ISSN: 1648-715X / eISSN: 1648-9179

VILNIUS TECH
Vilnius Gediminas Technical University

INTERNATIONAL JOURNAL OF STRATEGIC PROPERTY MANAGEMENT

2026
Volume 30
Issue 1
Pages 76–94
https://doi.org/10.3846/ijspm.2026.26143

ESTIMATING THE EXTENT TO WHICH GREEN SWAN EVENTS DISRUPT HOUSING MARKETS: EVIDENCE FROM CHINA

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Article History:
- received 25 June 2025
- accepted 14 October 2025

Abstract. Shocks from climate change and transitioning to a low-carbon economy can have a green swan effect on economies. To assess the extent to which green swan events may disrupt housing markets in the future, this study examines how the prices of carbon trading pilot sites in four Chinese cities (Beijing, Shanghai, Tianjin, and Chongqing) affect housing prices in these cities and whether the green swan effect increases with a rise in policy risks. This paper first performs simulations to determine the extreme risk of housing returns (value at risk) and whether this risk is affected by the exogenous shock of carbon returns. Then, this study examines the correlation between carbon prices and housing prices from the perspectives of returns and volatility. In terms of risk transmission effects, all four real estate markets are affected by carbon price risk spillovers. It verifies that China's real estate market may be negatively impacted by "green swans" when carbon prices experience significant fluctuations. The findings provide investors with a means to evaluate whether the housing market is susceptible to a green swan effect, and also underscore the need for authorities to evaluate the impact of carbon reduction policies on the housing market.

Keywords: green swans, climate change, low-carbon economy, carbon trading pilot, China's housing market.

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1. Introduction

Climate change has a multifaceted impact, affecting individual behaviors, businesses, and government policies. Bolton et al. (2020) explain that climate change brings new systemic risks, and this is often referred to as a green swan effect. Krogstrup and Oman (2019) suggest that countries seeking to mitigate climate change must make a massive shift to a low-carbon economy. Moreover, Mercure et al. (2019) argue that adjustments to energy and climate-related policies can have significant economic impacts. Therefore, Svartzman et al. (2021) state that the so-called "green swans" are a new systemic risk associated with climate change and the transition to a low-carbon economy. Specifically, government actions to reduce the impact of economic development on the climate (e.g., policies to limit carbon emissions) are typical green swan events.

Svartzman et al. (2021) suggest that while central banks have begun addressing the new systemic risks posed by green swan events, existing climate and economic models fail to account for increasing uncertainty. This has limited central banks' ability to maintain financial stability. Thus, Svartzman et al. (2021) recommend macroeconomic research with systematic approaches and quantitative tools to assess the green swan effect. Several studies argue that central banks must preemptively assess green swan effects and, accordingly, propose financial stability policies (e.g., Bolton et al., 2020; da Silva, 2020; Schellekens & van Toor, 2019). Failure to manage these risks could lead to financial crises. Research predominantly focuses on the impact of transitioning to a low-carbon economy across countries and markets, including finance (Semieniuk et al., 2021), energy (Nieto et al., 2020), and commodities (Lehtonen et al., 2022; Watari et al., 2018). However, there is currently no literature exploring such "green swans" in the housing market. Thus, this study examines the vulnerability of the housing market to carbon-linked financial risks. By taking China's markets as examples, the goal of this paper is to provide a priori research on climate change and its policy implications in the housing markets, which can offer crucial supplements to the existing literature.

The housing sector is inextricably linked to the practice of sustainability goals (Cova et al., 2021; Ruddock & Ruddock, 2022; Lai et al., 2023). In illustrating the importance of green construction, Zuo and Zhao (2014) highlight that the construction industry is increasingly destructive toward the natural environment, and buildings of a residential function are often accompanied by energy-intensive consumption behaviors. Thus, high economic development in a city will drive its housing demand (Moreno-Monroy et al., 2020) and housing prices (Ehrlich et al., 2018). The resultant increase in carbon emissions (Cai et al., 2021) will cause the city to deviate from its environmental and sustainability goals. Therefore, a country's low-carbon transformation will be closely related to the housing market. Therefore, low-carbon transformation policies proposed by governments around the world often involve the housing market. However, this also carries the risk of rising production and consumption costs, as well as housing price volatility. For example, the Chinese government proposed the "Carbon Emission Peak Implementation Plan in Urban and Rural Construction" on June 30, 2022. This plan requires construction companies to increase the construction of green buildings (low-carbon residences) and raise the standard of low-carbon buildings. According to the findings of Morris et al. (2020), we can expect that this type of policy will increase construction costs and housing use costs, and hence increase the risk of housing price volatility.[1]

In recent years, China has been actively working toward carbon reduction. In addition to setting up more carbon trading pilot sites, a higher number of production activities will be subjected to carbon costing or maximum carbon credits.[2] Campiglio and van der Ploeg (2022) point out that starting the transition to a low-carbon economy without complete planning may cause excessive volatility in asset prices and trigger financial market crises. Green swans pose new risks to several industries. In the real estate industry, production and consumption are characterized by high carbon emissions and energy consumption. Thus, compared with other industries, the housing market is more prone to green swan effects, highlighting the urgent need to assess the issue. China's proactive transformation policies provide us with a sample of measurable policy risks.

This paper illustrates the impact of carbon reduction policies and prices on the housing market through two key points: first, the potential for increased housing user costs due to rising carbon emissions costs; second, the potential for builders to pass on production costs to consumers, impacting housing supply and prices. Both points illustrate the potential impact of green swan events on the housing market. This paper then develops two hypotheses, demonstrating that the volatility risk of housing prices is affected by carbon prices (green swan risk), and that policy risk can increase this green swan risk in the housing market. Subsequently, this study explores the extent to which carbon price risks in green swan events impact the housing market by using data from China. In other words, this paper attempts to estimate the carbon system risk in the Chinese housing markets to verify the two hypotheses. Locations with both carbon markets and active housing markets provide us with sound samples to estimate such market risks. Thus, we focus on carbon trading activities in four pilot cities in China (Beijing, Shanghai, Tianjin, and Chongqing) to assess the impact of the carbon trading market on housing prices in the cities.

The remainder of this paper is organized as follows. Section 2 is a literature review. First, we discuss the literature on housing and carbon prices and why the housing market is more prone to the green swan effect. We then explore research on the impact of policy risks on housing and carbon prices and the role of policy risks in increasing the green swan effect in the housing market. We propose two hypotheses based on the literature review. Section 3 describes the methodology adopted in this study, including a model to measure the risk correlation between housing prices and carbon prices and a model to estimate the effect of policy risk on the correlation between the two prices. Section 4 shows the empirical results and Section 5 presents conclusions and offers recommendations.

2. Literature review and hypotheses

2.1. Housing and carbon prices: Green swan effect on the housing market

Bridge et al. (2020) argue that given the global trend toward carbon reduction, more social science research is needed to critically address "carbon finance" issues and the financial conversion of carbon value. The majority of housing market studies focus on the financial value of greener, more energy-efficient, and carbon-reducing properties, that is, the premium of green buildings (Kim et al., 2020; Li et al., 2024). However, such research tends to be conducted at the microeconomic level.

To the best of our knowledge, no research measures the magnitude of carbon-linked financial risks in the housing market, although a few related works may serve as a reference. Chen and Lee (2020), for example, are one of few studies that examine the relationship between real estate investment and air pollution and find that cities with larger populations, as well as higher GDPs and development, are more likely to report greater air pollution. Fan and Zhou (2019) study the impact of urbanization and real estate investment on carbon emissions and highlight the pollution transfer effect. That is, urbanization negatively impacts local carbon emissions and has spillover effects of increased carbon emissions on neighboring regions. Real estate investment, on the other hand, only increases local carbon emissions but has no spillover effect. Using data on Chinese provincial panels, Sun et al. (2018) verify a long-term equilibrium relationship between carbon emissions, GDP, energy consumption structure, and urbanization. Yu et al. (2021) find that urbanization is an important factor affecting carbon emissions, and higher housing prices contribute to increasing per capita carbon emissions.

The abovementioned four papers show that urbanization, real estate investment, and housing prices are strongly correlated with the performance of the housing market in China, and these variables positively affect carbon emissions or air

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[1] Morris et al. (2020) calculate that if a carbon tax were added to energy prices, there would be a significant impact on house prices.

[2] In 2021, China officially launched a national emissions trading system, which is presently the world's largest carbon market (World Bank, 2021).

pollution. The potential adoption of policies to reduce carbon emissions or air pollution by China's local governments will inevitably impact highly developed cities and their housing markets. China's policy direction toward carbon emission reduction became evident in its 12th Five-Year Plan (2011–2015), in which it planned for seven carbon emission trading pilots: Beijing, Shanghai, Shenzhen, Tianjin, Chongqing, Guangdong, and Hubei. By 2014, these pilots were opening for trading, and in February 2021, China's national emissions trading system became the world's largest carbon market. Thus, there is an urgent need to examine the risk of carbon reduction policies and the impact of carbon prices on housing markets. Unlike the four papers, this study examines the impact of carbon prices on the housing market, specifically housing prices. The effects of carbon prices on the extreme risk of housing prices; and the outcomes of risk transmission.

China's proactive transition policy implies that production and consumption activities will gradually need to account for increased carbon spillover costs. This will bring about transition risk costs in the housing market (green swan effects), and the higher the carbon price, the higher the risk. Two arguments could infer this. First, including the cost of carbon emissions from high energy consumption in the cost of housing use should reduce housing demand and, thus, housing prices. Therefore, it will increase the risk of housing price volatility. Second, accounting for the costs of carbon emissions from production processes in the cost of housing construction will reduce the supply of housing construction. Housing prices increase when builders transfer these costs to consumers. Therefore, changes in carbon reduction policies and carbon prices are likely to raise housing prices and, consequently, investment risks in the housing market. From these two points, we can see that the impact of increased carbon emission costs on housing prices may be different from the consumption and production perspectives. A decrease in housing demand and a reduction in housing supply will cause housing prices to fall and rise, respectively. Although the direction of the impact of carbon prices on housing prices might differ through consumption or production aspects, these effects will all cause the risk of housing price fluctuations to increase.

