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HOW DOES ECONOMIC POLICY UNCERTAINTY AFFECT GREEN INNOVATION?

Xin-Yu PENG[1], Xing-Yun ZOU[1*], Xin-Xin ZHAO[2], Chun-Ping CHANG[3#]

[1]School of Economics and Management, Changsha University of Science & Technology, Hunan, China
[2]School of Economics and Finance, Xi'an Jiaotong University, Shaanxi, China
[3]Department of Marketing Management, Shih Chien University, Kaohsiung, Taiwan

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Abstract. This research examines the impact of economic policy uncertainty (EPU) on green innovation by using the panel fixed effects model from 2000 to 2017 for the samples of 31 provinces in China. The general conclusion is that there exists a positive link from EPU to green innovation, and that the impact of EPU varies significantly among different provinces that have diverse levels of marketization and trade openness. Specifically, provinces with higher marketization and degrees of trade openness have witnessed stronger positive effects from EPU on green innovation, whereas the correlation is rather weak in regions with low levels of those two factors. Our findings serve as a research reference for how governments may boost green innovation in the face of increasing EPU.

Keywords: economic policy uncertainty, green innovation, marketization, openness, China.

JEL Classification: F40, G10, O30.

Introduction

Economic policy uncertainty (EPU) is commonly defined as the phenomenon in which microeconomic entities are unable to foresee whether, when, or how a government's current economic policies will change (Gulen & Ion, 2016; Su et al., 2019a, 2019b). Governments have frequently adjusted their existing economic policies to smooth out economic swings after the 2008 financial crisis, and such economic uncertainty is mostly realized as EPU[1]. Bloom (2009) points out that EPU is one important cause of an economic recession, and other scholars show that about 2/3 of the decline in U.S. corporate investment between 2007

[1] According to Baker et al. (2016), economic uncertainty includes both real economic uncertainty and economic policy uncertainty, and EPU has accounted for a significant portion of economic uncertainty since the 2008 global financial crisis.

*Corresponding author. E-mail: *xingyunzou@126.com*
#Corresponding author. E-mail: *cpchang@g2.usc.edu.tw*

to 2009 was attributed to EPU (Gulen & Ion, 2016). To lessen the negative effects of the COVID-19 outbreak in 2020, countries and regions have initiated several rounds of extraordinary economic relief policies, and such frequent government intervention increased the uncertainty of world economic policies (Sharif et al., 2020; Altig et al., 2020).

In China, the role of the government in the economy is quite obvious, and the tools of its intervention therein are diverse (Bertuad, 2012). Following the 2008 financial crisis, the old economic growth model has been difficult to continue, and with economic reforms becoming more imperative, the government of China has adopted a range of economic initiatives in order to prevent a serious recession. The introduction of such economic policies, on the one hand, can alleviate the difficulties faced by its domestic economy in the short term but, on the other hand, may increase EPU (Hu et al., 2021). Therefore, it is critical to investigate the economic consequences of EPU in China, both theoretically and practically.

Browsing the existing literature related to EPU, we find that most scholars focus on its macroeconomic effects, including economic fluctuations (Bloom, 2009; Villaverde et al., 2015), financial conditions (Li & Zhong, 2020; Phan et al., 2021), stock market (Liu & Zhang, 2015; Chiang, 2019), and oil price (You et al., 2017; Hailemariam et al., 2019). Other researchers pay attention to its effects on micro-economic activities, such as enterprise investment (Bloom et al., 2007; Wang et al., 2014), corporate cash holding (Demir & Ersan, 2017; Phan et al., 2019), and a firm's carbon emissions (Adedoyin & Zakari, 2020; Anser et al., 2021). However, up to now, there are only a few empirical studies exploring EPU's effects on innovation. Adopting state elections in the United States as an exogenous variable of EPU, Atanassov et al. (2015) suggest that EPU stimulates enterprise research and development (R&D). Based on 12,408 U.S. firms, Xu (2020) proposes that EPU hinders corporate innovation through transmission channels of traditional investment irreversibility and the cost of capital. However, the major problem of previous studies is that they use the EPU index at a national level, but the proxy variable of innovation is at a corporate level. Furthermore, previous literature concentrated on general innovation rather than green innovation, which is one of the most effective approaches to alleviate environmental degradation.

Environmental issues in parallel have increasingly become a worldwide problem, thus attracting the attention of academics to green innovation. The World Health Organization (WHO) said in 2018 that more than 90% of the global population breathes in high levels of pollutants and that about 7 million deaths a year are attributed to poor air quality. In response to this environmental crisis, global environmental awareness has risen rapidly. At a national level, several developed countries and regions are committed to maintaining and gaining national core competitive advantages through green innovation. In 2020, China committed itself to reach a peak in CO_2 emissions by 2030 and carbon neutrality by 2060. At a corporate level, environmental management has become an important part of a firm's organizational strategy. Those enterprises that can quickly change the traditional way of providing products and services and carry out green innovation and reform will have more competitive advantages (Chang, 2011; Qiu et al., 2020). In the traditional economic development model, economic development is facing problems with serious environmental pollution, tightening resource constraints, and ecosystem degradation. Green innovation thus becomes an unavoidable option for achieving "win-win" development of economic transformation and environmental protection (Li et al., 2021). In this context, the correlation between EPU and green innovation remains a mystery, and so it is both theoretically and practically essential to explore how EPU affects green innovation. Therefore, we advance several questions. Does EPU affect green innovation? Do the effects of EPU on green innovation differ significantly between different levels of marketization and trade openness regions?

We aim to clarify the theoretical mechanism for why EPU presents a significant impact on green innovation as follows. First, corporate cash holding acts as a mediating mechanism for EPU promoting green innovation. Cash holding can be seen as a hedge against uncertainty and is positively affected by EPU (Demir & Ersan, 2017). When EPU rises, corporate risks increase, enterprises' investment activities decrease (Bloom et al., 2007), firms' cash holdings rise, and such abundant cash stimulates corporate green innovation (He et al., 2020). Second, EPU affects green innovation through market competition. According to the theory of strategic growth options, EPU increases investment opportunities and thus exacerbates market competition, especially in an imperfectly competitive market (Guan et al., 2021). Under such an environment, timely preemption innovation investments will give companies the ability to capitalize on further growth opportunities and gain a competitive advantage by preventing competitors from entering or inducing them to make concessions (Kulatilaka & Perotti, 1998). Hence, increased market competition will drive corporate green innovation. Third and finally, government subsidies amplify the positive effects of EPU on green innovation. According to the theory of market failure, the externalities and spillover effects of technological innovation cause firms' innovation investment to be lower than the socially optimal level. However, direct government transfer payments or indirect tax breaks provide net cash flow to firms, reducing the capital cost of R&D operations as well as the uncertainty and risk of innovation, making it conducive to motivating enterprises to choose green innovation (Almus & Czarnitzki, 2003; Hall & Lerner, 2010).

