

ISSN 2090-3359 (Print)
ISSN 2090-3367 (Online)



Advances in Decision Sciences

Volume 31
Issue 1
March 2027

Michael McAleer (Editor-in-Chief)

Chia-Lin Chang (Senior Co-Editor-in-Chief)

Wing-Keung Wong (Senior Co-Editor-in-Chief and Managing Editor)

Aviral Kumar Tiwari (Co-Editor-in-Chief)

Montgomery Van Wart (Associate Editor-in-Chief)

Shin-Hung Pan (Managing Editor)



亞洲大學
ASIA UNIVERSITY



SCIENTIFIC &
BUSINESS
WORLD

Published by Asia University, Taiwan and Scientific and Business World

Financial Technology Development and Regional Economic Growth in China: Evidence from Demand-Side Transmission Channels

TSANG Chun Kei

Business, Economic and Public Policy Research Centre,
Department of Economics and Finance, Hong Kong Shue Yan University
Email: cktsang@hksyu.edu

CHAN Ka Lok

Department of Public and International Affairs, City University of Hong Kong
Email: chankl@hksyu.edu

HUNG Tsz Hin

Lee Shau Kee School of Business and Administration, Hong Kong Metropolitan University
* *Corresponding Author* Email: rhung@hkmu.edu.hk

Received: September 30, 2025; First Revision: September 1, 2026;

Last Revision: September 15, 2026; Accepted: September 20, 2026;

Published: October 1, 2026

Abstract

Purpose: This study examines whether financial technology (FinTech) development promotes regional economic growth in China and identifies the demand-side transmission channels through which this effect operates at the provincial level.

Design/methodology/approach: Using a balanced panel of 31 Chinese provinces from 2012 to 2020, the study measures FinTech development by the growth rate of the Peking University Digital Financial Inclusion Index and economic performance by the growth rate of gross regional product per capita. A HANK-informed framework motivates the focus on three demand-side channels: fixed investment, retail consumption, and exports. Two-way fixed-effects panel regressions are employed, supplemented by diagnostic tests, panel-corrected standard error robustness checks, and lagged-variable specifications.

Findings: The results show that FinTech development significantly promotes regional economic growth. A one-percentage-point increase in FinTech growth is associated with approximately a 0.022-percentage-point increase in per capita GDP growth. Channel decomposition reveals that fixed investment is the dominant transmission mechanism, accounting for about 23 percent of the total effect. In contrast, the retail-consumption and export channels are economically negligible. The remaining direct effect, accounting for roughly 75 percent of the total association, suggests the presence of additional unobserved mechanisms such as productivity gains, financial deepening, and entrepreneurship.

Implications: The findings highlight the importance of digital financial infrastructure in easing investment constraints and supporting capital formation as a pathway to regional growth. From a decision-science perspective, the results demonstrate how FinTech-driven financial innovation influences regional economic decision-making through investment, consumption, and export processes. However, the analysis is conducted at the provincial level and is limited to the period 2012-2020, which may mask within-province heterogeneity and does not capture post-pandemic developments. Future research could employ more disaggregated data and extended time horizons to further explore the mechanisms through which FinTech affects economic growth.

Originality/value: This study contributes to the decision sciences literature by being among the first to provide a quantitative decomposition of the regional growth effects of FinTech development across multiple demand-side transmission channels within a HANK-informed framework. The study further strengthens the empirical evidence through a comprehensive set of panel diagnostic and robustness tests.

Keywords: Financial technology, economic growth, transmission channels, panel data, digital financial inclusion, China

JEL Classifications: E22, E44, G23, O33, O47, R11

1. Introduction

Over the past decade, financial technology (FinTech) has emerged as a major force in the global transformation of financial intermediation, reshaping how households and firms access payments, credit, savings, and investment services. The Financial Stability Board (FSB, 2017) defines FinTech as technology-enabled innovation in financial services that can generate new products, processes, or business models with material effects on the provision of financial services. This transformation has been especially pronounced in China, which has become one of the most important FinTech markets in the world, supported by the rapid diffusion of mobile payments, digital lending platforms, and digitally enabled financial inclusion (Claessens et al., 2018; Frost et al., 2019). These innovations have altered the traditional financial landscape by reducing transaction costs, lowering information asymmetries, expanding credit coverage, and broadening access to formal finance for previously underserved users (Boot et al., 2021; Thakor, 2020). In the Chinese context, the Peking University Digital Financial Inclusion Index has emerged as a widely used measure of regional FinTech development, capturing important dimensions of coverage breadth, usage depth, and digitalization (Guo et al., 2020; PKU Institute of Digital Finance, 2019).

Existing research has generated substantial evidence on the role of FinTech in promoting financial inclusion, easing credit constraints, and improving firm-level outcomes such as financing access, innovation, and operating performance (Ding et al., 2022; Fuster et al., 2019; Hau et al., 2024). At the macroeconomic level, cross-country studies report that digital lending and mobile money adoption are positively associated with GDP growth, particularly in economies with high initial levels of financial exclusion (Cevik, 2025; Sahay et al., 2020). In the Chinese context, provincial-level studies using the Peking University Digital Financial Inclusion Index confirm that FinTech development is positively associated with regional growth, consumption expansion, and industrial upgrading (Guo et al., 2020; Zhao et al., 2022). However, much less is known about whether FinTech development contributes to macroeconomic growth *at the regional level* through specific demand-side channels, and the relative importance of these channels remains largely unquantified (Li et al., 2020; Lin et al., 2022). This omission is important because the diffusion of FinTech has been highly uneven across provinces, suggesting that its aggregate effects may also vary spatially (Guo et al., 2020). More importantly, even fewer studies have attempted to decompose the total growth effect of FinTech into distinct transmission mechanisms, leaving the underlying channels insufficiently understood (Beck et al., 2000; Rajan & Zingales, 1998).

The unresolved question of how FinTech affects regional economic growth is also relevant to decision sciences. FinTech alters the information environment in which households, firms, and policymakers make economic decisions by affecting access to finance, investment opportunities, and resource allocation. Understanding the channels through which FinTech influences economic outcomes therefore contributes to the decision-sciences literature by providing evidence on how technology-enabled financial innovations shape decision-making processes and regional economic performance.

This paper addresses that gap by examining the effect of FinTech growth on per capita economic growth, *at the regional level*, across 31 Chinese provinces from 2012 to 2020. FinTech development is measured by the growth rate of the Peking University Digital Financial Inclusion Index, while economic performance is captured by the growth rate of gross regional product per capita. Beyond estimating the overall growth effect, the study decomposes the total effect into three demand-side transmission channels — fixed investment, retail consumption, and exports — and quantifies their relative contributions. This channel selection is motivated by a HANK-informed theoretical framework, which emphasizes that financial-friction shocks may affect constrained households and firms more strongly than unconstrained agents. In this setting, FinTech-induced relaxation of borrowing constraints and transaction frictions provides a rationale for examining fixed investment, retail consumption, and exports as distinct demand-side channels (Auclert et al., 2021; Kaplan et al., 2018).

Empirically, the analysis employs panel fixed-effects regressions with cross-section and period effects and uses robust standard errors to address *heteroskedasticity*. The study then applies a transmission-channel decomposition to separate the total effect of FinTech into direct and indirect components, followed by a robustness check based on one-period lagged FinTech growth. The results indicate that FinTech growth significantly promotes per capita GDP growth, with the fixed investment channel serving as the dominant transmission mechanism. The export and retail sales channels are economically and statistically negligible in the full decomposition, while the remaining direct component — which may reflect unmeasured mechanisms such as productivity gains, entrepreneurship, financial deepening, as well as other residual factors — accounts for approximately three-quarters of the total association.

The study contributes to the literature in three ways and offers several novel insights. More broadly, the findings provide evidence on how digital financial innovation affects economic decision outcomes through identifiable transmission channels, thereby advancing decision-science research on technology-enabled resource allocation. *First*, it uses the **growth rate** rather than the level of the FinTech index as the key explanatory variable, which is econometrically appropriate given that both the FinTech index and GDP per capita exhibit strong trending behavior, and growth-rate specifications ensure stationarity and avoid spurious regression (Granger & Newbold, 1974). *Second*, it provides a quantitative decomposition of the relative importance of three demand-side channels, revealing that fixed investment dominates while consumption and export channels are negligible — a finding that has not been previously documented at the provincial level in China. *Third*, it grounds the channel selection in a HANK-informed framework that emphasizes heterogeneous exposure to borrowing constraints and financial frictions. This allows the decomposition to move beyond an ad hoc discussion of channels while preserving the reduced-form interpretation of the empirical estimates.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the analytical motivation for the study. Section 3 presents a HANK-motivated conceptual framework for the empirical channel decomposition. Section 4 describes the data, variables, and empirical strategy. Section 5 presents the baseline regression results and the channel decomposition analysis. Section 6 reports the robustness checks. Section 7 discusses the findings and their implications. Section 8 concludes.

2. Literature Review

The literature on FinTech and regional economic development can be organized around three related questions. The first concerns whether FinTech and digital finance contribute to macroeconomic development. The second concerns the channels through which financial development, and specifically FinTech, may affect aggregate growth. The third concerns the empirical strategies used to identify these effects and decompose transmission channels. The present study lies at the intersection of these three complementary research streams: the finance–growth nexus, the macroeconomic consequences of FinTech-led financial innovation, and heterogeneous-agent macroeconomic frameworks that emphasize borrowing constraints and distributional frictions.

2.1 The Finance–Growth Nexus

The first strand begins with the broader finance–growth tradition, which argues that financial systems promote development by mobilizing savings, allocating capital toward productive uses, facilitating risk sharing, and supporting technological innovation. Schumpeter (1911) proposed that finance fosters innovation-led growth by identifying entrepreneurs and reallocating resources toward new technologies. Modern empirical research provides cross-country evidence that financial depth and market functioning predict higher long-run growth, faster capital accumulation, and productivity improvements (Beck et al., 2000; King & Levine, 1993; Levine & Zervos, 1998). Mechanism-oriented work further highlights that financial development disproportionately benefits activities that depend more on external finance, implying that reductions in financing frictions can change the sectoral and regional composition of growth (Rajan & Zingales, 1998). At the same time, the modern finance–growth debate stresses that the impact of finance can be nonlinear, and that the growth effects depend on how intermediation resources are allocated rather than their sheer quantity (Arcand et al., 2015). This motivates focusing on FinTech not as “more finance” per se, but as a potentially different form of intermediation that may reallocate credit access, payment efficiency, and risk management capacity toward the real economy.

2.2 FinTech and Macroeconomic Growth

Within this broader framework, FinTech is commonly defined as technology-enabled innovation in financial services that can generate new products, processes, or business models with material effects on the provision of financial services (FSB, 2017). Reviews of the FinTech literature emphasize a shift from relationship-based, branch-intensive finance toward data-driven screening, automated underwriting, and platform-based distribution, with implications for market structure, competition, and the cost of credit (Boot et al., 2021; Thakor, 2020). Micro-level evidence shows that digital lenders can use alternative data and automation to improve prediction and reduce processing costs, expanding credit access rather than only displacing incumbent banks (Berg et al., 2020; Fuster et al., 2019). Hau et al. (2024) use a regression discontinuity design exploiting Ant Group’s automated credit algorithm to show that FinTech credit boosts vendor sales growth, with stronger effects for firms facing greater information asymmetry. Gambacorta et al. (2023) analyze over two million Chinese firms and find that big tech credit responds to firm-specific transaction data rather than local business conditions or house prices, demonstrating that FinTech

substitutes data for collateral. Related work highlights how regulation and technology jointly shape the boundary between banks and nonbanks (Buchak et al., 2018; Tang, 2019). In addition, BigTech entrants combine large user bases with proprietary behavioral data and strong network effects, reshaping the structure of financial intermediation and creating new policy tradeoffs between inclusion, competition, and stability (Frost et al., 2019).