If a particular factor causes high volatility risks in housing markets across different regions, then a significant shock from this factor in the future could potentially pose a systemic risk of a market crash. Therefore, it is crucial to assess in advance the correlation between housing prices and carbon prices and how this will affect the volatility risks of housing markets. This study poses the following key questions. Will the risk of high volatility in carbon prices be the green swan of the housing market? In other words, will the high volatility of carbon prices bring a significant downside risk to the housing market? Further, will the carbon price risk be transmitted to housing prices? Accordingly, this study proposed the following hypothesis:

Hypothesis 1: There is a green swan effect in the housing market; that is, the carbon price will affect the risk of housing price volatility.

2.2. Effect of policy risk on housing and carbon prices: policy risk and green swan events in housing markets

Wang et al. (2021b) study the relationship between carbon prices in China and Europe. They find that while global carbon markets are correlated in the long run, in the short run, the performance of carbon prices in China is largely influenced by domestic market demand and policies. Since the demand for carbon credits is determined by policy prescriptions, policy changes or uncertainties can pose increasing risks to the carbon market. Some studies have also found that the Chinese government's policy intervention in the housing market has a broad impact (Zhang et al., 2024).

Numerous studies have used Baker et al.'s (2016) economic policy uncertainty (EPU) index to examine outcomes related to carbon prices. Given the impact of policy changes and risks on firms' willingness to invest in carbon-reducing production, EPU can be used to predict firm behaviors and variables associated with the carbon economy. Zhang et al. (2022) find that EPU can predict the volatility (risk) of European carbon market futures. Adekoya et al. (2021) evidence that policy risks posed by the US EPU could be passed on to the EU carbon market, suggesting the role of EPU in the correlation between carbon prices and other commodities and financial markets. Several researchers have adopted data on China's EPUs. Mei et al. (2022), for example, demonstrate the predictive power of EPU in the context of China's low-carbon index volatility, indicating the implications of policy risks transmitting to a low-carbon industry.

Since policy uncertainty will affect the stability of carbon policy implementation, it will affect the public's and businesses' expectations of carbon emission costs and thus influence their decision-making behavior. There is substantial evidence that EPU has a significant impact on carbon prices. Dou et al. (2022), for example, analyze policy risks in Europe's carbon market and find that EPU significantly reduces carbon futures price returns in the long run. Li et al. (2022) document the effect of EPU on China's carbon price. They suggest that the Chinese government must adopt a firmer policy stance to achieve carbon reduction targets and prevent drastic fluctuations in carbon prices. Yu et al. (2021) and Zhang et al. (2022) empirically evidence that an increase in China's EPU will result in higher carbon emissions, indicating the detrimental effect of policy risks on carbon reduction targets.

Xia et al. (2020) show that EPU has varying effects on housing markets depending on their level of development. Wang et al. (2020a) find that the magnitude of policy uncertainty affects monetary policies' ability to regulate housing markets. If the relationship between monetary policy and housing prices is subject to policy risks, and the amount of carbon emissions depends on policy risk (Yu et al., 2021; Zhang et al., 2022), thus, the effect of carbon prices on housing prices is likely to be influenced by the level of policy risk.

Huang et al. (2020) show that the trend of China's housing market is dominated by EPU, and greater policy risks (i.e., greater change in EPU) result in housing market traders quoting higher risk premiums. If the EPU transmits risks to the carbon market and increases the likelihood of a green swan event, then both housing market risk and risk premiums demanded by traders will increase, causing housing prices to crash. Therefore, this study posits the following hypothesis on EPU, carbon price, and housing price.

Hypothesis 2: Policy risk affects the risk of green swan events in the housing market. That is, the level of policy risk is a key factor that can influence the degree to which the risk of housing price volatility is affected by carbon price varies.

Numerous studies use Chinese data to demonstrate that EPU affects the stock market (e.g., Wang et al., 2020b) and transmits risks to the foreign exchange market (Chen et al., 2020) and stock market (Wang et al., 2021a). Based on Hypothesis 2, we infer that EPUs may also transmit risks to the carbon and housing markets, or that certain carbon market risks are transmitted to the housing market through EPUs. This inference is consistent with findings from the previous literature. Chow et al. (2017), for instance, find that EPUs lead information on housing market returns in China. Yin et al. (2021) demonstrate EPUs' information-leading function and empirically evidence that monetary policy risks (i.e., uncertainty) are likely to be transmitted to the housing market in first-tier cities. Furthermore, by verifying Hypothesis 2, this paper proposes a method to assess green swan risk in housing markets.

3. Empirical model

In this study, we explore the carbon-linked financial risks in housing markets. We use three models to estimate the effects of carbon returns on the extreme risk of housing returns and the outcomes of risk transmission. First, we employ the generalized autoregressive conditional heteroskedasticity (GARCH)-X model (Han, 2015) to estimate the effect of carbon returns on the risk of housing returns. We employ the estimation results to calculate the value at risk (VaR) of housing price returns, which is the measure of extreme risk. Second, we adopt the vector autoregressive (VAR) bivariate GARCH (BGARCH) model to examine the risk transmission effect of carbon returns on housing returns and to test Hypothesis 1. Finally, we implement the VAR-BGARCH-X model to measure if EPU as an exogenous variable (X) affects green swan risks in the housing market (risk transmission effect) and to test Hypothesis 2. The three models are detailed in the following subsections.

3.1. Extreme risk of housing prices: VaR estimation using the GARCH-X model

Studies have found that normal distribution often does not apply to asset returns, especially in extreme cases wherein the probability of occurrence is higher than that of normal distribution. This phenomenon is also known as fat tail (Jelito & Pitera, 2021; Paolella et al., 2019). The GARCH model is often used to estimate the risk of returns volatility when asset returns are not only fat tailed but also self-correlated with volatility (e.g., Fakhfekh et al., 2023; Yong et al., 2021). For long, research has demonstrated the heterogeneity and autocorrelation of housing price returns (Miles, 2008; Miller & Peng, 2006). Some have also used the GARCH model to estimate the risk of housing market volatility (Chu & Tsai, 2020; Wang & Hartzell, 2022; Liu et al., 2024).

Therefore, to estimate the effect of carbon returns on the extreme risk of housing returns, we use the GARCH model to fit the housing price return. ΔHP_t denotes the return of the housing price index in time *t*, and δ_t^2 is conditional volatility. We describe the GARCH (q_1, q_2) model as follows.

$$\Delta HP_t = \mu + \varepsilon_t,\ \ \varepsilon_t \sim N\left(0, \delta_t^2\right); \tag{1}$$

$$\delta_t^2 = c + \sum_i^{q_1} \phi_i \varepsilon_{t-i}^2 + \sum_i^{q_2} \psi_i \delta_{t-i}^2 . \tag{2}$$

We adopt Schwarz's information criterion to determine the length of the lag term in the model. Attaching the exogenous variables to the estimation of the conditional variables estimation produces the GARCH-X model. That is, we add carbon price returns to Eq. (2):

$$\delta_t^2 = c + \sum_i^{q_1} \phi_i \varepsilon_{t-i}^2 + \sum_i^{q_2} \psi_i \delta_{t-i}^2 + w_i \Delta CP_{t-1}, \tag{3}$$

where ΔCP_{t-1} denotes carbon price returns at time *t*–1. We use this GARCH-X model to estimate the volatility of asset returns over time ($\widehat{\delta_t^2}$). Next, we estimate VaR_{T+k}, where x_{T+k} represents asset returns at time *T*+*k*. Therefore, *VaR* is a measure of the maximum possible loss of return on assets for a given period under a certain probability. *VaR* is a quantile of the left-tailed (the adapted GARCH-X model) return distribution. From a statistical viewpoint, this symbolizes the downside risk of the housing market, which is the focus of this study.

VaR_{T+k} is the maximum possible loss of holding an asset in *k* periods at a reliance level of 1–*p* for the information set at time *T* (I_T). After estimating the volatility influenced by the carbon price return using the GARCH-X model, we calculate:

$$\widehat{VaR}_{T+k} = \hat{\mu}_T - z_{1-p}\widehat{\delta_T} . \tag{4}$$

We dynamically estimate $\widehat{VaR}$ under $k = 1$. That is, we estimate a series of $\widehat{VaR}$ changing over time, and each $\widehat{VaR}$ is estimated using all information from the previous periods.

3.2. Risk transmission effect of carbon returns on housing returns: VAR-BGARCH model

The GARCH-X model estimates the effect of carbon price returns on the risk of housing price returns using exogenous variables. Studies have found that housing prices also affect carbon emissions (Yu et al., 2021). Researchers also have highlighted the heterogeneous feature of carbon price returns and recommended using GARCH models for related estimations (Huang et al., 2021; Liu & Huang, 2021). In addition, both housing prices and carbon prices are influenced by other factors within their own markets. To exclude the influence of these other factors, we need to consider the past returns and fluctuations of both housing prices and carbon prices. Through a bivariate model, by making both prices endogenous, we can focus on discussing the additional impact of carbon prices on housing prices.[3] Therefore, this study examines the risk transmission effect of carbon returns on housing returns using a two-variable GARCH model.