Our research contributes to this area of study in four ways. For the first contribution, to our limited knowledge this research is the first work to explore the correlation between EPU and green innovation by using provincial panel data in China from 2000 to 2017, thus enriching EPU's research and expanding the field of study on political economics and innovation economics. We confirm that green patent applications increase with rising EPU, indicating EPU affects green innovation positively in general. The second contribution is that we utilize the latest EPU index constructed by Yu et al. (2021) for 31 provinces in China. Compared to existing research that only uses the EPU index at a national level, this provincial EPU index allows us to measure the effects of EPU at a finely-grained level. Third, we employ a panel fixed effects model to examine the correlation between EPU and green innovation, and then utilize the system generalized method of moments (GMM) and a bias-corrected least squares dummy variable estimation (LSDVC) to deal with potential endogenous problems and obtain an unbiased estimate. The resulting estimates of EPU's effects on green innovation are similar to the primary findings. Finally, we look at whether EPU's influence on green innovation varies significantly among provinces with different levels of marketization and trade openness. We offer evidence that EPU has a greater positive impact on green innovation in provinces with higher marketization and trade openness, while such correlation is not significant in regions with low levels.

The remainder of this work is structured as follows. Section 1 presents a literature review on EPU and green innovation. Section 2 describes the variable definitions and empirical methods. Section 3 reports the regression results as well as the robustness tests. Final section proposes the conclusions and policy implications.

1. Literature review

1.1. The impacts of EPU on economic activities

Economic policy uncertainty (EPU) is commonly defined as the divergence of public predictions of government economic policies (Baker et al., 2016). In the existing literature, a number of studies have investigated the impacts of EPU on various economic activities, which can be summarized into two categories: macro-economy entities and micro-economy activities.

One general idea among previous studies is that rising EPU will hinder macroeconomic development. Bloom (2009) proposes that higher uncertainty leads firms to suspend investment and hiring activities, which in turn harm output and the labor market. As Liu and Zhang (2015) claim, higher EPU causes an increase in market volatility, and EPU exhibits a significant predictive power of market volatility. In addition, Mumtaz and Surico (2018) investigate the relationship between the U.S. economy and four types of policy uncertainty and conclude that about 25% of output volatility is attributed to policy uncertainty, particularly government debt. By employing a panel VAR model estimation with stochastic search specification selection, Christou et al. (2017) declare that EPU hurts stock market returns. As Phan et al. (2021) state, EPU has an adverse effect on financial stability. Moreover, such an effect is greater if a country possesses smaller financial systems, lower regulatory capital, and higher competition.

Some researchers also investigate the relationship between EPU and micro-entity activities, including enterprise investment, corporate cash holding, and firm CO_2 emissions. As Wang et al. (2014) suggest, there exists a negative correlation between EPU and enterprise investment behavior, and such an effect is moderated by firms' heterogeneity and is smaller for firms that have a higher capital return, rely less on external finance, and are non-state-owned. Gulen and Ion (2016) investigate the link between EPU and investment using the augmentations of panel regressions, finding that EPU prevents corporates from investing by inducing precautionary delays. Other scholars target the correlation between EPU and cash holding and obtain that EPU exerts a positive effect on corporate cash holding. Demir and Ersan (2017) and Phan et al. (2019) conclude that companies tend to keep more cash under uncertainty since enterprises' conservative motives and investment delays. Moreover, by employing the autoregressive distributed lag model, Adedoyin and Zakari (2020) declare that EPU has a short-term positive effect on the environment, but the long-term effect is negative. Anser et al. (2021) also present a similar conclusion that higher EPU reduces CO_2 emissions in the short run while increasing them in the long run. Although existing literature has investigated the influence of EPU at both macro- and micro-levels, scanty research investigates whether green innovation is affected by EPU and how does this effect works.

1.2. The influencing factors of green innovation

Green innovation is a concept derived from the traditional innovation theory that emphasizes sustainable economic development and green ecological concepts and is also known as "sustainable innovation", "eco-innovation", or "environmental innovation", which is a process of improving green efficiency and innovation efficiency. The academic community has paid much attention to the influencing factors of green innovation. First, at the corporate level, Brunnermeier and Cohen (2003) propose that firms' investment in environmental management costs positively affects their green patents. As Li et al. (2017) state, firms' profit is a decisive factor in green product innovation. Using a panel threshold regression model, Liu et al. (2021) study the correlation between foreign direct investment and green innovation and find several structural breakpoints. Second, at the level of government, Berrone et al. (2013) claim that governmental environmental regulation has a positive effect on green technology innovation, and institutional pressure can spur companies to increase R&D investment. Lin et al. (2014) investigate political capital's impact on corporate green innovation and conclude that higher political capital inhibits enterprise green innovation. Moreover, government efficiency and legal origins have a significant correlation with green innovation (Wen et al., 2021, 2022). From a heterogeneous perspective, Luo et al. (2021) examine the relationship between various environmental regulations and green innovation using panel data of China's 30 provinces, finding that market-based supervision hurts green innovation, but foreign direct investment promotes green innovation.

1.3. The effects on green innovation from EPU

Previous literature concerning the effect of EPU on general innovation has not reached a consistent conclusion with various opposing viewpoints. Some researchers claim a strong negative correlation between EPU and innovation, due to increased capital cost, operational risk, and financial distress. Bhattacharya et al. (2017) examine the influence of EPU on corporate innovation using panel data from 43 countries and conclude that EPU inhibits firms' innovation, especially for those with small financing constraints. Similarly, Xu (2020) employs an instrumental variable approach and finds that EPU increases the capital costs for companies and thus decreases enterprise innovation. Cui et al. (2021) state that EPU exposure can negatively affect corporate innovation investment through the two channels of financial distress and operational risk. However, the EPU index they chose was developed by Baker et al. (2016) whose text source is simply South China Morning Post, which does not really represent the Chinese scenario, and their heterogeneity analysis is poor.

