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# CAN DIGITAL FINANCE PROMOTE LOW-CARBON TRANSITION? EVIDENCE FROM THE PEOPLE'S REPUBLIC OF CHINA

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**Abstract**

Using panel data of cities in the People's Republic of China from 2011 to 2019, this paper analyzes the impact of digital finance on low-carbon transition derived from a super-efficiency slacks-based measure data envelopment analysis. We find that digital finance promotes low-carbon transition, and this finding is robust with respect to the choice of sample, potential presence of measurement issue, choice of study period, presence of other policies, and potential endogeneity, among others. This impact, at least in part, is through increased green innovations. We also find evidence for impact heterogeneity across locations and by the level of low-carbon transition. This paper provides policy implications for the low-carbon transition of the region from a digital finance perspective.

**Keywords:** digital finance, low-carbon transition, green innovation, slacks-based measure data envelopment analysis

**JEL Classification:** G20, Q54, Q55

# Contents

# 1. INTRODUCTION

With the development of information technology, digital finance‒which refers to the use of digital technologies in the provision of or access to financial services—has grown rapidly in recent years. Digital finance is an important factor influencing the economy, finance, and energy (Zhang, Jin, and Wang 2015) and may enable a higher level of consumption and promote inclusive development, for example, through increased availability of loans for small and medium-sized enterprises and vulnerable groups. Digital finance has also contributed to green innovation and reduced pollution (Meng and Zhang 2022; Zhang and Ling 2022). Digital finance can be expected to play an important role in low-carbon transition, or a shift towards lower emissions of pollutants (Chen 2012). This is because the key driver of low-carbon transition is green innovation, which requires substantial financial support from the financial sector. Nevertheless, the impact of digital finance on low-carbon transition has been underexplored in the existing literature. This study fills this research gap.

Digital finance may affect low-carbon transition by contributing to green innovation through the provision of funding for green and clean projects. This is possible, since digital finance may absorb funds from long-tail groups,[1] thereby reducing borrowing costs for firms and individuals and facilitating green innovation projects with potentially high risks and long payback cycles, which are typically excluded from traditional finance. Our findings are indeed consistent with the relevance of green innovation.

There are at least three additional theoretical channels through which digital finance can affect low-carbon transition. First, digital finance includes some ecological restoration projects (such as Alipay's Ant Forest), which aim to encourage the public to reduce carbon emissions. Second, digital finance facilitates the green consumption of disadvantaged groups by providing them with funds that contribute to low-carbon transition. Finally, digital finance breaks through time and space constraints and reduces transaction costs for consumption. While these three channels are potentially important, the analysis of these channels is beyond the scope of this paper due to the lack of available data.

The discussion above merely suggests the possible causal channel running from digital finance to low-carbon transition, and whether digital finance indeed influences low-carbon transition is an empirical question. Thus, we explore this question using panel data from 283 cities in the People's Republic of China (PRC) between 2011 and 2019. There are three important reasons why we study cities in the PRC. First, the PRC is the second largest economy and the largest developing country in the world. Further, the PRC is already highly urbanized with 63% of the population living in urban areas in 2020. Given the number of large cities in the PRC and the continuing trend of urbanization, cities in the PRC are of interest to study. Second, the PRC is the largest carbon emitter in the world, accounting for more than 30% of the world's carbon emissions from fossil fuels and industry but without accounting for land use change, according to the Global Carbon Atlas. Finally, cities are the basic unit for policy implementation in the PRC and play a vital role in reaching peak carbon emissions. With 70% of global carbon emissions coming from cities, cities are also relevant to the analysis of green transition both inside and outside of the PRC.

[1] The long-tail group refers to individuals or small businesses with relatively small financial assets but large numbers.

Measuring digital finance and low-carbon transition is critical in this study. For the measurement of the former, this paper employs the *Peking University Digital Financial Inclusion Index of China* (PKU_DFIIC), which provides an overall index for digital finance as well as its subindices for coverage breadth, usage depth, and digitization level. To measure low-carbon transition, we use the technical efficiency measure derived from unoriented slacks-based measure data envelopment analysis (SBM-DEA) and its super-efficiency counterpart with undesired outputs. The technical efficiency measure tends to be higher when a city uses fewer inputs and produces more desired outputs and fewer undesired outputs compare to other cities.

Using these measures, we regress the low-carbon transition on the digital finance index and other control variables. The baseline regression results indicate that digital finance significantly accelerates low-carbon transition. This conclusion is robust with respect to the exclusion of the four direct-administered municipalities, exclusion of certain outliers, changes in the study period, and inclusion of potentially confounding policies. Further, addressing the potential endogeneity of digital finance by a type of shift-share instrument variable (*SSIV*) also does not change the results. We argue that this is a plausibly valid instrument, because the inverse of the spherical distance between a city and Hangzhou is positively correlated with digital finance on the one hand and the inverse of the spherical distance between a city and Hangzhou is largely irrelevant to the low-carbon transition on the other. In addition, based on the approach proposed by Conley, Hansen, and Rossi (2012), this paper finds that the positive effect of digital finance on the low-carbon transition is robust with respect to a modest violation of the exclusion restriction.

We then analyze the mechanisms through which digital finance influences low-carbon transition. The results indicate that digital finance drives low-carbon transition at least in part by promoting green innovation, which includes all types of innovations that enable the production of goods and services while reducing or removing undesirable impacts on the environment and natural resources. We also analyze the impact heterogeneity with respect to various city characteristics. This analysis suggests that digital finance in cities to the east of the Heihe–Tengchong line—a hypothetical line that extends from the city of Heihe in the northeast to the city of Tengchong in the southwest—promoted low-carbon transition, but this is not the case for cities to the west of this line. We also find that digital finance only facilitates low-carbon transition in cities above the median low-carbon transition.

There are three innovations in this paper. First, previous studies typically ignored the presence of potential endogeneity concerns. We propose a new type of SSIV for digital finance defined as the product between the inverse of the spherical distance between the city and Hangzhou multiplied by the PRC digital finance index for each year. As elaborated subsequently, this IV is plausibly exogenous and our results are robust to a modest violation of the exogeneity of the SSIV. Second, this paper analyzes whether the impact of digital finance on low-carbon transition is heterogeneous across cities with different low-carbon transition levels, a point that has also been previously ignored. Third, unlike previous studies, this paper offers a granular analysis of green innovation as a channel through which digital finance affects low-carbon transition by dividing it into low-level and high-level innovations.

The paper is structured as follows. Section 2 reviews the related literature. Section 3 presents the data, methods, and model. Section 4 shows the empirical results and analysis. Section 5 presents the heterogeneity analysis. Finally, Section 6 offers conclusions and policy implications.

# 2. LITERATURE REVIEW

This paper is related to the body of literature on digital finance. In the early literature, scholars assessed the impacts of digital finance on economic outcomes, such as entrepreneurship (Xie et al. 2018), economic growth (Qian et al. 2020), and income disparity (Ji et al. 2021). More recently, studies have examined the environmental effects of digital finance. For example, Wan, Pu, and Tavera (2023) find a significant negative relationship between digital finance and pollutant emissions. Fu et al. (2023) used PRC provincial data to find an inverted U-shaped effect of digital finance on energy efficiency.

In particular, this paper adds to the literature on the analysis of the impact of digital finance on carbon emissions and green economy efficiency. Digital finance has been found to reduce carbon emissions in the PRC based on provincial data by Zhao et al. (2021) and city-level data by Wang and Guo (2022). Wang et al. (2022) identified that digital finance improves green economy efficiency by strengthening credit constraints on highly polluting firms.

