The U-Shaped Impact of FinTech Development on Urban Economic Growth: Evidence from 17 Korean Cities

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ABSTRACT

The U-Shaped Impact of FinTech Development on Urban Economic Growth: Evidence from 17 Korean Cities

Existing fintech literature typically assumes uniformly positive growth effects, yet little is known about how early-stage disruption costs shape urban economic development. This study examines the nonlinear relationship between fintech development and urban economic growth using panel data from 17 Korean cities over 2014–2023. Employing a fixed-effects model with city-level fintech patent applications as the core measure, we document a robust U-shaped pattern: fintech initially depresses per capita GRDP through adjustment costs, but generates increasingly positive effects once development surpasses a critical threshold of approximately 24 patent applications (ln≈3.18), with marginal effects reaching 0.278 at peak levels. Identification strategies including lag/lead specifications and exclusion of Seoul and COVID-19 years confirm causality. Heterogeneity analysis reveals stronger positive effects in capital-region cities, service-oriented economies, and areas with higher initial fintech levels or larger corporate sectors. These findings underscore the need for differentiated regional policies supporting early-stage fintech ecosystems while maximizing mature ecosystem benefits.

Keywords : Fintech development, Urban economic growth, U-shaped relationship, Patent applications, Korea

1. Introduction

The rapid development of fintech has fundamentally reshaped urban economies around the world. Existing literature identifies several channels through which fintech may stimulate economic development, such as lowering transaction costs, promoting financial inclusion, and improving allocation efficiency (Lee and Shin, 2018). However, these studies typically suggest that fintech exerts a uniformly positive effect on urban economies, overlooking its underlying complexity—particularly during the early stage of fintech adoption. This study challenges the prevailing assumption of a linear relationship by examining whether the impact of fintech on urban economic growth in Korea exhibits nonlinear characteristics. Using per capita GRDP data for 17 Korean cities from 2014 to 2023, we provide strong evidence of a U-shaped relationship: fintech initially exerts a negative effect on per capita GRDP at low development levels, but becomes positive only after exceeding a threshold of approximately 24 patent applications. Moreover, the growth benefits are concentrated in capital-region cities, service-driven economies, and areas with large corporate sectors.

The motivation for this study arises from Korea's pressing policy challenges amid rapid fintech expansion. First, although extensive research has examined the microeconomic impacts of fintech on corporate financing and household financial access (Oh & Park, 2019; Song & Kim, 2021), far less attention has been paid to fintech's aggregate effect on urban economic growth—particularly whether early-stage disruptive costs outweigh potential long-term benefits. Second, since launching the IT-Finance Integration Support Plan in 2015, Korea has undergone one of the world's fastest fintech transformations, with open-banking API platforms reaching 118% penetration among the economically active population by 2022 (Lee et al., 2024). However, this transformation has, to some extent, widened regional gaps between the Seoul metropolitan area and other cities, raising questions about whether fintech can reduce regional economic disparities within Korea and how spatial inequality may be alleviated. Third, from a policy perspective, understanding the nonlinear effect of fintech is crucial for designing more targeted interventions. If fintech exhibits threshold effects on urban economic development, universal promotion strategies may generate negative outcomes for cities below the threshold, while providing insufficient support for cities above it. Therefore, this study contributes to addressing these challenges by uncovering the nonlinear relationship between fintech and urban economic growth in Korea.

The research framework of this paper is as follows. First, based on existing literature, we propose a theoretical model integrating creative destruction, network externalities, and financial deepening to explain why fintech may exhibit a U-shaped relationship with urban growth. We then construct a fixed-effect nonlinear panel model, using fintech patent applications as the core explanatory variable, per capita GRDP as the dependent variable, and internet penetration, government expenditure, export volume, urbanization, and human capital as control variables. The baseline regression confirms the U-shaped hypothesis, with a turning point at ln(fintech) ≈ 3.18. We further address endogeneity concerns through multiple identification strategies, including ruling out reverse causality, introducing lagged and lead terms, and performing robustness checks excluding Seoul and the COVID-19 period. In addition, heterogeneity analysis reveals that the nonlinear relationship is more pronounced in the Seoul metropolitan area, service-oriented economies, cities with higher initial levels of fintech, and regions with greater corporate asset scales. These findings contribute to fintech literature and regional development policy, demonstrating that fintech's growth effects are neither uniformly positive nor

evenly distributed but instead depend on local economic structures, initial fintech conditions, and other contextual factors.

