or less in each city from 2008 to 2020 to obtain *ABCDI8*. Then, per capita *ABCDI8* is calculated to obtain *rCGRT*, which serves as another proxy variable for CGRT.

On the basis of the independent and dependent variables being constructed, we examine the direct effect of CGRT on CFTI with a city and year two-way fixed effects model. Drawing on Chen et al. (2022, 2023a) and Chen (2023), we test the indirect effect of CGRT on CFTI with a city's market vitality and the governmental technology investments as mediating variables. Finally, using city financial technology innovation enthusiasm, city population density and city extent of environmental penalties as categorical variables and drawing on Florackis and Sainani's (2018) approach to typology, we investigate the heterogeneity of CGRT's impact on CFTI via a variable coefficient city and year two-way fixed effects model. We find that, first, for every one standard deviation increase in CGRT, CFTI increases by 0.1294 standard deviations. CFTI is a high-risk behaviour, and according to the TPB, an individual's decision to perform a behaviour is closely related to his or her intention to do so, which depends on attitudes towards the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991; Hagger et al., 2022; Yuriev et al., 2020). The higher the CGRT is, the more likely an individual in the city is to evaluate CFTI behaviour as favourable, resulting in positive attitudes; the higher the CGRT is, the more likely the individual's specific reference group will also positively evaluate their implementation of CFTI, resulting in positive subjective norms. At the same time, the higher the CGRT is, the more positively the individual evaluates their control over the resources required for CFTI behaviour, thus enhancing the individual's perceived behavioural control. Ultimately, CGRT increases individuals' intention to implement CFTI, which in turn promotes CFTI. Second, CGRT improves market vitality and promotes governmental technology investments in cities, the latter two of which are both favourable to CFTI. Third, the role of CGRT in promoting CFTI in cities is heterogeneous. The role is greater in cities with a high level of enthusiasm for financial technology innovation, in cities with high population densities and in cities with high environmental penalties.

First, our study contributes to some of the CFTI literature. Concerning CFTI, recent research has focused on climate-friendly behaviours (Otte, 2021), financial support (Fischer et al., 2012; Nguyen et al., 2024), social spillovers from learning and imitation (Carattini et al., 2020), social norms (Carattini et al., 2019) and international cooperation (Halleck-Vega et al., 2018; Golombek & Hoel, 2011), among others. For example, the greatest challenge in implementing CFTI is project financing, yet venture capital financing for CFTI has been declining (Nguyen et al., 2024). In developing countries, the financial sector tends to be particularly hesitant about CFTI projects because of a lack of capacity to assess financial viability and an overreliance on balance sheets as a measure of creditworthiness (Fischer et al., 2012). Through learning and imitation, social spillovers can drive CFTI and applications such as solar panels and hybrid cars (Carattini et al., 2020). The financial sector is an industry that operates and manages risk. CGRT may increase risk-taking in the financial sector, thus promoting CFTI. However, there is a lack of research in the existing literature on the relationship between CGRT and CFTI. Our study provides new evidence to promote CFTI and enriches the literature related to CFTI.

Second, our study contributes to the literature related to risk-taking. With respect to risk-taking, the existing literature focuses on three micro dimensions, namely, firm risk-taking, bank risk-taking, and household risk-taking, as well as the influencing factors of risk-taking. There are relatively few studies on the economic impact of risk taking. Scholars believe that corporate risk-taking reflects the risk preferences of firms in their investment decisions. The higher the level of risk-taking of firms is, the more willing they are to choose risky investment projects (Acharya et al., 2011; Faccio et al., 2011; Lumpkin & Dess, 1996). Firms with high levels of risk-taking hold less cash (Al-Hamshary et al., 2023). Notably, excessive risk-taking by firms can lead to financial distress, whereas extreme risk aversion can impede growth and shareholder value (Bhuiyan et al., 2024). Bank risk-taking has traditionally been a focus of scholarly attention. In terms of economic impact, the greater the bank's level of risk-taking, the more likely it is to increase credit allocations to firms (Chen et al., 2022); however, excessive bank risk-taking induces systemic financial risk (Ali et al., 2022). Household risk-taking is an increasing function of household resources (Hubar et al., 2020). The greater the degree of household risk-taking is (Hubar et al., 2020), the greater the likelihood that the household will hold risky assets (Bäckman et al., 2020; Hubar et al., 2020). Overall, the existing literature examines the economic impact of risk-taking mainly at the individual level. This study enriches the literature related to risk-taking by expanding the research perspective to the macro level and studying the impact of CGRT on CFTI.

Finally, our study expands the research approach of technological innovation. The TPB is a well-known theory of attitudinal–behavioural relationships in the field of social psychology (Ajzen, 1991) and has been successfully used to explain and predict individual behaviours in a wide range of domains, such as privacy protection, sports, tourism, and consumption (Ajzen, 2020; Yuriev et al., 2020). The theory suggests that attitudes towards behaviour, subjective norms, and perceived behavioural control determine the willingness to perform a behaviour. China is a collectivist culture. This means that the behaviours of the individuals within a city are influenced by the group within the city. Firms are the main body of technological innovation, and their climate-friendly technological innovation behaviours require decision-makers to implement decisions. Therefore, CGRT influences the attitudes of the decision-makers in a city, encourages them to implement risky behaviours such as CFTI and changes the attitudes of specific reference groups while also influencing their perceptions of decision-makers' implementation of such risky behaviours, which also increases the decision-makers' confidence in implementing such behaviours. Therefore, the TPB is the best theory for analysing the impact of CGRT on CFTI. However, to the best of our knowledge, no studies have drawn macrolevel conclusions on the basis of a microanalysis and the TPB. Therefore, our study expands the research approach.

The structure of the remainder of this study is outlined as follows: In Section 2, we delineate our testable hypotheses. Section 3 details the research methodology employed in our study. In Section 4, we present the primary empirical results, accompanied by robustness checks. Section 5 is dedicated to the results of mechanism tests. Section 6 offers an analysis of heterogeneity. Section 7 engages in a comprehensive discussion of our findings. Finally, we conclude with a summary of the entire study.

2. Testable hypotheses

2.1 Direct influence analysis based on the theory of planned behaviour

The TPB is a well-known theory of attitudinal–behavioural relationships in the field of social psychology that has been successfully used to explain and predict individual behaviours in many fields, such as technology (Ajzen, 2020; Yuriev et al., 2020). The TPB suggests that attitudes towards behaviours (ATT), subjective norms (SN), and perceived behavioural control (PBC) determine the intention to behave (Ajzen, 1991; Hagger et al., 2022; Yuriev et al., 2020). In general, the more favourable the attitudes and subjective norms towards a behaviour are and the stronger the perceived behavioural control is, the stronger the individual's intention to perform the behaviour (Ajzen, 1991; Hagger et al., 2022). In the case of CFTI, CGRT acts on attitudes towards the behaviour, subjective norms, and perceived behavioural control, respectively, to enhance the individual's intention to perform CFTI behaviours and, in turn, to facilitate the individual's conversion of intention to perform CFTI behaviours (Figure 1).

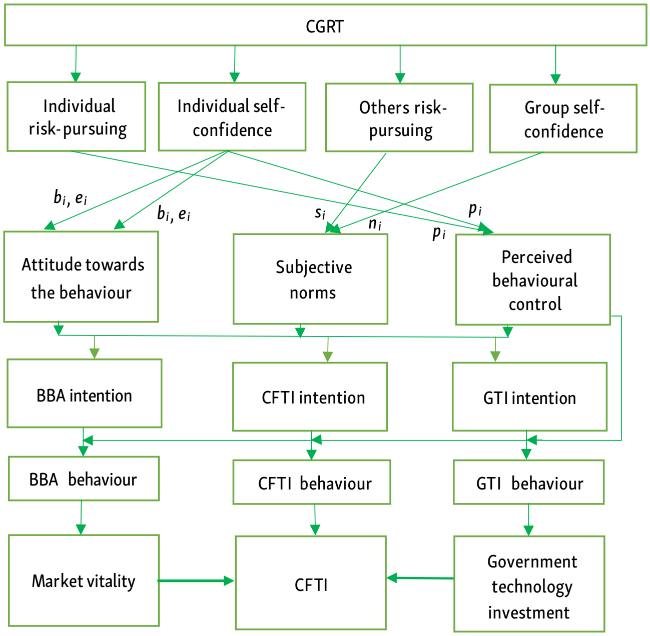

Figure 1. Mechanism of the effect of CGRT on CFTI

First, CGRT improves individuals' attitudes towards CFTI behaviours. According to the TPB, an individual's attitude towards a behaviour is the individual's evaluation of the favourable or unfavourable aspects of the behaviour in question (Ajzen, 1991; Hagger et al., 2022; Yuriev et al., 2020). Individuals' attitudes towards behaviours depend on their behavioural beliefs, which are individuals' subjective evaluations based on their assessment of the various consequences produced by the behaviour and the probability of their occurrence (Ajzen, 2020).

$$ATT \propto \sum b_i e_i. \tag{1}$$

ATT is the individual's attitude towards the behaviour, b_i is the individual's subjective judgement of the consequences produced by the behaviour, and e_i is the individual's subjective evaluation of the probability of the consequences occurring. The individual's attitude towards the behaviour depends on the combined beliefs generated by the various consequences of the behaviour and their probability of occurrence; the stronger the combined beliefs are, the more positive the individual's attitude towards the behaviour (Ajzen, 2020). In the case of CFTI behaviours, the higher the CGRT is, the more risk-seeking the individual is (Chen et al., 2023a), and the more self-confident the individual is (Pauley et al., 2008; Skaar et al., 2014). This leads to a more positive appraisal of the consequences of the behaviour b_i and a greater subjective appraisal of the probability of the behaviour's consequences e_i, which leads to a more positive attitude towards CFTI behaviours to form a more positive attitude. That is, the higher the CGRT is, the more positive the attitudes of the individuals in the city towards CFTI behaviours.