Other scholars declare the opposite perspective that EPU promotes innovation, due to increasing market opportunities, abundant cash holding, and decreasing business operating costs and risks. Based on a sample of 282 cities in China, Jin et al. (2019) investigate the relationship between EPU and innovation, concluding that EPU can stimulate innovation, and such a positive effect is strong in developed cities and coastal cities. By employing the panel Tobit model, He et al. (2020) claim that the impact of EPU on innovation may have temporal heterogeneity. More specifically, EPU encourages firms to innovate during the low EPU period preceding 2008, but discourages firms from innovating during the higher EPU period following 2008. Guan et al. (2021) empirically test EPU's effect on business model innovation and corporate technological innovation, finding that EPU affects the former negatively, but affects the latter positively. However, they do not investigate the various consequences of EPU on innovation in different regions of a country, and green innovation, which is an environmentally-friendly form of innovation, has long been neglected by most researchers.

To sum up, few research papers look directly at the correlation between EPU and green innovation. However, EPU can have a direct or indirect impact on innovation and exert a substantial influence on green innovation (Zhu et al., 2021; Xu & Yang, 2021). Because EPU accounts for the majority of types of economic uncertainty and as green innovation is the most promising and effective way to realize environmental-friendly sustainable development, it is imperative to examine how EPU affects the level of green innovation. In comparison to previous works, we extend along the line of political economics to further analyze the socio-economic consequences of its subdivisions and further expand innovation economics in the direction of the ecological economy, which is of great significance for exploring sustainable development and green growth.

2. Data and methodology

2.1. Data and variables

2.1.1. Dependent variable

Patent: Among the existing literature, patents are considered useful in measuring technology innovation, since they not only measure innovation output, but also capture how effectively an enterprise uses its innovation inputs (Fang et al., 2014). As Griliches (1990) declared, a patent directly reveals the results of R&D and innovation activities, and the statistics of patents can be a good indicator of innovation performance. Acs et al. (2002) and Jalles (2010) also argued that patents can measure the output of innovation, while patent applications quantify intermediate products in the innovation process, and so we can study the dynamics of the innovation system through readily available patent databases. Therefore, based on the large amount of available patent data, patent applications can be utilized as an effective proxy for innovation, and we employ green patent applications as a proxy variable for green innovation in this study. Specifically, green patents are screened in accordance with the World Intellectual Property Organization's (WIPO) Green List of International Patent Classification[2]. Our study uses green patent applications of 31 provinces in China from 2000 to 2017 to measure provincial green innovation (proxied by *Patent*)[3], and we take the natural logarithm of patents following the method proposed by He et al. (2020).

[2] Transportation, waste management, energy conservation, alternative energy production, administrative regulation or design features, agricultural or forestry, and nuclear power generating are among the seven areas of green patents.

[3] The number of green patent applications is at the enterprise level, and the provincial data are the sum of all patents applied for by all firms in that province.

2.1.2. Independent variable

EPU: Economic policy uncertainty (EPU), as measured by a news index, is our primary explanatory variable of interest. In the existing literature, various measurement methods regarding the EPU index have been proposed for diverse aims. For example, early studies mainly utilize uncertainty, violation, and dispersion as proxies to measure EPU, including fiscal policy uncertainty (Villaverde et al., 2011), political environment uncertainty (Julio & Yook, 2012), and monetary policy uncertainty (Mumtaz & Surico, 2018). However, this method may have certain measurement errors that cannot gauge the dynamic effect. Baker et al. (2013) establish a synthetic EPU index based on text analysis to assess economic policy uncertainty and choose South China Morning Post as the text source in China. Following this work, Huang and Luk (2020) create an EPU index using ten Chinese representative newspapers. Li et al. (2020) construct a monthly EPU index using three national newspapers in China, which are Economic Daily, People's Daily, and Guangming Daily. However, these EPU indices are measured at a national level and fail to target regional heterogeneity within a country, which is quite significant for green innovation (Jin et al., 2019; Li et al., 2021).

By using text quantification techniques, Yu et al. (2021) select daily newspapers from 31 Chinese provinces and measure the EPU index at a provincial level. Particularly, they first calculate the total number of annual articles that include keywords expressing uncertainty and economic policy and then divide it by the total amount of articles containing the keyword "economy" in that year. Furthermore, they standardize the EPU article proportion in each province using the standard deviation of 31 provinces and finally obtain the standardized EPU index for these provinces. As our research focuses on regional heterogeneity, we employ the provincial EPU index constructed by Yu et al. (2021) and take its natural logarithm to represent the EPU (proxied by *EPU*) of 31 provinces in China.

2.1.3. Control variables

Existing research (Wen et al., 2018; Wang et al., 2020; Zheng et al., 2021) suggests that a province's green innovation could be affected by other explanatory variables, such as economic development level, industry structure, human capital, etc. To improve the validity of the regression model, our study controls the effects of these variables.

First, as noted by previous research, there exists a strong positive association between the expenditure on R&D and innovation (Pradhan et al., 2018). We present the innovation input of a province in terms of R&D expenditure (proxied by *R&D*) and measure it with the perpetual inventory method. Second, Jin et al. (2019) claim that economic development level has a substantial influence on green innovation, as higher economic development often implies more financial resources for R&D. This article utilizes per capita GDP (proxied by *GDP*) to measure economic development level, which is in line with Arin et al. (2011). Third, Frías et al. (2012) use data in Mexico and conclude that a better industrial structure leads to higher innovation. Following Kayal (2016), our research measures the regional industrial structure (proxied by *Industry*) through the share of secondary industry value-added in GDP. Fourth, according to Hottenrott and Peters (2012) and Song et al. (2015), foreign direct investment (FDI) likely spurs local green innovation due to the spillover effects of technologies provided by it and the alleviation of financing constraints. However, as Belloumi (2014) declares, FDI may hinder domestic green innovation due to the potential technological dependency and the fact that it primarily provides labor-intensive technologies with few spillover effects. Our research uses the actual utilization of foreign direct investment (proxied by *FDI*) to measure it. Fifth, Cheng (2010) proposes a strong link between urbanization and technological innovation, and the favorable conditions provided by urbanization can accelerate the diffusion of innovation. The level of urbanization (proxied by *Urban*) is measured as the share of the non-agricultural population in the total population of each province. Sixth, in the area of knowledge, human capital is taken as the bedrock of economic and social development. As Roper et al. (2017) state, general education can promote technological progress, because it stimulates the accumulation, increases the availability and ability, and improves the storage and flow of knowledge. Our research utilizes the number of students enrolled in ordinary colleges and universities to measure regional human capital (proxied by *Human*). Seventh, research suggests that the larger the population is, the greater is the likelihood of implementing new ideas, which spur the emergence and adoption of new technologies (Kremer, 1993), but other scholars reveal that the impact of population size on technical innovation is non-linear (Dong et al., 2016). This study thus uses the total population of a province at the end of the year to control for the effect of population size (proxied by *Pop*) on green innovation.