2. Theoretical analysis and research hypotheses

Most existing fintech research assumes a linear and positive relationship between fintech and economic growth (Lee and Shin, 2018). In contrast, this study develops a more refined U-shaped theoretical framework to more accurately capture the transitional dynamics of technological innovation within urban economies. The framework integrates three theoretical mechanisms—creative destruction, network externalities, and financial deepening—to explain why fintech may initially suppress urban economic performance but promotes economic growth once surpassing a critical threshold.

Stage 1: Creative Destruction (Negative Phase)

Based on Schumpeter's (1942) theory of "creative destruction," early-stage fintech development imposes substantial transition costs on urban economies. Digital financial innovations disrupt established banking systems, forcing traditional institutions to transform or exit (Philippon, 2016; Buchak et al., 2018). This displacement pressure leads to employment declines in conventional financial sectors, and recent studies have confirmed that regions with greater fintech exposure experience more significant net job losses in traditional financial occupations (Chen et al., 2025), thereby depressing short-term economic performance.

In Korea, such adjustment costs are particularly pronounced. After the Financial Services Commission launched the "IT–Finance Integration Support Plan" in 2015, the country entered a period of rapid fintech transformation (Seo and Yoo, 2020), which required comprehensive restructuring of its mature traditional banking system. In cities where the fintech ecosystem is still nascent, traditional financial networks are disrupted without sufficient scale to generate productivity gains, consistent with the negative early-stage effects observed in this study's empirical results.

Stage 2: Network Externalities (Inflection Phase)

The transition from negative to positive effects can be explained by the mechanism of network externalities (Katz and Shapiro, 1986). Before reaching a critical mass, fintech platforms commonly face coordination failures: consumers are reluctant to adopt digital payment tools before widespread merchant acceptance, while merchants hesitate to invest in related equipment before sufficient consumer demand emerges (Rochet and Tirole, 2003). However, once adoption surpasses a critical threshold—empirically identified in this study as approximately 24 patent applications ($\ln \approx 3.18$)—network effects become self-reinforcing. Transaction costs rapidly decline through economies of scale, complementary services begin to emerge, and knowledge spillovers among firms accelerate (Katz and Shapiro, 1986).

Shin and Choi (2019) show that Korea's fintech industry exhibits the strongest forward linkage effect among 31 industries, indicating its role as a platform technology with cross-sector spillovers—an effect that strengthens significantly once development exceeds a minimum scale. Additionally, as fintech firms continuously accumulate data and operational experience, their capabilities in risk assessment and financial intermediation improve, thereby generating positive spillover effects (Berg et al., 2020).

Stage 3: Financial Deepening (Positive Phase)

After exceeding the critical threshold, fintech promotes urban economic growth through multiple

financial-deepening channels (Levine, 2005). First, fintech alleviates information asymmetries using big data analytics and alternative credit-scoring technologies, enabling previously constrained SMEs to obtain financing (Berg et al., 2020). Second, digital platforms improve capital allocation efficiency by significantly enhancing lending-processing speed: FinTech lenders process applications approximately 20% faster than traditional banks, and this efficiency improvement does not come at the cost of higher default risk (Fuster et al., 2019). Third, fintech promotes financial inclusion by providing lower-cost digital financial services to underserved populations, thereby expanding the economically active population (Seo and Yoo, 2020).

Korea's open-banking API platform exemplifies this mature-stage growth: as of 2022, it had 34 million subscribers (equivalent to 118% of the economically active population), giving rise to sustainable business models that stimulate economic activity (Lee et al., 2024). Moreover, local fintech development can significantly reduce regional economic disparities by optimizing industrial structures, and such effects intensify once development surpasses key thresholds—supporting the U-shaped hypothesis proposed in this study (Yang and Zhou, 2024).