This study also contributes to the literature on the factors influencing low-carbon transition. Existing studies have examined various factors affecting low-carbon transition, such as industrial structure (Wang et al. 2019), industrial agglomeration (Zhang et al. 2019), technological innovation (Liu and Zhang 2021), green innovation (Zhang and Liu 2022), green bonds (Sartzetakis 2021), and green credit (Liu et al. 2022b). We complement this literature by examining green innovation as one of the key channels through which digital finance promotes low-carbon transition.

This study also carefully constructs a measure of low-carbon transition by adopting the (super-efficiency) SBM-DEA. This is an important point because the measurement can potentially affect our results. We employ the (super-efficiency) SBM-DEA with undesired outputs, since it allows us to compute the total factor efficiency, taking into consideration not only the inputs and desired outputs but also emissions (undesired outputs). This is in contrast to single-factor efficiency measures, such as per capita carbon emissions (Zheng et al. 2019), per capita energy consumption (Truong, Wiktor, and Boxall 2015), and carbon emissions per unit GDP (Liu et al. 2019). Since single-factor efficiency cannot fully reflect the multiple outcomes we are interested in, we argue that the total-factor efficiency in the DEA approach is more suitable. The DEA approach also has an advantage over parametric approaches, such as the stochastic frontier analysis, because we do not need to assume a particular form of production function.

Some other studies use the index system method to measure low-carbon transition. Tan et al. (2017) used the entropy weight method to construct a low-carbon economic index that reflects seven dimensions of (i) economic development, (ii) energy pattern, (iii) society and life, (iv) carbon and environment, (v) urban transportation, (vi) solid waste, and (viii) water. Deng and Yang (2019) applied the entropy weight method to construct an industrial low-carbon transition index from five dimensions of (i) resource saving, (ii) pollution reduction, (iii) industrial upgrading, (iv) productivity improvement, and (v) development sustainability. Sun et al. (2020) built a sustainable development indicator from the three dimensions of (i) environment, (ii) energy, and (iii) economy, and evaluated the sustainable development performance of South Asia. Huang et al. (2022) adopted entropy-weighted TOPSIS to comprehensively evaluate the level of green and low-carbon development from the three dimensions of (i) green benefits, (ii) low-carbon benefits, and (iii) economic and social benefits. We also consider a similar entropy-weighted index as an alternative measure of low-carbon transition, even though our preferred measure of low-carbon transition is based on the (super-efficiency) SBM-DEA.

As shown subsequently, the current study shows that digital finance affects low-carbon transition through the channel of green innovation. Therefore, this paper also relates to the existing studies that find a positive impact of digital finance on green innovation. For example, Liu et al. (2022a) find that digital finance promotes green innovation by alleviating financial constraints and increasing investment in R&D. Rao et al. (2022) discover that digital finance facilitates green innovation by increasing the financial liquidity of firms. Meng and Zhang (2022) believe that digital finance promotes green innovation by enhancing regional green financial services. While we do not analyze how digital finance affects green innovation, the findings of the current study are consistent with these findings.

This study also adds to a growing body of literature on the impact of green innovation on low-carbon transition. Green innovation is in line with the goal of sustainable development (Li and Liao 2020), as it emphasizes not only economic benefits but also environmental and ecological benefits. Based on sectoral data for 17 OECD countries from 1975 to 2005, Wurlod and Noailly (2018) find that green innovation reduces energy intensity (the inverse of energy efficiency). Xu et al. (2021) find a positive relationship between green innovation and carbon emission performance. Dong et al. (2022) detect improvement in carbon emission efficiency through green innovations using PRC data. Green innovation has become an effective means to promote sustainable development and low-carbon transition (Yu et al. 2021; Lin and Ma 2022). The current study corroborates these findings.

# 3. DATA, METHODOLOGY, AND EMPIRICAL MODEL

## 3.1 Data Sources

This paper studied 283 cities in the PRC from 2011 to 2019 due to data limitations. There are four main data sources for the empirical analysis in this paper. We obtain (i) carbon emission data from the *China Urban Construction Statistical Yearbook* and the *China City Statistical Yearbook*; (ii) the digital finance index from the PKU_DFIIC; (iii) variables on green innovation from the *Chinese Research Data Services Platform* (CNDRS); and (iv) various other city-level variables obtained from the *China City Statistical Yearbook*.

## 3.2 Measurement of Low-Carbon Transition

We measure low-carbon transition (LCT) using the technical efficiency in the unoriented (super-efficiency) SBM-DEA model with undesired output after Tone (2002). Here, we briefly describe the intuition behind the SBM-DEA model and then steps taken to compute LCT.

To motivate the use of DEA, note that it is essential to have either multiple inputs or outputs, the latter of which may contain undesirable ones. If instead we had just one input and one output, we could create a technical efficiency measure by taking the ratio of output to input. But this simple approach does not work in a more general situation with multiple inputs, multiple outputs, or both. The DEA allows us to address this issue. While there are many variants of DEA models, we typically consider a best linear combination of decision-making units (DMUs) and determine how efficient a given DMU is relative to this best linear combination. To facilitate an intuitive understanding, let us consider a case where there is one type of input and two types of outputs, where higher levels of outputs for a given level of input are more desired. In Figure A1, there are four DMUs labeled from A to D, and each point represents the combination of outputs that a given DMU produces from a unit input. The kinked line that goes through DMUs A, B, and D is called the “efficiency frontier,” since this represents the set of outputs that can be produced from a linear combination of efficient DMUs. In the traditional DEA, the technical efficiency is measured by how efficiently a DMU produces outputs relative to the efficiency frontier. Those DMUs that are on the efficiency frontier have a unit technical efficiency measure and those which are not have a technical efficiency strictly below unity. In Figure A1, the technical efficiency for DMU C can be computed as the ratio of $\overline{OC}$ to $\overline{OD}$.

One potential disadvantage of the traditional DEA is that it does not allow us to create a ranking among efficient DMUs. The super-efficiency DEA approach overcomes this issue by restricting the linear combination to those DMUs that exclude the DMU under consideration. For example, when considering the technical efficiency of DMU D, we consider the linear combination of DMUs A and B. In Figure A1, point E represents the combination of two outputs that can be attained by a linear combination of DMUs A and B that has the same mix of outputs as DMU D. Therefore, the technical efficiency for DMU D in the super-efficiency DEA would be the ratio of $\overline{OD}$ to $\overline{OE}$. As this example shows, the technical efficiency measure in a super-efficiency DEA can exceed unity.

DEA and super-efficiency DEA models have been used in a wide variety of contexts. Our application in particular relates to the applications to the analysis of production inefficiency in the presence of undesirable outputs by Wang and Feng (2015) and the evaluation of urban environmental sustainability by Yu and Wen (2010). We take each of the 283 cities in each observation period in the data as a decision-making unit. We consider three inputs of labor, capital, and energy, which are respectively measured by the number of employees in the city (unit: 10,000 persons), the city’s capital stock (unit: 10,000 yuan) estimated by the perpetual inventory method, and the city’s electricity consumption (unit: 10,000 kWh). We choose city’s electricity consumption because there is a high correlation between electricity consumption and energy consumption in the PRC. The desired output is taken to be the city’s real GDP at constant prices in 2000 (unit: 10,000 yuan). The undesired output is carbon emissions in the city (unit: 10,000 tons), which is calculated by summing the carbon emissions generated from electricity, gas, LPG, transportation, and thermal energy consumption.[2] The details of the calculation process can be found in Wu and Guo (2016).