2.1.4. Data description

Our data sources include the China Statistical Yearbook, the State Intellectual Property Office of China, the Provincial EPU index (Yu et al., 2021), the World Intellectual Property Organization (WIPO), Chinese Research Data Services Platform (CNRDS), and China's provincial marketization index (Wang et al., 2019b). After merging all variables, we collect provincial panel data for 31 administrative regions of China from 2000 to 2017[4]. The table of variable definitions and data sources is reported in Table 1, and the province list table is shown in Table 1A in Appendix.

The descriptive statistics for the main variables are presented in Table 2. The average value of *Patent* is 6.396, with a standard deviation of 1.966, indicating that its polarization is relatively serious and green innovation varies greatly across provinces in China. *EPU* exhibits a similar pattern, with a minimum of 0.826 and a maximum of 6.472, showing prominent variations across the observation period. Because of the huge variance, a large bias may arise if we use the simple regression method of ordinary least squares (OLS), hence our study chooses the panel fixed-effect model to control for the heterogeneity characteristics.

To investigate possible multicollinearity problems in the main variables, the correlation coefficients and variance inflating factors for major control variables are displayed in Table 3. As Craney and Surles (2002) state, to be independent of each other, the VIF value should be less than 10, and the tolerance value should be greater than 0.1. According to the results in Table 3, we argue that all variables are independent and do not significantly correlate with each other, implying that our model does not have a severe multicollinearity problem (Abban et al., 2020).

[4] Due to data availability limitations, the provincial EPU index is currently only available for 31 provinces of China from 2000 to 2017.

Table 1. Variable definitions and data sources

Variable	Symbol	Definition	Data source
Green patent applications	*Patent*	Ln (number of total green patent applications +1)	Chinese Research Data Services Platform (CNRDS)
Economic policy uncertainty	*EPU*	Ln (EPU index)	Constructed by Yu et al. (2021)
R&D expenditure	*R&D*	Real R&D expenditure	China Statistical Yearbook
Per capita GDP	*GDP*	GDP divided by population	China Statistical Yearbook
Industry structure	*Industry*	Secondary industry value-added (% of GDP)	China Statistical Yearbook
Foreign direct investment	*FDI*	Real utilization of foreign direct investment	China Statistical Yearbook
Urbanization	*Urban*	Non-agricultural population (% of total population)	China Statistical Yearbook
Human capital	*Human*	Number of students enrolled in ordinary colleges and universities	China Statistical Yearbook
Population size	*Pop*	Total population at the end of the year	China Statistical Yearbook
Infrastructure	*Infra*	Length of highway mileage	China Statistical Yearbook
Government support	*Sandt*	Financial expenditures on science and technology (% of total financial expenditure)	China Statistical Yearbook
Environmental regulation	*ER*	Provincial environmental regulation index	China Statistics Yearbook on Environment

Table 2. Data description

Variable	Observations	Mean	Std. Dev.	Min	Max
Patent	558	6.396	1.966	0.000	10.864
EPU	519	4.500	0.534	0.826	6.472
R&D	557	2.238	3.601	0.002	23.436
GDP	558	3.043	2.397	0.292	12.904
Industry	558	0.450	0.083	0.190	0.590
FDI	558	53.465	75.312	0.000	893.587
Urban	527	0.484	0.157	0.190	0.896
Human	558	60.921	45.764	0.550	201.530
Pop	558	4.261	2.704	0.262	11.169

Table 3. Data descriptive statistics and correlation matrix

	R&D	GDP	Industry	FDI	Urban	Human	Pop	VIF	Tolerance
R&D	1.000							5.26	0.190
GDP	0.741	1.000						5.43	0.184
Industry	–0.003	0.031	1.000					1.55	0.645
FDI	0.793	0.663	0.240	1.000				3.84	0.260
Urban	0.531	0.777	0.073	0.545	1.000			3.39	0.295
Human	0.679	0.418	0.397	0.698	0.266	1.000		5.58	0.179
Pop	0.400	–0.004	0.360	0.470	–0.101	0.768	1.000	4.31	0.232

Note: Tolerance value greater than 0.1 and VIF value less than 10 indicate no multicollinearity.

2.2. Estimation method

The primary goal of our research is to analyze the association between EPU and green innovation in 31 provinces of China from 2000 to 2017. Compared to cross-sectional and time-series data, panel data allow for easier control of individual heterogeneity and avoidance of various cross-talk issues. In addition, panel data methods are better for examining dynamic adjustment processes, and larger sample sizes increase estimation accuracy and dramatically lower the effect of multicollinearity significantly (Hsiao, 2014; Yang et al., 2022). The advantages of the fixed effects model are as follows. First, this estimation method minimizes the endogeneity of the model by absorbing the effects of time-invariant observable and unobservable omitted variables (Wen et al., 2016; Fu et al., 2020). Second, adding time-fixed effects to the model allows us to control for characteristics that are unchanged in the current year (Wen et al., 2020; Hu et al., 2022). Based on these advantages, this research employs a two-way fixed effects model by controlling for provincial effects that vary by province but not time, and year fixed effects that vary by time but not province.