Integrating the above three-stage mechanisms, we propose the following hypothesis:

Hypothesis: *Fintech development and urban economic growth exhibit a U-shaped relationship.*

3. Research design

3.1 Variables design

3.1.1 Independent variable: fintech patent applications (FinTech)

This study adopts a fixed-effects nonlinear panel model to evaluate the nonlinear effects of Fintech development on urban economic growth. The core explanatory variable is the level of Fintech development in city i at time t, , measured by the natural logarithm of lagged Fintech-related patent applications (IPC codes G06Q20/G06Q30/G06Q40), namely $\mathrm{FinTech}_{i,t-1} = \ln(1 + \mathrm{patent}_{i,t-1})$. This patent-based measure follows the innovation and patent-counting approach widely used in the FinTech literature (Chen et al., 2019). To capture the nonlinear relationship, we include its squared term $\mathrm{FinTech}^2_{i,t-1}$. The lagged treatment helps mitigate endogeneity concerns such as reverse causality, as patent applications are predetermined relative to current GRDP.

3.1.2 Dependent variable: urban economic growth (ln_GRDP)

The dependent variable is the natural logarithm of per capita gross regional domestic product (GRDP) in each city, $\mathrm{lnGRDP}_{i,t}$, which measures economic growth at the city level. This variable is widely used in urban economics literature to assess regional productivity and development.

3.1.3 Control variables

The all control variables are defined as follows: URB (urban population/total population), ln_HUM (college students per 10,000 population, logged), INT (internet users/total population), IS (tertiary industry/GDP), GOV (local budget expenditure/GRDP), OPE (export growth rate), and ln_CAP (logged total assets of all Korean listed companies). These variables draw upon prior studies on regional disparities and industrial upgrading (Yang and Zhou, 2024; Wang et al., 2023), but are adapted to the Korean urban context to reflect data availability and structural characteristics.

To address potential multicollinearity (VIF <10), we apply principal component analysis (PCA) to seven original control variables, extracting two principal components that cumulatively explain 69.63% of the variance (PC1: 44.36%, PC2: 25.27%). PC1 primarily represents urbanization and economic development level (loadings: IS +0.516, ln_CAP +0.496, URB +0.480). PC2 primarily represents human capital (loadings: ln_HUM +0.807, IS +0.431, ln_CAP -0.333). The remaining three variables are retained directly: INT (internet users/total population), GOV (local general public budget expenditure/local GRDP), and OPE (export growth rate = (current exports - previous exports)/previous exports).

3.1.4 Other variables: fintech national average control variable

To control for nationwide common shocks (e.g., national Fintech policies or macroeconomic trends), we construct a national Fintech development level variable ($\mathrm{FinTech_National}_{t-1}$), defined as the simple average of $\mathrm{FinTech}_{i,t-1}$ across 17 cities, mathematically $\mathrm{FinTech_National}_{t-1} = \frac{1}{17}\sum_{i=1}^{17} \ln(1 + \mathrm{Patent}_{i,t-1})$. This variable is included in the baseline model to isolate local effects from national trends.

3.2 Model setting

The baseline empirical specification adopts a nonlinear fixed-effects panel model that incorporates both city-level FinTech development and national FinTech trends:

$$\ln\mathrm{GRDP}_{i,t} = \propto + \beta_1\mathrm{FinTech}_{i,t-1} + \beta_2\mathrm{FinTech}^2_{i,t-1} + \delta\mathrm{FinTech_National}_{t-1} + \gamma\mathrm{Controls}_{i,t} + \mu_i + \varepsilon_{i,t}$$

Here, $\mathrm{FinTech_National}_{t-1}$ is added to control for nationwide shifts in FinTech development that may simultaneously affect all cities. The vector $\mathrm{Controls}_{i,t}$ includes INT, GOV, OPE, PC1 and PC2. City fixed effects μ_i control for time-invariant heterogeneity, and standard errors are clustered at the city level.

3.3 Data sources and statistics

Data on GRDP, population, and control variables are obtained from KOSIS. Patent data come from KIPRIS (2012–2024), and corporate financial information used for ln_CAP is sourced from WRDS. The sample covers 17 Korean metropolitan cities and provinces from 2014 to 2023, yielding 170 observations. Descriptive statistics in Table 1 indicate reasonable variation without extreme outliers.

