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Foreign Capital, Digital Finance, and Regional Productivity: Spatiotemporal Evidence from China

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Abstract: This paper compares how foreign direct investment (FDI) and digital finance (DFI) are related to regional total factor productivity in China. Using panel data for 31 provinces from 2017 to 2024, we combine a random forest model with GeoTimeShapley decomposition to separate the standalone contributions of the two variables from their interactions with location and time. The interaction terms account for most of their model-based relevance. FDI has a larger contribution, but it is spatially concentrated and varies markedly across years. DFI follows a more gradual pattern and becomes more relevant as digital infrastructure and financial inclusion expand. External capital and domestic digital finance are therefore associated with productivity under different regional and temporal conditions.

Keywords: Foreign direct investment; Digital finance; Total factor productivity; Spatiotemporal heterogeneity; GeoTimeShapley

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1. Introduction

Finance affects productivity through the allocation of capital across firms, industries, and regions. Financial systems can improve aggregate efficiency by screening investment opportunities and directing funds toward more productive uses [1]. These functions need not have the same consequences across locations. Regional differences in industrial structure, market access, digital infrastructure, and openness can alter the way financial resources are translated into productivity. This issue is particularly relevant in China, where provincial economies differ substantially in their financial depth and production structures. Resource misallocation and firm restructuring have been shown to account for important differences in Chinese total factor productivity (TFP) [2]. Geography and local economic conditions also shape development within countries [3]. Estimates based only on average relationships may therefore miss an important part of the finance–productivity relationship.

We compare two financial channels. Foreign direct investment (FDI) connects regional economies to external capital, technology, managerial knowledge, and global production networks. Its productivity benefits, however, depend on the capacity of local firms to absorb foreign knowledge. Borensztein *et al.* emphasized the role of host-economy absorptive capacity [4], while Javorcik found that spillovers are more likely to arise through linkages between foreign firms and domestic suppliers [5]. Foreign entry may also displace domestic activity, and its benefits depend partly on domestic financial development [6]. The regional contribution of FDI is therefore likely to vary with local industrial conditions and external exposure.

Digital finance (DFI) represents a different channel. It works mainly through domestic financial access, information processing, and digital credit provision. Fintech can lower transaction costs, improve credit screening, and extend financial services to borrowers that are poorly served by traditional institutions [7]. Evidence on its productivity consequences is mixed. Jin *et al.* reported positive effects on manufacturing-firm TFP through financing and human-capital channels [8], and Guo and Wang identified an innovation channel [9]. By contrast, Chen *et al.* showed that digital financial inclusion does not improve firm productivity uniformly [10]. Related evidence also points to nonlinear and spatially heterogeneous effects [11,12]. These findings suggest that the productivity relevance of DFI depends on local digital capacity and the stage of financial development.

Most studies consider FDI and digital finance separately. As a result, less is known about whether external capital and domestic digital finance follow different spatial and temporal patterns. We examine this issue using data for 31 Chinese provinces from 2017 to 2024. A random forest model captures nonlinearities and interactions among financial and structural variables. We interpret its predictions through Shapley values. Building on GeoShapley [13], longitude, latitude, and year are combined into a joint contextual feature, denoted by GEOTIME. The resulting decomposition separates the standalone contribution of each financial variable from the part associated with location and time.

The results reveal a clear difference between the two channels. The interactions of FDI and DFI with GEOTIME are substantially more important than their standalone contributions. FDI has the larger interaction effect, but its contribution is spatially concentrated and varies markedly across years. DFI has a more gradual spatial profile and becomes more relevant after digital infrastructure and financial inclusion reach higher levels. The evidence therefore points to two distinct finance--productivity relationships: FDI is closely tied to openness and industrial linkages, whereas DFI is associated with the diffusion of domestic financial infrastructure.

2. Data and empirical motivation

We use a balanced panel of 31 provincial-level regions in China from 2017 to 2024, excluding Hong Kong, Macao, and Taiwan. Total factor productivity is measured using a data envelopment analysis framework. We apply the Banker–Charnes–Cooper model under variable returns to scale and use the Malmquist index to measure changes in productivity over time.