Bivariate GARCH models are often used to estimate the relationship between housing price returns and other variables (e.g., Christidou & Fountas, 2018). Multivariate GARCH models outperform single-variate ones in estimating asset price returns (Wang & Wu, 2012). However, recent studies have shown that estimating volatility without accounting for the correlation between two asset returns in a VAR model will produce biased results (Lucheroni et al., 2019; Okorie & Lin, 2020). Simultaneously estimating returns and volatility using a VAR-multivariate GARCH model will offer more comprehensive insights into the effect of returns and risk transmissions (Balcilar et al., 2018; Funke et al., 2022). Thus, we apply the VAR-BGARCH model for the estimation:

$$\begin{bmatrix}\Delta CP_t\\ \Delta HP_t\end{bmatrix} = \begin{bmatrix}\varphi_{CP,t}\\ \varphi_{HP,t}\end{bmatrix} + \begin{bmatrix}\sum_{i=1}^{k}\theta_{11,i}\Delta CP_{t-i}\\ \sum_{i=1}^{k}\theta_{21,i}\Delta CP_{t-i}\end{bmatrix} + ; \qquad (5)$$

$$\begin{bmatrix}\sum_{i=1}^{k}\theta_{12,i}\Delta HP_{t-i}\\ \sum_{i=1}^{k}\theta_{22,i}\Delta HP_{t-i}\end{bmatrix} + \begin{bmatrix}\omega_{CP,t}\\ \omega_{HP,t}\end{bmatrix};$$

$$\omega_t \Big| \Omega_{t-1} = \begin{bmatrix}\omega_{CP,t}\\ \omega_{HP,t}\end{bmatrix} \Bigg| \Omega_{t-1} \sim N\left(0, V_t\right). \qquad (6)$$

V_t is the conditional covariance matrix:

$$V_t = \begin{bmatrix}v_{CP,t} & 0\\ v_{CH,t} & v_{HP,t}\end{bmatrix} = \begin{bmatrix}c_{11} & 0\\ c_{21} & c_{22}\end{bmatrix} +$$

$$\begin{bmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{bmatrix}' \omega_{t-1}\omega_{t-1'} \begin{bmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{bmatrix} + \begin{bmatrix}b_{11} & b_{12}\\ b_{21} & b_{22}\end{bmatrix}' V_{t-1} \begin{bmatrix}b_{11} & b_{12}\\ b_{21} & b_{22}\end{bmatrix}. \qquad (7)$$

For all t, each of the conditional variances ($v_{CP,t}$ and $v_{HP,t}$) is positive. Also, the constant matrix of conditional correlation ($v_{CH,t}$) is positive definite.

We used Eq. (5) to estimate the conditional mean, which helps observe the impact of carbon price returns on housing price returns. We employ Eq. (7) to determine conditional variance, which helps determine the impact of new information ($\omega^2_{CP,t}$) and volatility ($v_{CP,t}$) in carbon prices on house price volatility ($v_{HP,t}$), that is, volatility (risk) transmission.

3.3. Risk transmission effect influenced by EPU: VAR-BGARCH-X model

We test Hypothesis 2 by adding the exogenous variable of policy risk to Eq. (6) in the VAR-BGARCH-X model. The other equation in the model, that is, the conditional mean, remains the same as that in Eq. (5):

$$\begin{bmatrix}\Delta CP_t\\ \Delta HP_t\end{bmatrix} = \begin{bmatrix}\varphi_{CP,t}\\ \varphi_{HP,t}\end{bmatrix} + \begin{bmatrix}\sum_{i=1}^{k}\theta_{11,i}\Delta CP_{t-i}\\ \sum_{i=1}^{k}\theta_{21,i}\Delta CP_{t-i}\end{bmatrix} + \begin{bmatrix}\sum_{i=1}^{k}\theta_{12,i}\Delta HP_{t-i}\\ \sum_{i=1}^{k}\theta_{22,i}\Delta HP_{t-i}\end{bmatrix} + \begin{bmatrix}\omega_{CP,t}\\ \omega_{HP,t}\end{bmatrix}. \qquad (8)$$

However, the equation for estimating the conditional covariance matrix is modified as follows:

$$V_t = \begin{bmatrix}c_{11} & 0\\ c_{21} & c_{22}\end{bmatrix} + \begin{bmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{bmatrix}' \omega_{t-1}\omega_{t-1'} \begin{bmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{bmatrix} +$$

$$\begin{bmatrix}b_{11} & b_{12}\\ b_{21} & b_{22}\end{bmatrix}' V_{t-1} \begin{bmatrix}b_{11} & b_{12}\\ b_{21} & b_{22}\end{bmatrix} + \begin{bmatrix}d_{11} & 0\\ d_{21} & d_{22}\end{bmatrix}' \Delta EPU_{t-1} \begin{bmatrix}d_{11} & 0\\ d_{21} & d_{22}\end{bmatrix}. \qquad (9)$$

where ΔEPU is the changing rate of the EPU index. We estimate coefficient d_{22} to observe if policy risks directly affect the volatility of housing price returns and coefficient d_{21} to examine the effects of policy risks on the relationship between housing price volatility and carbon price volatility.

4. Empirical analysis

4.1. Data description and preliminary analysis

To explore the relationship between carbon and housing prices, this study examines the prices of carbon trading pilot sites in four Chinese cities (Beijing, Shanghai, Tianjin, and Chongqing) and uses the sales price index of new residential units in these cities.[4] We used monthly data from January 2014 to February 2021. To validate the model estimates, we calculated the rate of return (%) using data

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[3] Numerous studies examining models of other market influences on housing price fluctuations have used this approach to exclude the influence of housing prices themselves (using lagged housing price fluctuations as control variables). This approach allows these studies to consider only the impact of intermarket shocks, for example, Alqaralleh et al. (2023) and Wang (2023).

[4] This paper infers that to cope with carbon emissions costs, builders may pass on production costs to consumers, or, if unable to do so, reduce housing supply, leading to increased housing price volatility. This phenomenon is more likely to occur in newly built homes. Therefore, this paper uses a newly built house price index.

Table 1. Descriptive statistics and characteristic tests

Unit: %	ΔCP_1	ΔCP_2	ΔCP_3	ΔCP_4	ΔEPU
Mean	–0.5940	0.3809	–0.2286	–0.3890	0.0075
Std. Dev.	13.8957	19.3041	19.5115	47.9922	0.3674
Skewness	–0.7255	0.4654	–2.2094	–0.0248	–0.0222
Kurtosis	2.9912	3.0079	17.8829	1.5454	–0.6613
J-B	**39.6065**	**35.5259**	**1215.9068**	**8.5667**	1.5742
	(0.0000)	(0.0000)	(0.0000)	(0.0138)	(0.4552)
PP test	**–9.1912**	**–8.3828**	**–12.8865**	**–9.0959**	**–23.2648**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unit: %	ΔHP_1	ΔHP_2	ΔHP_3	ΔHP_4	
Mean	0.4673	0.5324	0.3175	0.4014	
Std. Dev.	0.9663	1.0933	0.8569	0.6402	
Skewness	2.1030	1.8786	2.3900	–0.5853	
Kurtosis	6.0219	4.1728	6.8529	1.1861	
J-B	**193.3313**	**112.9764**	**250.1562**	**9.9509**	
	(0.0000)	(0.0000)	(0.0000)	(0.0069)	
PP test	**–3.2747**	**–2.6017**	**–2.7253**	**–2.6675**	
	(0.0013)	(0.0097)	(0.0069)	(0.0081)	

Notes: ΔCP_1, ΔCP_2, ΔCP_3, and ΔCP_4 respectively denote the returns of carbon price in Beijing, Shanghai, Tianjin, and Chongqing. ΔHP_1, ΔHP_2, ΔHP_3, and ΔHP_4 respectively denote the returns of newly-built house price index in Beijing, Shanghai, Tianjin, and Chongqing. ΔEPU denotes the changing rate of the EPU index. J-B stands for the Jarque-Bera normality test statistics with null hypothesis that series follows normal distribution. PP test is used to test the unit root of series. Number in parentheses is *p*-value. Number in bold stands for significance at 5%.

from the carbon and housing price indices. We obtained transaction prices (RMB/ton-CO2) for the four carbon pilot sites from the carbon trading website[5] and data on the housing price index from the National Bureau of Statistics in China.[6] We also employed policy uncertainty indicators for China to observe the impact of policy risks on the relationship between carbon and housing prices.

To quantify EPU in China, we adopted Baker et al.'s (2016) index that is based on news-based EPU indices for the United States. Index data for EPU can be downloaded from the website.[7] It estimated a scaled frequency count of news on policy-related economic uncertainty featured in the South China Morning Post. It can be used to assess the instability of government policies.

Table 1 presents the data characteristics, including descriptive statistics and two verification results. We conduct a Jarque-Bera test to determine if the variable follows a normal distribution (Jarque-Bera test) and a PP test to estimate if the variable has a unit root phenomenon. Figure 1 plots the original time series for all the data. It shows that the carbon price trend in Beijing relatively differs from those in the other three cities. In early 2014, carbon prices in Shanghai, Tianjin, and Chongqing were approximately RMB 30 (ton-CO2), and from 2016 to 2017, the price fell to less than RMB 10. After 2018, the prices gradually increased to RMB 20–30. In Beijing, by contrast, the carbon price was greater than RMB 30 for most of the study period and gradually increased to more than RMB 80 between 2018 and 2020. In 2021, however, its carbon price fell to a level close to those of the other three markets. The trend of housing price indexes in the four cities gradually increased during the data period. Housing prices sharply increased in all the cities except Chongqing in 2016, when the carbon price was at its lowest.

Compared with other cities, Chongqing's housing prices were lagging behind. Until 2017, there was an obvious rise in prices. However, there was a lag in the response of carbon prices. Carbon prices continued to increase in 2016 and were at their lowest in 2017. Figure 1 suggests an opposing trend for the carbon and housing markets. In addition, it shows increased policy uncertainty in China since 2017.

Next, we compare the performance of the two markets by region. In terms of average monthly returns, only Shanghai reported a positive return on carbon and the highest returns on housing among the four cities (Table 1). Beijing had the lowest carbon returns but the second highest housing returns. The normality test indicated that all data, except those on the rate of change in EPU, rejected the assumption of normal distribution. The unit root test showed that all carbon returns and housing returns significantly rejected the tested hypotheses, which means they are stationary. The changing EPU rate is also stationary, and thus, the data can be used to estimate the empirical model.

