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Blessing or curse? Fintech adoption and greenhouse gas emission intensity

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ABSTRACT

This study investigates the role of fintech adoption in shaping greenhouse gas (GHG) emissions. Exploiting China's setting and using panel data from 2400 observations and 281 prefecture-level cities in China from 2011 to 2019, we find that adopting fintech significantly reduces CO_2 and SO_2 emissions. Further analyses identify the underlying mechanisms as enhanced green innovation and increased fiscal transparency, which strengthen the ability of regions to protect the environment through public governance. To address the potential endogeneity issues arising from non-randomness and the non-exogenous shock of fintech adoption, we employ two novel instrumental variables as the geographical distance of the city to Hangzhou and the number of graduates to re-estimate our baseline results, which yield similar findings. We further find that this effect is more pronounced in regions with better Internet access and less intensive environmental regulations. Moreover, emissions reductions achieved from fintech adoption generate positive economic and social impacts.

1. Introduction

Climate change has become a critical global concern. October 2022 was the fourth-warmest October in the National Oceanic and Atmospheric Administration's (NOAA's) 143-year record as measured by the average surface temperature of the Earth over the month.[1] Furthermore, the Annual Greenhouse Gas Index (AGGI) developed by the NOAA reached a value of 1.49 by the end of 2021, indicating that the direct warming influence of human-produced greenhouse gases (GHGs) rose 49% above the baseline set in 1990. Of the total heating imbalance, 66% is attributed to increased carbon dioxide (CO_2) emissions, which rose from 22,149.4 million tons in 1990 to 36,390.3 million tons in 2018 (World Bank, 2020). Net-zero carbon emission is an urgent goal that the world is racing to achieve (Cao et al., 2022; Khan et al., 2021). As one of the world's biggest carbon producers, China emits over 6 billion tons of CO_2 each year (Zhang et al., 2022) and must, therefore, take urgent measures to achieve its goals of peak carbon emissions by 2030 and carbon neutrality by 2060 (Huang, Xiang, et al., 2021). Croutzet and Dabbous (2021) document the use of renewable energy to reduce carbon emissions and ensure sustainable development. They find that fintech triggers renewable energy use. Ullah et al. (2023) also show that fintech contributed significantly and positively to the energy transition in Belt and Road Initiative countries. However, whether fintech

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[1] For details, see https://www.ncei.noaa.gov/news/global-climate-202210.

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adoption results in carbon emission reduction remains in question and requires direct empirical investigation.

Fintech, including crowdfunding, blockchain technology, cryptocurrencies, peer-to-peer lending, digital wallets, and smart contracts, has experienced exponential growth, increasing from US$1 billion in global investment in 2008 to over US$31 billion in 2017 (Fung et al., 2020) and US$111.8 billion in 2018 (Croutzet & Dabbous, 2021). In particular, fintech such as Bitcoin and cryptocurrencies can act as a safe haven in markets with extreme turmoil; thereby, investors are able to earn higher risk-adjusted returns by including them in portfolios (Platanakis & Urquhart, 2020; Urquhart & Zhang, 2019), which also promotes the tremendous growth of fintech. Previous studies have shown that the technologies adoption in financial sectors has effects on firms' investment efficiency (Lv & Xiong, 2022), innovation (Ding et al., 2022; Dong & Yu, 2023), information asymmetry (Björkegren & Grissen, 2018), and carbon emissions (Cheng et al., 2023; Kim et al., 2020; Paramati et al., 2021). Macchiavello and Siri (2022) also demonstrated the relevance between sustainability, finance and technology, as well as the potential contribution of technology in achieving environmental goals. Thus, fintech may affect greenhouse gas emissions. On the one hand, fintech adoption is expected to play a critical role in facilitating the transition to renewable energy. For example, cryptocurrencies such as NRGcoin, which is based on blockchain, are used for renewable energy, serving all stakeholders in the smart grid and providing new payment options and lower-cost renewable energy for customers. Similarly, blockchain-based renewable energy certificates allow traceability or identification of the generating asset power stream.

On the other hand, St Louis and Cazier (2010) document that digital technologies may provide effective incentives to motivate greener consumer behavior. Many governments and financial institutions have claimed that fintech can be used to combat climate change. For example, the <*Fintech Development Plan* (2022–2025) > formulated by the People's Bank of China states that one of the key objectives of fintech is to promote low carbon emissions and green development in the economy.[2] Some financial institutions have taken action and achieved significant results. Andrei Cherney, CEO of Aspiration, a digital bank, stated that new products and business practices can help address global environmental issues. They explained, "The right kinds of products and services make actions to combat climate change easy and automated, and yet still really powerful."[3] Thus, fintech adoption can significantly promote innovation in energy-saving technologies, reduce energy consumption, and protect the environment. Therefore, we predict that fintech adoption will play a positive role in reducing emissions.

However, fintech adoption may also increase emissions. Specifically, developing countries such as China are undergoing transformational reforms, which may complicate the relationship between fintech adoption and energy consumption (Yue et al., 2019). For example, Ximiao Dong, lead researcher at Merchants Union Consumer Finance Company Limited (MUCFC), stated that widespread financial technology application has reduced risks, increased product diversity, and improved the coverage and availability of consumer finance, positively impacting domestic demand in China.[4] Many scholars also argue that financial development and technology adoption have positive effects on household consumption by facilitating consumption payment and alleviating credit constraints (Yang & Zhang, 2022). Yue et al. (2019) show that financial development facilitates consumer access to durable goods and the financial capital necessary to boost businesses and engage in other economic activities and investments, consequently increasing energy consumption. Song et al. (2020) also find that digital financial advancement significantly drives energy consumption, especially for rural households and poorer households in China. In addition, Huang et al. (2023) show that fintech prevents the consumption reduction of services under economic uncertainty by supplying entrepreneurship and employment opportunities. Thus, whether fintech adoption is a blessing or a curse in terms of environmental protection remains an empirical question. Our study directly investigates whether and how fintech advancement reduces CO_2 and SO_2 emissions in China.

Based on 281 prefecture-level data points (2400 city-year observations) from 2011 to 2019, we find a significant and negative association between fintech adoption and CO_2 emissions. For each one-unit increase in a city's fintech level, the city reduces its carbon emission at a rate of approximately 12.18 g per RMB10,000 of GDP. In addition, cities experience a decline in SO_2 emissions by approximately 63%, reducing emissions of about 420.84 g per RMB10,000 of GDP for each one-unit increase in their fintech level.

We further explore the mechanisms by which fintech affects GHG emissions. Previous studies have documented that fintech adoption can promote regional innovation (Chen et al., 2022; Ding et al., 2022), thereby providing support for GHG reductions. Our empirical evidence confirms this underlying mechanism. Additionally, we identify the underlying mechanism as increased fiscal transparency following fintech adoption. In China, fintech is increasingly used to support public green governance. For example, the Industrial and Commercial Bank of China (ICBC) has collaborated with the People's Government of Ningxia Hui Autonomous Region to develop the blockchain platform 'My Ningxia,' which enhances government transparency and public governance. This platform has significantly improved fiscal transparency in Ningxia, enhancing the transparency and accuracy of government fund allocation, especially for environmental protection, thereby safeguarding Ningxia's ecological environment.[5] Similarly, in the Inner Mongolia Autonomous Region of China, the benefits of fintech in enhancing corporate fiscal transparency and supporting environmental

[2] For details, see *The People's Bank of China issued the Fintech Development Plan (2022–2025)* https://www.gov.cn/xinwen/2022-01/05/content_5666525.htm.

[3] For details, see 'Climate fintech' is changing the way banks work | Popular Science (popsci.com).

[4] For details, see http://finance.people.com.cn/n1/2022/0616/c1004-32448134.html.

[5] For details, see *ICBC has achieved remarkable results in supporting the construction of digital government affairs* http://finance.people.com.cn/n1/2022/1223/c1004-32592292.html.

protection have also been observed.[6]

Previous studies have documented the importance of fintech development in decreasing information asymmetry among individuals, banks, and regulators (Björkegren & Grissen, 2018). Fiscal transparency has been a crucial policy tool for modernizing national governance systems and enhancing high-quality economic development in China(Chen & Neshkova, 2020; Liu et al., 2021). In terms of environmental protection issues, governments play a key role in regional environmental governance. Zhang and Wang (2021) document the positive impact of fiscal transparency on public governance efficiency of local environments. Therefore, fintech is expected to enhance fiscal transparency and high-quality public governance, particularly green governance, which facilitates pollution reduction.