The macro-level evidence on FinTech and growth has expanded rapidly, especially in developing economies where traditional financial exclusion has been more severe (Claessens et al., 2018). Cross-country studies find that digital lending, mobile money, and other forms of digital financial access are positively associated with GDP growth, particularly where conventional banking penetration is limited (Cevik, 2025; Sahay et al., 2020). These findings are often interpreted through the lens of financial inclusion, whereby FinTech can lower transaction costs, improve credit matching, and broaden financial inclusion for households and firms that were previously underserved by the formal banking system.

China occupies a central place in this literature because it represents one of the world's largest and most dynamic FinTech environments. The rapid spread of mobile payments, digital credit, online wealth management, and platform-based financial services has transformed both household finance and enterprise financing, particularly since the early 2010s (He & Wei, 2023). An important contribution of the Chinese literature has been the development of the Peking University Digital Financial Inclusion Index, which provides a systematic measure of digital financial development across dimensions such as coverage breadth, usage depth, and digitalization level (Guo et al., 2020; PKU Institute of Digital Finance, 2019). On the household side, evidence indicates that digital finance improves consumption by easing liquidity and transaction constraints (Li et al., 2020), while mobile payment adoption raises rural household consumption (Yang & Zhang, 2022; Zhao et al., 2022). More recent evidence suggests digital finance can also reshape consumption structure through channels including payment convenience and tighter constraint relaxation (Hu et al., 2023). On the firm side, digital finance can alleviate financing constraints for smaller and more informationally opaque firms, supporting investment and innovation (Ding et al., 2022; Lin et al., 2022). However, the literature also emphasizes risks and nonlinearities. Digital finance may expand credit participation while increasing household financial distress risk (Yue et al., 2022), and China's experience with P2P lending illustrates how rapid expansion under an incomplete regulatory perimeter can culminate in widespread platform failures and market closure (Chen et al., 2025). These findings suggest that the net growth impact of FinTech plausibly depends on the composition of FinTech services, baseline financial exclusion, and the regulatory environment.

2.3 Transmission Channels

The second strand of literature concerns the transmission channels from financial development to growth. In the traditional finance–growth literature, investment is one of the principal mechanisms. Financial development lowers the cost of capital, expands external finance, and improves the allocation of funds toward higher-return activities, thereby stimulating fixed capital formation and productivity-enhancing investment (Beck et al., 2000; Rajan & Zingales, 1998). In the FinTech context, this mechanism is

particularly relevant because digital lending, algorithmic credit scoring, and automated underwriting can reduce information asymmetries and collateral constraints for smaller, younger, and more opaque firms (Berg et al., 2020; Fuster et al., 2019; Gambacorta et al., 2023). China-focused evidence suggests that digital finance can lower financing costs for private enterprises, expand access to working capital and equipment finance, and support innovation-related spending (Ding et al., 2022; Lin et al., 2022). Because many private firms in China face persistent borrowing constraints in the bank-dominated credit system, FinTech may play a disproportionately large role in unlocking investment effects in provinces where formal financial access was historically limited. This makes fixed investment a theoretically compelling and empirically relevant channel through which FinTech may influence regional output growth.

Consumption provides a second major transmission channel. In standard macroeconomic theory, financial development can support consumption by relaxing liquidity constraints, enabling intertemporal smoothing, and improving access to payment infrastructure and consumer credit (Guerrieri & Lorenzoni, 2017). In the digital finance context, mobile payments, digital wallets, installment credit, and app-based consumer finance may lower transaction frictions and allow households to consume more efficiently and more frequently. Chinese studies using household and regional data report that digital finance can raise consumption, especially in rural and lower-income areas where traditional financial services were previously inaccessible or inconvenient (Li et al., 2020; Yang & Zhang, 2022; Zhao et al., 2022). At the same time, this channel is not unambiguously positive for welfare because short-run consumption gains could coexist with longer-run balance-sheet vulnerabilities (Yue et al., 2022). Accordingly, while the consumption channel is theoretically important, its net macroeconomic contribution remains an empirical question.

Exports and trade-related activity form a third channel. The classical literature argues that financial development facilitates trade by easing working-capital constraints, improving trade finance, and enabling firms to manage settlement risk and exchange-related frictions. In the FinTech context, digital payments, cross-border payment systems, and automated credit assessment can reduce transaction delays and improve access to trade finance. Emerging China-focused evidence suggests that digital finance may promote exports and support participation in global trade by reducing financing frictions and enhancing firms' innovation and market access (Li et al., 2025). However, compared with investment and consumption, the empirical literature linking FinTech to trade outcomes is sparser and more context-dependent, since trade effects depend on sectoral structure, openness, and the maturity of financial and logistics networks.

2.4 Methodological Approaches and Research Gaps

The third strand concerns methodological approaches. Much of the empirical literature on finance, digital finance, and growth relies on panel data methods because the effects of financial development are likely to vary across units and over time. **Two-way fixed-effects models** are widely used because they absorb time-invariant heterogeneity across provinces while time effects capture common macroeconomic shocks. At the same time, scholars have noted identification challenges — **reverse causality, omitted variable**

bias, and measurement error — and some studies attempt to address these concerns by complementing fixed effects with lag structures, alternative variable measures, or quasi-experimental designs (Bellemare et al., 2017; Chen et al., 2023).

A related methodological issue concerns how to analyze transmission channels. In the traditional finance–growth literature, channel decomposition often proceeds by estimating separate equations for candidate mediators and then linking these estimates to the main growth equation (Beck et al., 2000). Such methods are usually reduced-form and therefore do not, by themselves, identify structural mechanisms. This limitation is especially relevant for FinTech, which may affect consumption, investment, and trade simultaneously, and where one channel may offset or amplify another. Recent work in heterogeneous-agent macroeconomics, including the sequence-space Jacobian approach of Auclert et al. (2021), provides useful theoretical discipline for thinking about how micro-level financial frictions can aggregate into macroeconomic demand responses (Auclert, 2019; Kaplan et al., 2018). In the present study, this literature is used to motivate the selection of channels, while the empirical implementation remains a reduced-form provincial panel analysis.

Recent studies in decision sciences further highlight the growing importance of digitalization, financial innovation, and economic decision-making in shaping economic and financial outcomes. For example, digital transformation has been shown to affect firm performance and SME development (Alsafadi et al., 2026; Liang et al., 2024), while cashless payments have been linked to economic growth (Noman et al., 2023). Related evidence also suggests that innovation and financial-market dynamics can influence broader economic outcomes and risk transmission mechanisms (Bagadeem et al., 2025; Syed et al., 2025). Collectively, these studies underscore the increasing role of technology-enabled financial and economic processes, while leaving open important questions regarding how FinTech development contributes to regional economic growth through distinct transmission channels.

Several gaps emerge from this literature. *First*, most studies on digital finance in China focus on levels of digital finance rather than its **growth rate**, even though the dynamic expansion of FinTech may be more closely related to marginal changes in regional economic performance, and growth-rate specifications are econometrically preferable when underlying variables are non-stationary. *Second*, while many studies examine one mechanism at a time, few papers decompose the specific channels through which FinTech affects **regional** output growth in a common empirical framework. *Third*, the relative importance of fixed investment, retail consumption, and exports remains largely unknown, particularly at the provincial level in China. The present study addresses these gaps by examining the growth-rate effect of FinTech development on per capita output growth and by decomposing the total effect into three candidate channels: fixed investment, retail consumption, and exports. In doing so, it moves beyond ad hoc channel discussion and provides a quantitative decomposition of the relative importance of each demand-side transmission mechanism, informed by HANK macroeconomic theory but estimated in a reduced-form panel framework.

3. Conceptual Framework

This section outlines the theoretical motivation for the empirical specification and channel decomposition. The framework draws on the Heterogeneous Agent New Keynesian (HANK) literature to explain why financial-friction shocks may affect constrained households and firms differently from unconstrained agents. Rather than structurally estimating a HANK model, the paper uses this framework to motivate the selection of fixed investment, retail consumption, and exports as theoretically relevant demand-side channels through which FinTech development may influence regional output growth. Appendix A provides the formal mathematical development of the framework, while this section summarizes the key intuition and its mapping to the empirical model. The formal derivations are presented in the appendix to preserve the readability of the main text while allowing interested readers to examine the complete analytical structure underlying the channel decomposition.

3.1 Theoretical Motivation

Traditional Representative Agent New Keynesian (RANK) models assume perfect insurance and frictionless capital markets, which limits their ability to capture the distributional effects of financial shocks. HANK models, by contrast, incorporate uninsurable **idiosyncratic** income risk and borrowing constraints, generating a distribution of households with varying marginal propensities to consume (Kaplan et al., 2018). This heterogeneity is crucial for analyzing FinTech because digital financial inclusion is likely to affect liquidity-constrained households and financially constrained small and medium-sized enterprises (SMEs) more strongly than unconstrained agents.

The sequence-space Jacobian (SSJ) approach of Auclert et al. (2021) provides a computationally tractable method for solving heterogeneous-agent models by representing the household block as a linear mapping from sequences of aggregate inputs, such as after-tax resources and interest rates, to sequences of aggregate outputs, such as consumption and asset holdings. Auclert et al. (2024) further use this framework to derive the intertemporal Keynesian cross, demonstrating how intertemporal marginal propensities to consume shape aggregate demand responses. More broadly, Auclert et al. (2025) show how heterogeneous-agent frameworks have become central for analyzing the transmission of fiscal and monetary policy through household heterogeneity, liquidity constraints, and distributional channels.

3.2 The Household Block

The household side of the framework follows the standard HANK insight that households differ in their asset positions, income risk, and access to borrowing. Some households are liquidity-constrained, meaning that current resources have a high marginal value and their marginal propensity to consume is relatively large. FinTech innovations — such as mobile payments, digital micro-loans, and algorithmic credit scoring — can relax these constraints by lowering transaction costs and expanding access to short-term credit.

In the formal framework presented in Appendix A, household consumption is represented as a function of household resources, real interest rates, and borrowing capacity. Aggregating across heterogeneous

households yields a sequence-space representation in which changes in household resources affect aggregate consumption through a dynamic marginal propensity to consume matrix. This provides the theoretical basis for including retail sales growth as a consumption-related transmission channel.

However, the framework does not imply that the consumption channel must be empirically dominant. FinTech may increase payment convenience and liquidity, but the aggregate retail-sales response may be limited if digital finance mainly changes the mode of transactions rather than the total volume of household consumption.

3.3 Goods-Market Clearing and Demand-Side Channels

Regional goods-market clearing implies that output can be decomposed into consumption, investment, government spending, and net exports:

$$Y_{it} = C_{it} + I_{it} + G_{it} + NX_{it}.$$

Taking a first-order approximation around a steady state implies that output growth depends on the growth of its expenditure components, weighted by their relative shares in regional output. This accounting relationship motivates the use of demand-side channel variables, but it does not mechanically determine which channel is most important. The relative importance of each channel depends on how strongly FinTech development affects that component and how strongly that component is associated with regional output growth.

The present study focuses on three observable channels: fixed investment growth, retail sales growth, and export growth. Fixed investment captures the capital-formation channel. Retail sales proxy household consumption demand. Export growth captures the external-demand channel. Government spending is not treated as a separate channel because the paper focuses on market-facing transmission mechanisms associated with digital financial development.