Second, CGRT increases individuals' subjective norms towards CFTI behaviours. According to the TPB, subjective norms are the social pressures individuals feel about whether to perform the behaviour in question (Ajzen, 1991; Hagger et al., 2022; Yuriev et al., 2020), which are the perceptions of a specific reference group about the individual's performance of a specific behaviour (Wang et al., 2020). An individual's expected outcome of a behaviour on the basis of a specific reference group (e.g., friends, coworkers), multiplied by the weight the individual assigned to the specific reference group, can yield a subjective norm (Ajzen, 2020).

$$SN \propto \sum n_i s_i, \tag{2}$$

where SN is the individual's subjective norm for the behaviour, n_i is the specific reference group's view of the behaviour, and s_i is the importance rating of the specific reference group in the individual's mind. Individuals' subjective norms about a behaviour depend on the specific reference group's view of n_i and the importance of the specific group s_i. In terms of CFTI behaviours, the higher the CGRT is, the more risk-seeking other individuals in the city are (Chen et al., 2023a), the more self-confident all types of people are (Pauley et al., 2008; Skaar et al., 2014), and the more willing they are to give more positive ratings to CFTI. The perception n_i of a particular reference group increases. This ultimately increases individuals' subjective norms about CFTI behaviours.

Third, CGRT enhances an individual's perceived behavioural control in implementing CFTI. Perceived behavioural control is the individual's perceived ease of performing a behaviour and is their assessment of the feasibility of the behaviour (Ajzen, 1991, 2020; Yuriev et al., 2020). Perceived behavioural control depends on the individual's control beliefs; individuals make subjective appraisals of the strength of the resources required for the behaviour and the individual's control over the resources, and on the basis of their subjective appraisal measurements, the individual's accessible control beliefs are derived, from which perceived behavioural control is formed (Ajzen, 2020).

$$PBC \propto \sum c_i p_i. \tag{3}$$

PBC is the individual's perceived control over the behaviour, c_i is the strength of the resource required for the behaviour, and p_i is the individual's control over the resource. In terms of CTFI behaviours, the higher the CGRT is, the more risk-seeking the individual is (Chen et al., 2023a) and the more they tend to show confidence in making subjective evaluations (Pauley et al., 2008; Skaar et al., 2014), which increases the subjective appraisal of the resource's control p_i and thus enhances the individual's implementation of the CTFI's perceived behavioural control.

In summary, CGRT can increase individuals' intention to implement CFTI behaviours. Intention is the motive that determines people's behaviour and represents how much difficulty and effort they are willing to overcome to accomplish a specific behaviour (Ajzen, 1991; Yuriev et al., 2020). In general, the stronger the intention to engage in a behaviour is, the greater the likelihood that the behaviour will be performed (Ajzen, 1991, 2020; Hagger et al., 2022). Positive favourable attitudes and supportive subjective norms motivate behaviour, and the intention to achieve behaviour is converted into behaviour when perceived behavioural control is strong enough (Ajzen, 2020). Therefore, we argue that CGRT enhances CFTI in terms of the TPB. To this end, this study proposes the following Hypothesis.

H1: *CGRT can promote CFTI.*

BBA represents basic business activity, and GTI represents governmental technical investment.

2.2. Indirect effects of CGRT on CFTI

We further explore two channels of the indirect effects of CGRT on CFTI.

2.2.1. Market vitality

CGRT can increase the market vitality of a city. Investment, financing, and business activities are the basic activities of firms, and all of these activities involve risks. Long-term investments such as investment in fixed assets are risky (Liu et al., 2019), and firms making investments in financial assets such as stocks and bonds are equally risky (Yan & Chen, 2018). Firms conducting debt capital financing face the pressure of regular debt repayment and interest payment, and the same risks exist (Jensen & Meckling, 1976). The market in which a firm produces products is always uncertain, and there are many risks. CGRT facilitates the formation of positive attitudes towards the basic activities of the firm by the decision-makers of inner-city firms, enhancing their subjective norms and increasing their perceived behavioural control. First, in terms of implementing basic firm activity-related behaviours, the higher the CGRT is, the more risk-pursuing and self-confident the corporate decision-makers within the city are, which leads to higher subjective appraisals of the implementation of basic firm activity-related behaviours and, consequently, more positive attitudes towards the implementation of basic firm activity behaviours. Second, the higher the CGRT is, the more risk-pursuing and self-confident individuals in the city are across all categories of people in terms of basic firm activity-related behaviours (Pauley et al., 2008; Skaar et al., 2014). The specific reference group of business decision-makers tends to provide more positive appraisals of behaviours related to the implementation of basic business activities. This ultimately increases the subjective norms of firm decision-makers regarding the implementation of basic firm activity-related behaviours. Third, in terms of basic firm activity-related behaviours, the higher the CGRT is, the more risk-pursuing the firm decision-makers within the city are, and the more confident they tend to be in making subjective evaluations (Pauley et al., 2008; Skaar et al., 2014), which leads to increased subjective evaluations of the control of the resources available to the firm, which in turn enhances the firm decision-maker's implementation of basic firm activity-related behavioural control. According to the TPB, higher CGRT will motivate firms within the city to actively engage in investment, financing, and production activities, which will enhance the city's market dynamics.

The market vitality of cities is conducive to CFTI. The reasons for this are as follows: First, enhancing social networks promotes CFTI. Social networks can convey various types of information (Gompers et al., 2005), which is conducive to innovators' access to innovation-related information. The richer the social network is, the more favourable it is for individuals to learn the innovation model (Estrin et al., 2013), which promotes innovators in generating new creative ideas. Therefore, social networks are essential in innovation activities (Aidis et al., 2008; Estrin et al., 2013). The greater the market dynamics of a city are, the more frequent the exchanges between firms and individuals are, and the more intensive the exchange activities are, which is conducive to strengthening the social networks of innovators and thus promoting CFTI. Second, accelerating knowledge accumulation promotes CFTI. Firms' innovations, such as CFTI, are built on the basis of their accumulation of knowledge, which is closely related to the stock of knowledge. The greater the market vitality of a city is, the more frequent the exchanges between enterprises, and the faster the dissemination of knowledge among firms, which in turn stimulates the accumulation of knowledge needed for CFTI, which in turn facilitates the realisation of new products, services, and processes related to CFTI. Accordingly, we propose the following Hypothesis:

H2: *CGRT improves the market vitality of a city and thus promotes CFTI.*

2.2.2. Governmental technology investment

CGRT can increase governmental technology investment. After the implementation of the tenure system in China, to be recognised by the greater government during their limited tenure and to obtain political promotion opportunities, government officials in cities must implement innovation-driven strategies to promote the good and fast development of the local economy by accelerating the transformation of the mode of economic growth (Bian & Bai, 2017). However, technology innovation faces low explicit returns and a high risk of failure (Van Dyne & Pierce, 2004) and is a high-risk activity (Sweetman et al., 2011). Technology innovation is a long-term, uncertain, and high-spillover activity. City government officials also engage in risky government behaviour to promote local technology innovation by increasing governmental technology investment to encourage regional economic growth. CGRT facilitates the development of positive attitudes towards governmental technology investment by city public officials, enhancing their subjective norms and increasing their perceived behavioural control. First, in terms of governmental technology investment behaviours, the higher the CGRT is, the more risk-pursuing and self-confident government officials within the city are, which leads to higher subjective appraisals of the implementation of governmental technology investment behaviours and consequently more positive attitudes towards the implementation of governmental technology investment behaviours. Second, the higher the CGRT is, the more risk-pursuing individuals in the city are and the more self-confident all types of people are (Pauley et al., 2008; Skaar et al., 2014). The greater the specific reference group of government officials (e.g., other government officials) is, the more positive the appraisals of implementing governmental technology behaviours. This ultimately increases the subjective norms of government officials towards implementing governmental technology investment behaviours. Third, the higher the CGRT is, the more risk-pursuing the government officials within the city are, and the more confidence they tend to show in conducting subjective appraisals (Pauley et al., 2008; Skaar et al., 2014), which in turn improves subjective evaluations of the actual effects of the governmental technology investment and consequently enhances perceived behavioural control over the implementation of the governmental technology investment behaviours by government officials. According to the TPB, higher CGRT will motivate government officials within the city to actively implement governmental technology investment behaviours, which will increase government technology investment.

Government technology investment can promote CFTI. The reasons for this are as follows: First, governmental technology investment compensates for externalities. Most technology innovation results in knowledge and information, which are often characterised by high spillovers, and enterprises are often reluctant to carry out independent research and development but rather prefer to obtain spillovers from other innovators by "hitchhiking", imitation and other means (Bian & Bai, 2017). Therefore, for technology innovation, the market mechanism does not effectively allocate innovation resources and requires government support and subsidies for innovation (Arrow, 1962). CFTI is usually difficult to improve efficiency and increase output directly, and the incentive for enterprises to carry out independent R&D is even lower. The government can incentivise the innovation process when it compensates for the adverse effects of CFTI through fiscal means (Xu et al., 2015). Therefore, government technology subsidies can encourage enterprises to improve their innovation capacity, which can solve the externality problem of firms conducting climate-friendly R&D and thus promote CFTI (Li et al., 2022). Second, governmental technology investment can alleviate financing constraints. Technology innovation has a long cycle and slow results (Bian & Bai, 2017) and often requires continuous financial support. The government's provision of funds to firms through technology investment can partially solve the problem of insufficient funds needed for firms to conduct CFTI. More importantly, the governmental technology investment can play a guiding and modelling role for nongovernmental funds such as venture capital (Xu et al., 2015), which can send positive signals to banks, venture capital firms and other financial institutions, thus encouraging these financial institutions to provide funds to firms to implement CFTI to alleviate their financing constraints and then promote CFTI. In addition, the governmental technology investment can, to a certain extent, reduce R&D risks and increase enthusiasm for R&D (Howell, 2017). Accordingly, we propose the following Hypothesis:

H3: *CGRT can increase the governmental technology investment, which in turn promotes CFTI.*

3. Models, variables and data

3.1. Models

3.1.1. Models of direct impact

China's development is uneven, and each city has a unique factor that does not change over time, which affects its CFTI. To capture this unique city factor that does not vary over time, we control for city fixed effects. In addition, China is a government-dominated economy, and the central government issues different policies each year that affect all cities. For this reason, we control for year fixed effects. In conclusion, we draw upon the existing literature (e.g., Chen et al., 2022, 2023b) to establish the two-way fixed effects for year and city.

$$CFTI_{it} = \alpha_0 + \beta_1 * CGRT_{it} + \boldsymbol{\eta} * \boldsymbol{X} + \alpha_i + \lambda_t + \varepsilon_{it}, \quad (4)$$

where i and t are city and year subscripts, respectively; α_i captures city fixed effects; λ_t captures year fixed effects; and $\varepsilon_{i,t}$ is the random error term. $CFTI_{it}$ is the dependent variable, i.e., CFTI of the i-th city in the t-th year. $CGRT_{it}$ is the independent variable, i.e., CGRT of the i-th city in the t-th year. β_1 is the coefficient of the independent variable, and if it is significantly positive, then CGRT can contribute to CFTI. $\boldsymbol{X}$ is the control variable, as described below.