The analysis focuses on two financial variables. Digital finance is measured by the Peking University Digital Financial Inclusion Index. The index captures the development of digital payments, online credit, and other technology-based financial services. Foreign direct investment is measured as utilized foreign capital relative to regional GDP. It captures the exposure of each province to external capital and international production linkages.

We also include four structural controls commonly used in studies of regional productivity. Economic development (Eco) is measured by GDP per capita, urbanization (Urb) by the urban population share, industrial structure (Ind) by the relative size of the tertiary sector, and R&D intensity (Rdi) by R&D expenditure relative to GDP. These variables account for differences in market size, agglomeration, structural change, and absorptive capacity.

The data are drawn from the National Bureau of Statistics, the People's Bank of China, the China Market Index, and the China Economic Report. Isolated missing observations are filled by linear interpolation. **Table 1** reports variable definitions and data sources, while **Table 2** presents summary statistics. The sample displays substantial variation in TFP, FDI, and DFI across provinces and years.

Table 1. Variable definitions and sources

Variable	Description	Source
TFP	Total factor productivity estimated using DEA-BCC and the Malmquist index	DEA calculation
DFI	Digital Finance Index, measuring provincial digital financial inclusion	Peking University Digital Financial Inclusion Index
FDI	Foreign direct investment relative to regional GDP	NBS, PBC, CEI
Eco	GDP per capita as a proxy for regional economic development	NBS
Urb	Urban population as a share of total population	NBS
Ind	Growth rate of tertiary sector relative to secondary sector	NBS
Rdi	R&D expenditure relative to GDP	NBS, PBC, CEI

Table 2. Summary statistics of the main variables

Variable	Mean	Std. Dev.	Min	Max
TFP	1.037	0.319	0.351	2.037
DFI	0.321	0.150	0.076	0.740
FDI	0.238	0.231	0.008	0.977
Eco	76026.378	35221.002	29102.500	211395.720
Urb	0.640	0.111	0.332	0.905
Ind	1.547	0.802	0.751	5.690
Rdi	1.959	1.248	0.212	7.409

Figure 1 plots provincial TFP in 2017, 2020, and 2024. In 2017, high-productivity provinces were concentrated mainly in the Yangtze River Delta, the Pearl River Delta, and the Beijing–Tianjin–Hebei region. By 2020, the pattern had become less consistent with a simple east–west divide. Relatively high TFP appeared in parts of both eastern and western China, while several central provinces recorded lower values. The distribution changed again in 2024, when a number of previously high-productivity provinces moved into lower groups.

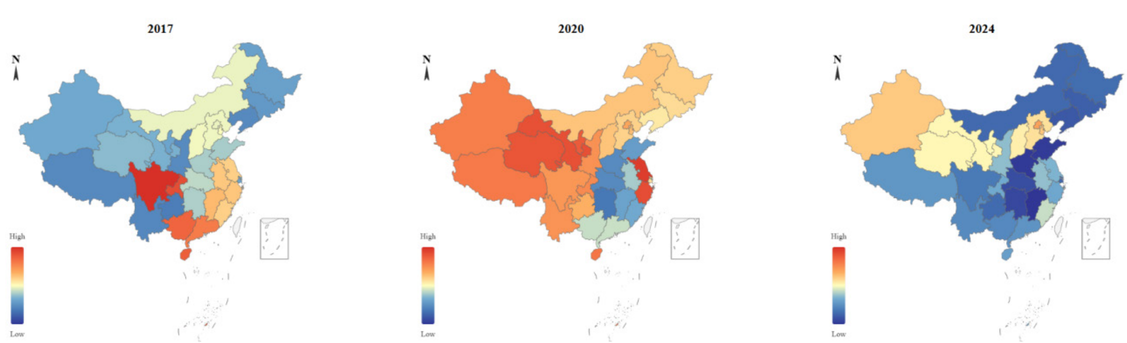

Figure 1. Spatial distribution of provincial TFP in 2017, 2020, and 2024

The maps do not identify the sources of these changes, but they show that provincial productivity has no stable spatial ranking over the sample period. This feature of the data motivates an empirical approach that allows the contribution of financial variables to vary jointly across location and time.