Importantly, the empirical channel decomposition is not a structural estimation of the goods-market-clearing equation. Because the variables are measured in growth rates and because exact expenditure-share weights are not imposed, the model should be interpreted as a reduced-form decomposition of the association between FinTech growth and regional output growth.

3.4 Mapping to the Empirical Specification

FinTech development is treated as a financial-friction shock that may influence regional output growth through both observed and unobserved mechanisms. The observed mechanisms are fixed investment growth, retail sales growth, and export growth. The unobserved mechanisms may include productivity gains, entrepreneurship, financial deepening, digital-infrastructure effects, and other residual factors not directly measured in the channel variables.

The baseline empirical specification is:

$$GR_{it} = \alpha_i + \delta_t + \beta_D FTG_{it} + \lambda_I INV_{it} + \lambda_C RETG_{it} + \lambda_X EXPG_{it} + u_{it},$$

where GR_{it} denotes per capita gross regional product growth, FTG_{it} denotes FinTech growth, INV_{it} denotes fixed investment growth per capita, $RETG_{it}$ denotes retail sales growth per capita, and $EXPG_{it}$ denotes export growth per capita. The province fixed effects α_i absorb time-invariant regional characteristics, while the year fixed effects δ_t absorb common macroeconomic shocks.

The channel equations specify how FinTech growth is associated with each demand-side component:

$$\begin{aligned} INV_{it} &= \alpha_i^I + \delta_t^I + \pi_I FTG_{it} + \varepsilon_{it}^I, \\ RETG_{it} &= \alpha_i^C + \delta_t^C + \pi_C FTG_{it} + \varepsilon_{it}^C, \\ EXPG_{it} &= \alpha_i^X + \delta_t^X + \pi_X FTG_{it} + \varepsilon_{it}^X. \end{aligned}$$

Combining the output-growth equation with the three channel equations gives the following reduced-form decomposition:

$$\beta_T = \beta_D + \lambda_I \pi_I + \lambda_C \pi_C + \lambda_X \pi_X.$$

Here, β_T is the total association between FinTech growth and regional output growth, β_D is the remaining direct component after controlling for the three observed channels, and $\lambda_j \pi_j$ represents the indirect component associated with channel j . This decomposition is theoretically motivated by the HANK framework, but the estimated coefficients are reduced-form panel estimates rather than structural HANK parameters. In the simultaneous decomposition reported later in Table 8, the coefficients λ_I , λ_C , and λ_X are estimated jointly from Model D1 rather than from separate single-channel regressions. Consequently, the corresponding indirect effects represent conditional channel contributions after accounting for the joint influence of the other mediators. By contrast, the single-channel decompositions reported in Tables 5-7 are partial decompositions estimated separately for each channel.

3.5 Testable Predictions

The HANK-motivated framework generates three testable predictions that guide the empirical channel decomposition:

Prediction 1 (Investment dominance). *Because FinTech can relax financing constraints for credit-constrained private firms and SMEs, the fixed-investment channel is expected to be the strongest observed transmission mechanism. This prediction extends the HANK insight that constrained agents respond more strongly to financial-friction shocks to the firm side, where improved credit access may raise capital formation.*

This prediction follows from the view that FinTech can alleviate financing constraints faced by SMEs and private firms. If this prediction is supported by the data, the fixed-investment channel

should account for a larger share of the overall FinTech-growth relationship than the consumption and export channels.

Prediction 2 (Consumption ambiguity). *The consumption channel may be positive but relatively weak in the aggregate. FinTech can relax household liquidity constraints and reduce payment frictions, but these effects may be partly offset if digital finance mainly shifts transactions from offline to online channels without substantially increasing total consumption.*

This prediction reflects the possibility that FinTech may increase payment convenience without substantially increasing aggregate household expenditure. Empirically, support for this prediction would be observed if the retail-sales channel is positive but contributes only a small proportion of the overall growth effect.

Prediction 3 (Export peripherality). *The export channel is expected to be positive but peripheral because FinTech primarily operates through domestic financial intermediation. Its effect on trade finance, cross-border payments, and export activity is likely to be indirect and highly dependent on provincial openness, industrial structure, and logistics capacity.*

This prediction arises because the impact of FinTech on trade-related activity is likely to be indirect and dependent on provincial trade characteristics. Empirical support would be reflected in a relatively small contribution of the export channel compared with the investment channel.

4. Data and Methodology

4.1 Data

A balanced provincial panel was constructed for 31 Chinese provincial-level units, including provinces, autonomous regions, and municipalities, over the period 2012 to 2020. The baseline sample therefore contained 279 province-year observations. The period 2012–2020 was selected because it captures the critical phase of large-scale FinTech expansion in China, beginning with the rapid acceleration of mobile payments and digital credit platforms in 2012 and extending through the regulatory maturation period. The endpoint of 2020 was chosen to avoid the structural macroeconomic disruptions introduced by the COVID-19 pandemic in subsequent years.

The dependent variable was defined as the growth rate of gross regional product per capita, denoted by *GR*, expressed in percentage terms. The key explanatory variable was the growth rate of FinTech development, denoted by *FTG*, computed as the percentage change in the Peking University Digital Financial Inclusion Index (PKU-DFIIC). The use of growth rates rather than levels is motivated by both econometric and substantive considerations. Econometrically, the PKU-DFIIC level exhibits strong upward trending behavior across virtually all provinces (rising from near zero to over 300 between 2011 and 2020), suggesting non-stationarity. Regressing trending variables can produce spuriously significant

results (Granger & Newbold, 1974). Growth-rate transformation converts the series to stationary form, as confirmed by formal panel unit root tests reported in Table 2. Substantively, the growth rate captures the marginal expansion of FinTech, which is more closely related to contemporaneous changes in regional economic performance than the cumulative level.

Three transmission channel variables were defined. Fixed investment growth per capita (*INVG*) was measured as the annual growth rate of fixed asset investment per capita, capturing the capital formation channel. Retail sales growth per capita (*RETG*) was measured as the annual growth rate of retail sales of consumer goods per capita, proxying aggregate household consumption demand. Export growth per capita (*EXPG*) was measured as the annual growth rate of export trade value per capita, capturing the external demand channel. All per capita variables were adjusted for population growth. Data on gross regional product, fixed asset investment, retail sales, exports, and population were obtained from the National Bureau of Statistics of China.

4.2 Descriptive Statistics

The descriptive statistics indicated substantial heterogeneity across provinces and over time (Table 1). The mean growth rate of gross regional product per capita was 7.91 percent, with a standard deviation of 3.69. The mean growth rate of FinTech development was 35.60 percent, with a markedly larger standard deviation of 57.37. This high dispersion reflected the fact that FinTech expanded rapidly during the sample period. The mean growth rates of the channel variables were 8.56 percent for fixed investment, 8.49 percent for retail sales, and 5.61 percent for exports, with exports displaying the highest variability (standard deviation of 24.80). The pairwise correlations were all positive and moderate (Table 1). The correlation between FinTech growth and per capita output growth was 0.37. The corresponding correlations between *FTG* and the three channel variables were 0.46 for *INVG*, 0.28 for *RETG*, and 0.39 for *EXPG*. These coefficients suggested that provinces with faster FinTech growth also tended to record stronger output growth and stronger demand-side performance, though the moderate magnitudes (all below 0.50) indicated no serious multicollinearity concerns.

Table 1: Correlation Coefficients and Descriptive Statistics

	GR	FTG	INVG	RETG	EXPG
GR	1.0000				
FTG	0.3723	1.0000			
INVG	0.4497	0.4638	1.0000		
RETG	0.4995	0.2759	0.4148	1.0000	
EXPG	0.3147	0.3856	0.2975	0.1730	1.0000
Mean	7.9094	35.6033	8.5616	8.4901	5.6111
STD	3.6856	57.3739	10.0637	9.9594	24.7976
OBS	279	279	279	279	279

Note:

GR: Growth rate of gross regional product per capita in percentage

FTG: Growth rate of FinTech development in percentage, Digital Financial Inclusion Index

INVG: Growth rate of fixed investment per capita in percentage

RETG: Growth rate of retail sales per capita in percentage

EXPG: Growth rate of export value per capita in percentage

4.3 Stationarity Tests

Recent studies have raised concerns about spurious relationships arising from nearly non-stationary series in panel analyses (Wong & Pham, 2022, 2026). Accordingly, prior to estimation, the time-series properties of the panel variables were examined using both first-generation and second-generation panel unit root tests. Specifically, Levin-Lin-Chu (LLC), ADF-Fisher, PP-Fisher, and Pesaran's (2007) Cross-Sectionally Augmented IPS (CIPS) tests were conducted, and the results are reported in Table 2. The null hypothesis under each test was that the variable contained a unit root.

Table 2: Results of Stationarity Tests

Variables	LLC test	ADF test	PP test	CIPS test
GR	-12.71***	151.20***	307.31***	-3.20***
FTG	-43.47***	379.02***	571.04***	-13.88***
INVG	-6.49***	70.49	146.22***	-3.99***
RETG	-2.23**	63.69	82.09**	-2.25**
EXPG	-15.75***	180.55***	314.94***	-3.10***

Note: The null hypothesis under each test is that the data are nonstationary. The *, **, and *** represent a 10, 5, and less than 1% significance level, respectively.

For *GR*, the null hypothesis was rejected at the 1 percent level by all three tests, with test statistics of -12.71 for LLC, 151.20 for ADF-Fisher, and 307.31 for PP-Fisher. For *FTG*, the null was also rejected at the 1 percent level by all three procedures, with corresponding statistics of -43.47 , 379.02 , and 571.04 . The same pattern was observed for *EXPG*, for which the LLC, ADF-Fisher, and PP-Fisher statistics were -15.75 , 180.55 , and 314.94 , respectively, all significant at the 1 percent level.

For *INVG* and *RETG*, the evidence was slightly mixed but still supportive of stationarity. The LLC and PP-Fisher tests rejected the unit root null for both variables, while the ADF-Fisher test did not. Specifically, *INVG* produced statistics of -6.49 under LLC and 146.22 under PP-Fisher, both significant at the 1 percent level, whereas the ADF-Fisher statistic of 70.49 was not significant. For *RETG*, the LLC statistic was -2.23 , significant at the 5 percent level, and the PP-Fisher statistic was 82.09 , significant at the 5 percent level, while the ADF-Fisher statistic of 63.69 was not significant. Given the short time dimension of the panel ($T = 9$), the ADF-Fisher test may lack power. Taking the evidence together, and considering that the LLC and PP-Fisher results were supportive, all variables were treated as stationary for the purposes of estimation.

The second-generation CIPS results are consistent with the first-generation LLC, ADF-Fisher, and PP-Fisher tests. The null hypothesis of a unit root is rejected for all variables at conventional significance levels, providing additional support for the stationarity of the growth-rate variables employed in the analysis.

These results confirm that the growth-rate specification is econometrically appropriate. The use of growth rates ensures that the panel regressions operate on stationary variables, avoiding the risk of spurious

inference that would arise from regressing non-stationary level variables (Granger & Newbold, 1974; Kao, 1999).

4.4 Empirical Strategy

The baseline empirical specification was estimated as:

$$GR_{it} = \alpha_i + \delta_t + \beta \cdot FTG_{it} + \gamma' X_{it} + u_{it},$$

where i indexed provinces and t indexed years. In this specification, α_i denoted cross-section fixed effects, δ_t denoted period fixed effects, and X_{it} denoted a vector of channel variables (*INVG*, *RETG*, *EXPG*) added sequentially. The fixed-effects structure was adopted so that time-invariant provincial heterogeneity and common year-specific shocks could be controlled for simultaneously. Estimation was conducted by panel least squares, and White diagonal standard errors with degrees-of-freedom correction were applied to address heteroskedasticity. In addition, formal diagnostic tests were subsequently conducted to assess cross-sectional dependence, serial correlation, and potential non-linearity. Where appropriate, alternative covariance estimators were employed to evaluate the robustness of the baseline findings.