3.1.2. Models of the indirect impact

To investigate the indirect effect of CGRT on CFTI, we establish the following model, drawing on insights from existing literature that examines the transmission mechanisms (e.g., Chen et al., 2022, 2023b).

$$MED_{it} = \alpha_0 + \beta_1 * CGRT_{it} + \boldsymbol{\eta} * \boldsymbol{X} + \alpha_i + \lambda_t + \varepsilon_{it;} \quad (5)$$

$$CFTI_{it} = \alpha_0 + \beta_1 * CGRT_{it} + \phi * MED_{it} + \boldsymbol{\eta} * \boldsymbol{X} + \alpha_i + \lambda_t + \varepsilon_{it}. \quad (6)$$

MED_{it} is the mediating variable, i.e., market vitality (*MVTA*) and governmental technology investment (*SCPD*) in the t-th year of the i-th city. *X* in Equations (5) and (6) are control variables, and the control variables in Equation (6) are identical to those in Equation (4).

3.2. Variables

With reference to the existing literature, the independent, dependent, and control variables of this study are presented in Table 1.

Table 1. Variable description

Type	Name	Symbol	Definition	Reference
Dependent variable	CFTI	*CFTI*	Number of climate-friendly patents granted in the city/total population of the city	Lu et al. (2021), Li and Yang (2018)
		rCFTI	Number of climate-friendly patent applications in the city/total population of the city	
Independent variable	CGRT	*CGRT*	(total city retail sales of consumer goods)/ (total city retail sales of consumer goods + city savings deposits)	Yang and Ran (2023), Zhang and Wu (2016)
		rCGRT	The ratio of ABCDI firms that are less than eight years old in the city to the total population of the city.	Astebro et al. (2014), Zahra and Bogner (2000)
Control variables	Economic development level	*PGDP*	Ln (real GDP per capita of the city), with 2008 as the base period	Chen et al. (2022, 2023a)
	Level of industrial structure	*INSR*	Third industry value added of the city/ secondary industry value added of the city	
	Level of foreign direct investment	*FDI*	FDI of the city/GDP of the city	
	Fiscal decentralisation	*FISD*	Fiscal revenue of the city/national fiscal revenue	
	R&D investment	*RD*	Ln (number of R&D personnel of the city)	
	Financial development level	*FSIZ*	Loan balance of the city/GDP of the city	
	Financial efficiency	*FEFF*	Loan balance of the city/deposit balance of the city	
	Urbanisation rate	*CITY*	City's urban population/city's total population	
	Population density	*PDEN*	Total population of the city/area of the city	

3.2.1. Dependent variable

The dependent variable in this study is climate-friendly technology innovation (*CFTI*). On the basis of the rationale described in Section 1, we calculate the number of climate-friendly patents granted per capita and the number of climate-friendly patent applications per capita in the city to obtain *CFTI* and *rCFTI* as proxy variables for CFTI in the city.

3.2.2. Independent variables

The independent variable in this study is city group risk-taking (*CGRT*). On the basis of the elaboration in Section 1, we calculate CGRT as follows: (total city retail sales of consumer goods)/ (total city retail sales of consumer goods + city savings deposits), to obtain *CGRT* as a proxy variable for CGRT. Meanwhile, *rCGRT* is calculated as the number of ABCDI firms within eight years/total population of the city and is another proxy variable for CGRT.

3.2.3. Mediating variables

The mediating variables in this study are market vitality (*MVTA*) and governmental technology investment (*SCPD*). We refer to Ding et al. (2023), where we divide the number of firms in a city by the area of the city to obtain the firm density as a measure of the city's market vitality (*MVTA*). Referring to Qin and Yu (2016), we divide a city's fiscal technology investment by the city's fiscal expenditure to obtain *SCPD*, which serves as a proxy variable for governmental technology investment.

3.2.4. Control variables

In Equation (4), the control variables included in our analysis align with the findings from previous studies (e.g., Chen et al., 2022, 2023b). These variables encompass the level of economic development, the industrial structure, the extent of foreign direct investment, fiscal decentralization, investment in research and development (R&D), the degree of financial development, financial efficiency, the urbanization rate, and population density. Turning to Equation (5), when assessing market vitality as a mediating variable, we refer to previous studies (e.g., Cao, 2020; Ding et al., 2023) and control for several factors, including the level of economic development, industrial structure, fiscal decentralization, financial efficiency, urbanization rate, foreign investment levels, population density, and total population size, the latter of which is denoted as Ln (total population of the city). Conversely, when considering governmental technology investment as the mediating variable, we follow the precedent established in prior research (Bian & Bai, 2017; Bai & Dai, 2017), controlling for the level of economic development, foreign direct investment, R&D expenditure, and fiscal decentralization.

3.3. Data

3.3.1. Data sources

Carbon reduction regulations in China can be traced back to 2008, and the data from the *China City Statistical Yearbook* (National Bureau of Statistics, 2021) is updated to 2020. For this reason, this study uses data from Chinese cities from 2008 to 2020 for the empirical analysis. In this study, we process the data as follows: (1) missing samples are eliminated;

(2) owing to missing data, we linearly interpolate savings deposits and total city retail sales of consumer goods in 2010; (3) the *China City Statistical Yearbook* (National Bureau of Statistics, 2021) stopped reporting foreign direct investment in cities in 2020, and therefore, we linearly interpolate foreign direct investment in 2020; (4) taking the natural logarithm can help mitigate the effects of outliers. Therefore, to further blueuce the influence of outliers, we apply Winsorization to the upper and lower 1% of the continuous variables, in addition to employing the natural logarithm transformation. Finally, we obtain 3,375 year-city observations.

The number of patent applications and grants for climate-friendly technology are from Suzhou Industrial Park Benepe Information Technology Co. (https://www.zhihuiya.com/), which is derived from the China National Intellectual Property Administration, but allows for a more convenient data query. The number of ABCDI firms established within eight years comes from Shanghai Da Zhi Cai Hui Technology Co., Ltd. (https://www.qyyjt.cn), which obtains its data from the State Administration for Market Regulation of China (https://www.samr.gov.cn). The other data come from the *China City Statistical Yearbook* (National Bureau of Statistics, 2021), the People's Bank of China (http://www.pbc.gov.cn), and the Wind database (https://www.wind.com.cn/).

3.3.2. Summary statistics

Table 2 reports the descriptive statistics of the variables. As shown in the Table 2, the mean of *CFTI* is 0.3967. This represents an average of 0.3967 climate-friendly patent applications per 10,000 persons. The minimum value observed is 0.0000, while the maximum value reaches 4.5562, indicating a substantial disparity between the two endpoints. The mean of CGRT is calculated to be 0.3400. Additionally, the minimum and maximum values for this metric are 0.1580 and 0.4957, respectively, highlighting a similarly large gap. This situation reflects the broader context of uneven development that is characteristic of China.

Table 2. Summary statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
CFTI	3,375	0.3967	0.7374	0.0000	4.5562
rCFTI	3,375	1.0081	2.1153	0.0033	14.5689
CGRT	3,375	0.3400	0.0700	0.1580	0.4957
rCGRT	3,375	0.5598	1.3448	0.0000	8.9808
MVTA	3,375	1.8114	3.3261	0.0198	22.1627
SCPD	3,375	1.6254	1.4428	0.1116	7.5281
PGDP	3,375	1.2941	0.7347	–1.0364	3.7957
INDS	3,375	2.2763	0.1435	1.8312	2.6431
FDI	3,375	0.1801	0.1750	0.0000	1.0918
FISD	3,375	0.1556	0.3207	0.0077	2.9433
RD	3,375	–0.7356	1.1806	–4.6052	4.2727
FSIZ	3,375	0.1824	0.7266	0.0001	4.1574
FEFF	3,375	0.6588	0.1779	0.2890	1.1945
CITY	3,375	0.3663	0.2397	0.0618	1.0000
PDEN	3,375	0.4431	0.3094	0.0107	1.5344

4. Results

4.1. Correlation matrix

Table 3 reports the correlation matrix of the main variables. As shown in the Table 3, first, the correlation coefficient between *CGRT* and *CFTI* is 0.0699, $p < 0.0001$, and both are significantly positively correlated at the 1% significance level. Second, the correlation coefficient between *CGRT* and *MVTA* is 0.0460, $p < 0.0001$, and both are significantly positively correlated at the 1% significance level. The correlation coefficient of the latter with *CFTI* is 0.7939, $p < 0.0001$, and both are significantly positively correlated at the 1% significance level. Third, the correlation coefficient between *CGRT* and *SCPD* is 0.2190, $p < 0.0001$, and both are significantly positively correlated at the 1% significance level. The correlation coefficient of the latter with *CFTI* is 0.6727, $p < 0.0001$, and both are significantly positively correlated at the 1% significance level.

Table 3. Correlation matrix of the major variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) *CFTI*	1.0000					
(2) *rCFTI*	0.9086*** (0.0000)	1.0000				
(3) *CGRT*	0.0699 *** (0.0000)	0.0922*** (0.0000)	1.0000			
(4) *rCGRT*	0.7459*** (0.0000)	0.7328*** (0.0000)	0.0389** (0.0237)	1.0000		
(5) *MVTA*	0.7939*** (0.0000)	0.7175*** (0.0000)	0.0460*** (0.0076)	0.6819*** (0.0000)	1.0000	
(6) *SCPD*	0.6727*** (0.0000)	0.6408*** (0.0000)	0.2190*** (0.0000)	0.5109*** (0.0001)	0.6300*** (0.0000)	1.0000

4.2. Multivariate regression

In the context of controlling for year-fixed and city-fixed effects, Equation (4) is estimated using *CFTI* as the dependent variable and *CGRT* as the independent variable. We incrementally incorporate additional control variables within the fixed effects model (FE), with the results detailed in Table 4. From Table 4, the coefficients of *CGRT* are all significantly positive at the 1% significance level, and CGRT promotes CFTI. The empirical results support Hypothesis H1. Figure 2 shows the marginal effects and 95% confidence intervals of CGRT on CFTI based on the estimates in Columns (2)–(5) of Table 4. Figure 2 shows that as CGRT increases, CFTI increases.

The first subfigure above corresponds to Column (2), and the second subfigure corresponds to Column (3). The first subfigure below corresponds to Column (4), and the second subfigure corresponds to Column (5).