3. Methodology

This study uses a random forest model together with the GeoTimeShapley framework. Random forests are useful for modeling nonlinear relationships and interactions among TFP drivers. GeoTimeShapley then decomposes the fitted predictions into the contributions of individual variables and their interactions with geography and time. In this way, the method retains the flexibility of machine learning while providing interpretable evidence on where and when different factors matter. This framework is well suited to our purpose, as it allows the productivity contributions of FDI and DFI to be compared across provinces and years.

The Shapley value, introduced by Shapley (1953), allocates the marginal contribution of each player in a coalition game. For individual player j, the Shapley value is measured as.

$$\varphi_j = \sum_{S \subseteq M \setminus \{j\}} \frac{s!(p-s-1)!}{p!} \left(f\left(S \cup \{j\}\right) - f\left(S\right) \right), \tag{1}$$

Where p denotes the number of players, M is a set of all possible combinations of players, $M \setminus \{j\}$ refers to a set of all possible combinations of players excluding j , S is a player set in $M \setminus \{j\}$ with a size of s . f denotes the random forest estimation, $f(S)$ represents the outcome of S , and $f(S \cup \{j\})$ refers to the outcome with players in S plus player j .

The output prediction is the sum of marginal contributions from each feature j , according to Strumbelj and Kononenko (2014):

$$\hat{y}_i = \varphi_0 + \sum_{j=1}^{p} \varphi_{ji}, \tag{2}$$

where φ_{ji} is the Shapley value for feature j of observation i , and φ_0 is constant base value.

This study optimizes GeoShapley to Geotimeshapley based on Li (2024), by incorporating time and geographic location as a joint spatio-temporal feature (GEOTIME) into the analysis.

The intrinsic spatio-temporal effect ϕ_{GEOTIME} , representing the marginal contribution of the spatio-temporal feature to the predicted value, is defined as:

$$\phi_{\mathrm{GEOTIME}} = \sum_{S \subseteq M \setminus \{GEOTIME\}} \frac{s!(p-s-g)!}{(p-g+1)!} \left(f\left(S \cup \{GEOTIME\}\right) - f\left(S\right) \right), \tag{3}$$

where GEOTIME denotes the spatio-temporal feature with dimensiong. In this study,g=3 , representing longitude, latitude, and year for each province. The GeoShapley value of a non-locational feature X_j demonstrates the marginal contribution by location-invariant effect, which is measured as:

$$\phi_{\mathrm{j}} = \sum_{S \subseteq M \setminus \{j\}} \frac{s!(p-s-g)!}{(p-g+1)!} \left(f\left(S \cup \{j\}\right) - f\left(S\right) \right). \tag{4}$$

The spatio-temporally varying interaction effect $\phi_{(\mathrm{GEOTIME,j})}$ between GEOTIME and feature j is computed as:

$$\phi_{(GEOTIME,j)} = \sum_{S \subseteq M \setminus \{GEOTIME,j\}} \frac{s!(p-s-g-1)!}{(p-g+1)!} \Delta_{\{GEOTIME,j\}}, \tag{5}$$

Where $\Delta_{\{GEOTIME,j\}}=\left(f\left(S\cup\{GEOTIME,j\}\right)-f\left(S\cup\{GEOTIME\}\right)-\mathrm{f}\left(S\cup\{j\}\right)+f\left(S\right)\right)$.

The final prediction is obtained by summing the results from Equations (2) (3) (4) :

$$\hat{y}=\phi_0+\phi_{GEOTIME}+\sum\nolimits_{j=1}^{p}\phi+\sum\nolimits_{j=1}^{p}\phi_{(GEOTIME,j)}, \tag{6}$$

where ϕ_0 is a constant base value as a global intercept. When no spatial effect exists, $\phi_{\mathrm{GEOTIME}}=0$ and $\phi_{(\mathrm{GEOTIME,j})}=0$, and Equation (6) would be identical to Equation (2).