We therefore define our benchmark model as follows:

$$\ln(Patent+1)_{it} = \alpha \ln EPU_{it} + \beta X_{it} + \mu_i + u_t + \varepsilon_{it}. \quad (1)$$

Here, $Patent_{it}$ is the measurement of green innovation, $EPUt_{it}$ is a particular year's economic policy uncertainty index, which is the explanatory variable of interest, X_{it} refers to a set of other control variables, μ_i represents province-specific effects, which includes other unobserved time-invariant factors that may affect green innovation, u_t represents year-specific effects, which controls for similar patterns or other occurrences related to green innovation in target provinces, and ε_{it} is a random disturbance term. To increase the credibility of our research, we further employ system GMM and LSDVC models to address endogeneity in our robustness tests.

3. Empirical results

3.1. Baseline results

Table 4 displays the regression findings of the main variables after accounting for the fixed effects of province and year. Column (1) focuses solely on the influence of EPU on green innovation. On this basis, we add R&D expenditure and per capita GDP in column (2), add industry structure and foreign direct investment in column (3), and add urbanization and human capital in column (4). In addition, column (5) adds population size, including all explanatory variables. The estimation results show that the coefficient of *EPU* is 0.062 at a 5% significant level after considering all control variables, demonstrating that higher EPU increases green innovation in the sample provinces. The economic importance is then calculated by multiplying the *EPU*'s coefficient by the standard deviation of *EPU* divided by the standard deviation of green patent applications (*Patent*). Green patent applications rise by 1.684% of a standard deviation for one standard deviation increase in EPU [(0.062*0.534)/1.966].

Table 4. Estimation results of the two-way panel fixed effect model

Variable	(1)	(2)	(3)	(4)	(5)
EPU	0.084^{*} (1.95)	0.083^{**} (2.35)	0.080^{**} (2.22)	0.060^{**} (2.32)	0.062^{**} (2.41)
R&D		0.029 (1.43)	0.040^{*} (1.78)	0.028 (1.34)	0.036 (1.44)
GDP		−0.063 (−1.00)	−0.061 (−0.97)	−0.022 (−0.33)	−0.024 (−0.35)
Industry			2.250^{**} (2.42)	1.097 (1.29)	0.992 (1.31)
FDI			0.000 (0.78)	0.001 (0.71)	0.001 (0.71)
Urban				5.565^{***} (4.19)	5.483^{***} (4.12)
Human				0.000 (0.22)	0.000 (0.18)
Pop					−0.156 (−0.83)
Constant	4.414^{***} (27.74)	4.463^{***} (32.90)	3.530^{***} (8.33)	1.881^{***} (3.17)	2.602^{**} (2.68)
Province	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	519	518	518	488	488
R^2	0.950	0.951	0.955	0.959	0.959

Notes: Values in parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The above result is consistent with Aghion et al. (2005), who claims that when businesses face increasing uncertainty and market competition, they tend to increase innovation in order to expand their market power. The following are some possible explanations for this outcome. From the corporate perspective, as EPU rises, enterprise investment falls (Wang et al., 2014), and hence firms will have more cash on hand, which can spur corporate green innovation (Phan et al., 2019). From the industry perspective, economic uncertainty can produce an "Incentive Effect" on enterprises, forcing them to increase their innovation efforts to boost long-term returns (Gu et al., 2018). From the government perspective, government subsidies are effective at supporting green innovation (Huang et al., 2019). When the external environment is uncertain, government subsidies reflect its recognition and support for enterprises and industry, and such a signal is conducive to reducing information asymmetry and attracting credit investment and venture capital, thereby stimulating green innovation (Liu et al., 2019).

In terms of control variables, the coefficient of *R&D* is 0.040 at a significant level of 10% and the coefficient of *Industry* is 2.250 at a significant level of 5% in column (3), but this positive correlation is not significant in other columns, indicating that improving R&D expenditure and industry structure increases green innovation to a limited extent. We can see from the estimation results in columns (4) and (5) that the *Urban* coefficients are positive and pass the significance test at the 1% level, implying that green patent applications increase when urbanization improves. These empirical results are in line with other scholars who declare that urbanization boosts local innovation capabilities while stifling innovation in surrounding areas (Chen et al., 2020). In any other column of Table 4, the empirical estimation results show no significant relationship between other explanatory variables and green innovation.

3.2. Heterogeneity analysis

3.2.1. The heterogeneity results of different levels of marketization

As the leader among developing countries, China is undergoing a critical period of socio-economic development transition, and the marketization process varies greatly from region to region (Zeng et al., 2021). Moreover, corporates in more market-oriented regions are more vulnerable to EPU, and hence we suspect that EPU's impact on green innovation may differ across provinces with varying levels of marketization (Wang et al., 2014). The reason for this could be that a perfect and effective market system can foster a favorable environment for businesses, reduce the difficulty of financing, promote property rights protection, and boost green innovation (Wang & Wen, 2019). Furthermore, regions with a higher level of marketization can promote regional knowledge transfer and inter-regional knowledge spillover, which can enhance innovation capacity (Sun & Zhan, 2016).

The China sub-provincial marketization index we use herein is from the China Market Index Database, which is created by Wang et al. (2019b) and is based on five different aspects of marketization[5]. To this end, we divide 31 provinces into two groups to further explore the heterogeneity of EPU's impact on green innovation, with provinces with marketization levels equal to or higher than the median value belonging to the high marketization group and the remaining provinces belonging to the low marketization group. Table 5 reports the estimation results, and we conclude that the effects of EPU on green innovation show significant heterogeneity between provinces with different marketization levels. Column (1) reveals that the coefficient of *EPU* is similar to the basic regression result at a significant level of 10%, demonstrating that EPU promotes green innovation in these sub-samples. However, the data in column (2) show that EPU's effect on green innovation is not significant in provinces with low levels of marketization.

3.2.2. The heterogeneity results of different degrees of trade openness

Economic development and degree of trade openness also appear to be uneven across provinces in China. Keller (2010) and Nasreen and Anwar (2014) claim that trade is a significant channel for technology diffusion, and the degree of a region's trade openness to the outside world determines the rate of technology spillover (Sun et al., 2019). Hence, it is meaningful

[5] The comprehensive marketization index contains five indices: the interaction between the government and the market, the degree of non-state economic development, the degree of factor market development, the degree of product market development, and the development of intermediate organizations and the legal system environment.