The measurement of low-carbon transition is divided into two steps. First, we calculate the efficiency score $\delta_{ct}$ in city *c* in year *t* using the SBM-DEA model with undesirable outputs, where $x_{ct}^{i}$, $y_{ct}$, and $b_{ct}$ are the *i*-th input, desired output, and nondesired output, respectively. Specifically, we solve the following minimization problem in Eq. (1).

$$\delta_{ct} = min_{\lambda_{c't'},s_{x,i},s_y,s_b} \frac{1 - \frac{1}{3}\sum_{i=1}^{3}\left(s_{x,i}/x_{ct}^{i}\right)}{1 + \frac{1}{2}\left(s_y/y_{ct} + s_b/b_{ct}\right)}$$

2 This paper focuses on carbon emissions from the production side. Due to the unavailability of inter-city input–output tables, it is unable to accurately measure carbon emissions from the consumption side of cities.

$$s.t.\begin{cases} x_{ct}^{i} = \sum \lambda_{c\prime t\prime} x_{c\prime t\prime}^{i} + s_{x,i}, \ i = 1,2,3 \\ y_{ct} = \sum \lambda_{c\prime t\prime} y_{c\prime t\prime} - s_{y} \\ b_{ct} = \sum \lambda_{c\prime t\prime} b_{c\prime t\prime} + s_{b} \\ \lambda_{c\prime t\prime} \geq 0, s_{x,i} \geq 0, s_{y} \geq 0, s_{b} \geq 0 \end{cases} \qquad (1)$$

where $\lambda_{c\prime t\prime}$ is the weight for creating the linear combination of DMUs, and $s_{x,i}$, $s_y$, $s_b$ are slack variables for the *i*-th input, desired output, and nondesired output, respectively. These slack variables respectively represent the excess of inputs, shortfall of desired outputs, and excess of undesired outputs relative to the linear combination of efficient DMUs. Therefore, they can be interpreted as measures of the distance from the efficiency frontier in a particular dimension. It is straightforward to verify that $\delta_{ct}$ is unity when all the slack variables are equal to zero. When at least one of the slack variables is strictly positive, $\delta_{ct}$ is strictly less than unity, indicating that city *c* in year *t* is inefficient.

Next, we calculate the super-efficiency score $\gamma_{ct}$ for DMUs using the super-efficient SBM-DEA considering undesirable outputs in Eq. (2).

$$\gamma_{ct} = min_{\lambda_{c\prime t\prime}, s_{x,i}, s_y, s_b} \frac{1 + \frac{1}{3}\sum_{i=1}^{3}\left(s_{x,i}/x_{ct}^{i}\right)}{1 - \frac{1}{2}\left(s_y/y_{ct} + s_b/b_{ct}\right)}$$

$$s.t.\begin{cases} \overline{x^{\iota}} \geq \sum_{c't' \neq ct} \lambda_{c't'} \, x_{c't'}^{i}, \quad i = 1,2,3 \\ \bar{y} \leq \sum_{c't' \neq ct} \lambda_{c't'} \, y_{c't'} \\ \bar{b} \geq \sum_{c't' \neq ct} \lambda_{c't'} \, b_{c't'} \\ \overline{x^{\iota}} = x_{ct}^{i} + s_{x,i} \\ \bar{y} = y_{ct} - s_y \\ \bar{b} = b_{ct} + s_b \\ \bar{y} \geq 0 \\ \lambda_{c't'} \geq 0, s_{x,i} \geq 0, s_y \geq 0, s_b \geq 0 \end{cases} \qquad (2)$$

where, $\overline{x^{\iota}}$, $\bar{y}$, $\bar{b}$ are efficiency frontiers excluding DMU in city *c* in year *t*, respectively. $s_{x,i}$, $s_y$, $s_b$ represent slack variables for the *i*-th input, desired output, and nondesired output, respectively. These slack variables represent the reduction in inputs, excess of outputs, and reduction in undesired outputs relative to the linear combination of efficient DMUs. Put differently, $\gamma_{ct}$ tells us how well city *c* in year *t* does compare to other efficient DMUs. Since the slack variables for inefficient DMUs are zero, $\gamma_{ct}$ is equal to unity for inefficient units. Therefore, we only need to compute $\gamma_{ct}$ for efficient units (i.e., $\delta_{ct}$ = 1) in practice and $\gamma_{ct}$ allows us to rank efficient DMUs.

To solve the minimization problems in eqs. (1) and (2), we use the Charnes–Cooper transformation to convert it into a linear programming problem. For example, we obtain the following transformation from eq. (2):

$$\gamma_{ct} = min_{\lambda_{c't'}, s_{x,i}, s_y, s_b}\left(t + \frac{t}{3}\sum_{i=1}^{3}\left(s_{x,i}/x_{ct}^{i}\right)\right)$$

$$s.t.\ \begin{cases} tx_{ct}^{i} + ts_{x,i} \geq \sum_{c't' \neq ct} t\lambda_{c't'}\, x_{c't'}^{i}, \quad i = 1,2,3 \\ ty_{ct} - ts_{y} \leq \sum_{c't' \neq ct} t\lambda_{c't'}\, y_{c't'} \\ tb_{ct} + ts_{b} \geq \sum_{c't' \neq ct} t\lambda_{c't'}\, b_{c't'} \\ t - \frac{t}{2}\left(s_y / y_{ct} + s_b / b_{ct}\right) = 1 \\ \lambda_{c't'} \geq 0, s_{x,i} \geq 0, s_y \geq 0, s_b \geq 0, t \geq 0 \end{cases} \tag{3}$$

Once we obtain the efficiency and super-efficiency scores, we take their product to arrive at the following measure of low-carbon transition $Lct_{ct}$:

$$Lct_{ct} = \delta_{ct}\gamma_{ct} = \begin{cases} \delta_{ct} & if\ \delta_{ct} < 1 \\ \gamma_{ct} & if\ \delta_{ct} = 1 \end{cases}.$$

$Lct_{ct}$ measures how well city *c* in year *t* transforms inputs into desired outputs without producing undesired outputs. Hence, if $Lct_{ct}$ is high, it means that the city *c* in time *t* can produce more GDP and fewer carbon emissions with fewer inputs (labor, capital, and energy).

## 3.3 Measurement of Digital Finance and Control Variables

The primary independent variable of interest in this study is digital finance (*Df*), which is the digital finance inclusion index from the PKU_DFIIC by Guo et al. (2020) divided by 100 to rescale. The PKU_DFIIC index is based on a total of 33 underlying indicators, which are normalized to range between 0 and 100 (and hence between 0 and 1 after rescaling) in the base year of 2010 and aggregated using the weights by a combination of the coefficient of variation and analytic hierarchy process methods. The PKU_DFIIC also comes with subindices consisting of coverage breadth (*Cb*), usage depth (*Ud*), and digitization level (*Dl*), each of which is constructed from multiple underlying indicators.[3] *Cb* measures how widely digital finance covers the city's population, whereas *Ud* gauges the actual use of digital financial services. It includes both indicators of total actual use (i.e., the number of Alipay users using these services per 10,000) and indicators of active use (i.e., the number of transactions per capita, value of transactions per capita). *Dl* takes into account the mobility, affordability, credit, and convenience of digital finance. It embodies the advantages of the low cost and low threshold of digital financial services. The more convenient, less costly and more creditworthy the services of digital finance are, the more digitization it implies. Based on the dimensionless processing of each indicator, Guo et al. (2020) then combined subjective with objective weighting methods (coefficient of variation and the analytic hierarchy process) to determine the weight of each indicator, finally using the arithmetic mean synthetic model to calculate the PKU_DFIIC index.

Since digital finance may correlate with some city-level characteristics that have independent effects on low-carbon transition, it is critical to control for variables affecting the low-carbon transition. Economic development potential (*Edp*) is proxied by the GDP growth rate. This is an important variable to control for, because economic development potential can affect energy consumption and thus influence the low-carbon transition. We also include industrial structure (*Is*), which is defined as the ratio of the value added by the tertiary sector to the value added by the secondary sector. Industrial structure determines the energy allocation among different industries (Bai et al. 2018). Li, Gao, and Li (2022) find that industrial structure affects energy

[3] The details of the underlying indicators used to construct *Cb*, *Ud*, and *Dl* can be found in Table A1.

efficiency. We also control for population density (*Pd*) as measured by the city's population in 10,000 people per square kilometer.