The inclusion of cross-section fixed effects absorbed time-invariant regional characteristics such as geographic location, historical institutional quality, economic structure, and cultural propensity toward technology adoption. Period fixed effects absorbed common aggregate shocks, including national monetary policy shifts, regulatory changes, global macroeconomic cycles, and common technology diffusion trends. Together, the two-way fixed effects isolated within-province, within-period variation in FinTech growth as the source of identification, minimizing the risk that observed effects were driven by unobserved confounding factors (de Chaisemartin & D'Haultfœuille, 2020).

A sequence of model specifications was estimated in order to test the sensitivity of the FinTech coefficient and to identify the relative importance of alternative channels. Model A1 included only *FTG* together with cross-section and period fixed effects, providing the benchmark estimate of the total effect. Models B1, B2, and B3 added *EXPG*, *RETG*, and *INVG*, respectively, as individual controls. Models C1, C2, and C3 introduced pairwise combinations of the channel variables. Model D1 included all three channel variables simultaneously, providing the most controlled specification and yielding the direct effect of FinTech net of the three observed demand channels.

A common concern in finance–growth regressions is potential reverse causality: regions experiencing faster GDP growth may simultaneously attract greater FinTech investment, generating upward bias in the estimated coefficient. The present study addresses this concern through several complementary strategies. First, the two-way fixed effects control for both time-invariant provincial confounders and common temporal shocks, isolating within-province variation over time. Second, a robustness check using one-period lagged FinTech growth (FTG_{t-1}) is reported in **Section 6**, which ensures that the FinTech measure is predetermined relative to the dependent variable and mitigates contemporaneous reverse causality.

Third, the growth-rate specification itself reduces the risk of confounding from common trends, since both the treatment and outcome variables are expressed as deviations from their own previous levels. While these strategies do not constitute a formal instrumental variable approach, they are consistent with the identification practices employed in the applied panel finance literature (Baker et al., 2022; Levine et al., 2000) and provide a credible basis for interpreting the estimated coefficients as reflecting the effect of FinTech growth on regional output growth, conditional on the assumption that remaining unobserved confounders do not systematically co-move with within-province FinTech growth after controlling for province and year effects.

4.5 Channel Decomposition

A channel decomposition procedure was implemented to separate the total effect of FinTech growth on per capita output growth into direct and indirect components. The total effect was taken from Model A1, in which GR was regressed on FTG without the three channel variables. This total effect was decomposed into a remaining direct component and a set of indirect components associated with the candidate channels.

For each channel j , the indirect effect was calculated as the product of two coefficients. The first coefficient was the estimated effect of channel j on GR from the corresponding output-growth equation. The second coefficient was the estimated effect of FTG on channel j from the channel equation. Three auxiliary channel equations were estimated for this purpose: Model E1 regressed $EXPG$ on FTG , Model E2 regressed $RETG$ on FTG , and Model E3 regressed $INVG$ on FTG . All channel equations included cross-section and period fixed effects with robust standard errors.

The overall decomposition was obtained by summing the direct effect and the indirect effects across the three channels. Channel shares were calculated by dividing each indirect effect by the total effect from Model A1. This approach permitted not only an assessment of whether FinTech growth was associated with regional output growth, but also a quantification of how much of that association was statistically accounted for by fixed investment, retail consumption, and exports, respectively. In the simultaneous decomposition reported later in Table 8, the coefficients linking the channel variables to economic growth are obtained from Model D1, where all three mediators enter the regression jointly. As a result, the indirect effects reported in Table 8 should be interpreted as conditional channel contributions rather than isolated single-channel effects.

An important clarification is warranted regarding the use of GDP expenditure components as transmission channel variables. While the national income accounting identity implies that any effect on aggregate GDP must be distributed across its expenditure components, the **distribution** across components is an empirical question with theoretical content. The identity constrains only the sum of component effects, not their individual magnitudes, signs, or statistical significance. Moreover, the use of growth-rate specifications breaks the exact additive identity constraint, since the growth rate of a sum is not equal to the sum of the growth rates of its components but rather their share-weighted average. Our channel analysis therefore reveals which specific components of aggregate demand are most responsive to FinTech development, providing evidence on economic mechanisms rather than restating the accounting identity.

4.6 Robustness Check

To evaluate the reliability of the baseline findings, several complementary robustness procedures were implemented. First, formal diagnostic tests were conducted to assess whether the panel specifications were affected by cross-sectional dependence or serial correlation. Specifically, Pesaran's (2007) Cross-Sectional Dependence (CD) test and Wooldridge's (2002) test for first-order serial correlation in panel data were applied to all estimated models.

Second, alternative covariance estimators were employed to examine the sensitivity of the results to the treatment of residual dependence. In addition to the baseline White diagonal covariance estimator, the models were re-estimated using panel-corrected standard errors (PCSE) under both Cross-SUR and Period-SUR specifications. These estimators provide more robust inference when residual dependence is present in panel-data settings.

Third, the possibility of a non-linear relationship between FinTech development and regional economic growth was examined by augmenting the baseline specification with a quadratic term for FinTech growth (FTG^2). This approach follows the conventional finance-growth literature and provides a direct test for diminishing or increasing marginal effects. This test allows the analysis to assess whether the growth effects of FinTech exhibit increasing or diminishing marginal returns.

Finally, a lagged-variable robustness check was performed by replacing contemporaneous FinTech growth with its one-period lag, $FTG(t-1)$. This procedure was adopted to mitigate concerns regarding reverse causality, since stronger contemporaneous economic growth may itself encourage FinTech adoption and expansion. The lagged specification reduces the sample to 248 observations, corresponding to the period 2013-2020. All baseline and channel equations were subsequently re-estimated using the lagged variable.

While these procedures improve the robustness of the empirical findings, they do not eliminate all endogeneity concerns. In particular, the lagged specification does not fully address dynamic endogeneity or omitted time-varying factors. Consequently, the results should be interpreted as robust reduced-form evidence on the association between FinTech growth and regional economic growth rather than as definitive causal estimates.

5. Results

5.1 Baseline Results

Table 3 reports the baseline fixed-effects estimates of the association between FinTech growth and per capita output growth. In Model A1, the coefficient on FTG was 0.0222, with a t-statistic of 3.71, and the estimate was significant at the 1 percent level. The adjusted R-squared was 0.6058. Accordingly, a 1-percentage-point increase in the growth rate of FinTech development was associated with a 0.0222-percentage-point increase in per capita GDP growth, holding all other factors constant.

Table 3: The Effect of FinTech Development on the Growth Rate

Estimations:	A1	B1	B2	B3	C1	C2	C3	D1
	Dependent variables							
	GR	GR	GR	GR	GR	GR	GR	GR
FTG	0.0222*** (3.71)	0.0214*** (3.64)	0.0218*** (3.81)	0.0168*** (3.02)	0.0210*** (3.73)	0.0166*** (2.99)	0.0169*** (3.12)	0.0167*** (3.08)
INVG				0.0907*** (3.92)		0.0906*** (3.89)	0.0848*** (3.74)	0.0847*** (3.71)
RETG			0.0458** (2.17)		0.0458** (2.18)		0.0333 (1.59)	0.0333 (1.57)
EXPG		0.0023 (0.29)			0.0024 (0.30)	0.0006 (0.08)		0.0008 (0.10)
Constant	7.1183*** (26.02)	7.1329*** (26.38)	6.7432*** (20.63)	6.5330*** (20.94)	6.7579*** (20.82)	6.5375*** (21.01)	6.2982*** (18.28)	6.3036*** (18.36)
Cross-section and Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Redundant FE Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Adjusted R-squared	0.6058	0.6044	0.6147	0.6385	0.6132	0.6370	0.6424	0.6409
Obs.	279	279	279	279	279	279	279	279

Note: GR = growth rate of gross regional product per capita; FTG = growth rate of FinTech development; INVG = fixed investment growth per capita; RETG = retail sales growth per capita; EXPG = export growth per capita. Two-way fixed effects are included through province and year effects. White diagonal covariance estimation with degrees-of-freedom correction is employed. Absolute t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The coefficient on *FTG* remained positive and significant at the 1 percent level in all subsequent specifications. In Model B1, where *EXPG* was added, the coefficient on *FTG* was 0.0214 ($t = 3.64$, $p < 0.01$), while the coefficient on *EXPG* was 0.0023 ($t = 0.29$), which was not statistically significant. In Model B2, where *RETG* was added, the coefficient on *FTG* was 0.0218 ($t = 3.81$, $p < 0.01$), while the coefficient on *RETG* was 0.0458 ($t = 2.17$, $p < 0.05$). In Model B3, where *INVG* was added, the coefficient on *FTG* was 0.0168 ($t = 3.02$, $p < 0.01$), while the coefficient on *INVG* was 0.0907 ($t = 3.92$, $p < 0.01$). The adjusted *R*-squared increased from 0.6058 in Model A1 to 0.6385 in Model B3, indicating that fixed investment added the most explanatory power among the individual channel variables.

A similar pattern was observed in the two-channel specifications. In Model C3, the coefficient on *FTG* was 0.0169 ($t = 3.12$, $p < 0.01$), the coefficient on *INVG* was 0.0848 ($t = 3.74$, $p < 0.01$), and the coefficient on *RETG* was 0.0333 ($t = 1.59$), which was not statistically significant. The adjusted *R*-squared was 0.6424.

In the full specification, Model D1, the coefficient on *FTG* was 0.0167, with a *t*-statistic of 3.08, and remained significant at the 1 percent level. The coefficient on *INVG* was 0.0847 ($t = 3.71$, $p < 0.01$). The coefficient on *RETG* was 0.0333 ($t = 1.57$), which was not statistically significant, and the coefficient on *EXPG* was 0.0008 ($t = 0.10$), which was also not statistically significant. The adjusted *R*-squared in

Model D1 was 0.6409. Across Models A1 through D1, the FinTech coefficient ranged from 0.0167 to 0.0222, always significant at the 1 percent level. This stability indicated that the estimated effect of FinTech growth on regional output growth was not driven by omitted channel variables and was robust to the sequential inclusion of demand-side controls.

5.2 Transmission Channel Regressions

Table 4 reports the channel regressions used to estimate the effect of FinTech growth on each candidate mediator. In Model E1, where *EXPG* was regressed on *FTG*, the coefficient on *FTG* was 0.3336, with a *t*-statistic of 2.33, and the estimate was significant at the 5 percent level. In Model E2, where *RETG* was regressed on *FTG*, the coefficient on *FTG* was 0.0085, with a *t*-statistic of 0.58, and the estimate was not statistically significant. In Model E3, where *INVG* was regressed on *FTG*, the coefficient on *FTG* was 0.0592, with a *t*-statistic of 3.34, and the estimate was significant at the 1 percent level.