Table 4. FE estimated results of Equation (4)

Variables	(1) *CFTI*	(2) *CFTI*	(3) *CFTI*	(4) *CFTI*	(5) *CFTI*
CGRT	1.6635*** (0.2523)	1.8435*** (0.2549)	1.6140*** (0.2385)	1.5578*** (0.2306)	1.3631*** (0.2171)
PGDP		–0.2543*** (0.0885)	–0.2377*** (0.0900)	–0.1766* (0.0918)	–0.0260 (0.0805)
INDS		–1.2262*** (0.3070)	–1.2523*** (0.3179)	–1.2075*** (0.3284)	–1.1367*** (0.3490)
FDI		–0.6886*** (0.0923)	–0.6726*** (0.0921)	–0.6662*** (0.0913)	–0.6382*** (0.0866)
FISD			0.4464** (0.1984)	0.4131** (0.1955)	0.2813 (0.1769)
RD			0.1904*** (0.0273)	0.1893*** (0.0270)	0.1699*** (0.0268)
FSIZ				0.0911*** (0.0281)	0.0216 (0.0315)
FEFF				0.2490*** (0.0640)	0.2218*** (0.0640)
CITY					0.2714 (0.2654)
PDEN					1.2049*** (0.2496)
Constant	–0.4840*** (0.0940)	2.4950*** (0.6701)	2.7470*** (0.7111)	2.4804*** (0.7480)	1.6794* (0.9226)
City FE and Year FE	√	√	√	√	√
Obs.	3,375	3,375	3,375	3,375	3,375
R^2	0.3531	0.4016	0.4280	0.4343	0.4494
Number of cities	282	282	282	282	282

Note: Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1. The same applies below.

4.3. Robustness checks

4.3.1. Endogeneity

The Section 2 shows that CGRT significantly affects CFTI. Conversely, technological innovations such as CFTI can increase the competitiveness of firms and intensify industry competition (Dhliwayo & Chebo, 2024). Increased industry competition forces firms to increase their level of risk-taking to survive and thrive. This increases CGRT at the macro level; therefore, CFTI also affects CGRT. There is a bidirectional causal relationship between CGRT and CFTI. In addition, measuring CGRT in terms of the share of consumption and the share of digital technology entrepreneurship inevitably suffers from measurement error, which may lead to endogeneity.

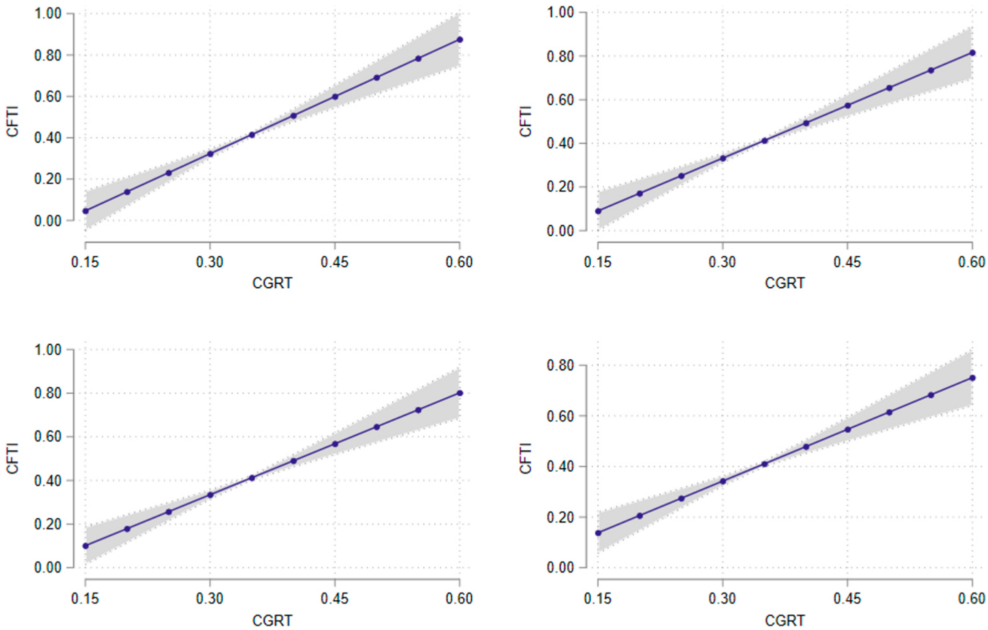

Figure 2. Marginal effects of *CGRT* on *CFTI* and 95% confidence intervals

For this reason, we first re-estimate Equation (4) by lagging the independent variables by one period, which results in Column (1) of Table 5. From Column (1), the coefficient of *L.CGRT* is significantly positive at the 1% significance level. *CGRT* in the previous period affects *CFTI* and conversely *CFTI* cannot affect *CGRT* in the previous period. Thus, Hypothesis H1 still holds while avoiding bidirectional causality. In addition, we also deal with endogeneity based on the instrumental variables approach. Based on the findings of Faccio et al. (2011), Chen et al. (2022, 2023a), Laeven and Levine (2007, 2009), this study calculates the average *CGRT* from other cities for the same year to derive *ivCGRT*, which serves as an instrumental variable. It is important to note that both the average *CGRT* from other cities and the *CGRT* of the focal city are influenced by measurement errors. Consequently, *ivCGRT* exhibits a correlation with *CGRT*, thereby fulfilling the "correlation" requirement for a valid instrumental variable. Conversely, it is less probable that the *CGRT* from other cities will impact the *CFTI* of the focal city, which allows *ivCGRT* to meet the "exogeneity" condition. Utilizing *ivCGRT* as the instrumental variable, this study employs the instrumental variable (IV) method to re-estimate Equation (4). The results from the first stage of the estimation indicate that *ivCGRT* has a significantly negative relationship at the 1% significance level with *CGRT*, confirming their notable negative correlation. Furthermore, the Cragg-Donald F statistic for testing weak instruments is register blue at 28,000, which substantially surpasses the critical threshold of 16.38 associated with a 10% bias. This finding leads to the rejection of the weak instrument hypothesis, thereby confirming *ivCGRT* as a valid instrumental variable.

By utilizing *CFTI* as the dependent variable and *ivCGRT* as the instrumental variable, we conducted a re-estimation of Equation (4) employing the instrumental variable (IV) method.

The resulting findings are presented in Column (2) of Table 5. Notably, Column (2) indicates that the coefficient of CGRT is significantly positive, achieving a significance level of 1%. This reinforces the conclusion that CGRT exerts a driving influence on CFTI, thereby confirming the robustness of Hypothesis H1 in the context of endogeneity exclusions.

Table 5. Estimated results of the robustness checks

Variables	(1) *CFTI*	(2) *CFTI*	(3) *rCFTI*	(4) *CFTI*	(5) *CFTI*	(6) *CFTI*	(7) *CFTI*
L.CGRT	1.7079*** (0.2775)						
CGRT		1.1502*** (0.2579)	3.7201*** (0.6926)		0.4446*** (0.1474)	1.3631*** (0.1757)	1.3045*** (0.2151)
rCGRT				0.2283*** (0.0142)			
MVTA					0.2625*** (0.0145)		
SCPD					0.0555*** (0.0095)		
City FE, year FE, and control	√	√	√	√	√	√	√
obs.	3,039	3,375	3,375	3,375	3,375	3,375	3,321
R^2	0.4493	0.4491	0.3953	0.6100	0.6666	–	278
Number of cities	282	282	282	282	282	282	0.4448

Note: No R-squared under maximum likelihood estimation (MLE).

4.3.2. Changing the measure of CFTI

We replace the dependent variable with *rCFTI* and re-estimate Equation (4) via FE with *CGRT* as the independent variable; the results are in Column (3) of Table 5. Column (3) indicates that even after the alteration of the *CFTI* measure, CGRT continues to exert influence over CFTI. This reinforces the robustness of the conclusion supporting Hypothesis H1.

4.3.3. Changing the measure of CGRT

Replacing the independent variable with *rCGRT* and using *CFTI* as the dependent variable, Equation (4) is re-estimated via FE, and the results are in Column (4) of Table 5. Column (4) indicates that even after the modification of the *CGRT* measure, the CGRT continues to exert influence on CFTI, thereby reinforcing the conclusion that Hypothesis H1 remains valid.

4.3.4. Controlling for mediating variables

The theoretical analysis shows that market vitality and governmental technology investment favour CFTI. We test the mechanism as a mediating variable and do not include it as a control variable. Here, we control for market vitality and government technology investment and re-estimate Equation (4) via FE, the results of which are in Column (5) of Table 5. Column (5) indicates that even after adjusting for the mediating variables, the CGRT continues to significantly influence the CFTI. This reinforces the conclusion that Hypothesis H1 remains valid and robust.

4.3.5. Changing the estimation method

To address the bias associated with the estimation method, we re-estimate Equation (4) using the maximum likelihood estimation (MLE) approach. The results of this analysis are presented in Column (6) of Table 5. As indicated in Column (6), our conclusion that Hypothesis H1 is supported remains robust.

4.4.6. Elimination of municipalities

China's municipalities, which consist of Beijing, Shanghai, Tianjin, and Chongqing, are classified as provincial administrative units. In contrast, other cities in the country hold a relatively lower rank and possess diminished administrative authority compablue to these four municipalities. Consequently, we exclude these four municipalities from our analysis and re-estimate Equation (4) using a FE approach. The results are presented in Column (7) of Table 5. As indicated in Column (7), it is evident that CGRT has the potential to induce CFTI, thereby reinforcing the robustness of our conclusion that H1 is upheld.

5. Mechanism tests

Here, we conduct mechanism tests via Equations (5) and (6).

5.1. Market vitality

Utilizing *MVTA* as the mediating variable and *CGRT* as the independent variable, we implement a fixed effects (FE) method to estimate Equation (5), with the results illustrated in Column (1) of Table 6, Panel A. Following this, we replace the independent variable with *rCGRT* and again apply the FE to estimate Equation (5), the details of which are presented in Column (2) of Table 6, Panel A. Additionally, we utilize *ivCGRT* as an instrumental variable to estimate Equation (5) through an instrumental variable (IV) method, with the results shown in Column (3) of Table 6, Panel A. Lastly, we evaluate Equation (5) using the maximum likelihood estimation (MLE), treating *CGRT* as the independent variable, with the relevant findings displayed in Column (4) of Table 6, Panel A. The results presented in Panel A suggest that CGRT has a positive influence on the market dynamics within the city context.