Population density is also an important control as it affects carbon emissions by influencing commuting distances or changing mobility patterns (He et al. 2019), which can have an impact on the low-carbon transition. Finally, we also include in the set of control variables the green degree (*Gd*), or the ratio of green coverage area—the vertical projection area of all vegetation in a city including trees, shrubs, and lawns—to the total area of the city. Greening degree influences the low-carbon transition by absorbing carbon emissions (Shao et al. 2022). The descriptive statistics of the main variables discussed above are presented in Table 1.

**Table 1: Descriptive Statistics of Main Variables**

| Variable | Meaning of Variables | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Lct | Low-carbon transition | 2,547 | 0.45 | 0.19 | 0.15 | 1.41 |
| Df | Digital finance | 2,547 | 1.66 | 0.65 | 0.17 | 3.22 |
| Cb | Coverage breadth | 2,547 | 1.56 | 0.63 | 0.02 | 3.11 |
| Ud | Usage depth | 2,547 | 1.63 | 0.68 | 0.04 | 3.32 |
| Dl | Digitization level | 2,547 | 2.02 | 0.82 | 0.03 | 5.81 |
| Edp | Economic development potential | 2,547 | 0.09 | 0.04 | –0.19 | 1.09 |
| Is | Industrial structure | 2,547 | 0.98 | 0.54 | 0.11 | 5.17 |
| Pd | Population density | 2,547 | 0.04 | 0.03 | 0.00 | 0.28 |
| Gd | Green degree | 2,547 | 0.40 | 0.10 | 0.01 | 3.77 |

## 3.4 Spatial Distribution of Key Variables

Since there is considerable spatial heterogeneity in cities in the PRC. By comparing the spatial distribution of low-carbon transition in cities in the PRC in 2011 and 2019, we find that cities in the PRC have made significant progress in the low-carbon transition between 2011 and 2019, with the average value of low-carbon transition increasing from 0.41 in 2011 to 0.53 in 2019. Similarly, digital finance has achieved rapid growth from 2011 to 2019, with its average value in the city increasing from 0.52 in 2011 to 2.46 in 2019. One striking pattern we observe is that coastal cities have substantially higher levels of digital finance than noncoastal cities (See also Figures 1 and 2 in Ge and Fujii (2023)).

Next, we analyzed each of the three subdimensions of digital finance, namely coverage breadth, usage depth, and digitization level. The coverage breadth is a prerequisite for the development of digital finance. Its average across cities has gone up from 0.51 in 2011 to 2.36 in 2019, reflecting the rapid expansion of the digital finance coverage population. It is notable that the coverage breadth between the east and west sides of the Heihe–Tengchong line appears to be similar. This indicates that direct financial services can cover a wider customer base than traditional financial services, which previously had difficulty in reaching backward areas due to high costs. The usage depth measures how intensively digital financial services are used, and the average of this index went up from 0.56 in 2011 to 2.41 in 2019 with a clear difference in usage depth between the east and west sides of the Heihe–Tengchong line . This indicates that there is still much potential to promote the use of digital financial products in less-developed areas. Finally, as with the two other subindices, the level of digitization, which reflects the convenience, cost, and efficiency of digital finance, also rose between 2011 and 2019, from 0.50 to 2.86. It is notable that the spatial distribution of the digitization level appears to have changed. In particular, the digitization level has significantly improved in the coastal areas relative to those areas to the west of the Heihe–Tenghchong line (See also Figure 2A of Ge and Fujii (2023)).

## 3.5 Empirical Model

This paper adopts the following linear two-way fixed-effects regression model to analyze the influence of digital finance on the low-carbon transition.

$$Lct_{ct} = \beta_0 + \beta_1 Df_{ct} + \beta_2 Edp_{ct} + \beta_3 Is_{ct} + \beta_4 Pd_{ct} + \beta_5 Gd_{ct} + \theta_c + \mu_t + \varepsilon_{ct},$$

where $\theta_c$ and $\mu_t$ are the city- and year-specific fixed effects terms, respectively, and $\varepsilon_{ct}$ is the idiosyncratic random error term. *Lct* and *Df* are the measures of low-carbon transition and digital finance, respectively. *Edp*, *Is*, *Pd*, and *Gd* are control variables. $\beta$'s are the coefficients to be estimated, and $\beta_1$ is the primary coefficient of interest.

# 4. EMPIRICAL RESULTS

## 4.1 Baseline Results

Table 2 shows the regression results of the digital finance index on low-carbon transition. The estimation results in column (1) show that the coefficient of *Df* when no control variables are included is 0.3333 and is significant at a 1% level. In column (2), we add the control variables and the coefficient of *Df* remains similar at 0.2811 and is significant at a 1% level. These results show that digital finance is positively correlated with low-carbon transition.

**Table 2: Baseline Regressions of Digital Finance on Low-carbon Transition**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Variables** | ***Lct*** | ***Lct*** | ***Lct*** | ***Lct*** | ***Lct*** | ***Lct*** |
| *Df* | 0.3333*** | 0.2811*** | | | | |
| | (0.0569) | (0.0550) | | | | |
| *Cb* | | | 0.0986 | | | 0.1055 |
| | | | (0.0747) | | | (0.0700) |
| *Ud* | | | | 0.1092*** | | 0.0846*** |
| | | | | (0.0332) | | (0.0324) |
| *Dl* | | | | | 0.0563*** | 0.0533*** |
| | | | | | (0.0146) | (0.0135) |
| *Edp* | | 0.2816* | 0.2519 | 0.2827* | 0.2790* | 0.2879* |
| | | (0.1588) | (0.1564) | (0.1635) | (0.1605) | (0.1626) |
| *Is* | | –0.0487** | –0.0584*** | –0.0575*** | –0.0566*** | –0.0496** |
| | | (0.0197) | (0.0209) | (0.0201) | (0.0197) | (0.0199) |
| *Pd* | | 1.8287** | 2.3273*** | 2.2461*** | 2.2942*** | 1.8871*** |
| | | (0.7216) | (0.6843) | (0.6903) | (0.6985) | (0.6967) |
| *Gd* | | 0.1788** | 0.1812** | 0.1805** | 0.1841** | 0.1798** |
| | | (0.0849) | (0.0853) | (0.0829) | (0.0804) | (0.0836) |
| N | 2,547 | 2,547 | 2,547 | 2,547 | 2,547 | 2,547 |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.724 | 0.735 | 0.730 | 0.732 | 0.734 | 0.735 |

Note: *Lct* means low-carbon transition. *Df* represents digital finance. *Cb*, *Ud*, and *Dl* refer to coverage breadth, usage depth, and digitization level, separately. *Edp*, *Is*, *Pd*, and *Gd* indicate economic development potential, industrial structure, population density, and green degree, respectively. Standard errors clustered by city are in parentheses. *, **, and *** represent statistical significance at 10, 5, and 1 % levels, respectively.

To understand which components of digital finance contribute to low-carbon transition, we separately analyze the three subindices of digital finance, or the coverage breadth, the usage depth, and the digitization level. The estimation results are shown in columns (3), (4), and (5) of Table 2. We find that the coefficient of *Cb* is 0.0986 but insignificant, indicating that the increase in the number of people involved in digital finance does not contribute to the low-carbon transition. The coefficient of *Ud* is 0.1092 and significant at the 1% level, indicating that the increase in the usage depth of digital finance promotes low-carbon transition. The coefficient of *Dl* is 0.0563 and highly significant, indicating that the level of digitalization promotes low-carbon transition. In column (6), the three subindices are simultaneously included in a regression model, and the results remain similar. These results suggest that improvements in the extensive margin of digital finance access do not necessarily promote low-carbon transition. In contrast, increasing the intensive margin of digital financial use and improving the sophistication of digital finance tend to facilitate low-carbon transition.