Table 5. Estimation results of different sub-samples

Variable	High marketization	Low marketization	High trade openness	Low trade openness
	(1)	(2)	(3)	(4)
EPU	0.067* (2.09)	–0.030 (–0.44)	0.088** (2.46)	–0.020 (–0.32)
R&D	0.033 (1.21)	0.017 (0.22)	0.008 (0.32)	0.026 (0.49)
GDP	0.023 (0.32)	–0.067 (–1.28)	0.018 (0.28)	–0.073 (–1.00)
Industry	2.034 (1.53)	1.319* (2.00)	1.176 (1.20)	2.051*** (3.57)
FDI	0.001 (0.54)	–0.010** (–2.47)	0.000 (0.60)	–0.003 (–1.32)
Urban	6.376*** (4.09)	4.265* (1.82)	7.743*** (3.80)	3.718** (2.38)
Human	–0.001 (–0.39)	0.007* (1.82)	0.001 (0.20)	0.003 (1.28)
Pop	–0.010 (–0.05)	–0.107 (–0.59)	–0.000 (–0.00)	–0.407** (–2.19)
Constant	1.569 (0.97)	2.343** (2.63)	0.702 (0.36)	3.933*** (5.67)
Province	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	242	246	234	254
R^2	0.975	0.948	0.970	0.954

Notes: Values in parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

to explore whether provinces with varying degrees of trade openness respond differently to EPU. For this purpose, we measure trade openness in terms of regional total import and export trade as a proportion of GDP and divide the sample provinces according to their trade openness degrees. A province belongs to the high openness group if its trade openness degree is equal to or greater than the median of all provinces; otherwise, it belongs to the low openness group.

The empirical findings are presented in columns (3) and (4) of Table 5, showing that EPU has a positive effect on green innovation at a significant level of 5% in provinces with high trade openness, while the correlation is not significant in provinces with low trade openness. In addition, the *EPU* coefficient in the high openness group is slightly higher than in the baseline regression, indicating that trade openness actively moderates EPU's impact on green innovation in regions with higher degrees of openness. This is consistent with Yang and Lin (2012), who claim there is a high correlation between trade openness and regional innovation. Specifically, trade openness degree affects economic development level and availability of cutting-edge technical information, and the strong competition brought by foreign trade stimulates local corporates to cut costs and encourages green innovation.

3.3. Robustness tests

Although the above analysis finds a positive correlation between EPU and green innovation, the relationship still needs to be further identified. And to confirm the validity of the benchmark regression, we run a series of robustness tests, including variable and regression method replacement and endogeneity tests.

3.3.1. Alternative dependent variables

First, green patent applications are split into two categories: green invention patent applications (proxied by *Patent_inv*) and green utility patent applications (proxied by *Patent_uti*), and green patent applications per capita (proxied by *Patent_rat*) are calculated by dividing green patent applications by population. In addition, our study uses these three proxies to represent green innovation, with actual results provided in Table 6. It is easy to observe that the coefficient of *EPU* is 0.070 at the significant level of 5% when green invention patent applications is used as the dependent variable in column (1), 0.047 at the significant level of 10% when green utility patent applications is used in column (2), and 0.064 at the significant

Table 6. Robustness tests: alternative dependent variables and regression models

Variable	Patent_inv	Patent_uti	Patent_rat	Panel Poisson	Panel negative binomial
	(1)	(2)	(3)	(4)	(5)
EPU	0.070** (2.48)	0.047* (1.73)	0.064** (2.66)	0.003*** (2.66)	0.003*** (4.77)
R&D	0.039 (1.48)	0.020 (0.72)	0.035 (1.46)	0.004 (0.20)	0.001 (0.21)
GDP	−0.001 (−0.01)	0.007 (0.11)	−0.026 (−0.41)	0.010 (0.15)	0.005 (0.22)
Industry	0.372 (0.45)	0.678 (0.84)	0.823 (1.13)	1.249 (1.63)	1.391*** (4.46)
FDI	0.001 (0.60)	0.001 (0.66)	0.001 (0.64)	0.001 (1.52)	0.001** (2.39)
Urban	7.998*** (6.08)	5.120*** (3.74)	6.569*** (6.21)	5.457*** (4.18)	3.784*** (8.29)
Human	0.001 (0.45)	0.001 (0.69)	0.002 (0.86)	0.000 (0.17)	0.001 (0.82)
Pop	−0.260 (−1.24)	−0.027 (−0.13)	−0.320 (−1.64)	0.131 (0.89)	0.164*** (4.89)
Constant	1.307 (1.25)	1.869* (1.81)	−5.132*** (−5.20)		−1.637*** (−5.28)
Province	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	488	488	483	488	488
R^2	0.955	0.949	0.960	0.1042	

Notes: Values in parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

level of 5% when per capita green patent applications is used in column (3). In conclusion, the regression results suggest that higher EPU promotes green innovation, and the findings are robust as there is no significant difference between the various measures of the green innovation variable.

3.3.2. Alternative estimation techniques

The dependent variable (patent applications) is discrete data of non-negative integers, making it suitable for regression analysis using the counting model. And Poisson regression and negative binomial regression are two counting models commonly used to discrete data (Gardner et al., 1995). To further examine the correlation between EPU and green innovation, this paper uses the panel Poisson regression model in Table 6 column (4) and panel negative binomial regression model in column (5). According to their regression characteristics, we use green patent applications and EPU index without taking natural logarithms as our dependent and independent variables. The regression results suggest that the coefficients of *EPU* are positive at a significant level of 1% in columns (4) and (5), which again verifies that the promotion of EPU on green innovation does not differ depending on the regression model, which further validates the robustness of our empirical results.

3.3.3. Considering the issue of cross-sectional dependence

Advanced communication and transportation in recent years have made individuals become increasingly connected in both characteristics and behaviors. Such correlations are frequently found in panel data models, and hence the cross-sectional correlation test has gained a lot of attention (Zhao et al., 2022). Pesaran develops the CD (Cross-section dependence) test and proposes cross-dependence in output innovations across many regions (Pesaran, 2021). In this research we first perform Pesaran's CD test in Table 7 and find that it rejects the null hypothesis of spatial independence at any standard level of significance.[6] Therefore, we run the panel PCSE (Panel-corrected standard errors) model developed by Beck and Katz (1995) to address the issue of cross-sectional dependence, with the empirical results reported in Table 7 column (1). Additionally, because the PCSE estimators do not account for non-contemporaneous dependence of different data cross-sections, we then employ the DK (Driscoll & Kraay, 1998) estimator, which employs a non-parametric technique to achieve a consistent variance, to further confirm the validity of our findings. Column (2) in Table 7 presents the results of this model. The preceding results demonstrate that even after accounting for cross-sectional dependence issues, our basic results are still robust at a 5% significant level.