To address the potential endogeneity issue arising from reverse causality, that is, the possibility that cities with fewer emissions are likely to adopt fintech, we employ a series of instruments, including the instrumental variable approach, dynamic system generalized method of moments (GMM) approach, propensity score matching (PSM) estimation and entropy balancing approach. In terms of instrumental variable approach, following previous studies (Hong et al., 2021; Yang & Zhang, 2022), we use the distance between a city and Hangzhou (the center of fintech advancement) and the number of graduates in each city as instrumental variables to re-estimate our baseline model, given that graduates are a key demographic with high demand for fintech services and serve as a crucial source of talent in the fintech sector. Our results remain the same. We find that the positive relationship between fintech adoption and emission reduction is more evident in cities with high Internet penetration and subject to less intensive environmental regulation. This is because fintech adoption relies heavily on Internet penetration. Without the Internet, it is impossible to complete fintech-based transactions. Finally, we find that emissions reductions resulting from fintech adoption generate positive economic and social impacts, including improving the business environment and enhancing citizen well-being.

Our paper relates to the literature on the economic consequences of fintech, particularly regarding environmental governance. Previous studies have shown that fintech adoption can positively impact alleviating consumption inequality (Yang & Zhang, 2022), upgrading industrial structure (Cheng et al., 2023), reducing financial constraints (Ding et al., 2022; Guo et al., 2023), promoting R&D investment (Chen et al., 2022; Ding et al., 2022; Tan et al., 2023), and mitigating information asymmetry (Björkegren & Grissen, 2018), as well as playing a significant role in market financial investment through technical applications (Ding et al., 2023b). However, few studies have investigated the direct effect of fintech on greenhouse gas emissions. Cao et al. (2021) show that fintech can improve China's energy-environmental performance through increased green technology innovation, whereas Wang, Wang, et al. (2022) find that fintech significantly increases carbon emissions alongside economic growth. Whether fintech adoption is a blessing or a curse in terms of environmental protection remains an empirical question in most papers (Wang, Wang, et al., 2022; Yue et al., 2019; Song et al., 2020).

Most pertinent to the current study, Cheng et al. (2023) find that fintech decreases carbon emissions through industrial structure upgrading, alleviating financing constraints and promoting green technology innovation. Similarly, Lee and Wang (2022) show that fintech has a carbon intensity reduction effect through industrial structure upgrading and green technology innovation. Chang (2022) finds that fintech can reduce China's agricultural carbon emissions through the mediating effects of farmers' entrepreneurship, agrarian technology innovation, and urbanization. However, there may be additional underlying mechanisms through which fintech influences emissions, particularly given the distinctive role of the government in China's environmental governance within its unique institutional context (Zhang & Barr, 2013). One such mechanism could be government fiscal transparency. Therefore, this paper investigates both the direct effects of fintech on greenhouse gas emissions and the unique mechanisms within the Chinese context.

Our study advances the literature on the relationship between fintech and greenhouse gas emissions and contributes to regulators, policymakers, and standard-setters in the following ways. First, we enrich the literature by directly investigating how fintech adoption affects emissions and providing insights into the underlying economic mechanisms and variations in baseline results. Importantly, our paper extends previous studies by introducing fiscal transparency as a novel underlying mechanism, which plays a crucial role in public governance, particularly green governance in China. In China, local governments are fully responsible for energy conservation and emission reduction within their administrative regions, and fiscal transparency and efficient use of financial resources are key elements in achieving this task. Our paper further provides evidence of the positive economic and social consequences of fintech adoption, adding to existing research (Dong & Yu, 2023; Kim et al., 2020; Lv & Xiong, 2022; Paramati et al., 2021) and extending the work of Cheng et al. (2023).

Second, to precisely estimate the greenhouse gas reduction effect of fintech, we employ the instrumental variable approach using two novel instrumental variables: the distance to Hangzhou (the center of fintech penetration) and the number of young graduates, who are both key consumers of fintech services and a significant source of a high-quality fintech workforce. This approach addresses potential endogeneity and enhances the robustness of our research findings. Third, our additional tests show that the impacts of fintech are more pronounced in cities with a high degree of Internet penetration and less intensive environmental regulation, which implies the necessity for a global strategy to address both the digital divide and environmental issues simultaneously. Furthermore, we demonstrate the important economic and social consequences of fintech, specifically that a city's fintech adoption reduces its emissions, thereby enhancing its business environment and citizens' well-being. These findings have important implications for regulators, policymakers, and local governments regarding the strategic promotion of fintech advancement.

The remainder of this paper is organized as follows. Section 2 introduces the data, methodology, and summary statistics. Section 3

[6] For details, see *Inner Mongolia Finance: Multiple Measures to Paint a "Green Picture" Along the Yellow River and Wholeheartedly Promote the Beautiful Transformation of the "Jizi Wan"* https://www.mof.gov.cn/zhengwuxinxi/xinwenlianbo/neimenggucaizhengxinxilianbo/202406/t20240628_3938271.htm.

presents the results of baseline models and endogenous tests. Section 4 reports the results of the additional tests. Section 5 summarizes the findings and discusses policy implications.

2. Data and methodology

We construct a regression model using CO_2 emission intensity (CO_2) measured as total CO_2 emissions divided by GDP (unit: kg/10^4 RMB) and SO_2 emission intensity (SO_2) measured as total SO_2 emissions divided by GDP (unit: kg/10^4 RMB), as dependent variables. Fintech adoption in China (*Fintech*) is the independent variable measured by the regional-level index of digital financial inclusion (Guo et al., 2020). The empirical model is set as follows:

$$Emission = \beta_0 + \beta_1 Fintech + \beta_2 Controls + City\ fixed\ effects + Year\ fixed\ effects + \varepsilon \tag{1}$$

City-level data were collected manually from the National Bureau of Statistics of China. We calculate *Gdp_capita* as the natural logarithm of per-capita GDP. *Gdp_growth* is measured as the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. To control for local environmental protection efforts, we also control for local environmental regulatory intensity (*Env_index*) using the regulatory intensity index from Liu and He (2021) and the natural logarithm of the number of employees of environmental protection institutions (*Env_staff*). Annex 1 presents definitions of the variables. The sample includes 281 prefecture-level cities in China from 2011 to 2019. After excluding cities with insufficient CO_2 and SO_2 emission data, our final sample consists of 2,400 valid city-year observations. To mitigate the effects of outliers, we winsorize the continuous variables at the 1% level in both tails.

Table 1 presents the descriptive statistics of the variables. The mean values of CO_2 and SO_2 are 0.105 and 0.668, respectively, indicating that there are 105 grams of CO_2 and 668 grams of SO_2 per RMB 10,000 GDP. The maximum value of SO_2 is 8.242, which is larger than that in previous studies such as Wang, Su, et al. (2022) since we used prefectural-level data instead of provincial data. The mean of *Fintech* is 1.625 and the maximum value is 3.216. This indicates that there are significant differences in fintech development among regions. The averages of *Industry1* and *Industry2* are 0.119 and 0.468, respectively. This finding is comparable to the results of relevant prior research (e.g., Muganyi et al., 2021).

Table 2 presents the variance inflation factors (VIF) and correlation coefficients for the different explanatory variables. It indicates that the coefficients between them are generally lower than the 0.6 mark, with only *Env_index* and *Env_staff* having a correlation of 0.746, and Env_staff and Env_index having a correlation of 0.640, which may suggest a problem with multicollinearity. To determine if multicollinearity affects the results, the independent variables were measured for their VIFs. After taking into account all of them, the average value of VIF is 1.66, while the maximum is 2.23. This indicates that there is no major problem with multi-collinearity between the explanatory variables.