4. Empirical analysis

4.1 Baseline Results

Table 2 reports the benchmark estimates of the non-linear panel model introduced in Section 3.2. The dependent variable is the log of real GRDP per capita, and the core explanatory variable is the log of city-level fintech patents with a one-year lag, together with its squared term. Across all specifications, the coefficient on fintech is negative while the coefficient on fintech² is positive and

highly significant, indicating a U-shaped relationship between fintech development and urban economic performance.

In Model (1), without any control variables, the fintech coefficient is negative but not statistically significant, whereas the squared term is positive and significant at the 1% level. After adding city-level controls (INT, GOV, OPE, PC1 and PC2) in Model (2), both fintech and fintech² become highly significant, and the within R-squared increases from 0.205 to 0.541, suggesting that the control variables explain a substantial share of the time-series variation in GRDP. When the national average of fintech (fintech_national) is further included in Model (3), the key coefficients remain very stable: the marginal effect of fintech is most negative at low levels and becomes less negative (and eventually positive) as fintech increases. This pattern supports the hypothesis that fintech may initially crowd out traditional activities or create adjustment costs, but once it exceeds a certain threshold, it starts to promote city-level economic growth.

To further clarify the nonlinear pattern, Figure 1 plots the marginal effect of FinTech on ln(GRDP). The marginal effect is negative at low levels of FinTech and becomes positive after the estimated turning point of 3.18. This threshold corresponds roughly to 24 patent applications. Cities below this level experience small and statistically insignificant negative effects, whereas those above the threshold show increasingly positive and significant effects. Table 6 summarizes these marginal effects at key percentiles.

4.2 Identification Strategy and Robustness Checks

This subsection examines whether the baseline findings are driven by reverse causality or by influential observations such as Seoul or COVID-19 years. The results are summarized in Tables 3 and 4.

4.2.1 Reverse Causality

To address potential reverse causality between fintech and GRDP, Table 3 estimates a series of specifications that shift the timing of fintech relative to GRDP. Specifically, the dependent variable remains ln_GRDP, while the key regressors are fintech at t−1, t−2, t+1 and t+2 (and their squared terms), respectively, with the full set of controls, the national fintech average and city fixed effects.

The estimates show that the U-shaped pattern is robust across different lags and leads. When fintech is measured at t−1, the results replicate the baseline finding: fintech is negative and significant, while fintech² is positive and significant at the 1% level, with an R-squared of 0.543. Using fintech at t−2, both coefficients remain significant and the explanatory power slightly increases, suggesting that the impact of fintech builds up over time. When future fintech at t+1 and t+2 is used, the magnitudes of the coefficients become smaller and significance weakens at t+2 (significant only at the 10% level), while the overall U-shape remains. Taken together, these patterns indicate that the strongest effect arises around the one-year lag, which is consistent with a causal impact of fintech on subsequent GRDP.

4.2.2 Excluding Seoul

Seoul is the political and financial center of Korea and may drive national trends. To check whether the baseline result is dominated by this single city, Column (2) of Table 4 re-estimates the model after excluding Seoul from the sample. The coefficients on fintech and fintech² remain negative and

positive, respectively, and retain statistical significance, although the R-squared decreases slightly from 0.543 to 0.523. This suggests that the non-linear effect is not solely driven by Seoul but is also present among non-capital cities.

Table 1
Descriptive statistics.

Variables	Mean	Std. Dev	Min	Max	Obs
ln_GRDP	1.048407e+01	0.293	9.890	11.305	170.0
fintech	3.599859e+00	1.311	0.693	7.372	170.0
fintech²	1.466719e+01	11.624	0.480	54.348	170.0
INT	8.561286e-01	0.071	0.592	0.976	170.0
GOV	1.527606e-01	0.060	0.047	0.322	170.0
OPE	2.803064e-02	0.145	-0.323	0.580	170.0
PC1	2.352941e-11	1.494	-2.902	4.189	170.0
PC2	-5.882353e-12	1.127	-2.169	2.265	170.0
fintech_national	3.599859e+00	0.419	2.902	4.157	170.0
IS	5.450410e-01	0.159	0.230	0.855	170.0
ln_CAP	1.784202e+01	1.771	13.987	22.793	170.0

Table 2
Results for benchmark model.