3.3.4. Endogeneity concerns

In the empirical analysis, whether the endogenous problems can be addressed effectively is crucial to the objectivity of the empirical results. There are many reasons for endogeneity, of which the most essential are bias in the omitted explanatory variables and reverse causality (Afesorgbor, 2019; Acemoglu et al., 2019).

[6] Pesaran's CD test is applied to panels, as a panel's cross-sectional dimension N and time dimension T tend to infinity in any order. A bias-adjusted LM (Lagrange multiplier) test of error cross-section independence is proposed by Pesaran et al. (2008), but we did not report it due to the length of the article.

Table 7. Robustness tests: considering cross-sectional dependence issues

Variable	PCSE estimator	DK estimator
	(1)	(2)
EPU	0.062** (2.39)	0.062** (2.70)
R&D	0.036** (2.17)	0.036* (1.92)
GDP	–0.024 (–0.66)	–0.024 (–1.12)
Industry	0.992* (1.67)	0.992 (1.24)
FDI	0.001* (1.72)	0.001 (1.14)
Urban	5.483*** (8.02)	5.483*** (7.05)
Human	0.000 (0.16)	0.000 (0.16)
Pop	–0.156** (–2.07)	–0.156 (–1.51)
Constant	3.654*** (6.25)	2.602*** (3.99)
Province	Yes	Yes
Year	Yes	Yes
N	488	488
R^2	0.984	
CD test: Pesaran's test of cross sectional independence = 20.612, Pr = 0.000		

Notes: Values in parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

3.3.4.1. Considering omitted variables

The possibility of omitted explanatory variables is an important problem that needs to be addressed right away. Controlling for other potential factors that may affect provincial green innovation as thoroughly as possible can greatly reduce the adverse effects of omitted variable bias in the regression statistics. First, infrastructure development's impact on enterprise green innovation has a scale effect of the product market and a crowding-out effect of the financial market (Cai & Ru, 2016; Gu et al., 2021). Second, as Roh et al. (2021) state, government support has a massive effect on green product innovation and green process innovation through the mechanism channel of open innovation. Third, environmental regulation has a significant influence on green innovation, which varies depending on the intensity of environmental regulation, and this relationship is regionally heterogeneous (Song et al., 2020).

We thus add infrastructure, government support, and environmental regulation into our regression model[7]. In addition, our study uses the number of highway mileage in each re-

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[7] The definitions and data sources of omitted variables are shown in Table 1.

gion to represent the level of regional infrastructure (proxied by *Infra*) and takes the ratio of provincial financial expenditures on science and technology to total financial expenditure to measure the government support policy (proxied by *Sandt*). We utilize a comprehensive index calculated based on industrial wastewater, industrial smoke, industrial solid waste, and industrial sulfur dioxide to measure environmental regulation (proxied by *ER*). Table 8 provides the basic regression outcome in column (1), and we add infrastructure in column (2), government support in column (3), and environmental regulation in column (4). The empirical findings show that *EPU* coefficients are all positive and pass significance tests at the 5% level, implying that EPU promotes green innovation after considering all of these variables. Therefore, we confirm that the regression results are robust at this stage.

Table 8. Robustness tests: add omitted variables

Variable	(1)	(2)	(3)	(4)
EPU	0.062** (2.41)	0.059** (2.41)	0.063** (2.64)	0.065** (2.59)
R&D	0.036 (1.44)	0.038 (1.50)	0.035 (1.49)	0.034 (1.25)
GDP	–0.024 (–0.35)	–0.032 (–0.47)	–0.036 (–0.53)	–0.028 (–0.37)
Industry	0.992 (1.31)	1.047 (1.41)	1.156 (1.57)	0.894 (1.08)
FDI	0.001 (0.71)	0.001 (0.67)	0.001 (0.63)	0.000 (0.55)
Urban	5.483*** (4.12)	5.589*** (4.07)	5.340*** (4.12)	5.962*** (4.71)
Human	0.000 (0.18)	0.002 (0.69)	0.002 (0.72)	0.003 (1.18)
Pop	–0.156 (–0.83)	–0.207 (–0.99)	–0.197 (–1.01)	–0.224 (–1.02)
Infra		–0.014 (–0.94)	–0.013 (–0.94)	–0.020 (–1.61)
Sandt			4.147 (1.65)	3.171 (0.85)
ER				0.030 (0.06)
Constant	2.602** (2.68)	2.791** (2.70)	2.702** (2.73)	2.817** (2.22)
Province	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	488	488	488	473
R^2	0.959	0.959	0.960	0.970

Notes: Values in parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.3.4.2. GMM and LSDVC estimators

Reverse causality is another essential factor that leads to endogenous issues. More specifically, EPU can be influenced by various factors in economic systems, such as investment in innovation and business cycles (Bloom, 2014; Bhattacharya et al., 2017). Regional green innovation can also have an impact on regional economic development, which then eventually affects economic uncertainty through a variety of mechanisms.

We first utilize the GMM estimator to address potential endogenous problems and dependent variable dynamics in provincial panel data. GMM estimations can be divided into two categories: the first difference GMM estimation by Arellano and Bond (1991) and the system GMM estimation by Blundell and Bond (1998). The difference GMM estimation is prone to cause problems of weak instrument variables and small sample sizes when endogenous variables resemble a random walk (Blundell & Bond, 1998). The system GMM estimation can be separated into "one-step" estimates and "two-step" estimates depending on the weight matrix selections. Bond et al. (2001) claimed that "two-step" system GMM estimation can better handle auto-correlation and hetero-scedasticity problems under a limited sample. Therefore, to improve the credibility of the regression findings, the difference GMM estimation and "two-step" system GMM estimation are performed on the sample data.