3. Result discussions

3.1. Results of the baseline models

Table 3 shows the baseline results for the regressions examining the association between *Fintech* and polluting gas emissions. We consider control variables and city- and year-fixed effects. First, we regress CO_2 on *Fintech*. As shown in Column (1), *Fintech* has a coefficient of −0.131 and is significant at the 1% level ($p < 0.01$), which only includes the main variable of interest, *Fintech*, city, and year fixed effects. To control for the fundamental city factors, we re-estimate the baseline model, and the results in Column (2) show that *Fintech* has a coefficient of −0.116, and that it is significant at 1%. This coefficient has a significant economic impact. Based on the results in Column (2), cities experience a decline in CO_2 emissions of approximately 11.6%, a reduction of about 12.18 (11.6%*

Table 1
Descriptive statistics.

This table provides descriptive statistics for key variables in 2011–2019. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from economic activities in primary industries to total GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the index measuring the local environmental regulatory intensity of a city, following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 1st and 99th percentiles.

Variable	N	Mean	Standard deviation	1st quartile	Median	3rd quartile	Maximum
CO_2	2400	0.105	0.249	0.010	0.029	0.086	3.691
SO2	2400	0.668	0.926	0.073	0.341	0.979	8.242
Fintech	2400	1.625	0.655	1.156	1.676	2.161	3.216
Gdp_capita	2400	10.670	0.607	10.270	10.640	11.060	13.060
Gdp_growth	2400	0.090	0.041	0.072	0.087	0.109	1.090
Industry1	2400	0.119	0.073	0.068	0.112	0.160	0.470
Industry2	2400	0.468	0.104	0.411	0.476	0.530	0.893
Env_index	2400	0.689	0.562	0.276	0.436	0.973	2.585
Env_staff	2400	8.982	0.590	8.604	8.933	9.364	10.200

Table 2
Variable correlation coefficients and VIF statistical values.

This table reports the correlation between all explanatory variables and variance inflation factors (VIF) for explanatory variables in the analysis. The Pearson correlations are presented below the diagonal and Spearman correlations are presented above the diagonal. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Fintech	*Gdp_capita*	*Gdp_growth*	*Industry1*	*Industry2*	*Env_index*	*Env_staff*
Fintech	1	0.301***	−0.565***	−0.096***	−0.359***	0.093***	0.126***
Gdp_capita	0.289***	1	−0.221***	−0.769***	0.150***	−0.000	−0.002
Gdp_growth	−0.433***	−0.165***	1	0.101***	0.224***	0.009	−0.028
Industry1	−0.101***	−0.681***	0.039*	1	−0.316***	0.013	0.023
Industry2	−0.331***	0.162***	0.168***	−0.403***	1	−0.030	−0.029
Env_index	0.097***	0.035*	−0.013	0.003	−0.020	1	0.746***
Env_staff	0.085***	−0.021	−0.014	0.033	−0.030	0.640***	1
VIF		1.98	1.07	2.23	1.27	1.70	1.70
Mean VIF	1.66						

Table 3
Results of the baseline model.

This table shows the effect of fintech on greenhouse gas (CO_2, SO_2) emissions using ordinary least squares regression for panel data. *CO_2* is CO2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. We use city-fixed and year-fixed effects to account for unobservable city-specific and year-specific characteristics. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *CO_2*	(2) *CO_2*	(3) *SO_2*	(4) *SO_2*
Fintech	−0.131***	−0.116***	−0.669***	−0.630***
	(−3.61)	(−3.21)	(−2.77)	(−2.60)
Gdp_capita		−0.029***		−0.113*
		(−2.99)		(−1.71)
Gdp_growth		−0.047		−0.079
		(−0.76)		(−0.19)
Industry1		−0.367**		0.322
		(−2.42)		(0.32)
Industry2		−0.360***		−0.824**
		(−5.82)		(−1.98)
Env_index		−0.006		0.251***
		(−0.52)		(3.42)
Env_staff		0.071		0.134
		(1.63)		(0.46)
Constant	0.180***	0.090	1.451***	1.638
	(9.17)	(0.22)	(11.08)	(0.60)
City & Year FE	Yes	Yes	Yes	Yes
N	2400	2400	2400	2400
Adjusted R^2	0.033	0.061	0.201	0.209
F value	8.119	9.083	58.813	37.139

0.105*1000) grams per RMB10,000 of GDP, when their fintech level increases by one unit.

Second, we regress *SO_2* on *Fintech*. Column (3) reports results only incorporating *Fintech*, city, and year-fixed effects. The *Fintech* coefficient is −0.669 and significant at the 1% level. Column (4) shows the results, including the fundamental factors as control variables. We find a significantly negative association between SO_2 emissions and the regional fintech level (the coefficient of *Fintech* is −0.630 and significant at the 1% level). Based on the results shown in Column (4), cities experience a decline in SO_2 emissions of approximately 63%, which reduces emissions by about 420.84 (63%*0.668*1000) grams per RMB10,000 of GDP when their Fintech level increases by one unit. Collectively, all these results indicate a negative and significant association between fintech and greenhouse gas emissions.

Fig. 1 illustrates the relationship between fintech adoption and emissions. Fig. 1 shows the changes in fintech adoption and CO_2 and SO_2 emissions from 2011 to 2019, indicating that regions with a higher level of fintech adoption experienced a greater decline in emissions.

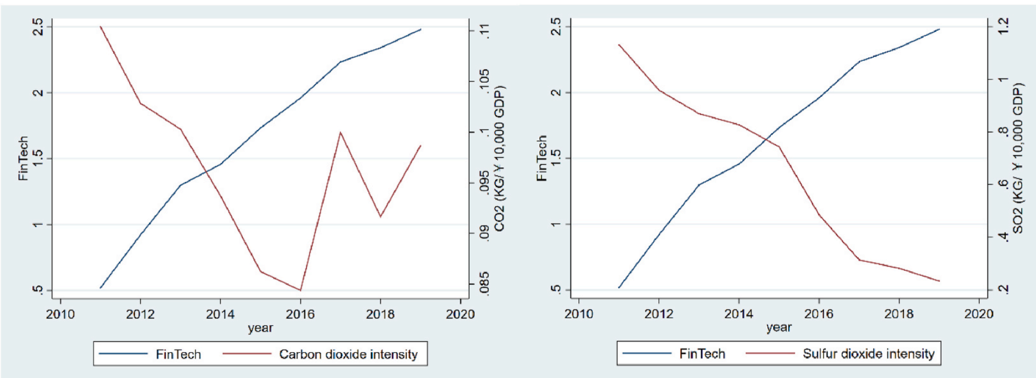
3.2. Instrumental two-stage estimation

Although we explicitly control for prefectural economic development and environmental regulation variables in the regression, there is still a potential endogeneity issue between fintech level and polluting gas emissions. One possibility is that high-speed economic development leads to a higher level of fintech, which could simultaneously result in both increased reductions in pollutant gas emissions and lower emissions overall. This could create a spurious correlation between fintech and polluting gas emissions. We perform a 2SLS estimation to address this issue. Roberts and Whited (2013) note that an appropriate instrument must satisfy both the relevance and exclusion criteria. For our 2SLS estimation, we identify two plausible instruments.

First, we follow Hong et al. (2021) and use the geographical distance of a city from Hangzhou (*Distance*) as an instrumental variable to predict the development level of fintech adoption in various cities. Yang and Zhang (2022) argue that Chinese fintech development is concentrated near Hangzhou, where the Ant Group is headquartered, and cities geographically close to Hangzhou experience more fintech adoption. As stated in Hong et al. (2021), Ant Group initially cooperated with the local government in Hangzhou and then gradually expanded through ground promotion on digital payment methods. Furthermore, as early as 2013, Ant Group had established strategic partnerships with provincial governments on cloud computing and big data. By 2018, Ant Group had become the leading vendor in China's digital government big data market. Besides, given that for most cities in inland China, the distances to Hangzhou and Shenzhen, where Tencent's headquarters is located, are similar, the distance variable may also reflect proximity to Shenzhen. More importantly, the distance of a city from Hangzhou hardly affects its polluting gas emissions. Thus, *Distance* is used as an instrumental variable to predict the intensity of fintech adoption across cities. Specifically, we first calculate the geographical distance of each city from Hangzhou and then take the logarithm to measure the variable *Distance*.