Table 4: The Transmission Channels

Estimations:	E1	E2	E3
	Dependent variables		
	<i>EXPG</i>	<i>RETG</i>	<i>INVG</i>
<i>FTG</i>	0.3336** (2.33)	0.0085 (0.58)	0.0592*** (3.34)
Constant	-6.2665 (1.30)	8.1888*** (10.55)	6.4533*** (7.45)
Cross-section and Period FE	Yes	Yes	Yes
Redundant FE Test	0.0000	0.0000	0.0000
Adjusted R-squared	0.2783	0.3167	0.4428
Obs.	279	279	279

Note: GR = growth rate of gross regional product per capita; *FTG* = growth rate of FinTech development; *INVG* = fixed investment growth per capita; *RETG* = retail sales growth per capita; *EXPG* = export growth per capita. Two-way fixed effects are included through province and year effects. White diagonal covariance estimation with degrees-of-freedom correction is employed. Absolute *t*-statistics are reported in parentheses. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

These estimates established the empirical inputs for the subsequent decomposition exercise. FinTech growth was significantly associated with export growth and fixed investment growth in the auxiliary equations, whereas no statistically significant association was observed between FinTech growth and retail sales growth.

5.3 Channel Decomposition

Tables 5 through 8 report the decomposition of the total effect of *FTG* on GR into direct and indirect components. Using the benchmark total effect from Model A1 (0.0222), the export channel was calculated as the product of the coefficient on *EXPG* in the growth equation (0.0023 from Model B1) and the coefficient on *FTG* in the export equation (0.3336 from Model E1). This yielded an indirect effect of 0.0008, which represented 3.6 percent of the total effect.

The retail sales channel was calculated in the same manner. The indirect effect through *RETG*. was 0.0004, based on 0.0458×0.0085 , which represented 1.8 percent of the total effect.

The fixed investment channel produced a larger indirect effect. The estimated indirect effect through *INVG* was 0.0054, based on 0.0907×0.0592 , which accounted for 24.3 percent of the total effect.

It is important to note that the decompositions reported in Tables 5-7 are estimated separately for each transmission channel. Accordingly, the indirect effects represent partial decompositions of the overall FTG-growth relationship. Because export growth, retail growth, and investment growth are likely to be correlated, the indirect effects obtained from these separate models are not additive and should not be interpreted as summing to the total effect. Consequently, the channel shares reported in Tables 5-7 cannot be added together to obtain 100 percent of the total effect. The purpose of Tables 5-7 is therefore to illustrate the relative importance of individual channels when considered in isolation.

Table 5: The Export Channel

Direct effect	0.0214
Export channel (a)	$0.0023 * 0.3336 = 0.0008$
Total effect (b)	0.0222 $[0.0214 + 0.0008] = 0.0222$
(a)/(b)	0.0360

Note: The summation inside the brackets [...] is the calculated total effect.

Table 6: The Retail Sales Channel

Direct effect	0.0218
Retail sales channel (a)	$0.0458 * 0.0085 = 0.0004$
Total effect (b)	0.0222 $[0.0218 + 0.0004] = 0.0222$
(a)/(b)	0.0180

Note: The summation inside the brackets [...] is the calculated total effect.

Table 7: The Fixed Investment Channel

Direct effect	0.0168
Fixed investment channel (a)	$0.0907 * 0.0592 = 0.0054$
Total effect (b)	0.0222 $[0.0168 + 0.0054] = 0.0222$
(a)/(b)	0.2432

Note: The summation inside the brackets [...] is the calculated total effect.

To provide a more comprehensive assessment of channel contributions, all mediators are subsequently incorporated into a simultaneous specification. Unlike Tables 5-7, this specification jointly considers the three transmission channels and therefore provides a coherent decomposition of the overall FTG-growth association. The decomposition reported in Table 8 is therefore regarded as the preferred estimate of the relative importance of the transmission mechanisms because it accounts for the joint influence of the three channels.

The full decomposition reported in Table 8 combined all three channels simultaneously. In contrast to Tables 5-7, the channel coefficients in Table 8 were estimated jointly in Model D1, so the resulting indirect effects should be interpreted as conditional rather than isolated channel contributions. In this specification, the direct effect was 0.0167, which represented 75.2 percent of the overall effect. The export channel contributed 0.0003, equivalent to 1.4 percent of the total effect. The retail channel also contributed 0.0003, equivalent to 1.4 percent. The fixed investment channel contributed 0.0050, equivalent to 22.5 percent. The overall effect was approximately equal to the benchmark total effect, with any small difference reflecting rounding in the reported coefficients.

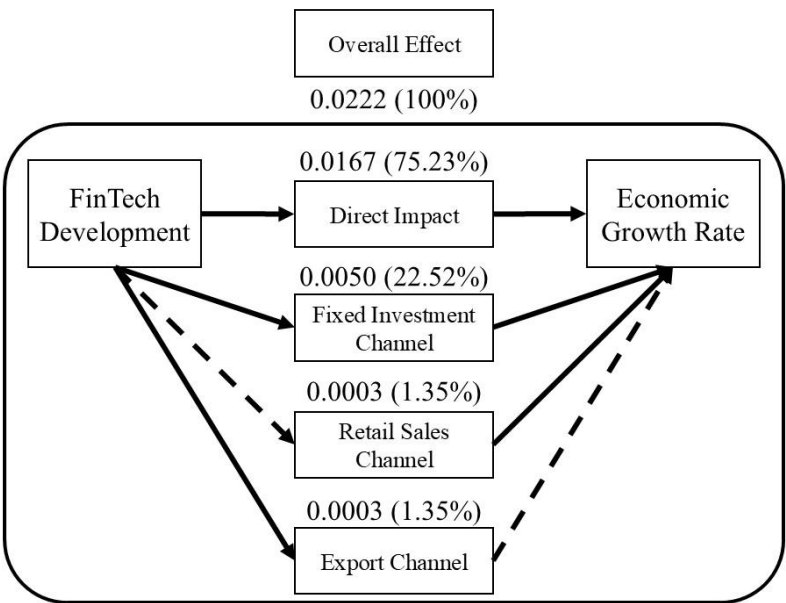
Table 8: Decomposition of the Transmission Channels

Direct impact (a)	0.0167 {0.7523}
Export channel (b)	$0.0008 * 0.3336 = 0.0003$ {0.0135}
Retail sales channel (c)	$0.0333 * 0.0085 = 0.0003$ {0.0135}
Fixed investment channel (d)	$0.0847 * 0.0592 = 0.0050$ {0.2252}
Overall effect	0.0222 [0.0223]

Note: The simultaneous decomposition is based on Model D1. The indirect effects are calculated as the product of the channel coefficient and the corresponding FTG coefficient from the channel equation. The number inside the brackets [...] is the calculated total effect that is equal to the summation of (a), (b), (c), and (d), subject to minor rounding differences in the reported coefficients, while that inside the braces {...} is the ratio of the respective channel to the overall effect.

To facilitate comparison of the relative importance of the direct effect and the three transmission channels, Figure 1 provides a visual summary of the channel-decomposition results. These results are consistent with Prediction 1 from the conceptual framework: the fixed investment channel was the dominant observed transmission mechanism, accounting for nearly one-quarter of the total association. Predictions 2 and 3 were also broadly supported: the consumption channel was weak and statistically insignificant, while the export channel was economically negligible in the full decomposition.

Figure 1: Summary of Effects



Note: The solid line represents a significant impact, while the dotted line represents an insignificant impact.

Figure 1 visually reinforces the dominance of the fixed-investment channel in the FinTech-growth relationship. While the export and retail-sales channels contribute only marginally to the overall effect, the investment channel accounts for a substantially larger share of the observed association. The figure also highlights the importance of the remaining direct effect, suggesting that additional mechanisms, such as productivity improvements, entrepreneurship, and financial deepening, may play important roles in linking FinTech development to regional economic growth.

6. Robustness Checks

6.1 Cross-Sectional Dependence and Serial Correlation Diagnostics

Before conducting additional robustness analyses, formal diagnostic tests were performed to examine whether the baseline panel specifications were affected by cross-sectional dependence or serial correlation. Pesaran's cross-sectional dependence (CD) test and Wooldridge's panel serial-correlation test were conducted for all estimated models. Table 9 reports the results. The Pesaran CD test failed to reject the null hypothesis of cross-sectional independence in all specifications. These findings indicate that residual cross-sectional dependence is not a significant concern in the present sample. In contrast, the Wooldridge test detected first-order serial correlation in most specifications. Accordingly, additional robustness analyses employing panel-corrected standard errors (PCSE) were conducted and are reported in the following subsection.

Table 9: Diagnostic Tests for Cross-Sectional Dependence and Serial Correlation

Model	Pesaran CD p-value	Wooldridge p-value
A1	0.2324	0.0000
B1	0.2366	0.0000
B2	0.1649	0.0000
B3	0.2982	0.0000
C1	0.1691	0.0000
C2	0.2995	0.0000
C3	0.2494	0.0000
D1	0.2512	0.0000
E1	0.5054	0.0016
E2	0.1045	0.8848
E3	0.0982	0.0292

6.2 Robustness to Alternative Covariance Specifications

To evaluate whether the baseline findings were sensitive to the presence of serial correlation, all specifications were re-estimated using panel-corrected standard errors (PCSE), following the approach of Beck and Katz (1995). Two alternative covariance structures were considered. The first employed Cross-SUR (PCSE), which allows for contemporaneous correlation across cross-sectional units. The second employed Period-SUR (PCSE), which allows for temporal dependence across periods. These estimators provide robust inference when residual dependence may be present in time-series cross-sectional data.

Table 10 reports the robustness results. Across all specifications, the estimated coefficient on FTG remained positive under both covariance estimators. For the benchmark specification (Model A1), the FTG coefficient remained statistically significant under both Cross-SUR ($p = 0.0159$) and Period-SUR ($p = 0.0016$) estimators. Similarly, in the fully specified model (Model D1), the FTG coefficient remained positive and statistically significant under both covariance structures, with p -values of 0.0558 and 0.0123, respectively.

The transmission-channel equations yielded similar conclusions. The export channel (Model E1) and the fixed-investment channel (Model E3) remained positive and statistically significant under both covariance estimators. By contrast, the retail-sales channel (Model E2) remained statistically insignificant across all specifications. Thus, the substantive conclusions regarding the relative importance of the transmission mechanisms were unchanged.

Overall, the robustness analysis indicates that the principal findings are not dependent on the choice of covariance estimator. In particular, the positive association between FinTech growth and regional economic growth remains robust after accounting for possible cross-sectional and temporal dependence in the error structure.

Table 10: Robustness Checks Using Alternative PCSE Estimators

Model	Main Variable	Cross-SUR (PCSE) Coef.	p-value	Period-SUR (PCSE) Coef.	p-value
A1	FTG	0.0222**	0.0159	0.0222***	0.0016
B1	FTG	0.0214**	0.0245	0.0214***	0.0041
B2	FTG	0.0218**	0.0205	0.0218***	0.0013
B3	FTG	0.0168*	0.0558	0.0168**	0.0123
C1	FTG	0.0218**	0.0205	0.0218***	0.0013
C2	FTG	0.0166*	0.0731	0.0166**	0.0180
C3	FTG	0.0169*	0.0605	0.0169***	0.0099
D1	FTG	0.0168*	0.0558	0.0168**	0.0123
E1	FTG	0.3336***	0.0000	0.3336***	0.0015
E2	FTG	0.0085	0.5343	0.0085	0.5349
E3	FTG	0.0592**	0.0291	0.0592***	0.0024

Note: FTG = growth rate of FinTech development. Cross-SUR and Period-SUR refer to alternative panel-corrected standard error (PCSE) estimators. Cross-SUR allows contemporaneous correlation across cross-sectional units, while Period-SUR allows contemporaneous correlation across time periods. All models include province and year fixed effects. PCSE estimates are based on degrees-of-freedom-corrected covariance matrices. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Non-Linearity Test

A potential concern is that the effect of FinTech development on regional economic growth may be nonlinear. To examine this possibility, the baseline specification was augmented by including the squared term of FinTech growth (FTG²). The purpose of this test was to determine whether the relationship between FinTech growth and regional output growth exhibits increasing or diminishing marginal effects.