In our analysis, we employed *MVTA* as the mediating variable, *CFTI* as the dependent variable, and *CGRT* as the independent variable. The results of estimating Equation (6) using fixed effects (FE) approach are presented in Column (1) of Table 6, Panel B. We then substituted the dependent variable with *rCFTI* and re-estimated Equation (6), as illustrated in Column (2) of Table 6, Panel B. Additionally, we replaced the independent variable with *rCGRT* and estimated Equation (6) again using the FE method; the results are displayed in Column (3) of Table 6, Panel B. To further our investigation, we calculated the average digital economy development index (refer to Appendix A) for other cities in the same year, and utilizing *ivMVTA* alongside *ivCGRT* as instrumental variables, we re-estimated Equation (6) through the instrumental variable (IV) method, with results shown in Column (4) of Table 6, Panel B. The findings in Panel B indicate that market vitality exerts a positive influence on CFTI. When we integrate observations from Panels A and B, it becomes evident that CGRT enhances city market vitality, which subsequently contributes to the promotion of CFTI. Consequently, Hypothesis H2 is validated and remains robust. Figure 3 illustrates the marginal effects along with the 95% confidence intervals for *CGRT*'s impact on *MVTA*, as well as *MVTA*'s influence on *CFTI*, all derived from the estimates presented in Table 6. The portrayal in Figure 3 demonstrates that an increase in *CGRT* corresponds with a rise in *MVTA*, which in turn leads to an increase in *CFTI*.

The four subfigures above correspond to Columns (1)–(4) of Panel A from left to right, and the four subfigures below correspond to Columns (1)–(4) of Panel B from left to right.

5.2. Government technology investment

Utilizing *SCPD* as the mediating variable, and in accordance with the details outlined in Section 5.1, we have re-estimated Equations (5) and (6). The outcomes of this analysis are presented in Table 7. Panel A shows that CGRT improves governmental technology input in cities. In Panel B, governmental technology investment in cities favours CFTI. Therefore, Hypothesis H3 is valid and robust. Figure 4 shows the marginal effects and 95% confidence intervals of *CGRT* on *SCPD* and the marginal effects and 95% confidence intervals of *SCPD* on *CFTI* based on the estimates in Table 7. Figure 4 shows that as *CGRT* increases, *SCPD* increases, and thus, *CFTI* increases.

Table 6. Estimated results of the market vitality mechanism

Panel A				
Variables	(1) *MVTA*	(2) *MVTA*	(3) *MVTA*	(4) *MVTA*
CGRT	3.0999*** (0.5646)		2.6354*** (0.6190)	3.0999*** (0.4168)
rCGRT		0.6041*** (0.0356)		
City FE, year FE, and control	√	√	√	√
Obs.	3,375	3,375	3,375	3,375
R^2	0.5069	0.6988	0.5067	-
Number of cities	282	282	282	282
Panel B				
Variables	(1) *CFTI*	(2) *rCFTI*	(3) *CFTI*	(4) *CFTI*
CGRT	0.5830*** (0.1526)	1.3422*** (0.4743)		0.6452** (0.2957)
rCGRT			0.1110*** (0.0135)	
MVTA	0.2712*** (0.0143)	0.8267*** (0.0449)	0.2014*** (0.0139)	0.2052*** (0.0749)
City FE, year FE, and control	√	√	√	√
Obs.	3,375	3,375	3,375	3,375
R^2	0.6596	0.5961	0.6827	0.6470
Number of cities	282	282	282	282

Note: Instrumental variables are tested for validity.

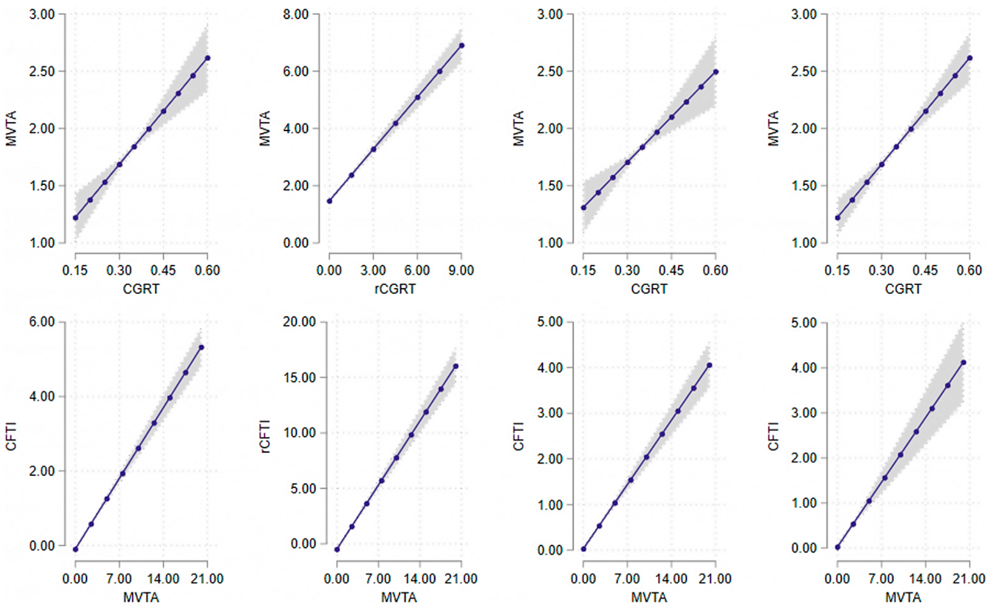

Figure 3. The marginal effect of *CGRT* on *MVTA* and its 95% confidence interval, and the marginal effect of *MVTA* on *CFTI* and its 95% confidence interval

Table 7. Estimated results of the government technology investment mechanism

Panel A				
Variables	(1) *SCPD*	(2) *SCPD*	(3) *SCPD*	(4) *SCPD*
CGRT	3.3682*** (0.4211)		3.1844*** (0.4368)	3.3682*** (0.3540)
rCGRT		0.1777*** (0.0223)		
City FE, year FE, and control	√	√	√	√
Observations	3,375	3,375	3,375	3,375
R-squared	0.1640	0.1831	0.1639	–
N	282	282	282	282
Panel B				
Variables	(1) *CFTI*	(2) *rCFTI*	(3) *CFTI*	(4) *CFTI*
CGRT	1.0512*** (0.2027)	2.6753*** (0.6460)		0.8067*** (0.2476)
rCGRT			0.2179*** (0.0144)	
SCPD	0.1058*** (0.0128)	0.3545*** (0.0410)	0.0642*** (0.0105)	0.1251*** (0.0178)
City FE, year FE, and control	√	√	√	√
Obs.	3,375	3,375	3,375	3,375
R^2	0.4755	0.4255	0.6194	0.4745
Number of cities	282	282	282	282

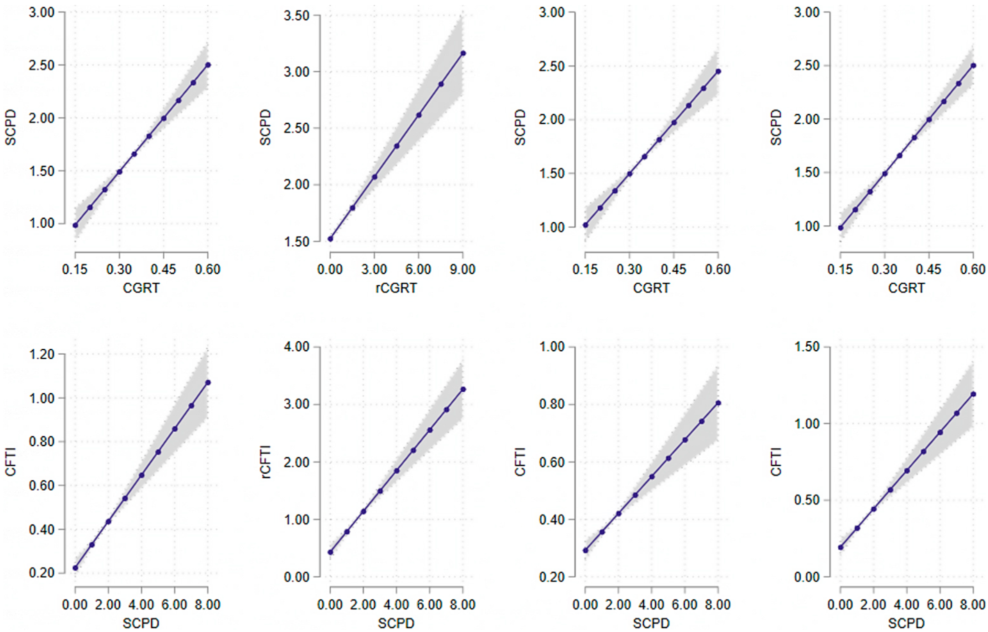

Figure 4. The marginal effect of *CGRT* on *SCPD* and its 95% confidence interval, and the marginal effect of *SCPD* on *CFTI* and its 95% confidence interval

The four subfigures above correspond to Columns (1)–(4) of Panel A from left to right, and the four subfigures below correspond to Columns (1)–(4) of Panel B from left to right.

6. Heterogeneity analysis

6.1. Heterogeneity of enthusiasm for financial technology innovation

The greatest challenge for firms in implementing CFTI is the availability of financing, but venture capital financing for climate-friendly technologies has been declining (Nguyen et al., 2024). In developing countries such as China, the financial sector tends to be particularly hesitant about CFTI projects because of a lack of capacity to assess financial viability and an over-reliance on balance sheets as a measure of a project's creditworthiness (Fischer et al., 2012). On the other hand, since the global financial crisis in 2008, the deep integration of digital technologies such as AI and big data with finance has produced financial technology (Chen et al., 2022). On the basis of technologies such as big data, financial technology reduces the information asymmetry between banks and firms. Instead of relying solely on the balance sheet as a measure of a project's creditworthiness, banks can make a more comprehensive judgement of a project's creditworthiness with the help of technologies such as big data. This means that financial technology can improve the supply of financial resources needed for CFTI. Encouraged by the central bank, cities in China are vigorously developing financial technology, and cities are enthusiastic about financial technology innovation. However, China is a vast country with unbalanced development. The enthusiasm for financial technology innovation is not the same across cities, given the positive effect of financial technology on CFTI. We speculate that the role of CGRT in promoting CFTI will be greater in cities with higher enthusiasm for financial technology innovation.