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[5] http://www.tanjiaoyi.com

[6] http://www.stats.gov.cn/

[7] http://www.policyuncertainty.com/scmp_monthly.html

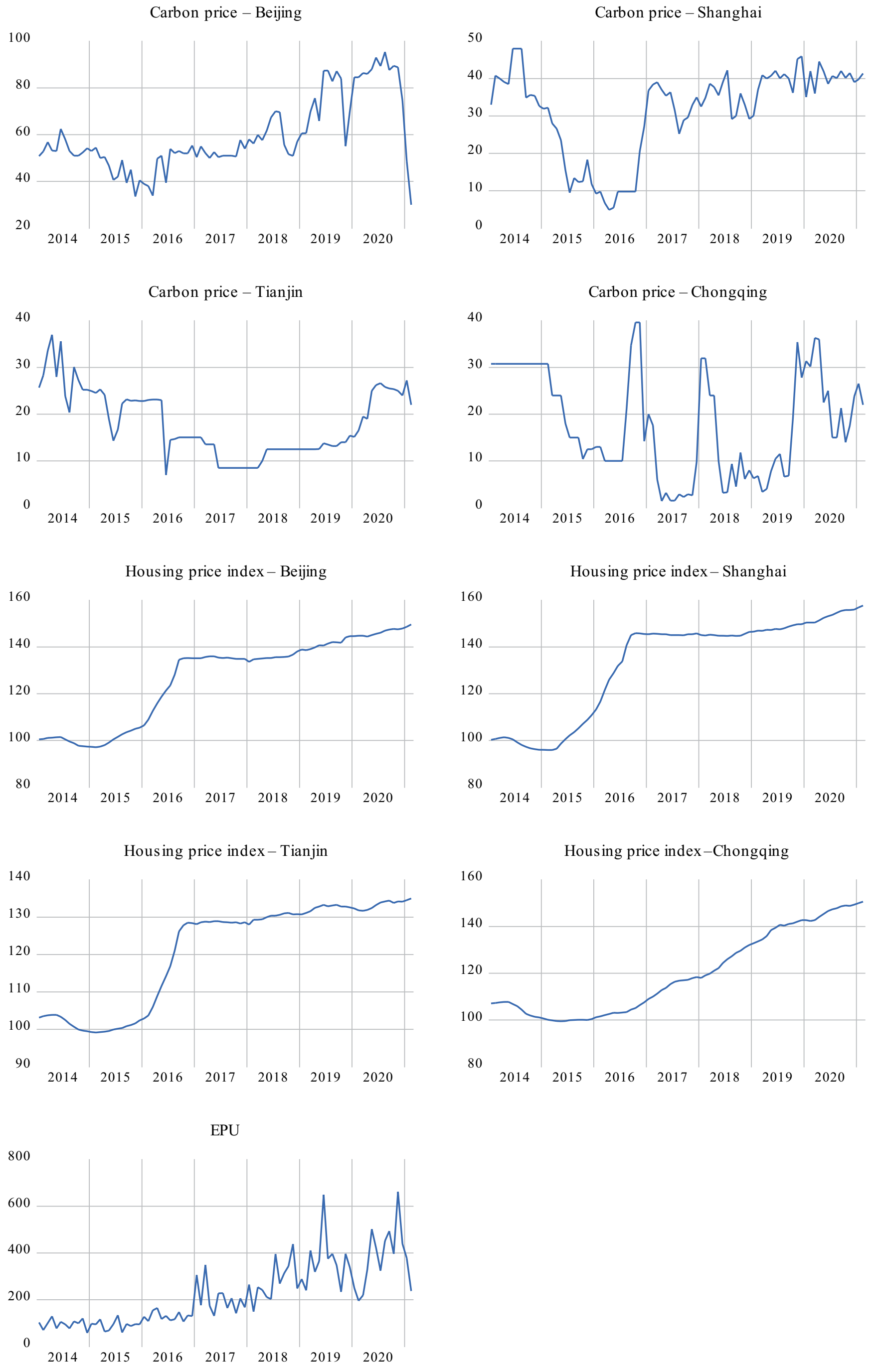

Figure 1. Carbon price, housing price index, and EPU

4.2. Estimation results of extreme housing price risk

The Basel II regulatory framework defines market, credit, and operational risks in terms of estimated VaR and requires banks to manage these risks. VaR is one of the most commonly adopted methods to assess extreme risks. We use the GARCH-X model in Eq. (3) to estimate the volatility of housing price returns over time ($\widehat{\delta_t^2}$), which includes the effect of carbon returns, and to calculate VaR_{T+k}. For comparison, we calculate two confidence intervals, p = 99% and p = 95%. We estimate the maximum possible loss of holding the asset for k periods in the two extreme cases (1% and 5%). With k = 1, we present a dynamic estimation $\widehat{VaR}$ series. That is, each VaR is estimated using all available information from the previous period (Figure 2).

Boudoukh et al. (1998) and Escanciano and Pei (2012) highlight the popularity of historical simulations (HS) as a VaR forecast approach adopted by international commercial banks. HS has the advantage of being a convenient approach. It can be used to estimate the performance of asset returns in extreme cases without using hypothetical

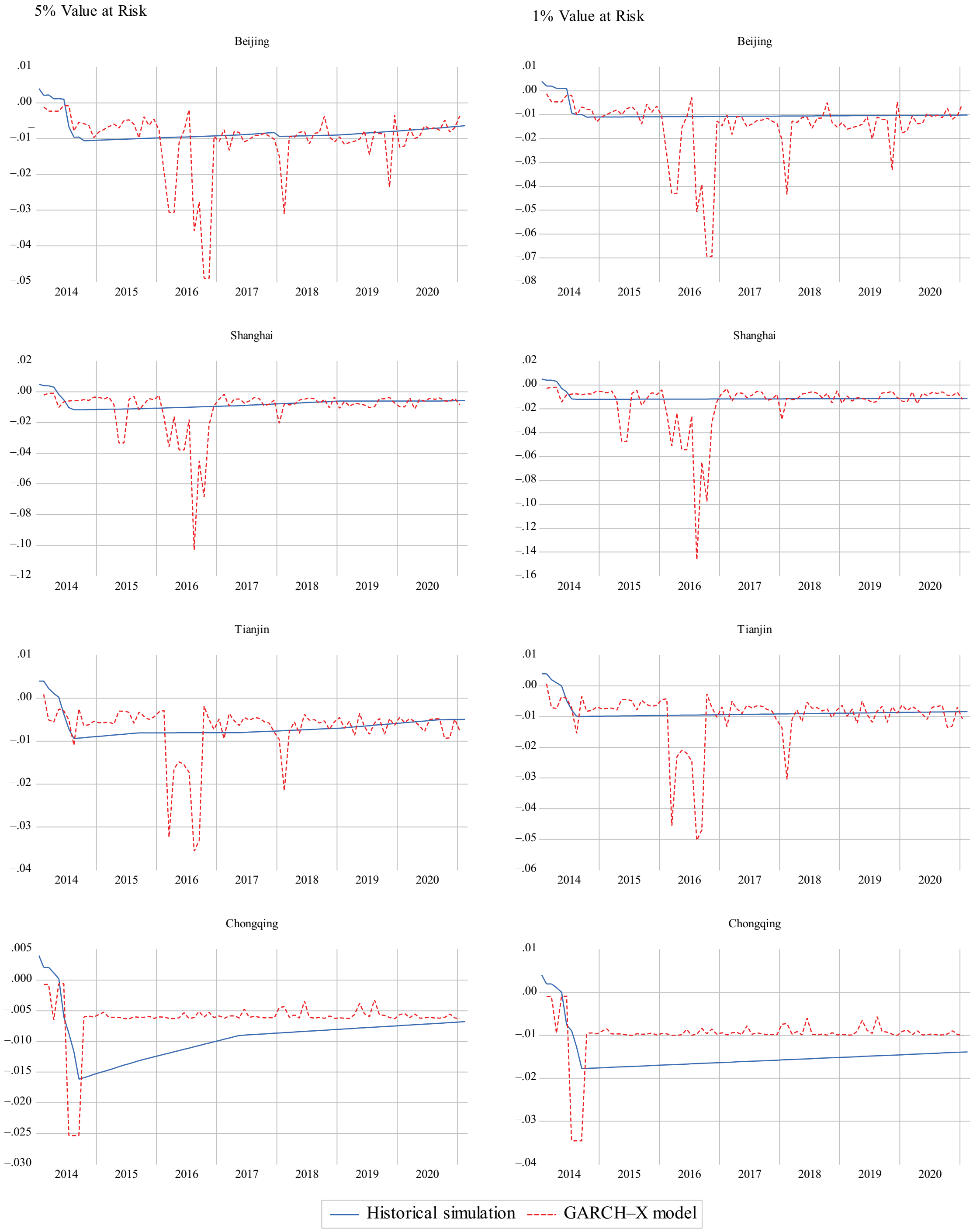

Figure 2. Value at risk

distributions and to calculate the maximum loss of invested assets. Pritsker (2006) and Escanciano and Pei (2012), however, point out the limitations of HS. It is not suitable for long-term estimations with large data variations. Hull and White (1998) suggest using a GARCH model to significantly improve HS-estimated VaR. Figure 2 plots the HS estimation results for comparison.

The estimation results show no significant variations in the VaR estimated using HS for the sample interval. By contrast, there is a significant variation in housing prices (Figure 1), which implies a higher probability of extreme conditions or greater extreme losses triggered by significant fluctuations in housing prices. In Figure 2, the VaR is estimated using the GARCH-X model, which includes the effect of carbon prices and serves as a more accurate measure of changes in VaR during periods of high market volatility. In 2016, housing prices in all cities except Chongqing significantly increased, and there was a high probability of downward revisions in these markets after accounting for the possible exogenous impact of carbon prices.

4.3. Risk transmission effects of carbon prices on housing prices

This study used the VAR-BGARCH model, in which carbon price returns are the endogenous variable, to estimate the correlation between carbon and housing prices from the viewpoints of returns and volatility. Table 2 presents the estimation results of the model. Studies have found that the relationship between the carbon price and local city variables differs from that between carbon price and other city variables. In addition, this study analyzes the relationship between housing prices and the average prices of the other three (non-local) carbon trading pilot sites to determine if carbon prices in the local city and those in other cities have differing effects on housing prices.