	Model (1)	Model (2)	Model (3)
	No Controls	With Controls	With Controls + National
fintech	-0.1546	-0.2088***	-0.2105***
	(0.1029)	(0.0596)	(0.0608)
fintech²	0.0397***	0.0299***	0.0331***
	(0.0135)	(0.0082)	(0.0070)
INT		0.7579**	0.8405**
		(0.3608)	(0.3995)
GOV		3.1304***	3.2460***
		(0.9859)	(0.9302)
OPE		0.0471	0.0587
		(0.0305)	(0.0393)
PC1		0.0395	0.0355
		(0.0842)	(0.0812)
PC2		0.1461	0.1418
		(0.1166)	(0.1182)
fintech_national			-0.0378
			(0.0501)
Controls	NO	YES	YES
National Control	NO	NO	YES
Fixed Effects	YES	YES	YES

N	170	170	170
R-squared	0.205	0.541	0.543

*Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-values. Standard errors are clustered at the city level.*

Table 3
Causal Identification Models.

Variable	(1)	(2)	(3)	(4)
	Baseline	t-2	t+1	t+2
fintech	-0.2105***			
	(0.0608)			
fintech²	0.0331***			
	(0.0070)			
fintech (t-2)		-0.1293***		
		(0.0392)		
fintech² (t-2)		0.0355***		
		(0.0052)		
fintech (t+1)			-0.1253***	
			(0.0431)	
fintech² (t+1)			0.0221***	
			(0.0054)	
fintech (t+2)				-0.0625*
				(0.0327)
fintech² (t+2)				0.0083**
				(0.0041)
Controls	YES	YES	YES	YES
National Control	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES
N	170	170	170	153
R-squared	0.543	0.581	0.546	0.531

*Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-values. Standard errors are clustered at the city level.*

4.2.3 Excluding COVID years

The COVID-19 pandemic may distort both fintech activities and local economic performance. Column (3) of Table 4 re-estimates the baseline model after dropping 2020 and 2021. The coefficients on fintech and fintech² remain significantly negative and positive at the 1% level, and the R-squared rises to 0.616. This indicates that the main conclusion is robust to excluding pandemic years and may even become slightly stronger when crisis-related noise is removed.

Table 4
Excluding Seoul & COVID years

	(1) Baseline	(2) Exclude Seoul	(3) Exclude COVID years
fintech	-0.2105***	-0.2106**	-0.1953***
	(0.0608)	(0.0865)	(0.0694)
fintech²	0.0331***	0.0335***	0.0321***
	(0.0070)	(0.0114)	(0.0092)
Controls	YES	YES	YES
Fixed effects	YES	YES	YES
N	170	160	136
R-squared	0.543	0.523	0.616

*Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-values. Standard errors are clustered at the city level*

Table 5-1

Heterogeneous effects of fintech on GRDP: capital region, initial fintech level

	(1) Capital	(2) Non-capital	(3) High Fintech	(4) Low Fintech
fintech	-0.3139***	-0.1848*	-0.2562***	-0.1074
	(0.0676)	(0.0953)	(0.0439)	(0.1315)
fintech²	0.0465***	0.0294**	0.0336***	0.0276
	(0.0050)	(0.0130)	(0.0092)	(0.0209)
Controls	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
N	30	140	90	80
R-squared	0.891	0.502	0.761	0.459

Table 5-2

Heterogeneous effects of fintech on GRDP: industrial structure, and firm size

	(5) High Service	(6) Low Service	(7) Large Firms	(8) Small Firms
fintech	-0.2166***	-0.2290**	-0.2105***	-0.1619
	(0.0298)	(0.1055)	(0.0448)	(0.1057)
fintech²	0.0319***	0.0434***	0.0302***	0.0278*
	(0.0076)	(0.0145)	(0.0087)	(0.0150)
Controls	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
N	90	80	90	80
R-squared	0.783	0.392	0.828	0.355

*Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-values. Standard errors are clustered at the city level*

4.3 Heterogeneity Analysis

This subsection examines whether the impact of fintech on GRDP differs across city types. Tables 5-1 and 5-2 report subgroup regressions based on capital status, initial fintech level, industrial structure, and firm size. Except for the capital–non-capital split, the other three groups are divided into high and low categories using the 2014 median values.