## 4.2 Robustness Checks

To examine the robustness of the baseline regression results, this paper conducts a series of robustness checks. First, the sample of cities used in the baseline regressions include the four direct-administered municipalities of Beijing, Tianjin, Shanghai, and Chongqing. Unlike other cities that are under the provincial government, these four direct-administered municipalities are directly under the central government. These cities have a great deal of economic autonomy and are more likely to be able to implement measures to attract investment on their own. Furthermore, due to their unique political, economic, and cultural status, direct-administered municipalities enjoy preferential policy advantages over other cities, such as tax breaks. To exclude the influence of these factors on our estimation results, we re-estimate the sample after excluding the four municipalities. The estimation result is shown in column (1) of Table 3. The coefficient of *Df* does not change much and remains significant at the 1% level.

Second, to prevent the interference of outliers, we drop top and bottom 1% [5%] in the *Lct* in column (2) [column (3)] of Table 3. This is a potential concern, since the technical efficiency in super-efficiency SBM-DEA can be affected by the presence of outliers among efficient DMUs. However, as columns (2) and (3) suggest, the effects of digital finance on low-carbon transition are not driven by the presence of outliers.

Third, to demonstrate that our results are not driven by the particular low-carbon transition measure we use, we consider an alternative outcome measure. Specifically, we construct a low-carbon transition index and calculate the comprehensive low-carbon transition index (*Clcti*) using the entropy weight method with a similar set of indicators as those used by Huang et al. (2022) (see Table 4). We chose to use the entropy weighting method because it is an objective weighting method and determines the indicator weights based on the degree of variability of the indicator values, as the regression result in column (4) of Table 3 shows, and the conclusion that digital finance facilitates low-carbon transition remains unchanged.

**Table 3: Robustness Checks with Respect to Sample Selection and Measurement of Low-Carbon Transition**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Variables** | ***Lct*** | ***Lct*** | ***Lct*** | ***Clcti*** | ***Lct*** | ***Lct-new*** |
| *Df* | 0.2600*** | 0.2664*** | 0.2250*** | 0.0370** | 0.2791*** | 0.2611*** |
| | (0.0538) | (0.0543) | (0.0453) | (0.0157) | (0.0570) | (0.0515) |
| *Edp* | 0.2724* | 0.2728* | 0.1718 | 0.0580 | 0.0961 | 0.2838* |
| | (0.1566) | (0.1588) | (0.1198) | (0.0353) | (0.0980) | (0.1590) |
| *Is* | –0.0583*** | –0.0551*** | –0.0555*** | 0.0017 | –0.0585*** | –0.0522*** |
| | (0.0187) | (0.0194) | (0.0136) | (0.0047) | (0.0166) | (0.0180) |
| *Pd* | 1.7197** | 1.8643*** | 1.6016 | –1.6145** | 0.3597 | 1.5312** |
| | (0.7780) | (0.6343) | (1.0176) | (0.8127) | (0.8415) | (0.6481) |
| *Gd* | 0.1837** | –0.0238 | –0.0706* | –0.0372 | –0.0256 | 0.1445* |
| | (0.0819) | (0.0866) | (0.0387) | (0.0293) | (0.0841) | (0.0790) |
| N | 2,511 | 2,496 | 2,291 | 2,547 | 1,981 | 2,547 |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.738 | 0.717 | 0.735 | 0.838 | 0.788 | 0.744 |

Note: *Lct* means low-carbon transition. *Df* represents digital finance. *Edp*, *Is*, *Pd*, and *Gd* indicate economic development potential, industrial structure, population density, and green degree, respectively. Column (1) excludes the four direct-administered municipalities of Beijing, Tianjin, Shanghai, and Chongqing from the sample. Columns (2) [Column (3)] drops the top and bottom 1% [5%] observations in the *Lct*. Column (4) uses the comprehensive low-carbon transition index (*Clcti*) as the dependent variable. Column (5) uses the sample research period from 2013 to 2019. Standard errors clustered by the city are in parentheses. *, **, and *** represent statistical significance at 10, 5, and 1 % levels, respectively. With the super-efficient SBM-DEA, column (6) uses the result of low-carbon transition that puts undesirable outputs as inputs (*Lct-new*).

**Table 4: Low-Carbon Transition Index System**

| Index Level | Index Attribute |
|---|---|
| Harmless treatment rate of domestic waste | + |
| Greening coverage rate | + |
| Gardening area per 10,000 people | + |
| Per capita domestic water consumption | – |
| GDP per unit of carbon dioxide emissions | + |

Fourth, we also check the robustness of our results with respect to the choice of study period. Notably, the year 2013 is considered the first year of digital finance development in the PRC, when Yu'ebao, Alipay's spare change management platform, was launched (Huang and Huang 2018; Mu 2014). Further, since the digital finance index *Df* was also updated to incorporate the usage information of Yu'ebao, our results may be influenced by the start of Yu'ebao. To address this potential confounding, we alternatively set the study period to be from 2013 to 2019. As can be seen from column (5) of Table 3, the coefficient of *Df* remains similar and statistically significant at a 1% level.

Fifth, this paper also uses an alternative idea to calculate the low-carbon transition. Considering that *Lct* increases as undesirable outputs decrease, we put undesirable output as input and use the super-efficiency SBM-DEA model to calculate a new low-carbon transition (*Lct-new*). As can be found in column (6) of Table 3; the coefficient of *Df* does not change much and remains significant at the 1% level.

Sixth, we also control for the effect of other policies that potentially confound our results. We identify the following two policies during our study period that may affect low-carbon transition: the low-carbon city pilot policy; and the carbon emissions trading pilot policy.

The low-carbon city pilot policy has been launched in three batches since 2010. The first batch started in July 2010 and included five provinces and eight cities. The second batch was determined in November 2012 and involved 1 province and 28 cities. The third batch of pilots began in January 2017 and included 41 cities and 4 districts or counties. The main objectives of the low-carbon city pilot policy are to control greenhouse gas emissions, explore green and low-carbon development modes, and lead low-carbon development. To control the effect of the low-carbon city pilot policy on the *Lct*, we include *Lcc*, a dummy variable for the low-carbon city pilot policy, which takes the value of one if the city implemented the policy in a given year and zero otherwise. Since we have city- and time-specific fixed effects terms, the baseline model effectively becomes a difference-in-differences model with respect to the low-carbon pilot policy.

The carbon emissions trading pilot is one of the environmental governance tools to achieve low-carbon development in the PRC. In response to climate change, 'the PRC's National Development and Reform Commission approved seven provinces and cities—Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen—to conduct carbon emissions trading pilots in October 2011. In 2016, Fujian became the eighth carbon emissions trading pilot in the PRC. To control for the impact of the carbon emissions trading pilot policy in our analysis, we also include *Cet*, a dummy variable for the carbon emission trading pilot, which takes one if it is implemented in the city in a given year and zero otherwise. As with *Lcc*, our model effectively becomes a difference-in-differences model with respect to *Cet* once *Cet* is included.

In columns (1) and (2) of Table 5, we individually control for *Lcc* and *Cet*, respectively. The coefficients of *Df* remain positive and significant at a 1% level. It is also notable that the coefficient on *Lcc* is positive and significant at a 5% level, whereas the coefficient on *Cet* is small and statistically insignificant. In column (3) of Table 5, we simultaneously control for both *Lcc* and *Cet*, and the coefficients on *Df*, *Lcc*, *and Cet* remain similar. These results indicate that the low-carbon city pilot policy has promoted low-carbon transition, but the carbon emissions trading pilot policy did not. Therefore, our results do not appear to be confounded with other policies, such as the low-carbon city pilot policy and carbon emissions trading pilot policy, even though the former may affect low-carbon transition.