Table 2. The impact of carbon returns on house returns: The VAR-BGARCH

Beijing						Shanghai					
	Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic
Mean model: $\Delta CP_{1,t}$			Mean model: $\Delta MCP_{1,t}$			Mean model: $\Delta CP_{2,t}$			Mean model: $\Delta MCP_{2,t}$		
θ_{11}	–0.0173	–0.1402	θ_{11}	**0.2328**	1142.4742	θ_{11}	–0.0765	–0.8069	θ_{11}	–0.0722	–0.6661
θ_{12}	1.4469	1.1506	θ_{12}	**–0.7546**	–140.1434	θ_{12}	1.4642	0.5035	θ_{12}	1.2098	0.9570
$\varphi_{CP,t}$	–0.3222	–0.2869	$\varphi_{MCP,t}$	**–1.4450**	–877.8356	$\varphi_{CP,t}$	–0.1296	–0.0827	$\varphi_{MCP,t}$	–0.5880	–0.4620
Mean model: $\Delta HP_{1,t}$			Mean model: $\Delta HP_{1,t}$			Mean model: $\Delta HP_{2,t}$			Mean model: $\Delta HP_{2,t}$		
θ_{21}	0.0022	0.5201	θ_{21}	**0.0023**	3616.3174	θ_{21}	**0.0049**	4.0707	θ_{21}	**–0.0087**	–3.0287
θ_{22}	**0.6895**	10.6512	θ_{22}	**0.1406**	2045.7855	θ_{22}	**0.8029**	25.5518	θ_{22}	**0.8577**	19.5003
$\varphi_{HP,t}$	0.0601	1.1875	$\varphi_{HP,t}$	**0.0985**	9560.1465	$\varphi_{HP,t}$	–0.0031	–0.0965	$\varphi_{HP,t}$	0.0266	1.0474
Variance model			Variance model			Variance model			Variance model		
c_{11}	**6.3116**	4.1188	c_{11}	**6.1786**	21.6399	c_{11}	**7.5196**	3.2952	c_{11}	**8.0646**	5.0324
c_{21}	**0.1701**	2.3335	c_{21}	**–0.0083**	–21.6569	c_{21}	–0.0123	–0.1333	c_{21}	–0.1083	–1.4160
c_{22}	<–0.0000	<–0.0000	c_{22}	<–0.0000	–0.2718	c_{22}	**–0.2165**	–5.3078	c_{22}	<0.0000	<0.0000
a_{11}	**0.7876**	4.9515	a_{11}	**0.0226**	4.1877	a_{11}	0.1218	0.8535	a_{11}	–0.0445	–0.3857
a_{12}	0.0063	0.9663	a_{12}	**–0.0180**	–513.4102	a_{12}	0.0034	1.3434	a_{12}	**–0.0186**	–3.7212
a_{21}	**6.1208**	1.9822	a_{21}	**1.2028**	2.3178	a_{21}	–8.7774	–1.4244	a_{21}	–7.4425	–1.4077
a_{22}	**0.6690**	4.3962	a_{22}	**1.5640**	511.4113	a_{22}	**1.2840**	8.4660	a_{22}	**1.0546**	6.7483
b_{11}	**0.5876**	4.2053	b_{11}	**0.8095**	33.1296	b_{11}	**0.3906**	2.6329	b_{11}	**0.5748**	2.9000
b_{12}	**–0.0257**	–6.2511	b_{12}	**–0.0011**	–33.1186	b_{12}	0.0051	1.4181	b_{12}	**0.0141**	3.8127
b_{21}	–4.7633	–1.7454	b_{21}	**–3.7859**	–23.0964	b_{21}	**–19.9000**	–3.4224	b_{21}	**7.7220**	3.0603
b_{22}	0.2610	1.4414	b_{22}	**0.0051**	22.9372	b_{22}	0.0835	0.8047	b_{22}	0.2069	1.1227
Tianjin						Chongqing					
	Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic
Mean model: $\Delta CP_{3,t}$			Mean model: $\Delta MCP_{3,t}$			Mean model: $\Delta CP_{4,t}$			Mean model: $\Delta MCP_{4,t}$		
θ_{11}	**0.2065**	1.9738	θ_{11}	–0.0621	–0.6246	θ_{11}	0.0843	0.7108	θ_{11}	**–0.3266**	–3.8413
θ_{12}	**–6.2375**	–2.5469	θ_{12}	**2.6550**	2.1767	θ_{12}	0.0586	0.0106	θ_{12}	**2.3681**	2.4478
$\varphi_{CP,t}$	0.6241	0.4744	$\varphi_{MCP,t}$	–1.6757	–1.6412	$\varphi_{CP,t}$	–1.1999	–0.3406	$\varphi_{MCP,t}$	–1.3175	–1.6265
Mean model: $\Delta HP_{3,t}$			Mean model: $\Delta HP_{3,t}$			Mean model: $\Delta HP_{4,t}$			Mean model: $\Delta HP_{4,t}$		
θ_{21}	0.0033	1.2642	θ_{21}	0.0010	0.2682	θ_{21}	0.0006	0.7182	θ_{21}	0.0071	1.1952
θ_{22}	**0.3670**	5.6592	θ_{22}	**0.6235**	6.4067	θ_{22}	**0.7727**	10.4201	θ_{22}	**0.7243**	10.8359
$\varphi_{HP,t}$	0.0389	1.1412	$\varphi_{HP,t}$	0.0416	1.3132	$\varphi_{HP,t}$	0.0878	1.7482	$\varphi_{HP,t}$	**0.1118**	2.1999
Variance model			Variance model			Variance model			Variance model		
c_{11}	**8.5178**	6.3514	c_{11}	**6.4641**	10.8145	c_{11}	**11.5379**	3.1162	c_{11}	**4.8934**	5.0824
c_{21}	–0.0317	–0.6890	c_{21}	**–0.2268**	–6.5057	c_{21}	**0.2010**	2.7911	c_{21}	–0.1135	–1.4922
c_{22}	**0.1966**	5.0746	c_{22}	–0.0001	–0.0002	c_{22}	<–0.0000	<–0.0000	c_{22}	<–0.0000	<–0.0000
a_{11}	**–0.6491**	–4.3262	a_{11}	–0.1741	–1.5004	a_{11}	**0.4951**	6.8176	a_{11}	**1.0607**	6.2951
a_{12}	0.0026	0.6858	a_{12}	0.0043	1.0778	a_{12}	–0.0012	–1.1894	a_{12}	–0.0039	–0.5257
a_{21}	4.2596	1.0135	a_{21}	**4.2388**	2.1526	a_{21}	9.0813	0.8670	a_{21}	–2.6900	–0.9239
a_{22}	**1.0431**	7.6747	a_{22}	**0.9203**	7.2679	a_{22}	**0.5033**	3.9748	a_{22}	0.1035	0.5281

End of Table 2

Tianjin						Chongqing					
	Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic
b_{11}	–0.1677	–0.9539	b_{11}	**–0.5861**	–8.9068	b_{11}	**0.8267**	10.8102	b_{11}	0.0320	0.2302
b_{12}	–0.0038	–1.2303	b_{12}	–0.0080	–1.0235	b_{12}	–0.0042	–1.8249	b_{12}	**–0.0247**	–2.9474
b_{21}	**–16.0362**	–4.3833	b_{21}	5.4016	1.7329	b_{21}	–9.0903	–0.4076	b_{21}	**5.6511**	2.3469
b_{22}	–0.1996	–1.5967	b_{22}	0.1890	1.1485	b_{22}	**–0.6326**	–4.6284	b_{22}	**0.7265**	7.4424

Notes: ΔCP_1, ΔCP_2, ΔCP_3, and ΔCP_4 respectively denote the returns of carbon price in Beijing, Shanghai, Tianjin, and Chongqing. ΔHP_1, ΔHP_2, ΔHP_3, and ΔHP_4 respectively denote the returns of newly-built house price index in Beijing, Shanghai, Tianjin, and Chongqing. ΔMCP_1, ΔMCP_2, ΔMCP_3, and ΔMCP_4 respectively denote average carbon price returns for three cities other than Beijing, Shanghai, Tianjin, and Chongqing. Number in bold stands for significance at 5%.

Table 2 indicates that only Beijing and Shanghai have significant information transmissions from carbon returns to housing returns. In terms of information transmission, the observed coefficient is θ_{21}, which is significant only for Beijing and Shanghai. Carbon price returns of other cities have a significantly positive impact on housing price returns in Beijing. By contrast, other cities' carbon price returns have a negative impact on Shanghai's housing price, whereas local carbon price returns have a significantly positive impact.

In Beijing, Tianjin, and Chongqing, carbon returns have a more significant impact on other cities' housing price returns than on local housing price returns ($\theta_{12} \neq 0$). Given the potential for inter-regional correlation in carbon price markets, housing market sentiments in other cities may affect carbon price returns in a given region, which may transmit information to local carbon prices. Table 2 also shows that the estimated results for a_{21} or b_{21} are significantly non-zero for all cities, indicating that even though the information transmission effect of the carbon price is not significant, the risk transmission phenomenon is prevalent in all four markets.