4. Empirical results

4.1. Importance and marginal profiles

Figure 2 reports the GeoTimeShapley importance ranking. The main result is that the interactions of FDI and DFI with GEOTIME are substantially more important than the standalone financial variables. Among the finance-related terms, FDI x GEOTIME ranks first, followed by DFI x GEOTIME. By contrast, the direct contributions of FDI and DFI are relatively small.

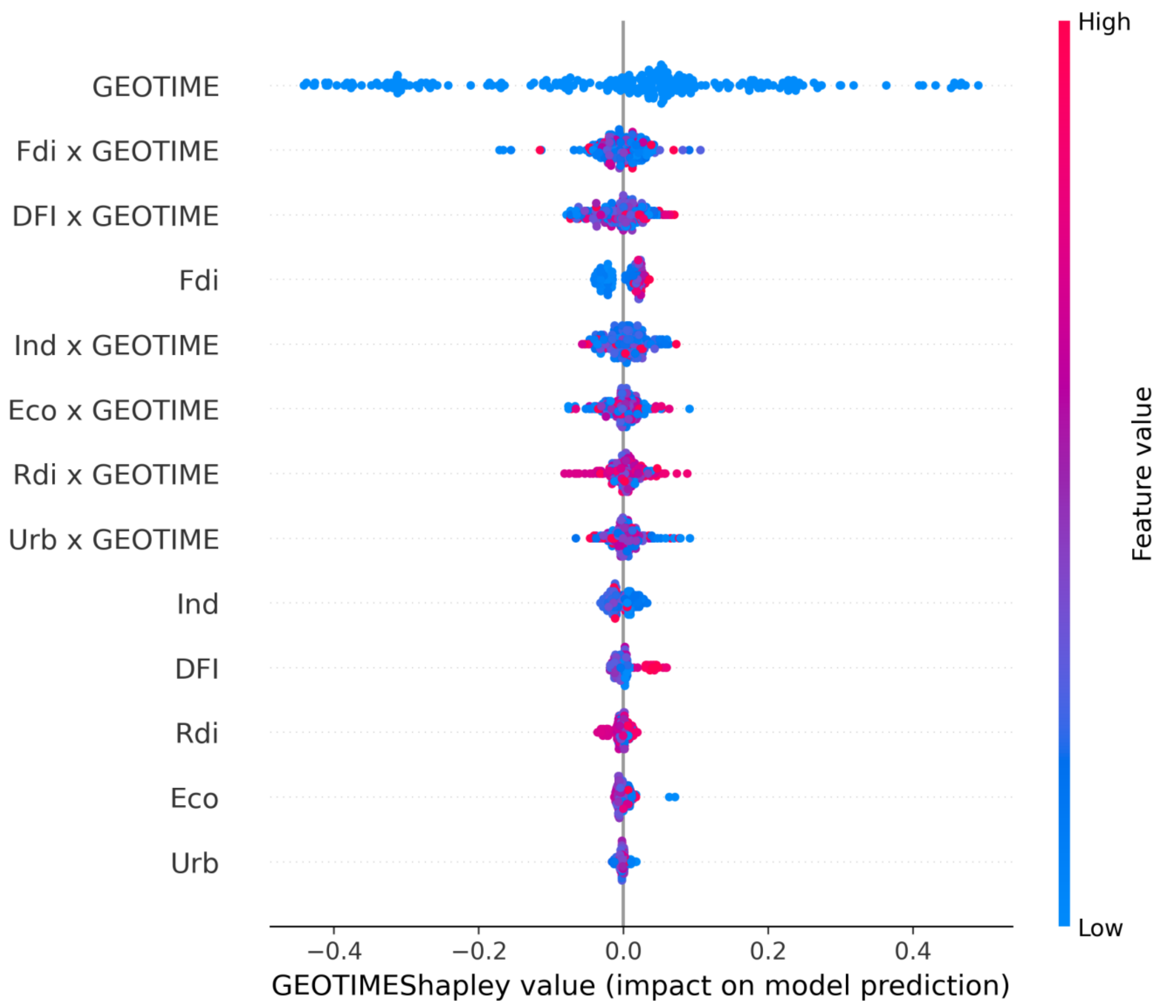

Figure 2. GeoTimeShapley feature-importance ranking

This ranking has an important economic interpretation. Provincial productivity is not closely related to the level of foreign capital or digital finance alone. The association depends more on the regional and temporal setting in which each form of finance operates. An increase in FDI, for example, need not have the same productivity relevance in a province with strong supplier networks as in one with weak industrial linkages. The same applies to digital finance when provinces differ in digital infrastructure, financial access, and firms' capacity to use online financial services. Average estimates may therefore conceal much of the variation that is economically relevant.

The two interaction terms are also consistent with the mechanisms identified in earlier work. FDI spillovers depend on host-economy absorptive capacity and linkages between foreign and domestic firms. Evidence on digital finance similarly points to effects that vary with financing conditions and innovation capacity [9,10]. The importance ranking does not establish causal effects, but it indicates that the finance--productivity relationship is strongly conditioned by location and time.