The empirical results of difference GMM estimation are shown in column (1) of Table 9, while those of system GMM estimation are shown in column (2). The corresponding P-values reveal that AR (2) statistics are not significant, implying there are no sequence correlation problems in error terms of the level equation. The results of the Sargan or Hansen test, which judge the over-identification problems of instrumental variables at well above 0.1, show that the selection of instrumental variables is effective overall. The following inferences can be taken from the provided results. (i) There is a significantly positive association between the lagging period of dependent variables and the current level of green innovation at the 5% level, showing that green innovation indeed exhibits "sustainability", which is consistent with Wang et al. (2019a). (ii) The coefficient estimation and the significance level of *EPU* maintain high consistency with the basic regression, showing that EPU promotes green innovation and further illustrating the robustness of benchmark regression.

When the sample size is tiny, system GMM estimation may suffer from weak instrumental variables, and the "two-step" system GMM estimation has a relatively significant variance in finite samples, which may lead to biased estimation results. Kiviet (1995) developed LSDVC estimator that can produce unbiased and consistent results. Hence, we utilize LSDVC (AB) and LSDVC (BB) estimators to further verify the robustness and reliability of estimation findings, and the empirical results are presented in Table 9. The coefficient of *EPU* is 0.631 in column (3) and 0.713 in column (4) at the 1% significance level, demonstrating that higher EPU leads to green innovation increases in the target provinces, which is consistent with our prior findings.

Table 9. Robustness tests: GMM and LSDVC estimators

Variable	Difference GMM	System GMM	LSDVC (AB)	LSDVC (BB)
	(1)	(2)	(3)	(4)
L.Patent	0.464*** (9.28)	0.875** (2.33)	0.631*** (14.36)	0.713*** (17.35)
EPU	0.047** (2.02)	0.246* (1.72)	0.048** (2.17)	0.044* (1.89)
R&D	0.011 (0.91)	0.047 (1.24)	0.015 (0.98)	0.008 (0.48)
GDP	–0.017 (–0.61)	–0.096* (–1.73)	–0.033 (–0.88)	–0.030 (–0.73)
Industry	1.187*** (3.15)	3.546 (1.39)	0.638* (1.68)	0.731* (1.78)
FDI	0.000 (0.60)	0.001 (1.02)	–0.000 (–0.07)	–0.000 (–0.17)
Urban	2.413*** (3.08)	0.753 (0.43)	0.484 (0.67)	–0.117 (–0.15)
Human	0.000 (0.10)	–0.003 (–0.71)	0.001 (0.43)	0.001 (0.71)
Pop	0.011 (0.10)	0.008 (0.08)	–0.097 (–0.90)	–0.071 (–0.59)
Constant		–0.956 (–0.53)	0.099*** (5.26)	0.085*** (4.37)
Province	Yes	Yes		
Year	Yes	Yes		
N	432	463	463	463
P-AR (1)	0.000	0.056		
P-AR (2)	0.191	0.335		
P-Sargan	0.163			
P-Hansen		0.940		

Notes: Values in parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Conclusions and policy implications

Green innovation is a useful instrument for resolving the dilemma of economic development and environmental pollution in China's current new economic normal. This paper empirically investigates how economic policy uncertainty affects regional green innovation based on panel data for 31 Chinese provinces from 2000 to 2017, using the provincial EPU index and the number of green patent applications. Our findings show that green patent applications increase as EPU rises, indicating a significantly positive relationship between EPU and green innovation. Moreover, our paper provides strong evidence that the effects of EPU on green innovation exhibit obvious regional heterogeneity. Specifically, provinces with higher marketization levels are more sensitive to EPU, and EPU promotes green innovation in such regions. In addition, EPU's impact on green innovation is significantly larger in provinces with higher degrees of trade openness. However, in provinces where marketization and trade openness levels are relatively low, such causality is not significant. In contrast to the previous studies, we analyze the correlation between EPU and green innovation at a provincial level and examine the heterogeneity results of the relationship, further expanding innovation economics in the direction of the political economy, which is essential for exploring economic uncertainty and green growth. Therefore, we put forward policy implications as follows.

Our results suggest that a favorable economic environment like a higher level of marketization or trade openness is necessary, as it can enhance the promotion effect of EPU on green innovation. Thus, under the condition of unstable global economic policies, the government should take measures to create a better external economic environment. Marketization can achieve optimal resource and element allocation, and hence enhancing social efficiency and boosting green innovation. The government can improve the marketization through structural tax cuts and across-the-board fee reductions, to further lighten the burden on enterprises, and stimulate green innovation capability. In addition, to expand trade openness and increase regional green innovation, the government can introduce and learn advanced new technologies from abroad, improve its technology market environment, and transform green innovation into market value. Provinces with a low degree of trade openness should increase technological exchanges and interactions with other regions to promote the free flow and efficient allocation of resource factors among provinces. Although a higher EPU has a beneficial effect on green innovation, there remain several negative effects when uncertainty grows, such as a decrease in enterprise investment and a rise of economic volatility. Therefore, governments should balance all of these effects of EPU when they introduce or adjust economic policies frequently to mitigate a recession and boost green innovation. Finally, to mitigate the negative economic impact of EPU, the government can increase enterprise subsidies, relieving corporate financial constraints and spurring their green innovation.

This study also has certain deficiencies that deserve to be explored follow-up research. First, this paper did not delve into more subdivided areas in the economic uncertainty or innovation field. For example, does a higher EPU lead to more energy innovation? How will real economic uncertainty affect green innovation? Second, aside from green innovation, the various effects of EPU on the price and market scale of green products in different provinces are also worth investigating. Third, the provincial EPU index is only available in 31 provinces from 2000 to 2017, due to data availability, and we expect that more sample regions and time periods can be examined in the future. Finally, we can look into the transmission mechanisms between EPU and green innovation empirically, such as corporate cash holding, market competition, government subsidy, and so on.

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APPENDIX

Table A1. Province list

Anhui	Beijing	Chongqing	Fujian	Gansu	Guangdong
Guangxi	Guizhou	Hainan	Hebei	Heilongjiang	Henan
Hubei	Hunan	Jiangsu	Jiangxi	Jilin	Liaoning
Neimenggu	Ningxia	Qinghai	Shaanxi	Shandong	Shanghai
Shanxi	Sichuan	Tianjin	Tibet	Xinjiang	Yunnan
Zhejiang					