To test this speculation, we refer to Li et al. (2020), construct 40 keywords (see Appendix B), and count the word frequencies from Baidu to measure the financial technology innovation enthusiasm in each city. Then, drawing on Florackis and Sainani's (2018) practice of dividing types by the annual median, we classify cities with fintech innovation enthusiasm above the median in each year as high-enthusiasm cities and vice versa as low-enthusiasm cities. Then, using *CFTI* as the dependent variable and *CGRT* as the independent variable, the variable coefficient individual fixed effect model is used to estimate Equation (4), and the results are shown in Column (1) of Table 8; replacing the dependent variable with *rCFTI*, the variable coefficient individual fixed effect model is used to estimate Equation (4), and the results are shown in Column (2) of Table 8. Replacing the independent variable with *rCGRT* and re-estimating Equation (4) following the previous sequence results in Columns (3) and (4) of Table 8.

First, the coefficients of *CGRT* are significantly positive at the 1% significance level for both high and low enthusiasm cities, and CGRT promotes CFTI. Second, the coefficients of *CGRT* are larger in high enthusiasm cities, and the role of CGRT in promoting CFTI is larger in high enthusiasm cities.

Table 8. Heterogeneity of enthusiasm for financial technology innovation

Variables	(1) *CFTI*	(2) *rCFTI*	(3) *CFTI*	(4) *rCFTI*
CGRT (low)	1.1546*** (0.2142)	2.8360*** (0.6947)		
CGRT (high)	1.5792*** (0.2585)	4.6144*** (0.8226)		
rCGRT (low)			0.2097*** (0.0251)	0.5419*** (0.0775)
rCGRT (high)			0.2264*** (0.0141)	0.7413*** (0.0443)
City FE, year FE, and control	√	√	√	√
Obs.	3,375	3,375	3,375	3,375
R^2	0.4563	0.4022	0.6131	0.5799
Number of cities	282	282	282	282

6.2. Population density heterogeneity

In the process of CFTI implementation, members of society learn to imitate each other, and good behavioural norms are constantly repeated and reinforced (Wei et al., 2021), which is ultimately conducive to the development of climate-friendly behaviours in individuals. From a psychological perspective, herding can play an important role in CFTI. A follower is a relatively common psychological phenomenon (Zhang et al., 2019; Zhang & Feng, 2014) that involves individuals aligning themselves with collective opinions under the influence of a group (Zhang

& Feng, 2014). Information crowding is a common type of crowding. To understand social information, individuals use others as sources of information, resulting in information herding (Deutsch & Gerard, 1955), to actively accept information from the group and engage in correct behaviour (Zhang & Feng, 2014). Overall, most of the decisions that individuals make daily are the result of combining multiple pieces of information and weighing them. Therefore, information herding is quite common. Existing studies have shown that an individual's herding behaviour is closely related to their size in the group and that individuals' herding behaviour increases as the size of the group increases (Asch, 1955; Xu & Li, 2015). Individuals in urban areas may be influenced by the herd mentality to implement CFTI, and their CFTI behaviour increases with the group size. Thus, we conjecture that CGRT facilitates CFTI more in densely populated cities with larger group sizes.

To empirically evaluate this conjecture, we utilize the typology established by Floracking and Sainani (2018), which is defined by the annual median population densities. We categorize cities exhibiting population densities exceeding the median for each year as high-density cities, while those falling below it are classified as low-density cities. Subsequently, we employ *CFTI* as the dependent variable and *CGRT* as the independent variable to estimate Equation (4) using a variable coefficient individual fixed effects model. The outcomes of this analysis are presented in Column (1) of Table 9. In a subsequent analysis, we substitute the dependent variable with *rCFTI* and apply the same variable coefficient individual fixed effects model to estimate Equation (4); the results of this estimation are displayed in Column (2) of Table 9. Lastly, we replace the independent variable with *rCGRT* and re-estimate Equation (4), adhering to the previously outlined sequence, with the corresponding results provided in Columns (3) and (4) of Table 9.

First, the coefficient of *CGRT* is significantly positive at the 1% significance level in both high- and low-density cities, and CGRT promotes CFTI. Second, the coefficient of *CGRT* is greater in high-density cities, and the role of CGRT in promoting CFTI is greater in high-density cities.

Table 9. Population density heterogeneity

Variables	(1) *CFTI*	(2) *rCFTI*	(3) *CFTI*	(4) *rCFTI*
CGRT (low)	1.2819*** (0.2307)	3.6145*** (0.7357)		
CGRT (high)	1.4618*** (0.3987)	3.9096*** (1.2554)		
rCGRT (low)			0.1615*** (0.0159)	0.4136*** (0.0480)
rCGRT (high)			0.2307*** (0.0144)	0.7606*** (0.0451)
City FE, year FE, and control	√	√	√	√
Obs.	3,375	3,375	3,375	3,375
R^2	0.4497	0.3961	0.6127	0.5836
Number of cities	282	282	282	282

6.3. Heterogeneity of environmental penalties

The Environmental Protection Law of the People's Republic of China (EPL) (National People's Congress of the People's Republic of China, 2014) stipulates the environmental protection obligations of firms, while city governments can impose administrative penalties (i.e., environmental penalties) for violations of the law, which is an important policy tool for addressing climate change. Firms constitute the main body of climate-friendly technology innovation (Nguyen et al., 2024), and government behaviour profoundly affects climate-friendly innovation (Carattini et al., 2020; Nguyen et al., 2024). As an important government action, environmental penalties, through the "information disclosure" system, can send signals to the market and exert regulatory pressure on firms (Yu et al., 2023), which can reduce the violations of penalised firms and promote the implementation of green technology innovations such as climate-friendly innovations by penalised firms and their counterparts (Nguyen et al., 2024; Barrett et al., 2018; Chen & Zhan, 2022). The stronger the environmental penalties of the city government are and the more frequent the penalties are, the more regulatory pressure the firms feel and the higher the level of climate-friendly technology innovation within the city. China is a vast country with unbalanced development, and cities have different cultural perceptions, social inclusiveness, and philosophies about penalising violations of the law. This means that the strength of the environmental penalties is not uniform across cities. Therefore, environmental penalties have a positive effect on CFTI. We hypothesise that the role of CGRT in promoting CFTI will be greater in cities with strong environmental penalties.

To achieve this, we calculate the extent of environmental penalties by dividing the number of penalties incurblue by firms within each city by the total population of that city. Subsequently, we utilize the typology established by Florackis and Sainani (2018), which is informed by the median number of years of received penalties, to categorize cities. Specifically, we classify those cities with environmental penalties exceeding the median threshold as having substantial environmental penalties, while those below the median are classified as having minor environmental penalties.

By treating *CFTI* as the dependent variable and *CGRT* as the independent variable, we proceed to estimate Equation (4) using a variable coefficient individual fixed effects model. The resulting data is presented in Column (1) of Table 10. In a subsequent estimation, we substitute the dependent variable with *rCFTI* and repeat the estimation of Equation (4) through the same variable coefficient individual fixed effects model, with the findings summarized in Column (2) of Table 10. Further, we replace the independent variable with *rCGRT*, re-estimating Equation (4) in accordance with our earlier methodology, with results displayed in Columns (3) and (4) of Table 10.

Analyzing the estimation outcomes, we observe that the coefficient for *CGRT* exhibits a significantly positive correlation at the 1% significance level for both cities with large and small environmental penalties, indicating that CGRT serves to enhance CFTI. Additionally, it is noteworthy that the coefficient of *CGRT* is more pronounced in cities characterized by significant environmental penalties, thereby suggesting that the influence of *CGRT* on promoting *CFTI* is indeed more substantial in those cities.

Table 10. Environmental penalty heterogeneity

Variables	(1) *CFTI*	(2) *rCFTI*	(3) *CFTI*	(4) *rCFTI*
CGRT (Small)	1.2852*** (0.2156)	3.5611*** (0.6904)		
CGRT (Big)	1.4467*** (0.2186)	3.8907*** (0.6978)		
rCGRT (Small)			0.1497*** (0.0165)	0.5066*** (0.0653)
rCGRT (Big)			0.2347*** (0.0141)	0.7689*** (0.0442)
City FE, year FE, and control	√	√	√	√
Obs.	3,373	3,373	3,373	3,373
R^2	0.4527	0.3969	0.6184	0.5847
Number of cities	282	282	282	282

7. Discussion

Our study, which is based on the TPB, reveals that CGRT promotes CFTI. Chen et al. (2023a), in their study on the effect of the male-to-female demographic ratio on financial technology innovation, concluded that an imbalance between men and women improves CGRT and thus promotes financial technology innovation. Our study reveals that CGRT promotes CFTI. Although financial technology innovation is not the same as CFTI, both are accompanied by many risks. Therefore, at the macro level, our study is consistent with that of Chen et al. (2023a). CGRT is closely related to the risk-taking of micro-individuals such as firms (Chen et al., 2023a). This implies that the higher the CGRT is, the greater the level of firm risk-taking. Firm risk-taking reflects the risk preferences of firms when making investment decisions, and firms with higher levels of risk-taking tend to choose risky investment projects (Acharya et al., 2011; Faccio et al., 2011; Lumpkin & Dess, 1996). CFTI is a risky investment project, and the higher the CGRT is, the greater the likelihood that firms within the city will choose CFTI as a risky investment program. Thus, at the micro level, our study is consistent with the findings of Acharya et al. (2011), Faccio et al. (2011), Lumpkin and Dess (1996).

Our study finds that CGRT improves governmental technology investment, and the latter facilitates CFTI. Alleviating financing constraints is an important reason why governmental technology investment promotes CFTI. This also corroborates the finding of Fischer et al. (2012) that the financial sector tends to be particularly hesitant about CFTI projects in developing countries because of a lack of capacity to assess financial viability and an overreliance on the balance sheet as a measure of creditworthiness. Our study concludes that CGRT enhances the market vitality of a city, and the latter enhances CFTI. Market vitality gives life to people (Montgomery, 1988) and can reflect a city's ability and potential for economic development (Zhong, 2020). The greater the market vitality of a city is, the greater its capacity and potential for economic development, and the more vigorous the market as a whole. In this way, the more optimistic enterprises are about prospects, the more they dare to implement innovations. In this sense, our findings are consistent with Montgomery (1988) and Zhong (2020).