Second, we use the number of a city's college graduates (*Num_graduate*) as the second plausible instrument to predict the popularity of fintech adoption at the city level. There are two main reasons why a higher number of college graduates might increase fintech adoption. On the demand-side, Islam (2021) shows that young Chinese students prefer online shopping on mobile devices because of the convenience of online payment tools. On the supply-side, a higher number of educated individuals in a city, the more technical and knowledgeable talent there is, which is more likely to enhance the effectiveness of fintech applications. Additionally, the rapid evolution of fintech, characterized by frequent knowledge updates, creates a high demand for skilled professionals (Zalan & Toufaily, 2017). Therefore, cities with a larger population of young college graduates are more likely to have a high-quality fintech workforce and advanced fintech applications. Consequently, the number of college graduates in a city is expected to be positively correlated with fintech development. Thus, cities with more college graduates are anticipated to exhibit higher levels of fintech adoption and development. At the same time, there is no reason to believe that the number of college graduates in a city affects pollution levels. Therefore, we expect the two instrumental variables to be uncorrelated with the error term.

The 2SLS estimation reslults are presented in Table 4. Column (1) reports the first-stage results for the dependent variable *Fintech*. As expected, the first instrumental variable, *Distance,* is negatively related to city-level fintech adoption, indicating that a city farther from Hangzhou has a lower fintech level. In addition, the second instrumental variable, *Num_graduate,* is positively related to city-level fintech adoption and is statistically significant at conventional levels. Columns (2) and (3) present the second-stage regression results, with CO_2 and SO_2 as measures of gas emissions. After controlling for endogeneity, *Fintech* remains negatively related to gas emissions. Tests are also conducted for the validity and exclusion conditions of our instruments. The first-stage regression F-statistic is 363.80, which indicates there are no weak instruments. To test for over-identifying restrictions, Hansen's J-test statistics are computed. Based on the J-statistics (2.317, 1.341), we fail to disprove the joint null hypothesis, which implies that our instruments are not related to the error term. This means that they're excluded correctly from the second-stage regressions.



A: Fintech and CO_2 emission intensity B: Fintech and SO_2 emission intensity

Fig. 1. Fintech and pollution emissions.
A: Fintech and CO_2 emission intensity B: Fintech and SO_2 emission intensity.

Table 4
Instrumental variable tests.

This table presents the results for 2SLS regressions. Two instrumental variables are included in the first-stage regression: (1) *Distance*, which is measured as the logarithm of a city's distance from Hangzhou, where Ant Group is headquartered and (2) *Num_graduate*, the logarithm number of a city's college graduates. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The first two statistics, the partial $R^{2,}$ and the F-statistical, are calculated to test the weak instruments' null hypothesis. The Hanson-J-test was then used to analyze the overidentifying restrictions. In the second stage, the two dependent variables are the greenhouse gas variables. We use city-fixed and year-fixed effects to account for unobservable city-specific and year-specific characteristics. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) 1st Stage *Fintech*	(2) 2nd-Stage dependent variable CO_2	(3) SO_2
Instrumented Fintech		−0.481***	−0.916**
		(0.185)	(0.361)
Distance	−0.098***		
	(0.011)		
Num_graduate	0.057*		
	(0.031)		
Gdp_capita	−0.012	0.133**	−0.086
	(0.019)	(0.060)	(0.149)
Gdp_growth	0.022	0.076	−2.736
	(0.180)	(0.168)	(2.109)
Industry1	−0.241*	0.470	−1.795**
	(0.139)	(0.357)	(0.893)
Industry2	−0.005	−0.051	−1.273*
	(0.103)	(0.139)	(0.748)
Env_index	0.080***	−0.025	0.181**
	(0.018)	(0.037)	(0.090)
Env_staff	−0.106***	0.018	−0.069
	(0.030)	(0.024)	(0.061)
Constant	1.445***	−1.426**	4.625***
	(0.370)	(0.672)	(1.645)
Observations	2400	2400	2400
City & Year FE	Yes	Yes	Yes
Adjusted R^2	0.205	0.205	0.033
Predictive power of excluded instruments			
Partial-R^2	0.152		
Robust F-statistic (instruments)	363.80		
F-statistic p-value	0.000		
Test of overidentifying restrictions			
Hansen J-statistic		2.317	1.341
P-value		0.128	0.247

3.3. Dynamic system GMM approach

We further address the potential endogeneity between prefectural fintech development and polluting gas emissions by employing the Arellano–Bond system GMM method, following Arellano and Bover (1995) and Blundell and Bond (1998). We include one- and two-year-lagged greenhouse gas emissions as independent variables in Eq. (1). Table 5 shows that fintech has significantly negative coefficients ($t = -3.43$ and -0.085). Moreover, AR (1) and AR(2) tests have p-values of less than 5% and more than 5%, respectively. Sargan's overidentification test has a p-value of less than 1%, while the p-values calculated in Difference-in-Hansen's exogeneity tests are 0.144 and 0.288. Based on the results of GMM tests, we believe our findings that fintech curbs GHG emissions are unlikely to be influenced by potential endogeneity.

3.4. PSM estimation

Since fintech development levels vary significantly across different regions, economic and social factors may play a role in reducing pollution gas, such as economic development, resource endowment, and industrial base, which also affect fintech development. To address sample selection bias, we apply propensity score matching (PSM) following the method described by Boubaker et al. (2016). To implement the PSM method, we use a probit model where the dependent variable is *Fintech_dum*, a dummy variable which equals 1 if the fintech level of a city in the year is larger than the median of city-year fintech, otherwise 0.

These explanatory variables were derived from studies that examined the development of financial technology (fintech) at the city level (Cheng et al., 2023; Ding & Xue, 2023a; Haddad & Hornuf, 2019; Lu et al., 2024). Specifically, we use (i) GDP per capita, (ii) GDP growth, (iii) percentage of secondary industries, (iv) intellectual property rights protection, and (v) network infrastructure. GDP per

Table 5
Dynamic system GMM approach.

The table reports the results of the dynamic GMM approach. We treat *Fintech*, *Gdp_capita*, *Gdp_growth*, *Industry1*, *Industry2*, *Env_index*, and *Env_staff* as endogenous variables. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) CO_2	(2) SO_2
$L.CO_2$	0.837***	
	(10.48)	
$L2.CO_2$	0.024	
	(0.32)	
$L.SO_2$		0.777***
		(36.23)
$L2.SO_2$		0.086***
		(5.12)
Fintech	−0.034***	−0.085***
	(−3.43)	(−4.22)
Gdp_capita	−0.013**	0.023***
	(−2.41)	(5.13)
Gdp_growth	−0.106*	−0.062*
	(−1.75)	(−1.91)
Industry1	−0.047	−0.381***
	(−1.32)	(−6.09)
Industry2	−0.002	−0.035
	(−0.10)	(−0.68)
Env_index	0.016***	0.018*
	(2.95)	(1.86)
Env_staff	−0.008**	−0.004
	(−2.12)	(−0.47)
Constant	0.164**	−0.048
	(2.16)	(−0.45)
AR(1) test (p-value)	0.011	0.000
AR(2) test (p-value)	0.189	0.451
Sargan test over-identification (p-value)	0.000	0.008
Difference-in-Hansen test of exogeneity (p-value)	0.144	0.288
Wald Chi^2	21085.32	36876.39
N	1808	1808

capita (*Gdp_capita*) is expected to increase the development of fintech since a city with a higher GDP per capita has a broader market for fintech (Haddad & Hornuf, 2019). Similarly, cities with a rapid speed increase in GDP (*Gdp_growth*) have higher levels of fintech. The percentage of the secondary industry (*Industry2*) is positively related to fintech since it provides a solid foundation for the development of contemporary cutting-edge technology. Ding and Xue (2023a) show that intellectual property rights protection (*IPRP*) plays an important role in motivating fintech innovation. We measure *IPRP* by the number of completed litigation cases that are intellectual property-based in a city. In addition, the regional network infrastructure plays a key role in the development of fintech because fintech is a technology-driven financial innovation (Cheng et al., 2023). Thus, we argue that network infrastructure construction can directly stimulate fintech development. Given that Internet access port is the crucial component of network infrastructure, we use the logarithm of Internet terminals in a city as a proxy for the network infrastructure level (*Internet infrastructure*).