Seventh, our results may potentially suffer from endogeneity issues, because low-carbon transition may raise the demand for digital finance or there may be a third factor that simultaneously influences low-carbon transition and digital finance. To address the reverse causality, we first add a one-period lag to both independent and control variables. In this formulation, the potential influence of low-carbon transition on digital finance in the current period does not affect our estimation results. As shown in column (4) of Table 5, the coefficient on the lagged *Df* is 0.2986 and is significant at a 1% level. This conclusion reinforces the robustness of the baseline regression result with respect to the potential presence of reverse causality.

**Table 5: Addressing Potential Confounding and Endogeneity**

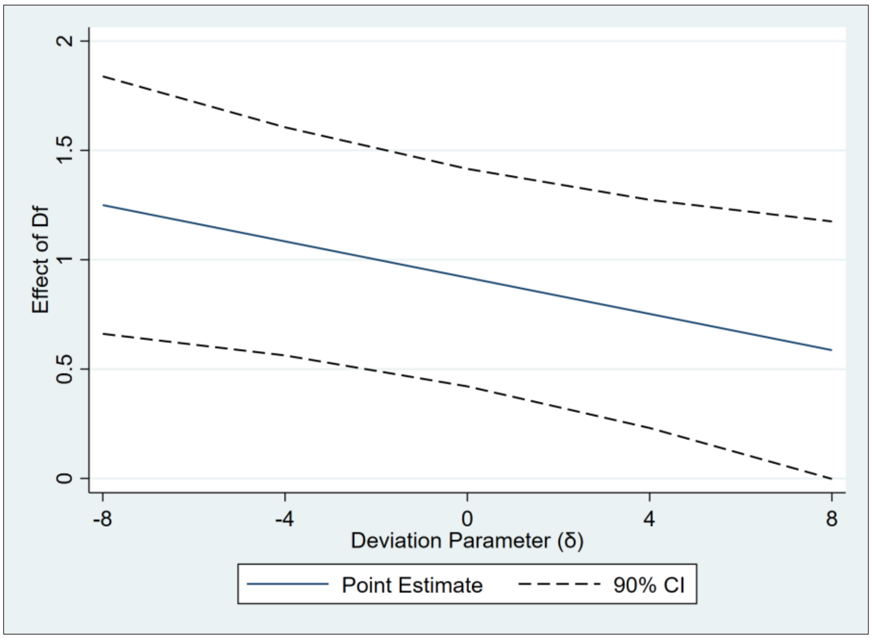
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Variables** | ***Lct*** | ***Lct*** | ***Lct*** | ***Lct*** | ***Df*** | ***Lct*** |
| *Df*[a] | 0.2644*** | 0.2792*** | 0.2619*** | 0.2986*** | | 0.9181*** |
| | (0.0532) | (0.0553) | (0.0535) | (0.0529) | | (0.3036) |
| *SSIV* | | | | | 12.0607*** | |
| | | | | | (2.3941) | |
| *Edp*[a] | 0.2736* | 0.2812* | 0.2730* | 0.3187* | –0.1146** | 0.3316** |
| | (0.1567) | (0.1590) | (0.1570) | (0.1683) | (0.0511) | (0.1632) |
| *Is*[a] | –0.0495** | –0.0483** | –0.0489** | –0.0679*** | –0.0378*** | –0.0185 |
| | (0.0193) | (0.0195) | (0.0191) | (0.0251) | (0.0081) | (0.0225) |
| *Pd*[a] | 1.8548** | 1.7945** | 1.8099** | 1.5233** | 2.5356*** | 0.2665 |
| | (0.7480) | (0.7176) | (0.7441) | (0.7233) | (0.8245) | (1.2668) |
| *Gd*[a] | 0.1803** | 0.1800** | 0.1820** | 0.1800*** | 0.0183 | 0.1688* |
| | (0.0828) | (0.0860) | (0.0839) | (0.0536) | (0.0159) | (0.0903) |
| *Lcc* | 0.0446** | | 0.0449** | | | |
| | (0.0188) | | (0.0188) | | | |
| *Cet* | | 0.0076 | 0.0100 | | | |
| | | (0.0257) | (0.0247) | | | |
| N | 2,547 | 2,547 | 2,547 | 2,264 | 2,538 | 2,538 |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.737 | 0.735 | 0.737 | 0.765 | | |

Note: *Lct* means low-carbon transition. *Df* represents digital finance. *Edp*, *Is*, *Pd*, and *Gd* indicate economic development potential, industrial structure, population density, and green degree, separately. *SSIV* means shift-share instrument variable. *Lcc* and *Cet* represent the low-carbon city pilot policy and the carbon emissions trading pilot policy. The superscript [a] for the independent and control variables indicates that they are lagged by one period in column (4) (but not in other columns). Standard errors clustered by city are in parentheses. *, **, and *** represent statistical significance at 10, 5, and 1 % levels, respectively.

We also use the instrumental variable method to mitigate the endogeneity problem and identify the net effect of digital finance on the low-carbon transition. Inspired by Nunn and Qian (2014) and Goldsmith-Pinkham, Sorkin, and Swift (2020), this paper uses a type of shift-share instrumental variable *SSIV*, which is defined as the PRC digital finance index for each year (time-dependent) multiplied by the inverse of the spherical distance between the city and Hangzhou (city-dependent). The PRC digital finance index for each year is the shift component. While the inverse of the spherical distance between the city and Hangzhou departs from the standard share component, it can be interpreted as a type of the share component. This is because Hangzhou is the origin of digital finance represented by Alipay and leads the expansion of digital finance. As a result, the inverse of the spherical distance between the city and Hangzhou is positively correlated with digital finance. We argue that the current low-carbon transition is unlikely to be directly affected by the spherical distance between the city and Hangzhou.

In column (5) of Table 5, we report the first-stage regression of *Df* on *SSIV*. The coefficient on *SSIV* is positive and statistically significant at a 1% level, confirming the relevance of *SSIV*. We also perform underidentification and weak identification tests for *SSIV*. The *p*-value of the Kleibergen–Paap *rk* Lagrange multiplier statistic is 0.000, strongly rejecting the null hypothesis. The Cragg–Donald Wald *F* and Kleibergen–Paap *rk* Wald *F* statistics are 156.16 and 25.38, respectively, suggesting that *SSIV* is a strong instrument. In column (6) of Table 5, we report the results of the second-stage regression. The coefficient on *Df* is statistically significant at a 1% level. Our results demonstrate that the positive impact of digital finance on low-carbon transition is not driven by endogeneity.

**Figure 1: Digital Finance Impact when SSIV Does Not Fully Satisfy the Exclusion Restriction**




While we have no compelling reason to believe that our *SSIV* does not satisfy the exclusion restriction, we are unable to fully exclude the possibility that the inverse of spherical distance to Hangzhou may be correlated with the heterogeneous secular time trend in low-carbon transition. To address this potential concern, we evaluate the robustness of the *SSIV* estimates when the exclusion restriction is violated using the local-to-zero (LTZ) method proposed by Conley, Hansen, and Rossi (2012). In this approach, we essentially allow for the potential presence of the direct effect of the instrument on the outcome of interest, which does not go through the channel of the endogenous variable. As with Conley, Hansen, and Rossi (2012), we use a deviation parameter δ to measure the degree of deviation from the exclusion restriction and assume that the direct effect of the *SSIV* on the *Lct* is normally distributed with the same mean and variance as the uniform distribution on [0, δ] (i.e., mean δ/2 and variance $\delta^2/12$). As shown in Figure 1, the 90% lower confidence bound for $\beta_1$ remains positive when the deviation parameter δ is less than 8. To put this figure into perspective, we run a reduced-form regression of *Lct* on *SSIV*, *Edp*, *Is*, *Pd*, and *Gd*. The coefficient on *SSIV* in this regression is about 11. Hence, since the mean direct effect of *SSIV* on *Lct* is 4(=8/2) when δ is equal to 8, well above a third of the total effect of *SSIV* on *Lct* needs to come from the direct effect if our conclusion were to be overturned. Given the way our *SSIV* is constructed, it seems unlikely that our results are driven by such a high level of direct effect within the total effect of *SSIV* on *Lct*. Therefore, we argue that our conclusion is robust to a plausible degree of violation of the exclusion restriction.