Table 3. Causal relationships estimated by the VAR-BGARCH model

Beijing					
Causality in mean					
	χ^2			χ^2	
$\Delta CP_1 \nrightarrow \Delta HP_1$	0.2705 (0.6030)		$\Delta MCP_1 \nrightarrow \Delta HP_1$	**13077751.5282** (0.0000)	
Causality in variance					
	χ^2	*F*-statistic		χ^2	*F*-statistic
$\Delta CP_1 \nrightarrow \Delta HP_1$	4.8312 (0.0893)	2.4156	$\Delta MCP_1 \nrightarrow \Delta HP_1$	**657.8119** (0.0000)	**328.9060**
Shanghai					
Causality in mean					
	χ^2			χ^2	
$\Delta CP_2 \nrightarrow \Delta HP_2$	**16.5709** (0.0000)		$\Delta MCP_2 \nrightarrow \Delta HP_2$	**9.1733** (0.0025)	
Causality in variance					
	χ^2	*F*-statistic		χ^2	*F*-statistic
$\Delta CP_2 \nrightarrow \Delta HP_2$	**14.1515** (0.0008)	**7.0757**	$\Delta MCP_2 \nrightarrow \Delta HP_2$	**9.5520** (0.0084)	**4.7760**
Tianjin					
Causality in mean					
	χ^2			χ^2	
$\Delta CP_3 \nrightarrow \Delta HP_3$	1.5983 (0.2061)		$\Delta MCP_3 \nrightarrow \Delta HP_3$	0.0719 (0.7886)	

End of Table 3

Causality in variance					
	χ^2	*F*-statistic		χ^2	*F*-statistic
$\Delta CP_3 \nrightarrow \Delta HP_3$	**20.4504** (0.0000)	**10.2252**	$\Delta MCP_3 \nrightarrow \Delta HP_3$	**6.4599** (0.0396)	**3.2300**
Chongqing					
Causality in mean					
	χ^2			χ^2	
$\Delta CP_4 \nrightarrow \Delta HP_4$	0.5159 (0.4726)		$\Delta MCP_4 \nrightarrow \Delta HP_4$	1.4285 (0.2320)	
Causality in variance					
	χ^2	*F*-statistic		χ^2	*F*-statistic
$\Delta CP_4 \nrightarrow \Delta HP_4$	0.7651 (0.6821)	0.3825	$\Delta MCP_4 \nrightarrow \Delta HP_4$	**6.7025** (0.0350)	**3.3513**

Notes: ΔCP_1, ΔCP_2, ΔCP_3, and ΔCP_4 respectively denote the returns of carbon price in Beijing, Shanghai, Tianjin, and Chongqing. ΔHP_1, ΔHP_2, ΔHP_3, and ΔHP_4 respectively denote the returns of newly-built house price index in Beijing, Shanghai, Tianjin, and Chongqing. ΔMCP_1, ΔMCP_2, ΔMCP_3, and ΔMCP_4 respectively denote average carbon price returns for three cities other than Beijing, Shanghai, Tianjin, and Chongqing. Number in parentheses is *p*-value. Number in bold stands for significance at 5%.

We use the results from Table 2 to estimate the causality test in Table 3 to further elucidate the effects of information and risk transmissions. In Table 3, only Beijing and Shanghai reported significant results in the causality test for the impact of carbon returns on housing returns. However, the causality test for variance revealed significant risk transmission from the carbon price to the housing price in all four cities, with the risk transmission effect being more significant in Shanghai and Tianjin's housing market. This is because local carbon returns volatility (risk) affects carbon returns volatility in Shanghai and Tianjin, and the effects of carbon returns volatility in other cities are significant. In contrast, the transmission effects of carbon price risks in other cities are only significant in Beijing and Chongqing's housing markets.

Drawing on the estimation results in Table 3, this study validates Hypothesis 1 and finds that the risk of housing price volatility is affected by carbon returns, highlighting a green swan effect in the housing market. The test results further echo the extreme risk in the housing market illustrated in Figure 2, which is better estimated owing to the inclusion of carbon returns and their effects. To illustrate the consistency in results with those in Figure 2 and to present the effect of the carbon price on housing price risks as estimated by the VAR-BGARCH model, we plot in Figure 3 the volatility of housing price returns and the correlation coefficient between carbon and housing price returns. The level of volatility helps estimate the risk of fluctuations in housing price returns, while the correlation coefficient shows whether there is a similar trend between the two price returns. As shown in Figure 3, both Tianjin and Chongqing have a particularly positive correlation between carbon returns and housing returns when there is a high risk of total housing price volatility.

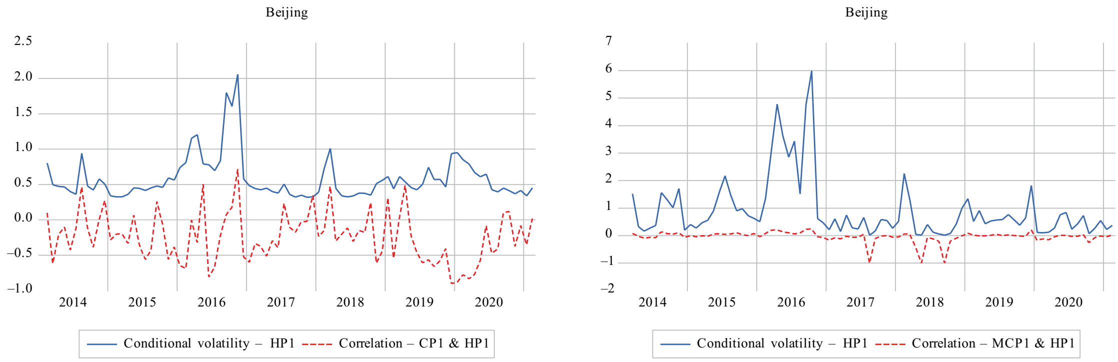

Figure 3. *To be continued*

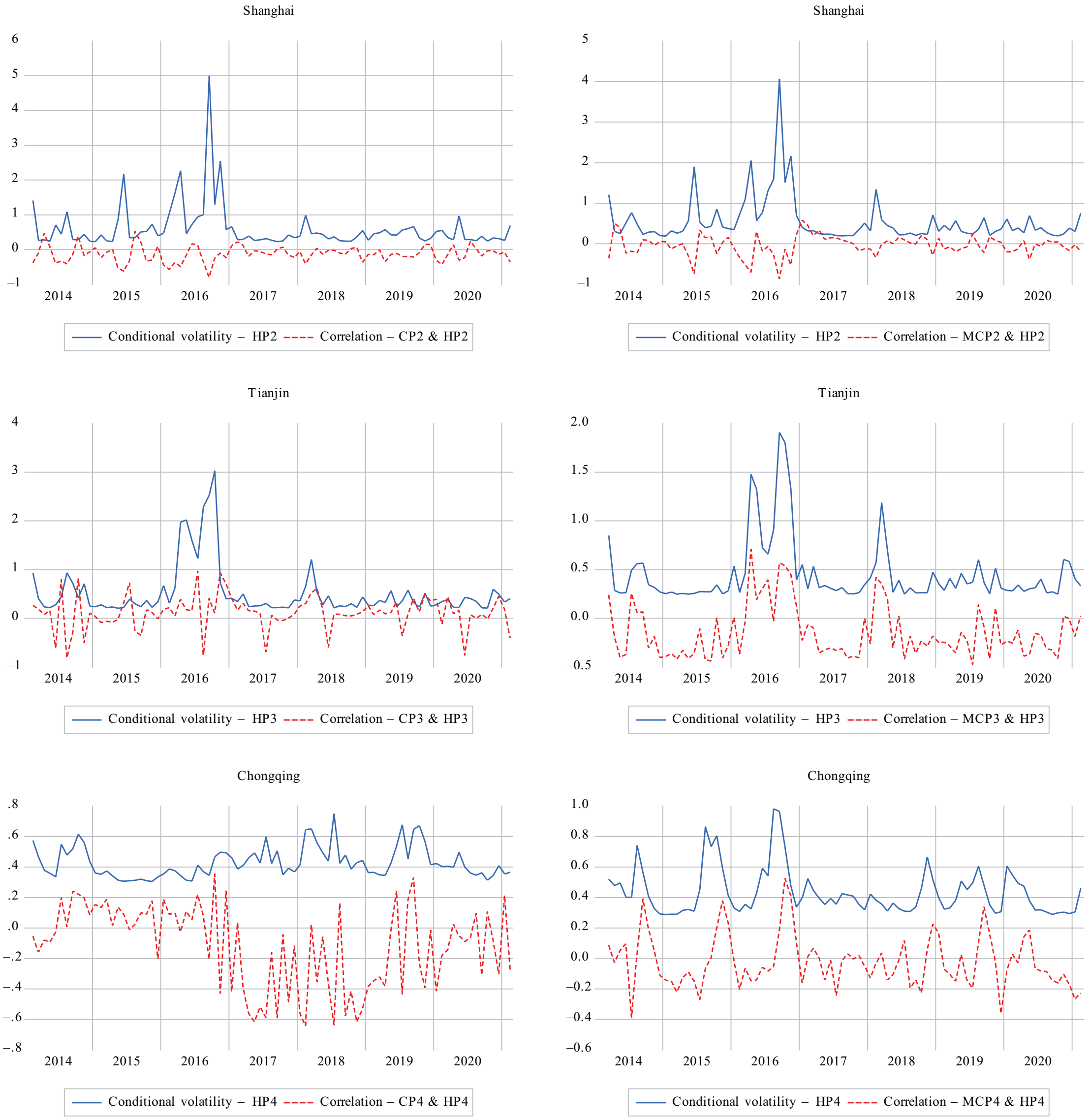

Figure 3. Conditional volatility and correlation (VAR-MGARCH model)

4.4. Impact of policy risk on risk transmission effect by carbon price on housing price

We test Hypothesis 2 to examine for green swan effects triggered by policy risks on the housing market. Table 4 presents the results of the VAR-BGARCH-X model, and Table 5 lists the results of the causality test. The causality test revealed that Beijing and Shanghai show information transmission effects by both local carbon returns and carbon returns in other cities, while Tianjin only shows information transmission effects by carbon returns in other cities. A comparative analysis of Table 3 and Table 5 indicate that the information transmission effect of carbon returns is more significant in other cities after accounting for policy risks.