8. Conclusions, implications and outlook

8.1. Conclusions

Our study conducted a qualitative analysis on the basis of the TPB. It was then empirically tested on data from Chinese cities from 2008 to 2020, using city and year two-way fixed-effects models, to investigate the effect of CGRT on CFTI. We found that, first, CGRT facilitates the improvement of individual attitudes towards CFTI behaviours, enhances subjective norms about the behaviours, and strengthens perceived behavioural control over the behaviours, thereby increasing individual willingness towards CFTI behaviour and thus increasing the level of CFTI in the city. Second, CGRT promotes the investment, financing and business activities of firms and the consumption behaviour of consumers, thereby increasing the market vitality of cities and promoting CFTI. CGRT increases risk-taking by city government officials and firms, which promotes governmental technology investment in cities, which, in turn, improves CFTI. Third, CGRT promotes CFTI in a heterogeneous manner, in which financial technology innovation cities with high enthusiasm, large population sizes and high environmental penalties play a greater role.

8.2. Implications

Our findings have the following theoretical and practical implications. First, our findings provide new ideas for China to realise low-carbon development. CFTI can effectively reduce carbon emissions and promote the realisation of low-carbon development. China is the world's largest developing country, and its low-carbon development is highly important for coping with global climate change. Our study reveals that increasing CGRT can increase China's CFTI, which in turn can promote the decarbonisation of China's economy. This provides a new way of thinking beyond economics and law for China to achieve low-carbon development and reach peak carbon and carbon neutrality goals. Second, our findings have implications for the realisation of low-carbon development in developing countries. As the world accelerates the promotion of low-carbon development, developing countries must take a low-carbon development path while accelerating their economic development. With respect to economic and financial instruments, realising low-carbon development is the conventional means, but these methods always face various constraints for the majority of developing countries. Our study provides a new entry point for the vast number of developing countries to promote CFTI and realise low-carbon development from the CGRT perspective. Finally, our findings are also of reference significance to developed countries in realising low-carbon development: CGRT is closely linked to the level of economic development, and developed countries, with more sound social security mechanisms and legal systems and more secure livelihoods, have more room to improve their CGRT. Increasing CGRT is conducive to CFTI, which in turn is conducive to low-carbon development. Therefore, developed countries can also utilise their own advantages to improve CGRT, promote CFTI, and have a spillover effect on the vast number of developing countries, which ultimately improves the ability of all of mankind to cope with climate change.

8.3. Outlook

Our paper has studied the impact of CGRT on CFTI. The following aspects are also worth studying in depth.

First, we address the impact of CGRT on digital technology and its underlying mechanism. Digital technology has strong low-carbon characteristics and is another important technology for realising low-carbon development. Does CGRT affect digital technologies? If so, what are the underlying mechanisms? We have not researched these issues, which is a deficiency of this paper and a direction for future research.

The second is the country-specific heterogeneity of the impact of CGRT on CFTI. We use Chinese city data to study the impact of CGRT on CFTI. Different countries have different economic, financial and legal systems, and there may be country-specific heterogeneity in the impact of CGRT on CFTI. This is one of the future research directions.

Third, the time span can be sustainably updated. Since 2021, city greening has undergone significant changes due to global environmentalism and China's domestic dual-carbon policy. This could also affect climate-friendly technological innovations. Nevertheless, due to the absence of statistical data, our sample does not encompass the years 2021 to 2023. This limitation represents a significant drawback of the present study and highlights an avenue for future research endeavors.

References

Acharya, V. V., Amihud, Y., & Litov, L. (2011). Creditor rights and corporate risk-taking. *Journal of Financial Economics*, *102*(1), 150–166. https://doi.org/10.1016/j.jfineco.2011.04.001

Aidis, R., Estrin, S., & Mickiewicz, T. (2008). Institutions and entrepreneurship development in Russia: A comparative perspective. *Journal of Business Venturing*, *23*(6), 656–672. https://doi.org/10.1016/j.jbusvent.2008.01.005

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314–324. https://doi.org/10.1002/hbe2.195

Al-Hamshary, F. S. A. A., Ariff, A. M., Kamarudin, K. A., & Abd Majid, N. (2023). Corporate risk-taking and cash holdings: The moderating effect of investor protection. *Capital Markets Review*, *31*(1), 1–23.

Ali, M., Alam, N., Khattak, M. A., & Azmi, W. (2022). Bank risk-taking and legal origin: What do we know about dual banking economies. *Journal of Risk and Financial Management*, *15*(5), Article 224. https://doi.org/10.3390/jrfm15050224

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173. https://doi.org/10.2307/2295952

Asch, S. E. (1955). Opinions and social pressure. *Scientific American*, *193*(5), 31–35. https://doi.org/10.1038/scientificamerican1155-31

Astebro, T., Herz, H., Nanda, R., & Weber, R. A. (2014). Seeking the roots of entrepreneurship: Insights from behavioral economics. *Journal of Economic Perspectives*, *28*(3), 49–70. https://doi.org/10.1257/jep.28.3.49

Ayres, R. U., & Williams, E. (2004). The digital economy: Where do we stand?. *Technological Forecasting and Social Change*, *71*(4), 315–339. https://doi.org/10.1016/j.techfore.2003.11.001

Bäckman, S. B., Brown, M., Fisman, R., Heimer, R., Keloharju, M., & Pursiainen, V. (2020). Risk taking during a global crisis: Evidence from Wuhan. *Covid Economics*, *5*, 106–146.

Bai, J. H., & Dai, W. (2017). The effects of fiscal decentralization on local government's science and technology investment. *Statistical Research*, *34*(3), 97–106.

Barrett, K. L., Lynch, M. J., Long, M. A., & Stretesky, P. B. (2018). Monetary penalties and noncompliance with environmental laws: A mediation analysis. *American Journal of Criminal Justice*, *43*, 530–550. https://doi.org/10.1007/s12103-017-9428-0

Bhuiyan, M. B. U., Liu, J., & Alam, A. (2024). Problem directors and corporate risk-taking. *British Journal of Management*, *35*(3), 1530–1558. https://doi.org/10.1111/1467-8551.12770

Bian, Y. C., & Bai, J. H. (2017). Officials' tenure and Chinese local government's S&T investment – An empirical Evidence from provincial samples. *R&D Management*, *29*(5), 147–158.

Cao, Y. P. (2020). Internet popularization, knowledge spillover and spatial economic agglomeration – Theoretical mechanism and empirical test. *Journal of Shanxi University of Finance and Economics*, *42*(10), 27–41.

Carattini, S., Levin, S., & Tavoni, A. (2019). Cooperation in the climate commons. *Review of Environmental Economics and Policy*, *13*(2), 227–247. https://doi.org/10.1093/reep/rez009

Carattini, S., Gosnell, G., & Tavoni, A. (2020). How developed countries can learn from developing countries to tackle climate change. *World Development*, *127*, Article 104829. https://doi.org/10.1016/j.worlddev.2019.104829

Chen, X., Teng, L., & Chen, W. (2022). How does FinTech affect the development of the digital economy? Evidence from China. *The North American Journal of Economics and Finance*, *61*, Article 101697. https://doi.org/10.1016/j.najef.2022.101697

Chen, X., & Zhan, M. (2022). Does environmental administrative penalty promote the quantity and quality of green technology innovation in China? Analysis based on the peer effect. *Frontiers in Environmental Science*, *10*, Article 1070614. https://doi.org/10.3389/fenvs.2022.1070614

Chen, X. (2023). Information moderation principle on the regulatory sandbox. *Economic Change and Restructuring*, *56*(1), 111–128. https://doi.org/10.1007/s10644-022-09415-2

Chen, X., Chen, W., & Lu, K. (2023a). Does an imbalance in the population gender ratio affect FinTech innovation?. *Technological Forecasting and Social Change*, *188*, Article 122164. https://doi.org/10.1016/j.techfore.2022.122164

Chen, X., Zhang, H., & Cheng, X. (2023b). Taoism and digital inclusive finance. *Heliyon*, *9*(4), Article e14965. https://doi.org/10.1016/j.heliyon.2023.e14965

Deutsch, M., & Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology*, *51*(3), 629–636. https://doi.org/10.1037/h0046408

Dhliwayo, S., & Chebo, A. K. (2024). A framework for sustainable technological innovation capability: A research and policy direction. *European Journal of Innovation Management*, *27*(3), 851–871. https://doi.org/10.1108/EJIM-02-2022-0085

Ding, C. M., Wang, C., & Chen, H. (2023). Optimizing urban business environment to promote balanced development of north-south economy-the evolution of restrictive economic order to open economic order. *The Journal of Quantitative & Technical Economics*, 1–20.

Djankov, S., Qian, Y., Roland, G., & Zhuravskaya, E. (2006). Who are China's entrepreneurs?. *American Economic Review*, *96*(2), 348–352. https://doi.org/10.1257/000282806777212387

D'souza, C., & Williams, D. (2017). The digital economy. *Bank of Canada Review*, *2017*, 5–18.

Estrin, S., Korosteleva, J., & Mickiewicz, T. (2013). Which institutions encourage entrepreneurial growth aspirations? *Journal of Business Venturing*, *28*(4), 564–580. https://doi.org/10.1016/j.jbusvent.2012.05.001

Faccio, M., Marchica, M.-T., & Mura, R. (2011). Large shareholder diversification and corporate risk-taking. *The Review of Financial Studies*, *24*(11), 3601–3641. https://doi.org/10.1093/rfs/hhr065

Fischer, C., Torvanger, A., Shrivastava, M. K., Sterner, T., & Stigson, P. (2012). How should support for climate-friendly technologies be designed?. *Ambio*, *41*, 33–45. https://doi.org/10.1007/s13280-011-0239-0

Florackis, C., & Sainani, S. (2018). How do chief financial officers influence corporate cash policies? *Journal of Corporate Finance*, *52*, 168–191. https://doi.org/10.1016/j.jcorpfin.2018.08.001

Golombek, R., & Hoel, M. (2011). International cooperation on climate-friendly technologies. *Environmental and Resource Economics*, *49*, 473–490. https://doi.org/10.1007/s10640-010-9442-x

Gompers, P., Lerner, J., & Scharfstein, D. (2005). Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999. *The Journal of Finance*, *60*(2), 577–614. https://doi.org/10.1111/j.1540-6261.2005.00740.x

Hagger, M. S., Cheung, M. W.-L., Ajzen, I., & Hamilton, K. (2022). Perceived behavioral control moderating effects in the theory of planned behavior: A meta-analysis. *Health Psychology*, *41*(2), 155–167. https://doi.org/10.1037/hea0001153

Halleck-Vega, S., Mandel, A., & Millock, K. (2018). Accelerating diffusion of climate-friendly technologies: A network perspective. *Ecological Economics*, *152*, 235–245. https://doi.org/10.1016/j.ecolecon.2018.05.007

Howell, S. T. (2017). Financing innovation: Evidence from R&D grants. *American Economic Review*, *107*(4), 1136–1164. https://doi.org/10.1257/aer.20150808

Hubar, S., Koulovatianos, C., & Li, J. (2020). The role of labor-income risk in household risk-taking. *European Economic Review*, *129*, Article 103522. https://doi.org/10.1016/j.euroecorev.2020.103522

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics*, *85*(2), 331–367. https://doi.org/10.1016/j.jfineco.2005.06.001

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, *93*(2), 259–275. https://doi.org/10.1016/j.jfineco.2008.09.003

Li, H., & Zhang, Y. (2007). The role of managers' political networking and functional experience in new venture performance: Evidence from China's transition economy. *Strategic Management Journal*, *28*(8), 791–804. https://doi.org/10.1002/smj.605

Li, C. T., Yan, X. W., Song, M., & Yang, W. (2020). Fintech and corporate innovation – Evidence from Chinese NEEQ-listed companies. *China Industrial Economics*, (1), 81–98.