After we perform a calibration procedure using a probit model, the nearest-neighbor method (Dehejia & Wahba, 2002) is utilized to match the cities with the high ($Fintech\_dum = 1$) and low levels ($Fintech\_dum = 0$) of fintech. Using this procedure, we produce a matched sample of 1,906 city-year observations. We verify that the matching method is able to produce a balanced sample of various cities and generates a sample of cities with different levels of fintech. According to Table 6, the mean values of all variables in the PSM model are almost indistinguishable between the two groups. The standardized bias is utilized to determine the degree to which places with and without *Fintech_dum* have different means (Rosenbaum & Rubin, 1983). A lower bias means a more balanced relationship between the two groups. As shown in Table 6, the PSM sample has an absolute bias of less than 9.9%, which indicates that the matches are reasonably balanced from every angle. In the case of *IPRP and Internet infrastructure,* the bias is less than 3%.

Further, the bias in the treated samples has been reduced by up to 96% compared to the control samples. Fig. 2 illustrates the density distributions of the treated and control samples before and after the matching. We can observe that the difference between the treatment and control samples is reduced after implementing PSM procedures.

After performing the above matching procedures, further regression tests are then carried out with the matched sample, and the outcomes are presented in the following Table 7. With exogenous variables controlled, the coefficients of the core explanatory variable *Fintech* are all significantly negative, which indicates that the results in baseline regression are robust.

Table 6
Comparison of variables determining the development level of fintech.

This table reports the comparison of variables determining the development level of fintech. We construct the variable *Fintech_dum*, a dummy variable that equals 1 if the fintech level of a city in the year is larger than the median of city-year fintech, and 0 otherwise. The mean values of the various factors that were considered to predict the development of financial technology are compared and contrasted in this table. *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *IPRP* is the number of completed cases heard by courts in each city with respect to intellectual property-based litigation. *Internet infrastructure* is the logarithm of Internet terminals in a city as a proxy for the level of network infrastructure. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Original sample			Propensity score-matched sample			Reduction in bias (%)
	Cities with Fintech_dum	Cities w/o Fintech_dum	Standardized bias (%)	Cities with Fintech_dum	Cities w/o Fintech_dum	Standardized bias (%)	
Gdp_capita	10.703	10.644	9.7	10.702	10.762	−9.9	−2.3
Gdp_growth	0.090	0.090	0.8	0.090	0.087	7.2	−793.4
Industry2	0.473	0.464	8.8	0.473	0.478	−4.1	53.7
IPRP	5.171	4.448	36.1	5.184	5.130	2.7	92.4
Internet infrastructure	7.640	7.366	34.9	7.657	7.657	−1.3	96.3

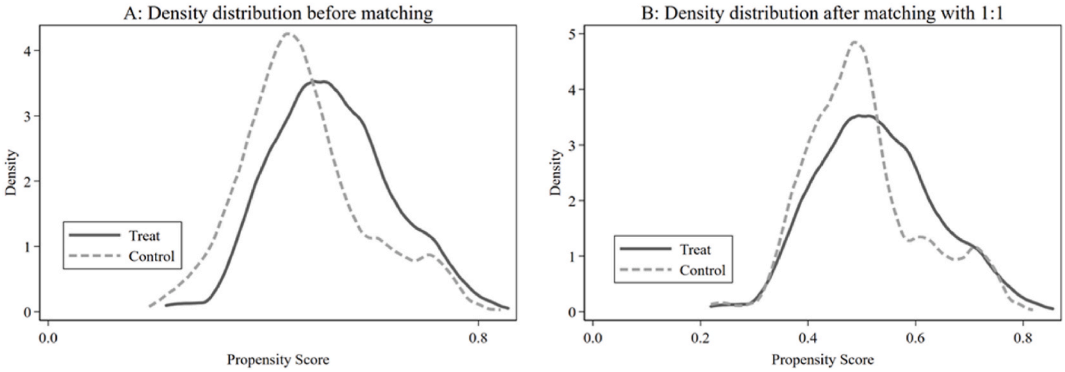


Fig. 2. Density distribution of treatment and control samples before and after matching.

3.5. Entropy balancing approach

Previous studies (Basu et al., 2022; Chapman et al., 2019) are then followed to analyze the baseline results and determine the sensitivity of the findings. We also utilize an entropy-balancing method to control for the varying differences between the control group (*Fintech_dum* = 0) and treatment group (*Fintech_dum* = 1), which have been constructed in section 3.4. This method ensures that there is proper balancing of the covariates between samples of cities with higher fintech levels and samples of cities with lower fintech levels by weighting observations.

We match the six covariate dimensions included in the baseline model. After re-weighting the data, we find that the covariates of the control and treatment groups are almost identical (presented in Panel A of Table 8). This indicates that proper equilibrium can be achieved.

Table 7
PSM estimation.

This table presents regression results using PSM estimation. The propensity score is the probability of *Fintech_dum* estimated from the probit regression in column (1). Each city with higher fintech (*Fintech_dum* = 1) is then matched with a city that has lower fintech (*Fintech_dum* = 0) and the closest propensity score in the same year. Columns (2)–(3) report the results of regressions using this matched sample (treatment group and control group). *Fintech_dum* equals 1 if a city has a higher fintech level than the median in the year, and 0 otherwise. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Fintech_dum*	(2) CO_2	(3) SO_2
Fintech		−0.139***	−0.600**
		(−3.36)	(−2.07)
Gdp_capita	0.103**	−0.030***	−0.126*
	(2.21)	(−3.05)	(−1.82)
Gdp_growth	−0.407	−0.170*	−0.008
	(−0.55)	(−1.88)	(−0.01)
Industry2	0.377	−0.462***	−0.491
	(1.33)	(−6.66)	(−1.01)
IPRP	0.087***		
	(3.62)		
Internet infrastructure	0.264***		
	(4.14)		
Industry1		−0.600***	1.764
		(−3.46)	(1.45)
Env_index		−0.010	0.264***
		(−0.84)	(3.16)
Env_staff		0.059	0.164
		(1.29)	(0.52)
Constant	−3.265***	0.322	1.119
	(−5.28)	(0.76)	(0.38)
City & Year FE	Yes	Yes	Yes
N	2400	1906	1906
Chi-2/F-value	136.88	8.320	27.340
Pseudo R^2/Adjusted R^2	0.041	0.072	0.203

The results of the study are then re-run using the balanced sample with post-weighted observations in Table 3. Following the removal of biases (Chapman et al., 2019; Hainmueller, 2012), the results of the regression tests are expected to be unbiased. Our baseline results based on entropy balancing remain economically and statistically significant. Hence, multivariate entropy balancing confirms our causal inferences regarding the effect of fintech on gas emissions in cities.

3.6. Alternative measure of independent variable

Following Zhao et al. (2022), we use the FinTech Baidu Index to proxy for fintech level for further robustness checks. It should be emphasized that the fintech inclusion index used in baseline test mainly reflects the degree of fintech application to individual users, while the Baidu index reflects public concern and demand for fintech. Table 9 reports the results using FinTech Baidu Index (*Fintech_alter*) as a measure of dependent variable. As shown in Table 9, *Fintech_alter* has negative coefficients that are significant at the 1% level ($p < 0.01$) in columns (1)–(2), which are consistent with the results in Table 3, indicating the robustness of the main finding.

Table 8

Entropy balancing approach.

Panel A: Differences in covariates after entropy balancing

This table reports the covariate distribution of the treatment (*Fintech_dum* = 1) and control groups (*Fintech_dum* = 0), obtained by using an entropy balancing method to match the covariances between the treatment and control sectors. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithmf the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. All continuous variables are winsorized at the 1st and 99th percentiles.