Figure 3 provides a second distinction between the two channels. The marginal profile of DFI is relatively flat at low and intermediate levels, and rises only at higher levels of digital-finance development. This pattern is consistent with a threshold interpretation. At an early stage, the availability of digital financial services may not be sufficient to change credit allocation or firm behavior. Digital platforms require data, user participation, payment infrastructure, and effective links with the real economy. Once these complementary conditions are in place, digital finance can reduce information and transaction costs and improve access to credit [7,14].

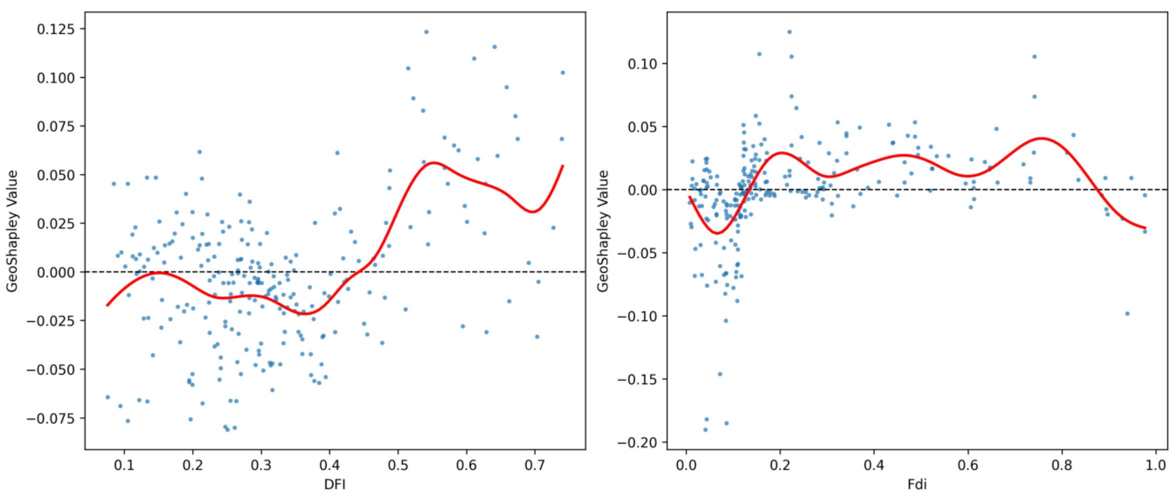

Figure 3. Partial dependence of DFI and FDI GeoShapley values

The FDI profile is different. Its marginal contribution is generally larger, but it varies more across the observed range. This uneven pattern is consistent with the conditional nature of foreign-investment spillovers. FDI may bring technology, managerial knowledge, and access to international production networks, but these benefits are not automatic. They depend on whether domestic firms can absorb foreign knowledge and participate in local supplier relationships. Foreign entry can also increase competitive pressure when these conditions are absent. FDI is therefore associated with potentially larger productivity gains, but also with greater variation across regional settings.