Furthermore, as in Table 2, Table 4 shows that the impact of carbon prices on housing prices is sometimes positive and sometimes negative when viewed in terms of the rate of return. This is consistent with our inference. This paper proposes that two factors may contribute to the carbon price’s impact on housing prices. Consumption-side effects would cause a carbon price increase to cause housing prices to fall. This is because the inclusion of carbon emissions from high energy consumption in the cost of housing use should reduce housing demand and prices. Supply-side effects, on the other hand, would cause a carbon price increase to have a positive impact on housing prices. Rising carbon emissions costs increase builders’ costs, and when builders pass these costs on to consumers, housing prices increase. Therefore, the effects of carbon prices on housing prices in Tables 2 and 4 are sometimes negative and sometimes positive, indicating whether the dominant carbon price impact in the housing market is from consumption or production, respectively.

Table 4. The impact of carbon returns on house returns: The VAR-BGARCH-X

Beijing						Shanghai					
	Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic
Mean model: $\Delta CP_{1,t}$			Mean model: $\Delta MCP_{1,t}$			Mean model: $\Delta CP_{2,t}$			Mean model: $\Delta MCP_{2,t}$		
θ_{11}	**–0.2970**	–19.4625	θ_{11}	0.0419	0.4991	θ_{11}	**–0.1130**	–18.6175	θ_{11}	**0.0314**	15.0575
θ_{12}	**2.3717**	95.4110	θ_{12}	**2.5141**	2.3318	θ_{12}	1.9660	1.2881	θ_{12}	**1.1611**	2.2600
$\varphi_{CP,t}$	**–1.5524**	–27.0024	$\varphi_{MCP,t}$	–2.6299	–1.6994	$\varphi_{CP,t}$	**0.4142**	3.2318	$\varphi_{MCP,t}$	**–0.1852**	–61.2597
Mean model: $\Delta HP_{1,t}$			Mean model: $\Delta HP_{1,t}$			Mean model: $\Delta HP_{2,t}$			Mean model: $\Delta HP_{2,t}$		
θ_{21}	**0.0113**	51.6589	θ_{21}	**0.0086**	2.1416	θ_{21}	**0.0056**	836.9285	θ_{21}	**–0.0091**	–6779.3384
θ_{22}	**0.4146**	1997.2582	θ_{22}	**0.6849**	10.0783	θ_{22}	**0.7534**	34.9643	θ_{22}	**0.8417**	326.5507
$\varphi_{HP,t}$	**0.1261**	2712.7193	$\varphi_{HP,t}$	0.0880	1.8026	$\varphi_{HP,t}$	**0.0022**	14.7634	$\varphi_{HP,t}$	**0.0385**	4268.0819
Variance model			Variance model			Variance model			Variance model		
c_{11}	**10.5232**	29.5045	c_{11}	**10.9303**	8.8495	c_{11}	**7.8642**	193.2903	c_{11}	**5.5387**	20.3574
c_{21}	**–0.1939**	–104.6297	c_{21}	–0.1095	–1.5409	c_{21}	**0.0234**	73.4606	c_{21}	**0.0295**	23.0622
c_{22}	**0.1315**	8.2970	c_{22}	0.0340	0.3278	c_{22}	**0.0903**	5.3636	c_{22}	**0.0007**	3.0624
a_{11}	**–0.1135**	–33.6977	a_{11}	**0.5185**	4.1134	a_{11}	**0.1528**	59.6465	a_{11}	**0.0779**	9.6199
a_{12}	**–0.0145**	–114.4350	a_{12}	**0.0285**	4.4732	a_{12}	**0.0059**	80.3866	a_{12}	**–0.0164**	–37.0936
a_{21}	1.9573	1.7574	a_{21}	–2.7813	–1.2228	a_{21}	**–13.3563**	–15.9614	a_{21}	**–5.5977**	–13.8088
a_{22}	**1.3017**	24.5266	a_{22}	**0.6171**	4.6863	a_{22}	**1.5335**	76.1222	a_{22}	**1.2114**	37.1166
b_{11}	**0.6430**	13.9817	b_{11}	0.0110	0.0627	b_{11}	**0.4815**	10.8788	b_{11}	**–0.8395**	–35.3058
b_{12}	**–0.0107**	–14.4881	b_{12}	**–0.0225**	–4.4253	b_{12}	**0.0024**	10.8259	b_{12}	**–0.0043**	–32.2215
b_{21}	–0.0589	–0.0766	b_{21}	–3.0804	–0.5808	b_{21}	**–13.1082**	–7.7207	b_{21}	–0.2864	–0.5270
b_{22}	0.0010	0.0769	b_{22}	–0.0991	–0.5132	b_{22}	**–0.0657**	–7.6759	b_{22}	–0.0015	–0.5261
d_{11}	**–0.0636**	–21.2892	d_{11}	**0.0921**	2.3802	d_{11}	**–0.0435**	–27.3719	d_{11}	–0.0081	–0.3607
d_{21}	**0.0005**	19.4770	d_{21}	–0.0018	–0.9724	d_{21}	**0.0005**	38.2603	d_{21}	**–0.0046**	–6.0967
d_{22}	**0.0040**	8.2957	d_{22}	0.0040	1.3933	d_{22}	**–0.0040**	–5.3638	d_{22}	**–0.0026**	–3.0505
Tianjin						Chongqing					
	Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic		Coefficient	*t*-statistic
Mean model: $\Delta CP_{3,t}$			Mean model: $\Delta MCP_{3,t}$			Mean model: $\Delta CP_{4,t}$			Mean model: $\Delta MCP_{4,t}$		
θ_{11}	0.0627	0.7845	θ_{11}	**–0.0171**	–14.2362	θ_{11}	0.1184	1.3887	θ_{11}	**–0.2951**	–3.9456
θ_{12}	**–6.6409**	–2.8603	θ_{12}	**2.8691**	149.6206	θ_{12}	**–7.3507**	–24.8978	θ_{12}	**2.7436**	3.8943
$\varphi_{CP,t}$	0.0021	0.0026	$\varphi_{MCP,t}$	**–2.6558**	–49.4959	$\varphi_{CP,t}$	**4.2259**	28.2924	$\varphi_{MCP,t}$	**–2.0413**	–2.5490
Mean model: $\Delta HP_{3,t}$			Mean model: $\Delta HP_{3,t}$			Mean model: $\Delta HP_{4,t}$			Mean model: $\Delta HP_{4,t}$		
θ_{21}	0.0040	1.7279	θ_{21}	**0.0013**	22.5500	θ_{21}	0.0001	0.1649	θ_{21}	0.0055	1.1334
θ_{22}	**0.5098**	5.0461	θ_{22}	**0.7199**	4838.5990	θ_{22}	**0.6938**	2488.1079	θ_{22}	**0.7630**	11.2275
$\varphi_{HP,t}$	0.0143	0.4969	$\varphi_{HP,t}$	**0.0283**	37.8519	$\varphi_{HP,t}$	**0.0590**	63.5251	$\varphi_{HP,t}$	**0.1127**	2.2596
Variance model			Variance model			Variance model			Variance model		
c_{11}	**4.7640**	3.4620	c_{11}	**8.5708**	260.9649	c_{11}	**8.1927**	4.4142	c_{11}	**3.3841**	3.8250
c_{21}	0.0958	1.1575	c_{21}	**–0.1036**	–36.5936	c_{21}	**0.1935**	3814.0604	c_{21}	–0.0223	–0.4258
c_{22}	**0.1978**	2.9638	c_{22}	**0.1676**	32.7568	c_{22}	**0.2703**	7.8148	c_{22}	0.1399	1.6780
a_{11}	**0.6942**	3.4121	a_{11}	**–0.1761**	–101.1754	a_{11}	**0.5111**	10.5099	a_{11}	**1.0438**	7.8401
a_{12}	**0.0199**	5.0048	a_{12}	**0.0012**	68.4355	a_{12}	**–0.0035**	–9.6742	a_{12}	–0.0019	–0.2996
a_{21}	0.6959	0.1935	a_{21}	**7.6494**	14.8020	a_{21}	**–18.8135**	–2.5623	a_{21}	**–5.1764**	–3.7797
a_{22}	**0.8018**	6.6282	a_{22}	**1.0629**	38.0468	a_{22}	**0.4953**	12.2092	a_{22}	–0.2076	–1.4497
b_{11}	0.0136	0.1263	b_{11}	**0.0701**	2.2118	b_{11}	**0.8380**	54.2589	b_{11}	0.1844	1.9374
b_{12}	0.0035	1.1650	b_{12}	**–0.0017**	–2.2064	b_{12}	**0.0008**	8.8192	b_{12}	**0.0211**	2.8446
b_{21}	**17.4960**	4.6520	b_{21}	**1.8103**	7.4507	b_{21}	**16.6837**	4.0332	b_{21}	3.0573	1.8617
b_{22}	–0.1462	–0.9332	b_{22}	**–0.0436**	–7.5055	b_{22}	**0.0154**	3.4756	b_{22}	**0.5941**	4.2102
d_{11}	**0.1939**	4.4514	d_{11}	**0.0266**	208.8232	d_{11}	–0.0570	–1.8562	d_{11}	**0.1129**	4.0193
d_{21}	–0.0022	–0.9473	d_{21}	**–0.0028**	–44.4783	d_{21}	**0.0026**	2674.1921	d_{21}	**–0.0055**	–3.5403
d_{22}	–0.0003	–0.1666	d_{22}	**–0.0036**	–32.7715	d_{22}	0.0038	7.8207	d_{22}	–0.0002	–0.0639

Notes: ΔCP_1, ΔCP_2, ΔCP_3, and ΔCP_4 respectively denote the returns of carbon price in Beijing, Shanghai, Tianjin, and Chongqing. ΔHP_1, ΔHP_2, ΔHP_3, and ΔHP_4 respectively denote the returns of newly-built house price index in Beijing, Shanghai, Tianjin, and Chongqing. ΔMCP_1, ΔMCP_2, ΔMCP_3, and ΔMCP_4 respectively denote average carbon price returns for three cities other than Beijing, Shanghai, Tianjin, and Chongqing. Number in bold stands for significance at 5%.