Covariate	Treat			Control			Std. Diff	Var. Ratio
	Mean	Variance	Skewness	Mean	Variance	Skewness		
Gdp_capita	10.700	0.328	0.128	10.700	0.328	−0.169	0.000	1.000
Gdp_growth	0.090	0.001	−0.444	0.090	0.001	−0.246	0.000	1.000
Industry1	0.112	0.005	0.818	0.112	0.005	1.244	0.000	1.000
Industry2	0.473	0.011	−0.176	0.473	0.011	−0.410	0.000	1.000
Env_index	0.770	0.354	0.896	0.770	0.354	0.908	0.000	1.000
Env_staff	8.968	0.315	−0.596	8.968	0.315	−0.672	0.000	1.000

Panel B: Gas emissions after entropy balancing

This table reports the empirical results of OLS regression models using the matched sample obtained by the entropy balancing approach. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) CO_2	(2) SO_2
Fintech	−0.152***	−0.713***
	(−4.06)	(−2.90)
Gdp_capita	−0.068***	−0.165
	(−4.40)	(−1.63)
Gdp_growth	−0.093	0.451
	(−0.97)	(0.72)
Industry1	−0.525***	1.803
	(−3.13)	(1.63)
Industry2	−0.287***	−0.463
	(−4.27)	(−1.05)
Env_index	0.006	0.275***
	(0.53)	(3.63)
Env_staff	0.080*	−0.043
	(1.68)	(−0.14)
Constant	0.408	3.362
	(0.89)	(1.12)
City & Year FE	Yes	Yes
N	2400	2400
Adjusted R^2	0.867	0.605
F-value	11.083	34.979

Table 9
Alternative measure of independent variable.

This table provides the empirical results of OLS regressions using alternative measure of independent variable. *Fintech_alter* is measured the Baidu index reflecting public concern and demand for fintech following Zhao et al. (2022). *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *CO_2*	(2) *SO_2*
Fintech_alter	−0.022***	−0.132***
	(-4.46)	(-3.56)
Gdp_capita	−0.030***	−0.209***
	(-3.06)	(-4.94)
Gdp_growth	−0.052	−0.104
	(-0.84)	(-0.21)
Industry1	−0.372**	−1.500***
	(-2.46)	(-4.14)
Industry2	−0.365***	−0.349*
	(-5.93)	(-1.69)
Env_index	−0.005	0.116***
	(-0.43)	(2.78)
Env_staff	0.072*	−0.034
	(1.66)	(-0.82)
Constant	0.027	3.902***
	(0.07)	(6.32)
City & Year FE	Yes	Yes
N	2400	2400
Adjusted R^2	0.065	0.050
F-value	9.759	321.702

3.7. Controlling for additional variables

To control for the omitted variable problem, we further control for additional variables in our model, including population size, urbanization level and Internet infrastructure which affect fintech development and greenhouse gas emissions simultaneously (Cheng et al., 2023; Qin et al., 2024). Following Cheng et al. (2023), we use population density to measure population size (*Population size*); calculate the ratio of urban population over permanent resident population to proxy for urbanization level (*Urbanization level*). As the crucial component of network infrastructure, the Internet access port is essential for Internet penetration. Thus, we use the number of Internet access ports in each province to proxy for Internet infrastructure (*Internet infrastructure*). Table 10 reports the regression results, showing that the coefficients of *Fintech* remain negative and significant at the 1% level ($p < 0.05$) in columns (1)–(2), indicating that our results are fairly robust.

4. Additional tests

4.1. Economic channels

4.1.1. Green innovation

To explore the mechanisms by which financial technology affects greenhouse gas emissions, we first analyze fintech's effect on greenhouse gas emissions from green innovation. Research by Ding et al. (2022) and Chen et al. (2022) reveals that financial technology can stimulate lending to firms and R&D investments in China. It is also noted that domestic R&D, especially green innovation, could help to cut down on carbon emissions (Huang, Xiang, et al., 2021). Thus, fintech is expected to promote green innovation by mitigating financial constraints and thereby reducing polluting gas emissions. Following Wen and Ye (2014) and Ozdemir et al. (2020), we first examine the effect of fintech on regional green innovation (*Greenpatent*), which is measured as the logarithm of green patent applications in a year. The results in Column (1) of Panel A of Table 11 show that fintech positively impacts green innovation, indicating that fintech adoption promotes regional green development. If fintech impacts greenhouse gas emissions through green innovation, the coefficient of *Greenpatent* is expected to be negative, and the coefficient of *Fintech* is expected to be negative when we include the variable *Greenpatent* in our model. Columns (2)–(3) in Panel A of Table 11 report the coefficients of *Greenpatent* and *Fintech*, which are both negative. Collectively, these results indicate that fintech affects pollutant gas emissions through increasing green innovation.

4.1.2. Fiscal transparency

Another important channel through which fintech adoption contributes to emissions reduction is the improvement of fiscal

Table 10
Control for additional variables.

This table provides the empirical results of OLS regressions after controlling for regional urbanization level (*Urbanization level*), population size (*Population size*) and Internet infrastructure (*Internet infrastructure*). *Population size* is measured using population density. *Urbanization level* is calculated using the ratio of urban population over permanent resident population. *Internet infrastructure* is mearsued using the number of Internet access ports in each province. CO_2 is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. SO_2 is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) CO_2	(2) SO_2
Fintech	−0.106***	−0.595**
	(-2.93)	(-2.45)
Gdp_capita	−0.028***	−0.108
	(-2.87)	(-1.63)
Gdp_growth	−0.046	−0.104
	(-0.75)	(-0.25)
Industry1	−0.346**	0.478
	(-2.28)	(0.47)
Industry2	−0.361***	−0.831**
	(-5.84)	(-2.00)
Env_index	−0.005	0.247***
	(-0.43)	(3.36)
Env_staff	0.077*	0.094
	(1.71)	(0.31)
Urbanization level	−0.100*	−0.848**
	(-1.77)	(-2.23)
Population size	−0.139***	0.009
	(-2.82)	(0.03)
Internet infrastructure	0.003	0.090
	(0.12)	(0.62)
Constant	0.869*	1.682
	(1.78)	(0.51)
City & Year FE	Yes	Yes
N	2400	2400
Adjusted R^2	0.065	0.211
F	8.128	31.284

transparency. Information transparency plays a very important role in decision- making and behavior biases (Danbolt et al., 2022; Liu et al., 2023). Several studies support the importance of fintech development in decreasing information asymmetry among individuals, banks, and regulators (Björkegren & Grissen, 2018). Thus, with the growing adoption of fintech, both fiscal revenue and the allocation of fiscal resources have become more transparent. Fiscal transparency has become an important policy tool in the modernization of national governance systems and capacities, as well as in high-quality economic development in China (Chen & Neshkova, 2020; Liu et al., 2021). In terms of environmental protection issues, Zhang and Wang (2021) document the positive impact of fiscal transparency on public governance efficiency of local environments. Therefore, fintech is expected to promote fiscal transparency and high-quality public governance, especially green governance, which further facilitates pollution reduction.

Then, we examine whether fiscal transparency is the channel through which fintech reduces environmental pollution. First, we examine the effect of fintech on regional fiscal transparency (*Transparency*), measured as the logarithm of the transparency score derived from reports on China's municipal government financial transparency by the China Financial Transparency Research Group. Column (1) of Panel B in Table 11 reports the results, showing that fintech positively impacts fiscal transparency, which is consistent with previous studies. We then include the variable *Transparency* in our model. The results in Columns (2)–(3) of Panel B in Table 11 show that the coefficient of *Transparency* is negative and the coefficient of *Fintech* is negative. This indicates that fintech affects greenhouse gas emissions through increasing fiscal transparency.

4.2. Heterogeneity analysis

4.2.1. Heterogeneity in internet penetration

Previous studies document that fintech is a technology-driven financial innovation that requires Internet and broadband network infrastructure (Cheng et al., 2023). Thus, we argue that cities lacking network infrastructure have less Internet penetration and a low level of fintech adoption. To determine the role of Internet penetration in our main findings, we split our sample into two groups according to cities' level of Internet penetration and perform heterogeneity analysis. Jin et al. (2023) document that China's broadband internet expansion provides fast Internet access for residents in cities that have been chosen and greatly improves local Internet penetration. Thus, we measure Internet penetration by whether cities are chosen for the construction of broadband networks

Table 11
Mechanisms.