To conclude, DFI and FDI are related to productivity in different ways. The contribution of DFI remains modest until digital and financial infrastructure becomes sufficiently developed. FDI has a larger marginal contribution, but its relevance varies more with local industrial conditions. The difference between the two channels therefore concerns both the size and the form of their productivity associations.

4.2. Spatiotemporal Differences between FDI and DFI

Figure 4 maps the interaction contributions of FDI and DFI in 2017, 2020, and 2024. Whereas **Figure 3** summarizes average marginal patterns, the maps show how those patterns differ across provinces and years. They reveal a clear spatial mismatch between the two financial channels.

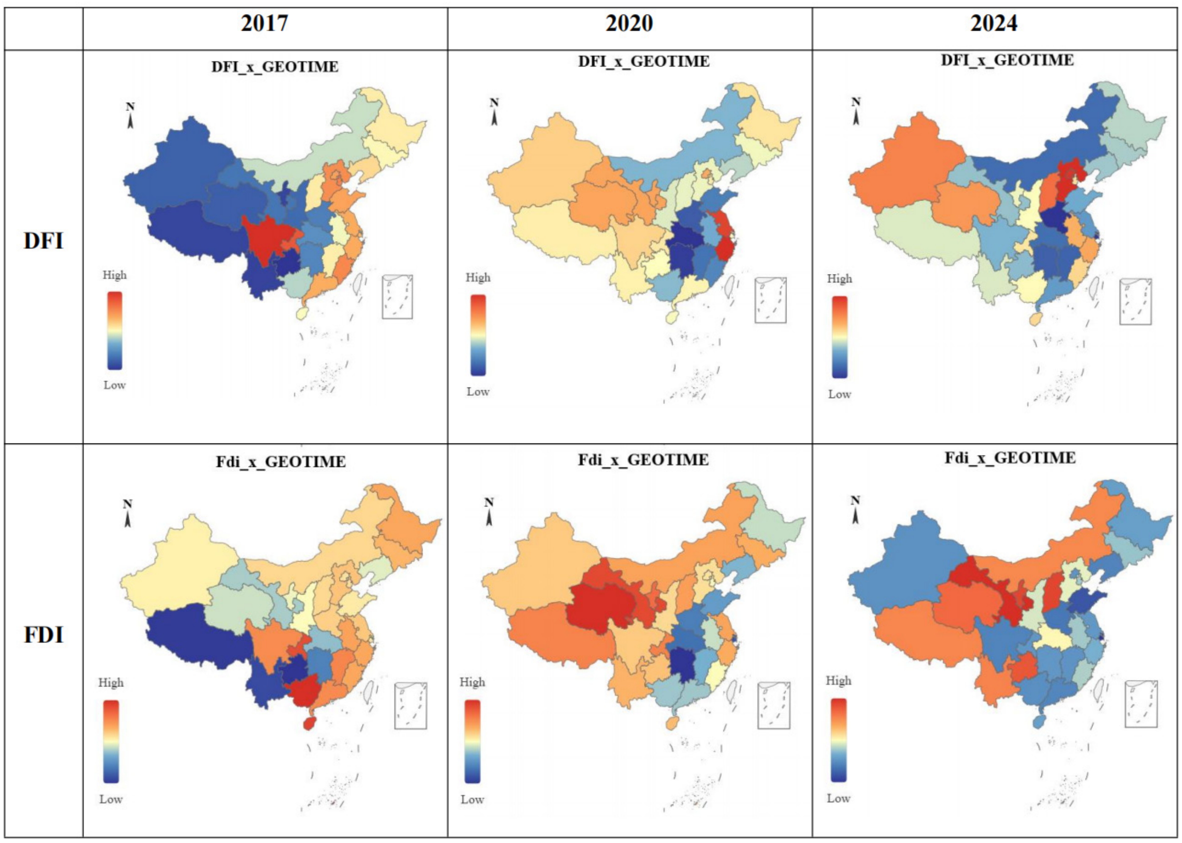

Figure 4. Spatiotemporal interaction maps for DFI x GEOTIME and FDI x GEOTIME, 2017, 2020, and 2024