## 4.3 Green Innovation as a Channel of Impact

We now examine the impact of digital finance on low-carbon transition through the channel of green innovation. To this end, we take the number of green patent granted (*Gi1*) and the number of green patent applications (*Gi2*) to measure green innovation from the *Chinese Research Data Services Platform* (CNRDS), where all the numbers for green patents in this paper are expressed in ten thousands.

**Table 6: Mediation through Green Innovation as Measured by the Number of Green Patents Granted**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Variables** | ***Gi1*** | ***Lct*** | ***Gi11*** | ***Lct*** | ***Gi12*** | ***Lct*** |
| *Df* | 0.1843*** | 0.1831*** | 0.0393*** | 0.1664*** | 0.1450*** | 0.1977*** |
| | (0.0407) | (0.0505) | (0.0091) | (0.0504) | (0.0327) | (0.0511) |
| *Gi1* | | 0.4410*** | | | | |
| | | (0.0959) | | | | |
| *Gi11* | | | | 2.4943*** | | |
| | | | | (0.4171) | | |
| *Gi12* | | | | | | 0.4602*** |
| | | | | | | (0.1218) |
| *Edp* | 0.0258 | 0.2492* | 0.0103 | 0.2348* | 0.0154 | 0.2535* |
| | (0.0271) | (0.1440) | (0.0066) | (0.1409) | (0.0209) | (0.1457) |
| *Is* | –0.0001 | –0.0578*** | 0.0015 | –0.0616*** | –0.0016 | –0.0571*** |
| | (0.0056) | (0.0184) | (0.0013) | (0.0183) | (0.0044) | (0.0185) |
| *Pd* | 5.8388*** | –0.8768 | 0.8789*** | –0.4942 | 4.9599*** | –0.5844 |
| | (1.0399) | (0.7373) | (0.1294) | (0.7006) | (0.9279) | (0.7790) |
| *Gd* | –0.0212*** | 0.1927** | –0.0040*** | 0.1933** | –0.0172*** | 0.1913** |
| | (0.0047) | (0.0815) | (0.0012) | (0.0812) | (0.0037) | (0.0817) |
| N | 2,505 | 2,505 | 2,505 | 2,505 | 2,505 | 2,505 |
| Adjusted $R^2$ | 0.857 | 0.748 | 0.872 | 0.752 | 0.841 | 0.746 |

Note: *Lct* means low-carbon transition. *Gi1* means the number of green patents granted. *Gi11* and *Gi12* refer to the number of green invention patents granted and the number of green utility model patents granted, respectively. *Df* represents digital finance. *Edp*, *Is*, *Pd*, and *Gd* indicate economic development potential, industrial structure, population density, and green degree, separately. Standard errors clustered by city are in parentheses. *, **, and *** represent statistical significance at 10, 5, and 1 % levels, respectively. City- and year-specific fixed effects are included in all regressions.

The estimated results of digital finance on green innovations, as measured by the *Gi1* and the *Gi2*, are shown in column (1) of Table 6 and column (1) of Table 7, respectively. In both cases, the coefficient of *Df* is positive and significant at a 1% level, suggesting that digital finance has boosted green innovations. To see whether green innovation is a possible channel of impact, we also simultaneously include measures of green innovation and digital finance in the regression of low-carbon transition. The estimation results with *Gi1* and *Gi2* are shown in column (2) of Table 6 and column (2) of Table 7. In both cases, both the coefficients on *Gi1* and *Gi2* are statistically significant. Further, the coefficient on digital finance remains significant, but the absolute value of the coefficient decreases from 0.2811 in column (2) of Table 2 to 0.1831 and 0.1770. These indicate that the effects of digital finance on low-carbon transition can be partly explained away by the digital finance’s impact on green innovation.

Next, we disaggregate the number of green patents granted (*Gi1*) into the number of green invention patents granted (*Gi11*) and the number of green utility model patents granted (*Gi12*). The estimation results with *Gi11* and *Gi12* corresponding to column (1) of Table 6 are shown in columns (3) and (5), respectively. In both columns, the coefficients of *Df* are both positive and significant at a 1% level. When we include *Gi11* and *Gi12* in the regression of low-carbon transition, the coefficients on these variables are statistically significant and the coefficient on *Df* also remains statistically significant, as shown in columns (4) and (6) of Table 6. Further, as with the case for *Gi1*, the coefficient on *Df* decreases to 0.1977 or lower from 0.2811 in column (2) of Table 2. These findings indicate that digital finance promotes low-carbon transition through both high- and low-level green innovations.

**Table 7: Mediation through Green Innovation as Measured by the Number of Green Patent Applications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Variables** | ***Gi2*** | ***Lct*** | ***Gi21*** | ***Lct*** | ***Gi22*** | ***Lct*** |
| *Df* | 0.3959*** | 0.1770*** | 0.1926*** | 0.1910*** | 0.2033*** | 0.1814*** |
| | (0.0999) | (0.0499) | (0.0531) | (0.0514) | (0.0492) | (0.0496) |
| *Gi2* | | 0.2111*** | | | | |
| | | (0.0376) | | | | |
| *Gi21* | | | | 0.3610*** | | |
| | | | | (0.0661) | | |
| *Gi22* | | | | | | 0.3893*** |
| | | | | | | (0.0940) |
| *Edp* | 0.0532 | 0.2611* | 0.0338 | 0.2602* | 0.0195 | 0.2648* |
| | (0.0622) | (0.1480) | (0.0342) | (0.1484) | (0.0285) | (0.1495) |
| *Is* | 0.0033 | –0.0587*** | 0.0069 | –0.0605*** | –0.0036 | –0.0566*** |
| | (0.0135) | (0.0184) | (0.0077) | (0.0184) | (0.0065) | (0.0184) |
| *Pd* | 13.3642*** | –1.1014 | 6.6339*** | –0.6748 | 6.7303*** | –0.8996 |
| | (2.6448) | (0.6795) | (1.3838) | (0.6613) | (1.2698) | (0.7728) |
| *Gd* | –0.0348*** | 0.1910** | –0.0118 | 0.1879** | –0.0231*** | 0.1926** |
| | (0.0132) | (0.0802) | (0.0074) | (0.0802) | (0.0061) | (0.0804) |
| N | 2,509 | 2,509 | 2,509 | 2,509 | 2,509 | 2,509 |
| Adjusted $R^2$ | 0.814 | 0.745 | 0.795 | 0.744 | 0.802 | 0.744 |

Note: *Lct* means low-carbon transition. *Gi2* means the number of green patent applications. *Gi21* and *Gi22* refer to the number of patent applications for green inventions and the number of green utility model patent applications, respectively. *Df* represents digital finance. *Edp*, *Is*, *Pd*, and *Gd* indicate economic development potential, industrial structure, population density, and green degree, separately. Standard errors clustered by city are in parentheses. *, **, and *** represent statistical significance at 10, 5, and 1 % levels, respectively. City- and year-specific fixed effects are included in all regressions.

In columns (3)–(6) of Table 7, we repeat a similar exercise by disaggregating the number of green patent applications (*Gi2*) into the number of patent applications for green inventions (*Gi21*) and the number of green utility model patent applications (*Gi22*). The conclusion remains similar. Our findings corroborate the findings in the existing literature that green innovation promotes low-carbon transition, such as Wurlod and Noailly (2018), Xu et al. (2021), Dong et al. (2022), Yu et al. (2021) as well as Lin and Ma (2022).