Panel A: Green innovation

This table provides the empirical results of OLS regressions of green innovation (*Greenpatent*) on fintech adoption (*Fintech*) and the effects of *Greenpatent* as a channel by which fintech promotes emission reduction. *Greenpatent* is measured as the logarithm of green patent applications in each city-year. *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Greenpatent*	(2) *CO_2*	(3) *SO_2*
Greenpatent		−0.043***	−0.122**
		(−4.83)	(−2.01)
Fintech	0.998***	−0.072**	−0.509**
	(11.42)	(−1.96)	(−2.04)
Gdp_capita	0.022	−0.028***	−0.110*
	(0.91)	(−2.91)	(−1.67)
Gdp_growth	0.073	−0.044	−0.070
	(0.49)	(−0.71)	(−0.17)
Industry1	1.090***	−0.320**	0.454
	(2.96)	(−2.12)	(0.44)
Industry2	0.251*	−0.349***	−0.794*
	(1.67)	(−5.67)	(−1.91)
Env_index	0.111***	−0.001	0.264***
	(4.20)	(−0.08)	(3.59)
Env_staff	−0.052	0.068	0.127
	(−0.49)	(1.58)	(0.44)
Constant	−0.313	0.076	1.600
	(−0.32)	(0.19)	(0.58)
City & Year FE	Yes	Yes	Yes
N	2400	2400	2400
Adjusted R^2	0.541	0.071	0.211
F-value	165.575	10.066	35.122

Panel B: Fiscal transparency

This table provides the empirical results of OLS regressions of fiscal transparency (*Transparency*) on fintech adoption (*Fintech*) and the effects of *Transparency* as a channel by which fintech promotes emission reduction. *Transparency* is measured as the logarithm of the transparency score derived from research reports on China municipal government financial transparency by the China Financial Transparency Research Group. *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Transparency*	(2) *CO_2*	(3) *SO_2*
Transparency		−0.037**	−0.467***
		(−2.32)	(−4.40)
Fintech	0.222***	−0.115***	−0.617**
	(9.31)	(−3.18)	(−2.56)
Gdp_capita	0.005	−0.029***	−0.107
	(0.53)	(−2.94)	(−1.62)
Gdp_growth	0.037	−0.047	−0.076
	(0.47)	(−0.75)	(−0.18)
Industry1	−0.038	−0.337**	0.709
	(−0.44)	(−2.21)	(0.70)
Industry2	−0.088*	−0.360***	−0.831**
	(−1.83)	(−5.83)	(−2.01)
Env_index	0.046***	−0.002	0.300***
	(4.77)	(−0.16)	(4.07)
Env_staff	−0.032***	0.077*	0.217
	(−3.20)	(1.78)	(0.74)
Constant	0.305**	0.026	0.827
	(2.19)	(0.06)	(0.30)
City & Year FE	Yes	Yes	Yes
N	2400	2400	2400

(*continued on next page*)

Table 11 (*continued*)

Adjusted R^2	0.601	0.063	0.217
F-value	220.35	8.870	36.331

and split our sample into the *High* group (cities chosen for network construction) and *Low* group (cities without broadband network construction). We further employ a bootstrap methodology of 500 times to determine the significance levels of the observed differences in the coefficient estimates of *Fintech* across groups. The regression results in Panel A of Table 12 indicate that fintech has more pronounced effects on emission reduction when regional internet penetration is higher.

4.2.2. Heterogeneity in environmental regulation

Studies have shown that implementing environmental regulations can help decrease greenhouse gas emissions and save energy (Zhou et al., 2021). They also indicated that the regulations could have various effects, including the carbon haven effect and the Porter effect. These effects could affect industrial shifts, labor practices, and corporate investments (Cao et al., 2022; Chen et al., 2022; Huang, Zhao, & Cao, 2021), thus indirectly affecting carbon emissions. To investigate the effects of environmental regulation intensity on the relationship between fintech adoption and GHG emissions, we use the local environmental regulatory index of a city following Liu and He (2021) to measure the regulation intensity. Our regression results, shown in Panel B of Table 12, indicate that cities with lower environmental regulatory intensity experience a greater reduction in pollution emissions subsequent to the development of fintech, which is consistent with previous studies that government regulation takes an important role in shaping microeconomic activities (Hemmings et al., 2018). This suggests that fintech could address deficiencies in environmental regulation.

4.3. Business environment and common prosperity

In economics, studies suggest that air quality could affect productivity, house prices, and corporate behaviors (Chay & Greenstone, 2005; Tan et al., 2021; Zivin & Neidell, 2012), thereby generating substantial effects on the regional business environment. Weng et al. (2023) document that air pollution-related healthcare costs have been reduced significantly in China through clean air initiatives aimed at improving air quality. To further investigate the broad economic and social impacts of polluting gas emission reduction resulting from fintech adoption, we examine the effects of such reduction on both regional business environments (*Business Environment Index*) and citizen well-being (*Residents' Income*). The results presented in Table 13 suggest that fintech adoption, by reducing GHG emissions, improves business environments and common prosperity.

5. Conclusions and policy implications

5.1. Conclusions

This study provides direct and solid empirical evidence of the relationship between fintech adoption and GHG emissions (CO_2 and SO_2). We find that adopting fintech significantly reduces CO_2 and SO_2, and these results are economically significant. We further find that increased green innovation and transparency are the underlying mechanisms through which fintech reduces emissions. Our heterogeneity tests show that our baseline results are more evident in cities with a high degree of Internet penetration and less intensive environmental regulation. Furthermore, we provide important economic and social consequences of fintech, namely that a city's fintech adoption reduces the city's emissions, which enhances the business environment and citizens' well-being in the city. Our results suggest that fintech adoption is a blessing rather than a curse for the ecological environment, business environment, and society.

5.2. Policy implications

The study's findings have important implications for policymakers and regulators, as well as local governments, regarding the promotion of financial technology. First, developing local financial technology can help address the environmental issues and achieve the goal of a low-carbon economy by reducing greenhouse gas emissions. It is also important that policymakers pay more attention to the construction of Internet infrastructure and information platforms, which provide a solid foundation for the development of fintech. Additionally, our study indicates that more young graduates can foster the adoption of fintech applications and enhance the quality of the fintech workforce. This suggests that policymakers should focus on nurturing young talent to achieve their intended objectives related to fintech and green governance.

Second, promote the integration of financial technology (fintech) and green governance. Our additional tests indicate that the impacts of fintech are more pronounced in cities with more Internet penetration and less intensive environmental regulation. Thus, coordination of fintech and environmental governance would effectively address digital divide and green issues at the same time. In detail, the government should improve the institutional design concerning fintech and carbon reduction by integrating the elimination of the digital divide and the promotion of environmental governance into a unified policy framework.

Third, to better serve green projects and green development using financial technology, it is necessary to strengthen cooperation with society and jointly commit to the technology research and development of green financial technology resource investment in emerging technologies such as artificial intelligence, big data, and blockchain. Additionally, the government should maintain close

Table 12
Heterogeneity analysis.