The FDI maps are concentrated and change considerably over time. In 2017, relatively strong FDI-related contributions appear in selected central and eastern provinces, while most western provinces record weaker values. By 2020, the stronger contributions shift toward other parts of eastern and central China. The 2024 map is more fragmented, with high and low values distributed across several regions. No stable group of provinces consistently records the largest FDI contribution.

This instability is consistent with the way foreign investment enters regional production systems. The productivity relevance of FDI depends on more than the inflow itself. Foreign firms need local suppliers, suitable human capital, and domestic firms capable of learning from external technology. Regions with stronger production networks are more likely to capture these benefits, while regions without such linkages may receive foreign capital without comparable productivity gains. The spatial movement in the FDI contribution therefore reflects changes in the regional conditions under which external capital becomes embedded in the local economy.

The DFI maps display a more gradual pattern. In 2017, stronger DFI-related contributions are limited to a relatively small number of provinces. In 2020 and 2024, they become more widely distributed, including in several inland regions. The DFI pattern is therefore less closely tied to the coastal geography of external openness. Its wider diffusion is more consistent with the expansion of digital payments, online lending, credit information, and other forms of technology-based financial access.

This does not imply that digital finance benefits all inland provinces equally. The marginal results in **Figure 3** suggest that digital finance becomes relevant only after complementary conditions reach a sufficient level. The maps indicate, however, that these conditions can spread beyond regions with established international production links. Improvements in digital infrastructure and financial access may relax constraints in regions where traditional banking and capital-market services remain less developed. Evidence on green innovation and green productivity also reports substantial regional variation in the role of digital finance [12,15].

The time profiles of the two channels differ as well. FDI-related contributions shift more sharply between the three years. This is consistent with the sensitivity of foreign investment to external demand, international capital flows, and changes in regional industrial structure. DFI-related contributions develop more gradually, in line with the cumulative adoption of digital infrastructure and financial services. FDI therefore appears more exposed to changes in external and regional conditions, whereas DFI follows a slower process of domestic diffusion.

In summary, FDI and DFI are associated with regional productivity under different spatial conditions. The contribution of FDI is stronger where foreign capital is embedded in established industrial networks and can be absorbed by local firms. DFI becomes more relevant as digital infrastructure and financial inclusion expand, including in regions outside the traditional centers of external openness. The two channels therefore follow different spatial patterns in their relationship with regional productivity.

5. Conclusion

This paper compares the productivity relevance of foreign direct investment (FDI) and digital finance (DFI) across Chinese provinces from 2017 to 2024. A random forest model combined with GeoTimeShapley decomposition shows that the two financial variables matter mainly through their interactions with location and time. Their standalone contributions are comparatively small.

The two channels follow different patterns. DFI has a threshold profile: its contribution remains limited at lower levels of digital-finance development and becomes stronger as digital infrastructure and financial inclusion expand. FDI has a larger but less stable contribution, reflecting its dependence on absorptive capacity, industrial linkages, and external conditions. The spatial results reinforce this distinction. FDI-related contributions are more concentrated and shift more across years, whereas DFI-related contributions spread more gradually, including toward inland regions. External capital and domestic digital finance therefore correspond to different regional productivity conditions.

Several limitations remain. The analysis is descriptive rather than causal. GeoTimeShapley identifies how model-based contributions vary across provinces and years, but it does not isolate exogenous changes in FDI or DFI. Further work could examine these relationships using more disaggregated data and research designs that provide stronger causal identification.

Disclosure statement

The authors declare no conflict of interest.

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