Table 11 reports the results. The coefficient on FTG remained positive and statistically significant at the 5 percent level. The coefficient on FTG² was negative and marginally significant at the 10 percent level ($p = 0.079$). This finding suggests limited evidence of a nonlinear relationship, with the marginal contribution of FinTech growth potentially declining at higher levels of FinTech expansion.

However, the statistical evidence is relatively weak and does not materially alter the principal conclusions of the study. The quadratic specification represents the most commonly used approach for assessing non-linearity in the finance-growth literature because it provides a direct test of increasing or diminishing marginal effects. Alternative approaches, such as BDS tests, threshold regressions, and non-parametric specifications, may also be employed to detect more complex forms of non-linearity. However, given the relatively short time dimension of the present panel ($T = 9$), these procedures may suffer from limited statistical power and unstable threshold identification. Consequently, the quadratic specification approach is adopted as the primary diagnostic. Given the modest significance of the FTG² term and the stability of the baseline estimates across alternative specifications, the main analysis continues to rely on the linear fixed-effects specification.

Table 11: Non-Linearity Test

Variable	Coefficient	t-statistic	p-value
FTG	0.0574	2.44	0.0154
FTG ²	-0.0001	-1.76	0.0792

Note: The model includes province fixed effects, year fixed effects, and the control variables used in Model D1 (INVG, RETG, and EXPG). The squared term FTG² is included to test for potential non-linearity.

6.4 Robustness Check Using Lagged FinTech Growth

A common concern in finance-growth studies is the possibility of reverse causality. Regions experiencing stronger economic growth may simultaneously attract greater FinTech investment and adoption, potentially biasing the estimated effect of FinTech development on regional economic growth. To examine whether the baseline findings are sensitive to this concern, the contemporaneous FinTech growth variable was replaced with its one-period lag, FTG_{t-1}. This specification ensures that FinTech growth is predetermined relative to the current-year growth outcome and therefore reduces the possibility that the estimated relationship is driven solely by contemporaneous feedback effects.

Tables 12 and 13 report the results. In the benchmark specification (Model A1), the coefficient on lagged FinTech growth remained positive and statistically significant at the 1 percent level. The estimated

coefficient was 0.0189, compared with 0.0222 in the baseline specification. Although the magnitude was slightly smaller, the result remained economically meaningful and statistically robust.

The positive effect of lagged FinTech growth persisted across all subsequent specifications. In the fully specified model (Model D1), the coefficient on FTG_{t-1} remained positive and statistically significant at the 1 percent level. Fixed investment growth continued to exhibit a positive and statistically significant association with regional economic growth, whereas export growth and retail sales growth remained statistically insignificant in the full specification.

The channel regressions reported in Table 13 yielded a similar pattern. Lagged FinTech growth remained positively associated with export growth and fixed investment growth, while its association with retail sales growth remained statistically insignificant. These findings are broadly consistent with the baseline channel regressions and continue to support the conclusion that fixed investment represents the most important observed transmission mechanism linking FinTech development and regional economic growth.

Overall, the lagged-variable analysis suggests that the principal findings are not driven solely by contemporaneous correlations. The positive association between FinTech growth and regional economic growth remains robust when a predetermined measure of FinTech development is employed. Although the lagged specification cannot completely eliminate endogeneity concerns, it substantially reduces the possibility that the baseline results are explained by reverse causality alone.

Table 12: Robustness Check on The Effect of FinTech Development on the Growth Rate

Estimations:	A1	B1	B2	B3	C1	C2	C3	D1
	Dependent variables							
	GR	GR	GR	GR	GR	GR	GR	GR
FTG_{t-1}	0.0189*** (5.56)	0.0177*** (4.93)	0.0156*** (3.81)	0.0150*** (4.54)	0.0174*** (4.95)	0.0143*** (4.15)	0.0150*** (4.57)	0.0143*** (4.22)
INVG				0.0814*** (3.42)		0.0801*** (3.33)	0.0766*** (3.27)	0.0753*** (3.18)
RETG			0.0376* (1.75)		0.0370* (1.76)		0.0266 (1.25)	0.0264 (1.25)
EXPG		0.0090 (0.96)			0.0084 (0.91)	0.0056 (0.61)		0.0054 (0.60)
Constant	6.8341*** (3181)	6.8527*** (26.38)	6.5564*** (23.91)	6.3874*** (24.04)	6.5782*** (24.04)	6.4064*** (23.88)	6.2175*** (20.75)	6.2371*** (20.72)
Cross-section and Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Redundant FE Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Adjusted R-squared	0.5943	0.5944	0.6005	0.6227	0.6004	0.6217	0.6248	0.6238
Obs.	248	248	248	248	248	248	248	248

Note: GR = growth rate of gross regional product per capita; FTG = growth rate of FinTech development; INVG = fixed investment growth per capita; RETG = retail sales growth per capita; EXPG = export growth per capita. Two-way fixed effects are included through province and year effects. White diagonal covariance estimation with degrees-of-freedom correction is employed. Absolute t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Robustness Check on The Transmission Channels

Estimations:	E1	E2	E3
	Dependent variables		
	EXPG	RETG	INVG
FTG _{t-1}	0.1375*** (3.96)	0.0093 (0.5840)	0.0481*** (2.99)
Constant	-2.0758 (1.02)	7.3826*** (8.51)	5.4871*** (6.03)
Cross-section and Period FE	Yes	Yes	Yes
Redundant FE Test	0.0000	0.0000	0.0000
Adjusted R-squared	0.2758	0.2936	0.3695
Obs.	248	248	248

Note: GR = growth rate of gross regional product per capita; FTG = growth rate of FinTech development; INVG = fixed investment growth per capita; RETG = retail sales growth per capita; EXPG = export growth per capita. Two-way fixed effects are included through province and year effects. White diagonal covariance estimation with degrees-of-freedom correction is employed. Absolute t-statistics are reported in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Taken together, the diagnostic tests, alternative PCSE estimators, non-linearity analysis, and lagged-variable specifications all support the same substantive conclusion. FinTech growth remains positively associated with regional economic growth across a wide range of model specifications. The evidence consistently identifies fixed investment as the dominant observed transmission channel, while the export channel remains economically limited and the retail-sales channel remains statistically weak.

7. Discussion

7.1 Main Finding: FinTech Promotes Regional Growth

The empirical results indicated that FinTech development was positively and significantly associated with regional economic growth in China during the sample period. Across all baseline specifications, the coefficient on FinTech growth remained positive and statistically significant at the 1 percent level, even after the sequential inclusion of fixed investment, retail sales, and export growth variables. This stability indicated that the association between FinTech and regional output growth was not attributable to omitted demand-side variables and reflected a robust empirical regularity. The robustness check using lagged FinTech growth preserved the direction, significance, and approximate magnitude of the baseline association, reducing concerns that the results are driven solely by contemporaneous reverse causality.

7.2 The Dominance of the Fixed Investment Channel

As discussed in Section 5.3, the channel contributions reported in Tables 5-7 represent partial decompositions estimated separately for each transmission mechanism. Therefore, the discussion below primarily relies on the simultaneous decomposition reported in Table 8 when comparing the relative importance of the channels.

A particularly important result was the dominance of the fixed investment channel. The decomposition exercise indicated that nearly one-quarter of the total effect of FinTech growth on regional output growth

operated through fixed investment growth per capita. This result was consistent with the HANK-motivated framework and the broader finance-growth literature: FinTech may enhance regional growth by relaxing financing constraints for firms and improving capital allocation, rather than by stimulating short-run household demand alone (Kaplan et al., 2018; Lin et al., 2022; Rajan & Zingales, 1998).

Several mechanisms may account for this pattern. First, FinTech platforms can lower the cost of credit intermediation by using algorithmic credit scoring and automated underwriting, thereby reducing information asymmetries, lowering transaction costs, and expanding the supply of credit through nontraditional channels (Berg et al., 2020; Fuster et al., 2019). Second, digital lending platforms may have widened credit access for private enterprises and small businesses that were previously excluded from formal bank lending because of insufficient collateral, limited credit history, or high monitoring costs (Buchak et al., 2018; Hau et al., 2024; Tang, 2019). Third, FinTech-enabled platforms may have channeled savings toward productive investment projects, thereby supporting business expansion and local capital formation (Gambacorta et al., 2023). In the Chinese context, these mechanisms may have been particularly potent because the bank-dominated financial system has historically favored state-owned enterprises and large-linked borrowers, leaving smaller private firms relatively credit-constrained (Ding et al., 2022; He & Wei, 2023). Under such conditions, FinTech development may have acted as a partial substitute for underdeveloped formal credit channels, unlocking investment capacity that was previously suppressed by institutional rigidities in the traditional banking sector.

7.3 The Weak Retail Sales Channel

By contrast, the retail sales channel was weak and statistically insignificant in the full decomposition. This finding may appear surprising in light of the well-established role of FinTech in promoting mobile payments, digital wallets, and consumer finance (Hu et al., 2023; Li et al., 2020; Yang & Zhang, 2022; Zhao et al., 2022). However, several explanations are plausible. One possibility is that the effect of FinTech on consumption was already partially embedded in the overall GDP growth rate, such that controlling for retail sales growth in the decomposition absorbed a portion of the FinTech–consumption association. Another possibility is that the consumption gains attributable to FinTech were concentrated in a shift from cash-based or informal transactions to digital transactions, without generating a sufficiently large increase in total retail sales at the provincial level (Yue et al., 2022). In this sense, a substitution effect may have dominated an expansion effect, with FinTech altering the mode of consumption rather than substantially raising aggregate household demand at the regional level.

7.4 The Negligible Export Channel

The export channel was also economically negligible, even though FinTech growth significantly predicted export growth in the auxiliary channel regression (Model E1). This combination of results suggested that FinTech may have facilitated trade-related activity without making exports a major driver of provincial output growth during the period under study. FinTech may have improved payment efficiency, reduced settlement delays, and expanded access to trade-related financial services, all of which could support export activity (Li et al., 2025). However, once export growth entered the output equation as a control, it

was not statistically significant, suggesting that during the 2012–2020 period, Chinese provinces were primarily experiencing domestic demand-driven growth rather than relying predominantly on export-led growth (Claessens et al., 2018). Under such conditions, FinTech-facilitated trade activity may have contributed to certain coastal and export-oriented provinces but did not operate as a general transmission channel across all provinces.

7.5 The Large Direct Effect

Another striking result was the magnitude of the direct effect. In the full decomposition model, 75.2 percent of the total effect of FinTech growth on regional output growth remained unexplained by fixed investment, retail sales, and exports. This large residual direct component suggests that the FinTech-growth association may operate partly through channels not captured by the three observed mediators. Several candidates are plausible. FinTech may have raised total factor productivity by improving the efficiency of financial transactions, reducing search and screening costs, and lowering the cost of financial transactions for households and firms (Boot et al., 2021; Thakor, 2020). It may also have promoted entrepreneurship by easing entry barriers for new businesses and self-employed workers who previously faced limited access to finance (Frost et al., 2019; Hau et al., 2024). In addition, FinTech may have improved resource allocation by directing capital toward higher-return activities, reducing misallocation, and strengthening financial deepening in regions with weaker formal banking infrastructure (Guo et al., 2020; Sahay et al., 2020). These mechanisms are consistent with a broader financial-frictions interpretation of the HANK-motivated framework, in which FinTech may relax borrowing constraints and improve the efficiency of intermediation in ways that are not fully captured by the three observed demand-side channel variables.