Panel A: Heterogeneity in Internet penetration

This table reports the moderating effect of Internet penetration on the negative relationship between fintech and GHG emissions. We divide the sample into two groups according to whether cities are piloted for the construction of broadband networks. If a city is piloted for construction of broadband networks, it is categorized into subsample with high Internet penetration (High), otherwise subsample with low Internet penetration (Low). *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. Following Cleary (1999), we employ a bootstrap methodology of 500 times to determine significance levels of observed differences in coefficient estimates of *Fintech* across different city categories. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *CO_2* High	(2) *CO_2* Low	(3) *SO_2* High	(4) *SO_2* Low
Fintech	−0.291***	0.044	−1.001**	−0.474
	(−3.75)	(1.37)	(−2.52)	(−1.52)
Gdp_capita	−0.039***	−0.016	−0.085	−0.124
	(−2.65)	(−1.07)	(−1.12)	(−0.86)
Gdp_growth	−0.108	0.036	−0.634	0.931
	(−1.04)	(0.52)	(−1.19)	(1.36)
Industry1	−1.493***	0.256**	−1.092	0.980
	(−4.31)	(1.96)	(−0.62)	(0.77)
Industry2	−0.871***	−0.037	0.021	−1.492***
	(−6.85)	(−0.63)	(0.03)	(−2.59)
Env_index	0.038	−0.025***	0.251**	0.242***
	(1.52)	(−2.67)	(1.97)	(2.70)
Env_staff	0.146*	−0.011	0.877**	−0.726*
	(1.82)	(−0.25)	(2.13)	(−1.74)
Constant	0.109	0.296	−5.236	9.495**
	(0.15)	(0.72)	(−1.37)	(2.36)
City & Year FE	Yes	Yes	Yes	Yes
N	898	1502	898	1502
Adjusted R^2	0.120	0.111	0.199	0.229
F-value	7.060	10.930	12.862	25.949
P-value (Difference in coeff. of *Fintech*)	0.030**		0.088*	

Panel B: Heterogeneity in environmental regulatory intensity

This table reports the moderating effect of Internet penetration on the negative relationship between fintech and GHG emissions using OLS regression for panel data. We divide our sample into two groups according to the median environmental regulatory intensity of all cities in a year. If a city has higher (lower) environmental regulatory intensity than the median, it is categorized into the subsample with high (low) regulatory intensity. *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. Following Cleary (1999), we employ a bootstrap methodology of 500 times to calculate the significance levels of the observed differences in the estimates of the coefficient of *Fintech* across different city categories. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *CO_2* High	(2) *CO_2* Low	(3) *SO_2* High	(4) *SO_2* Low
Fintech	−0.101**	−0.173***	−0.317	−0.923**
	(−2.34)	(−2.61)	(−0.86)	(−2.44)
Gdp_capita	−0.014	−0.057***	−0.147*	−0.116
	(−1.42)	(−2.76)	(−1.77)	(−0.98)
Gdp_growth	−0.030	−0.155	−1.271**	2.379**
	(−0.51)	(−0.89)	(−2.54)	(2.38)
Industry1	−0.120	−0.780***	−0.418	0.815
	(−0.68)	(−2.71)	(−0.27)	(0.50)
Industry2	−0.296***	−0.359***	−0.846	−0.565
	(−4.17)	(−3.14)	(−1.39)	(−0.86)
Env_index	0.026*	−0.028	0.069	0.397***
	(1.75)	(−1.58)	(0.54)	(3.94)
Env_staff	0.003	0.158*	0.094	0.394
	(0.06)	(1.68)	(0.22)	(0.73)
Constant	0.414	−0.270	2.572	−1.125
	(0.90)	(−0.30)	(0.66)	(−0.22)

(*continued on next page*)

Table 12 (*continued*)

City & Year FE	Yes	Yes	Yes	Yes
N	1156	1244	1156	1244
Adjusted R^2	0.087	0.076	0.220	0.222
F-value	5.479	5.167	16.175	17.987
P-value (Difference in coeff. of *Fintech*)	0.100*		0.030**	

Table 13
Economic consequences.

This table provides the empirical results of OLS regressions of business environment (*Business*) and resident disposal income (*Income*) on fintech adoption (*Fintech*). *Business Environment Index* is measured by China's regional business environment index from the National Bureau of Statistics of China. *Residents'Income* is the natural logarithm of the average disposable income of residents in China. *CO_2* is CO_2 emission intensity measured as total CO_2 emissions divided by GDP. *SO_2* is SO_2 emission intensity, measured as total SO_2 emissions divided by GDP. *Fintech* is measured by the overall development of fintech at the city level in China from Guo et al. (2020). *Gdp_capita* is the natural logarithm of the per-capita GDP of a city. *Gdp_growth* is the change in a city's GDP from the previous year's value. *Industry1* is the ratio of added value from the primary economic activity industry to GDP. *Industry2* is the ratio of added value from secondary industries of economic activity to GDP. *Env_index* is the local environmental regulatory intensity of a city, measured following Liu and He (2021). *Env_staff* is the natural logarithm of staff working in environmental protection institutions. The continuous variables are winsorized at the 99th and 1st percentiles. The values in the parentheses are derived from standard errors in the cities. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Business Environment Index*	(2) *Residents' Income*
Fintech	−0.015***	0.299***
	(−3.13)	(7.20)
Gdp_capita	−0.001	0.004
	(−0.65)	(0.36)
Gdp_growth	0.011	0.009
	(1.39)	(0.13)
Industry1	0.005	0.172
	(0.24)	(0.98)
Industry2	0.008	0.015
	(1.05)	(0.21)
Env_index	−0.014***	0.047***
	(−9.64)	(3.71)
Env_staff	−0.084***	−0.291***
	(−14.87)	(−5.81)
Constant	0.884***	11.798***
	(16.72)	(25.15)
City & Year FE	Yes	Yes
N	2400	2400
Adjusted R^2	0.287	0.856
F	84.136	970.145

interactions and cooperation with foreign governments and international organizations to promote China's green financial technology development concepts and financing strategies, and attract foreign capital to domestic green industries.

Authorship contributions

Wenwen Li: Conceptualization, Methodology, Software, Formal analysis, Funding acquisition, Writing- Original draft; Samar S. Alharbi: Supervision, Formal analysis, Visualization, Writing- Reviewing and Editing; June Cao: Data Curation, Project administration, Validation, Writing- Reviewing and Editing; Wanfu Li: Conceptualization, Funding acquisition, Investigation, Writing- Reviewing and Editing. All co-authors have made equal contributions to the paper.

Declaration of competing interest

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

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Annex 1. Variable definition

Variable	Definition	Data Source
Dependent variables		
CO_2	CO_2 emission intensity (unit: kg/10^4 RMB), measured as total CO_2 emissions divided by GDP.	National Bureau of Statistics of China and China Statistical Yearbook.
SO_2	SO_2 emission intensity (unit: kg/10^4 RMB), measured as total SO_2 emissions divided by GDP.	As above.
Variable of interest		
Fintech	General index assessing the overall growth of fintech at the city level from Guo et al. (2020).	Digital Financial Inclusion Index (DFI) from Peaking University.
Control variables		
Gdp_capita	Natural logarithm of a city's per-capita GDP.	The China Economic and Social Development Database and China Statistical Yearbook.
Gdp_growth	The change in a city's GDP from the previous year's value.	As above.
Industry1	The ratio of added value from the primary economic activity industry to GDP.	As above.
Industry2	The ratio of added value from secondary industries of economic activity to GDP.	As above.
Env_index	Index measuring the local environmental regulatory intensity of a city, following Liu and He (2021).	National Bureau of Statistics of China.
Env_staff	Natural logarithm of staff working in environmental protection institutions.	Carbon Neutral Research Database of China.
Variables used in robustness tests		
Distance	Natural logarithm of the geographic distance of a city to Hangzhou.	Chinese Research Data Services Platform and authors' calculations.
Num_graduate	Natural logarithm of college students in a city	As above.
IPRP	Natural logarithm of finished cases involving intellectual property litigation that courts in each city have heard.	As above.
Internet infrastructure	Natural logarithm of Internet terminals in a city.	As above.
Fintech_alter	The Baidu index at the city level reflecting public concern and demand for fintech following Zhao et al. (2022).	Baidu index Data sharing platform.
Population size	Population density following Cheng et al. (2023)	The China Economic and Social Development Database and China Statistical
Urbanization level	Ratio of urban population over permanent resident population.	The China Economic and Social Development Database and China Statistical.
Variables used in additional tests		
Greenpatent	Natural logarithm of green patents application in a city.	As above.
Business Environment Index	Regional business environment index.	National Bureau of Statistics of China.
Residents' Income	Natural logarithm of average disposable income of residents.	National Bureau of Statistics of China and China Statistical Yearbook.

Fig. 1 Illustrates the relationship between regional fintech adoption and greenhouse gas emissions in 2011 and 2019.
Fig. 2 Illustrates the density distribution of treatment and control samples before and after matching using 1:1 nearest matching.

Data availability

Data will be made available on request.

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