# 5. IMPACT HETEROGENEITY

As discussed above, there is a considerable gap in the state of digital finance between the east and west sides of the Heihe–Tengchong line. To find out whether there are differences in the impact of digital finance on low-carbon transition on these two sides, we divide the sample into the east and west sides of the Heihe–Tengchong line and conduct a subsample analysis for each side. The results of this analysis for the east and west sides are respectively shown in columns (1) and (2) of Table 8. On the east side, the coefficient of *Df* is relatively large at 0.2899 and statistically significant at a 1% level. This result indicates that digital finance on the east side significantly contributes to the low-carbon transition. On the other hand, the coefficient on *Df* on the west side is comparatively small at 0.1237 and statistically insignificant, indicating that digital finance on the west has no effect on low-carbon transition.

**Table 8: Impact Heterogeneity of Digital Finance on Low-Carbon Transition**

| | **East of Heihe–Tengchong Line** | **West of Heihe–Tengchong Line** | **Larger than Median of *Lct*** | **Less than Median of *Lct*** |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| **Variables** | ***Lct*** | | | |
| *Df* | 0.2899*** | 0.1237 | 0.3532*** | 0.0323 |
| | (0.0615) | (0.0810) | (0.1223) | (0.0242) |
| *Edp* | 0.2148 | 0.5615** | 0.6659** | 0.1241* |
| | (0.1552) | (0.2773) | (0.3301) | (0.0641) |
| *Is* | -0.0163 | -0.0552* | 0.0328 | -0.0406*** |
| | (0.0243) | (0.0311) | (0.0357) | (0.0094) |
| *Pd* | 1.6335** | -3.6135 | 2.3660*** | -0.0200 |
| | (0.7088) | (8.8926) | (0.6611) | (0.7399) |
| *Gd* | 0.2391*** | -0.1911 | 0.2471*** | 0.0524* |
| | (0.0542) | (0.1298) | (0.0464) | (0.0278) |
| N | 2,070 | 477 | 1,273 | 1,273 |
| City FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.745 | 0.754 | 0.617 | 0.676 |

Note: *Lct* means low-carbon transition. *Df* represents digital finance. *Edp*, *Is*, *Pd*, and *Gd* indicate economic development potential, industrial structure, population density, and green degree, separately. Standard errors clustered by city are in parentheses. *, **, and *** represent statistical significance at 10, 5, and 1 % levels, respectively.

We also consider the impact heterogeneity across different levels of carbon transition. To this end, we divide the sample according to whether the low-carbon measure *Lct* is above or below the median and report the regression results in columns (3) and (4) of Table 8, respectively. As column (3) shows, the coefficient on *Df* is relatively large at 0.3532 and statistically significant at a 1% level for the above-median subsample. On the other hand, the coefficient is very small and statistically insignificant for the below-median subsample. This shows that the digital economy did not promote the low-carbon transition in the low *Lct* group.

# 6. CONCLUSIONS AND POLICY IMPLICATIONS

In this study, we empirically analyze the impact of digital finance on low-carbon transition based on data from 283 cities in the People's Republic of China between 2011 and 2019. We find that digital finance promotes low-carbon transition, and this appears to be driven by usage depth and digitization level, but not by the coverage breadth. As the results of a series of robustness checks suggest, our main finding that digital finance positively affects low-carbon transition is robust. The impact of digital finance on low-carbon transition is, at least in part, driven by green innovation.

Further, the heterogeneity analysis shows that digital finance has a significant effect on low-carbon transition in the cities to the east side of the Heihe–Tengchong line, but this is not the case for the west side. The latter finding does not undermine the significance of our findings, given that 94% of the population lived on the east side of the Heihe–Tengchong line in 2015 (in an area corresponding to 43% of the PRC's land area). Somewhat similarly, digital finance appears to facilitate low-carbon transition only for the group that have a high low-carbon transition measure. Since the east of Heihe–Tengchong is more developed, these findings would collectively indicate that digital finance promotes low-carbon transition only when certain preconditions are met—even though investigation of such preconditions would require a separate study and is beyond the scope of the current paper. The empirical support for digital finance's positive impact on low-carbon transition in the PRC offered in this paper not only promotes the understanding of the PRC's current situation but also provides insights into how the PRC's low-carbon transition can be deepened going forward. Our results also potentially serve as a benchmark for other developing countries to achieve low-carbon transition.

Our results also come with three policy implications. First, cities should continue to encourage the development of digital finance, particularly by promoting the usage depth and digitization level of digital finance, because these two aspects significantly promote low-carbon transition. This means that digital financial services should be further increased in frequency, convenience, and efficiency. Second, the government may need to implement differentiated policies for various cities to narrow the expansion of low-carbon transition among cities. For example, the government should pay more attention to cities to the west of the Heihe–Tengchong line and cities with a low level of *Lct*, as digital finance does not appear to promote low-carbon transition in these cities. Further research is also needed to understand the preconditions for digital finance to help promote low-carbon transition. Finally, even though there are other potential channels through which digital finance affects low-carbon transition as discussed in Section 1, green innovation is among the important channels through which digital finance promotes low-carbon transition. Therefore the PRC and other countries aspiring to make a successful low-carbon transition should explore ways to strengthen the support for digital finance to promote green projects and innovations.

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# APPENDIX

### Table A1: Peking University Digital Financial Inclusion Indicator System

| First-level Dimension | Second-level Dimension | | Detailed Indicator |
|---|---|---|---|
| Coverage breadth | Account coverage ratio | | Number of Alipay accounts per 10,000 people |
| | | | Proportion of Alipay card users |
| | | | The average number of bank cards bound to each Alipay account |
| Usage depth | Payment operations | | Number of payments per capita |
| | | | Amount paid per capita |
| | | | Ratio of high-frequency active users (active 50 times a year or more) to those active 1 time or more per year |
| | Money fund operations | | Number of Yu'ebao purchases per capita |
| | | | Amount of Yu'ebao purchases per capita |
| | | | Number of people purchasing Yu'ebao per 10,000 Alipay users |
| | Credit operations | Personal consumption loans | Users of Internet consumer loans per 10,000 adult Alipay users |
| | | | Number of loans per capita |
| | | | Loan amount per capita |
| | | Small and micro operators | Number of users with Internet small and micro-business loans per 10,000 adult Alipay users |
| | | | Average number of loans for small and micro-operators |
| | | | Average loan amount of small and micro-operators |
| | Insurance operations | | Number of insured users per 10,000 Alipay users |
| | | | Number of insurance per capita |
| | | | Amount of insurance per capita |
| | Investment operations | | Number of people participating in Internet investment and financial management per 10,000 Alipay users |
| | | | Number of investment per capita |
| | | | Amount of investment per capita |
| | Credit operations | | Number of invocations per natural person credit |
| | | | Number of users using credit-based services (including finance, accommodation, travel, social, etc.) per 10,000 Alipay users |
| Digitization level | Mobility | | Proportion of mobile payment |
| | | | Proportion of mobile payment amount |
| | Affordability | | Average loan interest rate for small and micro-operators |
| | | | Average loan interest rate for individuals |
| | Credit | | Proportion of Ant Credit Pay payments |
| | | | Proportion of the payment amount for Ant Credit Pay<br>Proportion of Sesame Credit deposit-free transactions (compared to situations where a full deposit is required) |
| | | | Proportion of Sesame Credit deposit-free amount (compared to situations where a full deposit is required) |
| | Convenience | | Proportion of user QR code payment |
| | | | Proportion of the amount of user QR code payment |

Source: Guo et al. (2020).

**Figure A1: A Simple Illustration of DEA**