4.3.1 Capital vs Non-capital

Columns (1) and (2) of Table 5-1 split the sample into capital-region cities (Seoul, Gyeonggi-do and Incheon) and non-capital cities. In the capital region, the fintech coefficient is −0.3139 with a highly significant positive squared term (0.0465), and the R-squared reaches 0.891, indicating a very pronounced U-shaped relationship. In non-capital cities, the U-shape remains but is weaker in magnitude and significance. This suggests that while fintech brings both adjustment costs and growth benefits everywhere, capital-region cities are better positioned to convert fintech deepening into long-term gains.

4.3.2 High vs Low initial fintech

Columns (3) and (4) of Table 5-1 group cities by their initial fintech level in 2014. In the high-fintech group, both fintech and fintech² are strongly significant and the R-squared is about 0.76, pointing to a clear U-shaped pattern. In contrast, in the low-fintech group, the coefficients have the same signs but are not statistically significant. These results imply that cities starting from a more advanced fintech base can more effectively leverage further fintech development to enhance GRDP, whereas late-starting cities may still be in the early adjustment phase.

4.3.3 High vs Low service share

Columns (5) and (6) of Table 5-2 examine heterogeneity by industrial structure, using the 2014 share of the tertiary sector as the grouping criterion. A significant U-shape is observed in both high-service and low-service cities, but the fit of the model is better in high-service cities (R-squared of 0.783 vs. 0.392). This suggests that service-oriented economies, which typically rely more on information and financial services, benefit more systematically from fintech deepening.

4.3.4 Large vs Small firm sizes

Finally, Columns (7) and (8) of Table 5-2 split cities according to the log of total corporate assets. In large-firm cities, fintech and fintech² are both significant with an R-squared of 0.828, indicating a strong U-shaped relationship. In small-firm cities, the linear fintech term is insignificant and only the squared term is weakly significant at the 10% level. These findings imply that a sufficiently developed corporate sector is an important complement for fintech to translate into higher urban output.

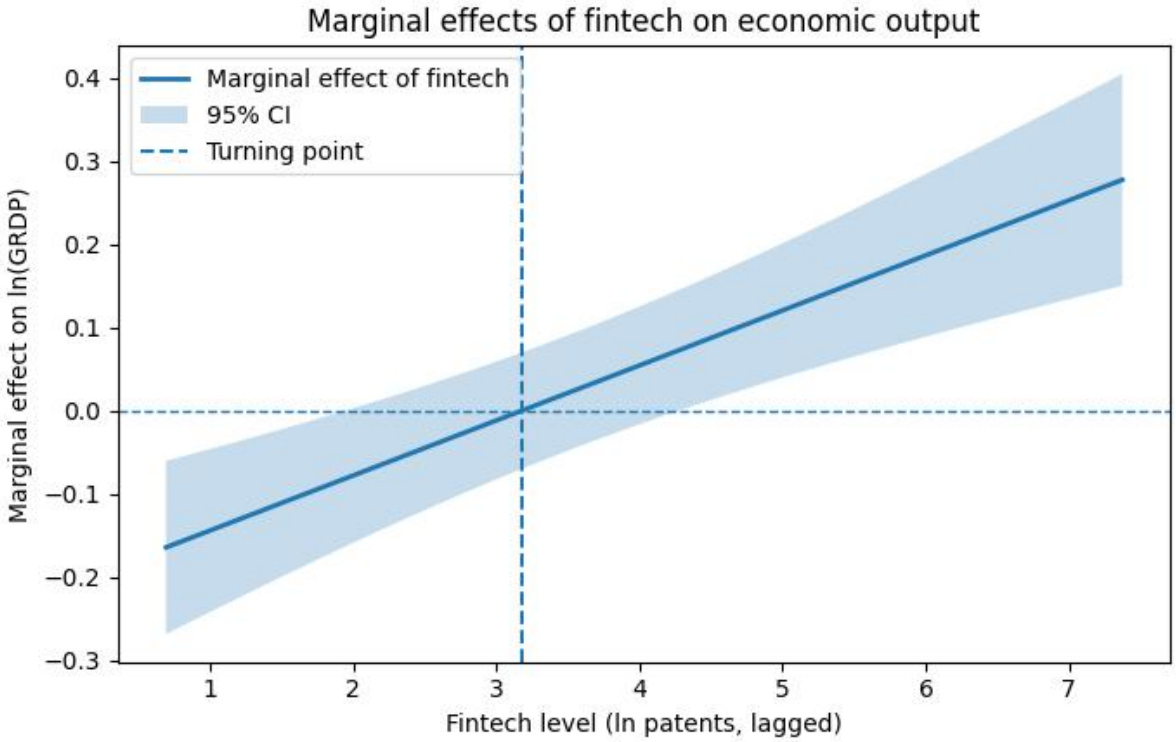
Overall, the heterogeneity analysis confirms that the non-linear effect of fintech on GRDP is robust but asymmetric: it is much stronger in capital-region, high-fintech, high-service and large-firm cities, highlighting the role of initial conditions and local economic structure in shaping the growth consequences of fintech.