Li, X. Y., Wang, F. Q., Yang, B. X., & Zhang, Y. (2022). Human capital, government investment in science and technology and regional innovation. *China Soft Science*, (11), 181–192.

Li, Z., & Yang, S. Y. (2018). Fiscal decentralization, government innovation preferences and regional innovation efficiency. *Management World*, *34*(12), 29–42+110+193–194.

Liu, G. C., Duan, Y. Z., & Liu, Y. Y. (2019). Economic policy uncertainty, asset reversibility, and real investment: Evidence from China. *Economic Research Journal*, *54*(8), 53–70.

Lu, J. J., Yang, S. Y., & Ma, C. (2021). Fiscal decentralization, financial decentralization and technological innovation. *South China Journal of Economics*, (6), 36–50.

Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review*, *21*(1), 135–172. https://doi.org/10.2307/258632

Ma, S., Guo, J., & Zhang, H. (2019). Policy analysis and development evaluation of digital trade: An international comparison. *China* & *World Economy*, *27*(3), 49–75. https://doi.org/10.1111/cwe.12280

Montgomery, J. (1998). Making a city: Urbanity, vitality and urban design. *Journal of Urban Design*, *3*(1), 93–116. https://doi.org/10.1080/13574809808724418

National Bureau of Statistics. (2021). *China statistical yearbook*. China Statistics Press. https://www.stats.gov.cn/sj/ndsj/2021/indexch.htm

National People's Congress of the People's Republic of China. (2014). *Environmental Protection Law of the People's Republic of China*. https://www.mee.gov.cn/ywgz/fgbz/fl/201404/t20140425_271040.shtml

Nguyen, Q. L., Nguyen, M. H., La, V. P., Bhatti, M. I., & Hoang, V. Q. (2024). Enterprise's strategies to improve financial capital under a climate change scenario – Evidence of the leading country. *Npj Climate Action*, *3*(1), Article 38. https://doi.org/10.1038/s44168-024-00121-5

Otte, P. P. (2021). What makes people act climate-friendly? A decision-making path model for designing effective climate change policies. *Current Opinion in Environmental Sustainability*, *52*, 132–139. https://doi.org/10.1016/j.cosust.2021.10.003

Pauley, K., O'Hare, D., & Wiggins, M. (2008). Risk tolerance and pilot involvement in hazardous events and flight into adverse weather. *Journal of Safety Research*, *39*(4), 403–411. https://doi.org/10.1016/j.jsr.2008.05.009

Rayna, T. (2008). Understanding the challenges of the digital economy: The nature of digital goods. *Communications & Strategies*, (71), 13–36.

Qin, X. L., & Yu, W. C. (2016). Impact of government technology investment on the environmental effects of FDI: An empirical study based on 257 spatial correlation cities. *Journal of Central University of Finance and Economics*, (10), 3–12.

Skaar, N. R., Christ, T. J., & Jacobucci, R. (2014). Measuring adolescent prosocial and health risk behavior in schools: Initial development of a screening measure. *School Mental Health*, *6*, 137–149. https://doi.org/10.1007/s12310-014-9123-y

Sweetman, D., Luthans, F., Avey, J. B., & Luthans, B. C. (2011). Relationship between positive psychological capital and creative performance. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration*, *28*(1), 4–13. https://doi.org/10.1002/cjas.175

Van Dyne, L., & Pierce, J. L. (2004). Psychological ownership and feelings of possession: Three field studies predicting employee attitudes and organizational citizenship behavior. *Journal of Organizational Behavior*, *25*(4), 439–459. https://doi.org/10.1002/job.249

Wang, J., Geng, J. N., & Xiao, Y. J. (2020). From intention to behavior: An integrated model of academic entrepreneurial behavior based on theory of planned behavior. *Foreign Economics & Management*, (7), 64–81.

Wei, Z. Y., Deng, X. S., & Zhao, Z. Y. (2021). The effect of conformity tendency on prosocial behaviors. *Advances in Psychological Science*, *29*(3), 531–539. https://doi.org/10.3724/SP.J.1042.2021.00531

Xu, X. Y., Kong, F. P., & Yin, C. (2015). Effect of government S&T investment on enterprises' technological innovation. *Research on Economics and Management*, *36*(7), 96–105.

Xu, Y., & Li, H. (2015). Influence of visibility range and degree of urgency on efficiency of evacuation: Mediating effect of herding behavior. *Studies of Psychology and Behavior*,*13*(3), 311–319.

Yan, H. Z., & Chen, B. Z. (2018). The financial assets of industrial listed corporations: The market effect and holding motivation. *Economic Research Journal*, *53*(7), 152–166.

Yang, X. J., & Ran, X. L. (2023). The impact of the proportion of elderly population on household savings rate in China: On the moderating effect of saving motives. *Population & Economics*, (6), 87–104.

Yu, Y. Z., Xia, L. L., & Duan, S. L. (2023). Market regulation and enterprise growth: Empirical analysis based on administrative penalties data. *China Industrial Economics*, (8), 118–136.

Yuriev, A., Dahmen, M., Paillé, P., Boiral, O., & Guillaumie, L. (2020). Pro-environmental behaviors through the lens of the theory of planned behavior: A scoping review. *Resources, Conservation and Recycling*, *155*, Article 104660. https://doi.org/10.1016/j.resconrec.2019.104660

Zahra, S. A., & Bogner, W. C. (2000). Technology strategy and software new ventures' performance: Exploring the moderating effect of the competitive environment. *Journal of Business Venturing*, *15*(2), 135–173. https://doi.org/10.1016/S0883-9026(98)00009-3

Zhang, X. X., & Feng, T. Y. (2014). The effect of decision confidence in informational conformity. *Journal of Psychological Science*, *37*(3), 689–693.

Zhang, L. W., & Wu, W. X. (2016). Risk attitudes and household wealth: A further discussion based on China micro survey. *Journal of Financial Research*, (4), 115–127.

Zhang, H., Ren, J. Y., Liu, C. Y., & Lu, J. (2019). Conformity effect of the evaluation of creative products. *Acta Psychologica Sinica*, *51*(6), 688–698. https://doi.org/10.3724/SP.J.1041.2019.00688

Zhong, Z. (2020). Factors influencing regional economic vitality based on regression analysis. *E3S Web of Conferences*, *214*, Article 02021. https://doi.org/10.1051/e3sconf/202021402021

APPENDIX

A. Calculation process of digital economy development index

Regarding the digital economy development index (*DECO*), we constructed the indicator system shown in Table A1, collected data from Shanghai Da Zhi Cai Hui Technology Co., Ltd. (https://www.qyyjt.cn), which obtains its data from the State Administration for Market Regulation of China (https://www.samr.gov.cn) and used factor analysis to calculate the city's digital economy development index. KMO and Bartlett's spherical tests are prerequisites for factor analysis. The KMO test showed that KMO = 0.788, which is greater than 0.6. The chi-squared statistic of Bartlett's test was 61937.382, with a p-value of <0.0001. The 11 data items met the prerequisite conditions for factor analysis. Based on the factor analysis method, we measured the city's digital economy development index *decoindex* for each city and then calculated the *DECO* according to (*decoindex* -Min(*decoindex*))/(Max (*decoindex*) –Min (*decoindex*)) * 10 as the proxy variable for the level of digital economy.

Table A1. City Digital Economy Development Index system

Primary Indicator	Secondary Indicator	Original Indicator	References
City Digital Economy Development Index	Digital industrialisation	Number of information and communication software and hardware enterprises	Chen et al. (2022), Ayres and Williams (2004), Ma et al. (2019)
		Number of data centres	
		Number of data element enterprises	
		Number of information and communication support enterprises	
		Number of emerging information and communication majors in colleges and universities	
		Number of colleges and universities offering new information and communication majors	
		Number of traditional information and communication majors in colleges and universities	
		Number of universities offering traditional information and communication majors	
	Industrial digitalisation	Number of digital primary industry enterprises	Chen et al. (2022); D'Souza and Williams (2017), Rayna (2008)
		Number of industrial enterprises in second place for digitalisation	
		Number of industrial enterprises in third place for digitalisation	

B. Calculation of enthusiasm for financial technology innovation

Regarding enthusiasm for financial technology innovation (*FTCH*),referring to the practices of Li et al. (2020), we constructed 48 keywords – including EB level storage, NFC payment, differential privacy technology, big data, third-party payment, multi-party security computing, distributed computing, equity crowdfunding, Internet finance, machine learning, open banking, brain-like computing, quantitative finance, stream computing, green computing, memory computing, blockchain, artificial intelligence, cognitive computing, fusion architecture, business intelligence, identity verification, deep learning, biometric technology, data visualization, data mining, digital currency, investment decision support system, graph computing, image understanding, Internet connection, text mining, Internet of Things, information physical system, virtual reality, mobile Internet, mobile payment, 100 million level concurrency, heterogeneous data, semantic search, voice recognition, cloud computing, credit reporting, intelligent financial contract, intelligent customer service, intelligent data analysis, intelligent investment advisor, and natural language processing.

We matched these keywords with the name of each city and searched for *city name* + *keywords* by year using Baidu News Advanced Search (e.g., "Tianjin + AI"). Thereafter, we summarized the number of search results for all keywords in the same city to obtain the total search volume *fintech*. Thereafter, in accordance with *fintech*/100, we obtained *FTCH*, the proxy variable for the city's financial technology innovation level.