7.6 Limitations

Several limitations should be acknowledged. First, the sample covered only the period from 2012 to 2020. This was the formative period of large-scale FinTech expansion in China, but the growth effects of digital finance may change over time as the sector matures, regulation evolves, and market penetration approaches saturation. Second, the analysis was conducted at the provincial level, which necessarily aggregated substantial within-province heterogeneity across cities, counties, and rural areas. Future studies employing city-level or county-level data could reveal important subnational patterns that are masked by provincial aggregation. Third, the Peking University Digital Financial Inclusion Index captures the breadth and depth of digital financial service usage but may not fully capture the quality, sustainability, or riskiness of FinTech activity. Fourth, while the two-way fixed effects and the lagged-variable robustness check mitigate several sources of endogeneity, they do not fully rule out bias from province-specific time-varying confounders that co-move with FinTech adoption. The identification strategy relies on the assumption that, conditional on province and year fixed effects, remaining unobserved confounders do not systematically co-move with within-province FinTech growth. This assumption, while standard in the applied panel literature (Baker et al., 2022; Levine et al., 2000), cannot be directly tested. Fifth, the channel decomposition assumes that the three demand-side variables are the primary mediators, but other channels

— such as total factor productivity, industrial upgrading, and labor market dynamics — may also operate and could be explored in future research.

7.7 Policy Implications

The findings carried several policy implications. The most direct implication was that provincial governments should treat digital financial infrastructure as a component of investment-led growth strategy. Because the strongest indirect effect operated through fixed investment, policies that improve digital credit access, payment systems, data infrastructure, and financial technology diffusion may generate regional growth dividends primarily by reducing investment bottlenecks and broadening the financing base for smaller firms and local projects (Ding et al., 2022; Lin et al., 2022). At the same time, the weakness of the retail and export channels suggested that complementary policies may be needed to convert transactional convenience into sustained welfare-enhancing demand growth (Chen et al., 2025; Yue et al., 2022). To strengthen the export pathway, FinTech development could be integrated with cross-border trade facilitation, digital customs, and international payment infrastructure, particularly in provinces with existing trade capacity. Finally, the large direct effect implied that a significant share of FinTech’s growth contribution operated through channels not directly captured by standard demand-side variables, suggesting that broader policies promoting digital literacy, data governance, financial regulation, and entrepreneurial ecosystems may be important complements to narrowly targeted financial inclusion measures.

8. Conclusion

This study examined whether FinTech development contributed to regional economic growth in China and sought to identify the channels through which this effect operated. Using balanced panel data for 31 Chinese provinces from 2012 to 2020, the analysis focused on the effect of FinTech growth, measured by the growth rate of the Peking University Digital Financial Inclusion Index, on per capita gross regional product growth. The empirical framework was motivated by a HANK-informed perspective, which provides theoretical rationale for examining how FinTech-induced relaxation of borrowing constraints and transaction frictions may operate through specific aggregate demand channels.

Three main findings emerged. *First*, FinTech growth was found to be positively and significantly associated with per capita GDP growth across Chinese provinces. In the baseline specification, the coefficient on FinTech growth was 0.022, indicating that a 1-percentage-point increase in FinTech growth was associated with a 0.022-percentage-point increase in per capita GDP growth. This result remained positive and statistically significant at the 1 percent level across all alternative specifications and was confirmed by the lagged-variable robustness check (coefficient = 0.019, $t = 5.56$). *Second*, the fixed investment channel was identified as the dominant transmission mechanism, accounting for approximately 24 percent of the total growth effect. The export and retail sales channels were economically negligible, each contributing less than 2 percent. *Third*, the remaining direct component — which may reflect unmeasured channels such as productivity improvements, entrepreneurship, financial deepening, and other residual factors — accounted for approximately 75 percent of the total association, suggesting that

the macroeconomic relevance of FinTech may extend beyond the three demand-side channels examined in this study.

These findings suggest that investment in FinTech infrastructure should be treated as part of a broader regional growth strategy, with particular emphasis on policies that channel digital financial innovation toward productive capital formation. Beyond its contribution to the FinTech and economic-growth literature, this study contributes to decision sciences by identifying how technology-driven financial innovations influence economic decision-making and resource allocation at the regional level. By quantifying the relative importance of investment, consumption, and export channels, the study provides evidence on how digital financial development shapes decisions affecting regional economic performance. Nevertheless, the results are subject to limitations arising from provincial-level aggregation, the 2012-2020 sample period, and potential residual endogeneity. Future research should examine the unmeasured channels through which FinTech affects growth, incorporate micro-level data to identify within-province heterogeneity, and extend the analysis beyond 2020 to assess how the growth effects of FinTech evolve as the sector matures and regulatory frameworks consolidate.

Acknowledgment: This work was primarily supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (UGC/FDS15/E04/25). The authors also acknowledge financial support from Hong Kong Shue Yan University (URG/23/16), which supported the initial stage of this research.

References

- Alsafadi, Y., Al-Okaily, M., Karim, R., Dhar, B. K., Roshid, M. M., & Ramachandaran, S. D. (2026). Strategic decision-making in SME growth: Harnessing digital transformation and innovation in Jordan. *Advances in Decision Sciences*, 30(1), 1–39.
- Arcand, J. L., Berkes, E., & Panizza, U. (2015). Too much finance?. *Journal of Economic Growth*, 20(2), 105–148.
- Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, 109(6), 2333–2367.
- Auclert, A., Bardóczy, B., Rognlie, M., & Straub, L. (2021). Using the sequence-space Jacobian to solve and estimate heterogeneous-agent models. *Econometrica*, 89(5), 2375–2408.
- Auclert, A., Rognlie, M., & Straub, L. (2024). The intertemporal Keynesian cross. *Journal of Political Economy*, 132(12), 4068–4121.
- Auclert, A., Rognlie, M., & Straub, L. (2025). Fiscal and monetary policy with heterogeneous agents. *Annual Review of Economics*, 17, 539–562.
- Bagadeem, S., Ahmed, H. M. S., Osman, M., Alzoubi, H. M., Woo, K. Y., & Chang, B. H. (2025). Terrorism, innovation, and economic channels: Insights from a panel ARDL model. *Annals of Financial Economics*, 20(1), 2550002.
- Baker, A. C., Larcker, D. F., & Wang, C. C. Y. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2), 370–395.
- Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review*, 89(3), 634–647.
- Beck, T., Levine, R., & Loayza, N. (2000). Finance and the sources of growth. *Journal of Financial Economics*, 58(1–2), 261–300.
- Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *Journal of Politics*, 79(3), 949–963.
- Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of FinTechs: Credit scoring using digital footprints. *The Review of Financial Studies*, 33(7), 2845–2897.
- Boot, A. W. A., Hoffmann, P., Laeven, L., & Ratnovski, L. (2021). Fintech: What's old, what's new? *Journal of Financial Stability*, 53, 100836.
- Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3), 453–483.
- Cevik, S. (2025). Is Schumpeter right? Fintech and economic growth. *Economics of Innovation and New Technology*, 34(7), 1095–1106.
- Chen, D., Deakin, S., Johnston, A., & Wang, B. (2025). Too much technology and too little regulation? The spectacular demise of P2P lending in China. *Accounting, Economics, and Law: A Convivium*, 15(3), 347–394.
- Chen, Y., Dong, Y., & Hu, J. (2023). In the shadow of big tech lending. *China Economic Review*, 79, 101913.
- Claessens, S., Frost, J., Turner, G., & Zhu, F. (2018). Fintech credit markets around the world: Size, drivers and policy issues. *BIS Quarterly Review* (September 2018).

- de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9), 2964–2996.
- Ding, N., Gu, L., & Peng, Y. (2022). Fintech, financial constraints and innovation: Evidence from China. *Journal of Corporate Finance*, 73, 102194.
- Financial Stability Board. (2017). Financial stability implications from FinTech. *FSB*.
- Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., & Zbinden, P. (2019). *BigTech and the Changing Structure of Financial Intermediation (BIS Working Papers No. 779)*. Bank for International Settlements.
- Fuster, A., Plosser, M., Schnabl, P., & Vickery, J. (2019). The role of technology in mortgage lending. *The Review of Financial Studies*, 32(5), 1854–1899.
- Gambacorta, L., Huang, Y., Li, Z., Qiu, H., & Chen, S. (2023). Data versus collateral. *Review of Finance*, 27(2), 369–398.
- Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, 2(2), 111–120.
- Griliches, Z., & Hausman, J. A. (1986). Errors in variables in panel data. *Journal of Econometrics*, 31(1), 93–118.
- Guerrieri, V., & Lorenzoni, G. (2017). Credit crises, precautionary savings, and the liquidity trap. *Quarterly Journal of Economics*, 132(3), 1427–1467.
- Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly*, 19(4), 1401–1418.
- Hau, H., Huang, Y., Lin, C., Shan, H., Sheng, Z., & Wei, L. (2024). FinTech credit and entrepreneurial growth. *The Journal of Finance*, 79(5), 3309–3359.
- He, Z., & Wei, S.-J. (2023). China's financial system and economy: A review. *Annual Review of Economics*, 15, 451–483.
- Hu, D., Zhai, C., & Zhao, S. (2023). Does digital finance promote household consumption upgrading? An analysis based on data from the China family panel studies. *Economic Modelling*, 125, 106377.
- Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90(1), 1–44.
- Kaplan, G., Moll, B., & Violante, G. L. (2018). Monetary policy according to HANK. *American Economic Review*, 108(3), 697–743.
- King, R. G., & Levine, R. (1993). Finance and growth: Schumpeter might be right. *The Quarterly Journal of Economics*, 108(3), 717–737.
- Levine, R., Loayza, N., & Beck, T. (2000). Financial intermediation and growth: Causality and causes. *Journal of Monetary Economics*, 46(1), 31–77.
- Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. *American Economic Review*, 88(3), 537–558.
- Li, H., Lin, X., & Zhang, Z. (2025). How does digital finance affect imports, exports and trade balance: Evidence from China. *International Review of Economics & Finance*, 99, 104054.

- Li, J., Wu, Y., & Xiao, J. J. (2020). The impact of digital finance on household consumption: Evidence from China. *Economic Modelling*, 86, 317–326.
- Liang, C., Yacob, M. R., Law, S. H., & Harun, I. (2024). Effects of digital transformation and green technology innovation on manufacturing's financial performance: Evidence from China. *Advances in Decision Sciences*, 28(4), 92–119.
- Lin, A., Peng, Y., & Wu, X. (2022). Digital finance and investment of micro and small enterprises: Evidence from China. *China Economic Review*, 75, 101846.
- Noman, M., Maydybura, A., Channa, K. A., Wong, W. K., & Chang, B. H. (2023). Impact of cashless bank payments on economic growth: Evidence from G7 countries. *Advances in Decision Sciences*, 27(1), 1–20.
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 265–312.
- PKU Institute of Digital Finance. (2019). *The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) 2011–2018 report*. Peking University.
- Rajan, R. G., & Zingales, L. (1998). Financial dependence and growth. *The American Economic Review*, 88(3), 559–586.
- Sahay, R., von Allmen, U. E., Lahreche, A., Khera, P., Ogawa, S., Bazarbash, M., & Beaton, K. (2020). *The promise of fintech: Financial inclusion in the post COVID-19 era (IMF Departmental Paper No. 2020/009)*. International Monetary Fund.
- Schumpeter, J. A. (1911). *The theory of economic development*. Harvard University Press.
- Syed, A., Lamine, A., & Loukil, S. (2025). Decoding market linkages and risk transmission: A dynamic analysis of G7 stock indices and currency pairs against a changing economic landscape. *Annals of Financial Economics*, 20(4), 2650002.
- Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? *The Review of Financial Studies*, 32(5), 1900–1938.
- Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, 100833.
- Wong, W. K., & Pham, M. T. (2022). Could the test from the standard regression model make significant regression with autoregressive noise become insignificant?. *The International Journal of Finance*, 34, 1–18.
- Wong, W. K., & Pham, M. T. (2026). Could the panel regression be used to examine the relationship between $I(0)$ and $I(1)$ series?. *Advances in Decision Sciences*, in press.
- Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.
- Yang, L., & Zhang, Y. (2022). FinTech adoption and financial inclusion: Evidence from household consumption in China. *Journal of Banking & Finance*, 145, 106668.
- Yue, P., Korkmaz, A. G., Yin, Z., & Zhou, H. (2022). The rise of digital finance: Financial inclusion or debt trap? *Finance Research Letters*, 47, 102604.
- Zhao, C., Wu, Y., & Guo, J. (2022). Mobile payment and Chinese rural household consumption. *China Economic Review*, 71, 101719.