Tabel 6
Marginal effects at representative values of Fintech

Point	fintech_value	Marginal Effect	Std. Error	t-stat
P25	2.848	-0.022	0.037	-0.598
P50	3.350	0.011	0.036	0.319
P75	3.993	0.054	0.036	1.493
Max	7.372	0.278	0.065	4.272

Note: The table reports marginal effects of FinTech at representative values of its empirical distribution. At the 25th percentile (FinTech = 2.85), the effect is slightly negative and statistically insignificant. At the median (3.35), the marginal effect becomes positive but remains insignificant. At the 75th percentile (3.99), the effect is moderately positive. At the maximum observed level (7.37), the marginal effect reaches 0.278 and is highly significant.

Figure 1
Marginal effects of Fintech development on economic growth



5. Conclusion

This study challenges the conventional assumption of a linear positive relationship between fintech development and urban economic growth by documenting a robust U-shaped pattern using panel data from 17 Korean cities over 2014–2023. Our findings reveal that fintech initially imposes adjustment costs on urban economies, generating negative or negligible effects on per capita GRDP at low development levels. However, once fintech intensity surpasses a critical threshold of approximately 24 patent applications (ln≈3.18), network externalities and financial deepening mechanisms activate, producing increasingly positive growth effects. This nonlinear relationship proves robust across

multiple identification strategies, including alternative time specifications and exclusion of influential observations such as Seoul and COVID-19 years. Notably, the U-shaped pattern exhibits pronounced heterogeneity: the growth benefits materialize more strongly in capital-region cities, service-oriented economies, cities with higher initial fintech bases, and areas with larger corporate sectors, highlighting how local economic structure and initial fintech conditions, and related factors in shaping the growth effects of fintech.

The above findings carry important policy implications for Korea's regional development strategy. For cities below the critical threshold—particularly non-capital regions where the fintech ecosystem remains in its nascent stage—the government should provide targeted support to help overcome coordination failures and achieve initial scale. For cities that have already surpassed the threshold, policy priorities should shift toward maximizing their ecosystem advantages and fostering growth through cross-regional knowledge spillovers. Given Korea's highly concentrated development pattern centered on the capital region, policy should also place special emphasis on helping non-capital cities build complementary strengths, rather than simply replicating Seoul's comprehensive fintech infrastructure.

This study offers a new perspective for understanding the growth effects of fintech, but several limitations remain and point to directions for future research. First, the sample covers a relatively short time span and includes only Korean cities, which may limit the generalizability of the findings to longer-term dynamics and other national contexts. Second, although patent applications can measure innovation activity, they cannot fully capture the overall level of fintech development in a city; future research could incorporate more comprehensive indicators such as digital payment transaction volumes or service penetration rates. Third, this study does not examine in depth the specific mechanisms through which fintech drives urban economic growth once the threshold is surpassed—for example, industrial upgrading, human capital accumulation, venture capital activity, or improvements in resource allocation efficiency. Future studies could conduct mechanism analyses to decompose the total effect and identify the relative importance of different channels, thereby providing more concrete guidance for designing targeted policy interventions.

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