Table 5. Causal relationships estimated by the VAR-BGARCH-X model

Beijing			Shanghai			Tianjin			Chongqing		
Causality in mean			Causality in mean			Causality in mean			Causality in mean		
	χ^2			χ^2			χ^2			χ^2	
$\Delta CP_1 \nrightarrow \Delta HP_1$	**2668.6386**		$\Delta CP_2 \nrightarrow \Delta HP_2$	**700449.2614**		$\Delta CP_3 \nrightarrow \Delta HP_3$	2.9856		$\Delta CP_4 \nrightarrow \Delta HP_4$	0.0272	
	(0.0000)			(0.0000)			(0.0840)			(0.8690)	
$\Delta MCP_1 \nrightarrow \Delta HP_1$	**4.5862**		$\Delta MCP_2 \nrightarrow \Delta HP_2$	**45959429.5007**		$\Delta MCP_3 \nrightarrow \Delta HP_3$	**508.5019**		$\Delta MCP_4 \nrightarrow \Delta HP_4$	1.2847	
	(0.0322)			(0.0000)			(0.0000)			(0.2570)	
Causality in variance			Causality in variance			Causality in variance			Causality in variance		
	χ^2	*F*-statistic		χ^2	*F*-statistic		χ^2	*F*-statistic		χ^2	*F*-statistic
$\Delta CP_1 \nrightarrow \Delta HP_1$	3.3057	1.6529	$\Delta CP_2 \nrightarrow \Delta HP_2$	**300.7987**	**150.3994**	$\Delta CP_3 \nrightarrow \Delta HP_3$	**25.1821**	**12.5910**	$\Delta CP_4 \nrightarrow \Delta HP_4$	**19.0459**	**9.5230**
	(0.1915)			(0.0000)			(0.0000)			(0.0001)	
$\Delta MCP_1 \nrightarrow \Delta HP_1$	2.1063	1.0531	$\Delta MCP_2 \nrightarrow \Delta HP_2$	**209.1866**	**104.5933**	$\Delta MCP_3 \nrightarrow \Delta HP_3$	**332.3792**	**166.1896**	$\Delta MCP_4 \nrightarrow \Delta HP_4$	**16.1846**	**8.0923**
	(0.3488)			(0.0000)			(0.0000)			(0.0003)	
$\Delta EPU \nrightarrow$ risk structure			$\Delta EPU \nrightarrow$ risk structure			$\Delta EPU \nrightarrow$ risk structure			$\Delta EPU \nrightarrow$ risk structure		
	χ^2			χ^2			χ^2			χ^2	
ΔCP_1 & ΔHP_1	**68.8192**		ΔCP_2 & ΔHP_2	**28.7701**		ΔCP_3 & ΔHP_3	0.0277		ΔCP_4 & ΔHP_4	**61.1630**	
	(0.0000)			(0.0000)			(0.8677)			(0.0000)	
ΔMCP_1 & ΔHP_1	1.9414		ΔMCP_2 & ΔHP_2	**9.3057**		ΔMCP_3 & ΔHP_3	**1073.9696**		ΔMCP_4 & ΔHP_4	0.0041	
	(0.1635)			(0.0023)			(0.0000)			(0.9491)	
$\Delta EPU \nrightarrow$ connection structure			$\Delta EPU \nrightarrow$ connection structure			$\Delta EPU \nrightarrow$ connection structure			$\Delta EPU \nrightarrow$ connection structure		
	χ^2			χ^2			χ^2			χ^2	
ΔCP_1 & ΔHP_1	**379.3535**		ΔCP_2 & ΔHP_2	**1463.8505**		ΔCP_3 & ΔHP_3	0.8973		ΔCP_4 & ΔHP_4	**7151303.5174**	
	(0.0000)			(0.0000)			(0.3435)			(0.0000)	
ΔMCP_1 & ΔHP_1	0.9456		ΔMCP_2 & ΔHP_2	**37.1694**		ΔMCP_3 & ΔHP_3	**1978.3148**		ΔMCP_4 & ΔHP_4	**12.5340**	
	(0.3308)			(0.0000)			(0.0000)			(0.0004)	

Notes: ΔCP_1, ΔCP_2, ΔCP_3, and ΔCP_4 respectively denote the returns of carbon price in Beijing, Shanghai, Tianjin, and Chongqing. ΔHP_1, ΔHP_2, ΔHP_3, and ΔHP_4 respectively denote the returns of newly-built house price index in Beijing, Shanghai, Tianjin, and Chongqing. ΔMCP_1, ΔMCP_2, ΔMCP_3, and ΔMCP_4 respectively denote average carbon price returns for three cities other than Beijing, Shanghai, Tianjin, and Chongqing. ΔEPU denotes the rates of change of economic policy uncertainty and trade policy uncertainty for China. Number in parentheses is *p*-value. Number in bold stands for significance at 5%.

In terms of volatility estimates, Table 4 shows that the estimates of local carbon prices in Beijing and other cities insignificantly reject the assumption that a_{21} or b_{21} is zero. However, the estimates of local carbon prices show that d_{21} is significant, indicating that the volatility correlation between carbon prices and housing prices in Beijing is significantly and positively influenced by policy risks. d_{22} is also significantly positive, suggesting that the policy risk effect is positive. In other words, higher policy risks increase volatility in housing price returns. The results in Table 5 further clarify that volatility in the relationship between local housing prices and carbon prices in Beijing is influenced by policy risks. The table also shows that in Shanghai and Chongqing, policy risks affect volatility in the relationship between housing and carbon returns in both local and other cities, whereas, in Tianjin, policy risks impact volatility in the relationship between housing and carbon returns in other cities.

We plot the VAR-BGARCH-X model in Figure 4 to observe the effect of carbon returns on housing returns risk. Figure 4 shows that when there is a high risk of volatility in total housing returns, carbon returns are particularly positively correlated with housing returns. This holds true, especially in Beijing. Further, there are larger fluctuations in carbon and housing returns in Figure 4 than in Figure 3. Similarly, the correlation coefficient between carbon and housing price returns is higher in Figure 4 than in Figure 3, indicating a more pronounced green swan effect on the housing market after accounting for policy risk. This study tested Hypothesis 2 on the basis of the results in Table 4, Table 5, and Figure 3.

Figure 4. Conditional volatility and correlation (VAR-MGARCH-X model)

5. Conclusions

This study explored the relationship between carbon prices and housing prices from the viewpoint of policy risks to determine the extent to which green swan events disrupt housing markets. To do so, it used prices of carbon trading pilot sites in four Chinese cities (Beijing, Shanghai, Tianjin, and Chongqing) and monthly data from new residential sales price indices for the cities from January 2014 to February 2021. The study also analyzed if policy uncertainty in China increased the scale of green swan effects.

This study performed historical simulations and employed a GARCH model with carbon price shocks as an exogenous variable to estimate the extreme risk (VaR) of housing prices. While the HS estimation results do not significantly vary the sample interval, the VaR estimated using the GARCH-X model more accurately measures changes in VaR during periods of significant market volatility.

Further, the study considered carbon price returns as an endogenous variable and estimated the correlation between the carbon price and housing price from the viewpoints of returns and volatility. In terms of returns information transmission, only Beijing and Shanghai reported significant carbon price transmission to housing prices. As for risk transmission effects, all four housing markets were affected by risk spillovers from the carbon price. These results validate the possibility of a green swan event in the housing market.

Finally, we estimated the impact of policy risks on the extent of volatility in the housing and carbon markets. We found that carbon and housing prices are subject to greater volatility when there are higher economic policy risks. In other words, the impact of green swan effects on the housing market increases with rising policy risk, primarily due to the carbon market in the local city.

A considerable number of studies and research institutions have warned that central banks in countries around the world must preemptively assess for green swan effects and, accordingly, propose financial stability policies (e.g., Bolton et al., 2020; da Silva, 2020; Schellekens & van Toor, 2019). The results of this paper indicate that if policy risks from carbon prices and climate change are not addressed, not only will the goal of sustainability be challenging to achieve, but failure to manage these risks could lead to financial crises.

Most research has examined the correlation between the carbon and housing markets from a macroeconomic perspective with a focus on the effect of housing markets on carbon markets (e.g., Yu et al., 2021). By contrast, this study complements empirical findings in the reverse direction, that is, the effects of carbon markets on housing markets. Furthermore, most related studies measure the premium of housing with energy- and carbon-savings advantages (Ofek & Portnov, 2020; Walls et al., 2017; Zhang et al., 2016), that is, the capitalization effect of carbon finance in the housing market. This study, however, focuses on premiums in housing markets linked to carbon prices. More specifically, it pays attention to the "downside risk" of the linkage between housing markets and carbon prices. This is a very important but rarely studied topic. Thus, the results of this paper complement the less validated themes in the extant literature.

From a practical viewpoint, the results remind housing investors and authorities of green swan events in the housing market. This paper recommends that central banks in various countries incorporate stress measures and tests including carbon and climate change risk when assessing market risk in banks and real estate market risk. It emphasizes the need to carefully assess the risk of a collapse triggered in the housing market and to explore measures that could prevent green swan events from triggering a financial storm in the housing market. The paper also illustrates the importance of policy risk for the stability of both markets. It is suggested that if the competent authorities are to efficiently and steadily contribute to the carbon reduction goal, they must reduce policy uncertainty.

This paper is the first to measure green swan risk in the housing market, demonstrating the importance of the green swan effect in housing market research. Subsequent research could build on this paper's findings and further expand the literature. For example, it is suggested that the green swan effect could be compared across different housing types. Comparisons of the green swan effect across multiple markets, including the housing market, should also be explored. We also recommend that subsequent research use theoretical models to first construct the impact of other housing market variables on housing prices before considering the transmission mechanism of carbon pricing.

Acknowledgements

We are immensely grateful to Professor Audrius Banaitis (Editor in Chief) and the two anonymous referees for the constructive comments of this paper. Funding from the National Science and Technology Council (Taiwan) under Project No. NSTC 113-2410-H-007-056-MY3 has enabled the continuation of this research and the dissemination of these results.

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