Appendix A: A HANK-Motivated Framework for the Empirical Specification

This appendix develops a HANK-motivated framework for the empirical specification used in the main text. The conceptual discussion is presented in Section 3 of the main text, whereas this appendix provides the complete mathematical derivation that motivates the empirical channel-decomposition framework. The purpose of the framework is not to structurally estimate a full Heterogeneous Agent New Keynesian (HANK) model. Rather, the framework provides theoretical discipline for the selection of the three transmission channels examined empirically: fixed investment, retail consumption, and exports.

The central idea is that FinTech development can relax borrowing constraints, reduce transaction costs, and improve the allocation of financial resources. In a heterogeneous-agent setting, these changes affect constrained households and firms more strongly than unconstrained agents. This provides a theoretical basis for examining whether FinTech growth affects regional output growth through observable demand-side channels. The resulting empirical coefficients should therefore be interpreted as reduced-form panel associations, not as structural HANK parameters.

A.1 Household Block and Borrowing Constraints

Consider a continuum of households indexed by i . Households face uninsurable idiosyncratic income risk and incomplete markets. Each household chooses consumption c_{it} at time t and end-of-period asset holdings $a_{i,t+1}$ to maximize expected lifetime utility:

$$\max_{\{c_{it}, a_{i,t+1}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t u(c_{it}),$$

where $0 < \beta < 1$, $u'(c) > 0$, and $u''(c) < 0$. For simplicity, labor supply is treated as exogenous in the empirical mapping, so the household's real after-tax resources are denoted by z_{it} .

The household budget constraint is:

$$c_{it} + a_{i,t+1} = (1 + r_t)a_{it} + z_{it},$$

where c_{it} denotes household consumption, a_{it} denotes beginning-of-period asset holdings, $a_{i,t+1}$ denotes end-of-period asset holdings, z_{it} denotes real after-tax resources, and r_t denotes the real interest rate. The household also faces a borrowing constraint:

$$a_{i,t+1} \geq -b_{it},$$

where $b_{it} \geq 0$ represents borrowing capacity. A larger value of b_{it} indicates a looser borrowing constraint.

FinTech development can relax the borrowing constraint by improving credit scoring, reducing information asymmetry, lowering transaction costs, and expanding access to digital credit. This can be represented as:

$$b_{it} = b_0 + \eta_b FTG_{it},$$

with:

$$\eta_b > 0.$$

where b_{it} denotes household borrowing capacity, b_0 is the baseline borrowing limit, FTG_{it} denotes FinTech growth, and η_b measures the effect of FinTech development on borrowing capacity. Thus, higher FinTech growth increases borrowing capacity and weakens the constraint faced by liquidity-constrained households.

The Lagrangian first-order condition for consumption is:

$$u'(c_{it}) = \lambda_{it},$$

where λ_{it} is the marginal value of household resources. The Euler condition is:

$$\lambda_{it} = \beta(1 + r_{t+1})E_t[\lambda_{i,t+1}] + \mu_{it},$$

where μ_{it} is the multiplier on the borrowing constraint. The complementary-slackness conditions are:

$$\begin{aligned} \mu_{it} &\geq 0, \\ a_{i,t+1} + b_{it} &\geq 0, \\ \mu_{it}(a_{i,t+1} + b_{it}) &= 0. \end{aligned}$$

For unconstrained households, $\mu_{it} = 0$, and the standard Euler equation holds. For constrained households, $\mu_{it} > 0$, implying that current resources have a high marginal value. These households tend to have high marginal propensities to consume. Therefore, a FinTech-induced relaxation of borrowing constraints can affect aggregate consumption by changing the behavior of constrained households.

This motivates the inclusion of retail consumption growth as one potential transmission channel in the empirical model. However, the theory does not require the consumption channel to be empirically dominant. FinTech may increase household liquidity and payment convenience, but the aggregate consumption response may be weakened by substitution effects, precautionary saving, or the conversion of informal transactions into formal digital transactions without a large increase in total spending.

A.2 Aggregation and the Sequence-Space Representation

Let $D_t(a, e)$ denote the cross-sectional distribution of households over assets a and idiosyncratic productivity e . Aggregate consumption is obtained by integrating individual consumption over the household distribution:

$$C_t = \int c_t(a, e) dD_t(a, e).$$

Following the sequence-space Jacobian approach, the household block can be represented as a linear mapping from sequences of aggregate inputs to sequences of aggregate outcomes around a steady state. Let ΔZ denote the sequence of deviations in aggregate household resources, and let Δr denote the sequence of deviations in real interest rates. The linearized household block can be written as:

$$\Delta C = J_{C,Z} \Delta Z + J_{C,r} \Delta r,$$

where ΔC denotes deviations in aggregate consumption, ΔZ denotes deviations in aggregate household resources, Δr denotes deviations in real interest rates, and $J_{C,Z}$ and $J_{C,r}$ are sequence-space Jacobian matrices. $J_{C,Z}$ is the sequence-space Jacobian mapping changes in household resources into aggregate consumption, and $J_{C,r}$ maps changes in real interest rates into aggregate consumption.

The matrix $J_{C,Z}$ can be interpreted as a dynamic marginal-propensity-to-consume matrix. Its (t, s) element measures the effect of a change in household resources at date s on aggregate consumption at date t :

$$[J_{C,Z}]_{t,s} = \frac{\partial C_t}{\partial Z_s}.$$

Because constrained households have high marginal propensities to consume, changes in financial access can have larger aggregate demand effects in economies with a larger share of constrained agents. This is the key HANK insight relevant to the present study.

The empirical implication is that FinTech development may affect regional demand by changing household liquidity, transaction efficiency, and access to consumer credit. This provides the theoretical basis for including retail sales growth as a consumption-related transmission channel.

A.3 Firm and SME Investment Channel

The household block alone does not fully explain the fixed-investment channel. Because the empirical analysis finds fixed investment to be the dominant observed channel, the framework must also account for financially constrained firms and entrepreneurs.

Consider firms or entrepreneurs that require external finance to undertake investment. Let I_{it} denote fixed investment in province i at time t , and let NW_{it} denote the net worth or internal resources of firms. A simple financing constraint can be written as:

$$I_{it} \leq \phi_{it} NW_{it},$$

where I_{it} denotes fixed investment, NW_{it} denotes firm net worth, and ϕ_{it} denotes the availability of external finance. A larger ϕ_{it} indicates that firms can finance a higher level of investment for a given amount of internal resources.

FinTech development can increase ϕ_{it} by improving digital credit screening, reducing information asymmetry, expanding nontraditional credit access, and lowering the fixed costs of lending to small and medium-sized enterprises. This can be represented as:

$$\phi_{it} = \phi_0 + \eta_I FTG_{it},$$

with:

$$\eta_I > 0.$$

When the financing constraint binds, an increase in ϕ_{it} raises feasible investment:

$$\frac{\partial I_{it}}{\partial FTG_{it}} > 0.$$

This mechanism provides the theoretical basis for treating fixed investment growth as a central transmission channel. It is especially relevant in China's provincial context because private firms and SMEs often face stronger financing constraints than larger or state-connected enterprises. Digital finance may therefore have a disproportionately strong effect on capital formation by expanding credit access to constrained firms.

This firm-side extension is not a full structural HANK firm block. Rather, it is a reduced-form credit-friction mechanism that complements the household HANK framework. It links the general HANK insight about constrained agents to the empirical investment channel used in the paper.

A.4 Export and Trade-Finance Channel

The third potential channel is exports. In an open regional economy, goods-market demand includes external demand. Let net exports be:

$$NX_{it} = X_{it} - M_{it},$$

where NX_{it} denotes net exports in province i at time t , X_{it} denotes exports, and M_{it} denotes imports. In principle, FinTech development can affect export activity by reducing trade-finance frictions, lowering cross-border payment costs, improving settlement speed, and facilitating access to working capital for exporting firms.

A reduced-form export relationship can be written as:

$$X_{it} = X(FTG_{it}, Open_i, TF_{it}, Q_{it}),$$

where $Open_i$ captures the province's trade openness, TF_{it} captures trade-finance conditions, and Q_{it} captures relative price or exchange-rate conditions. The expected partial effect of FinTech on exports is:

$$\frac{\partial X_{it}}{\partial FTG_{it}} > 0,$$

although the magnitude may vary substantially across provinces.

The empirical model uses export growth rather than net-export growth because province-level exports are more consistently observable and more directly connected to trade performance. Therefore, the mapping from the theoretical net-export term to the empirical export-growth variable should be interpreted as an approximation:

$$\Delta NX_{it} \approx \omega_X EXPG_{it},$$

where ΔNX_{it} denotes changes in net exports, $EXPG_{it}$ denotes export growth, and ω_X is a reduced-form scaling parameter linking the theoretical net-export term to the empirical export-growth variable. This approximation is reasonable for studying the export-related demand channel, but it should not be interpreted as a strict national-income-accounting identity.

Because FinTech's influence on exports is indirect and depends on sectoral structure, openness, logistics capacity, and trade-finance conditions, the export channel is expected to be weaker and more context-dependent than the investment channel.

A.5 Goods-Market Clearing

At the provincial level, aggregate output can be written as:

$$Y_{it} = C_{it} + I_{it} + G_{it} + NX_{it},$$

where Y_{it} is regional output, C_{it} is consumption, I_{it} is investment, G_{it} is government spending, and NX_{it} is net exports.

Taking a first-order approximation around a steady state gives:

$$\Delta Y_{it} = \Delta C_{it} + \Delta I_{it} + \Delta G_{it} + \Delta NX_{it}.$$

Dividing by steady-state output Y_i , the growth-rate approximation becomes:

$$g_{Y,it} \approx s_{C,i} g_{C,it} + s_{I,i} g_{I,it} + s_{G,i} g_{G,it} + s_{NX,i} g_{NX,it},$$

where:

$$s_{C,i} = \frac{C_i}{Y_i}, s_{I,i} = \frac{I_i}{Y_i}, s_{G,i} = \frac{G_i}{Y_i}, s_{NX,i} = \frac{NX_i}{Y_i}.$$

This expression shows that output growth depends on share-weighted growth in expenditure components. However, the empirical specification does not impose the exact accounting identity. Instead, it estimates reduced-form associations between regional output growth and the observed channel variables. This is appropriate because the empirical variables are measured as growth rates and because the purpose of the analysis is to identify which channels are most responsive to FinTech growth.

The empirical model focuses on three observed channels:

$$INVG_{it}, RETG_{it}, EXPG_{it},$$

which proxy fixed investment growth, retail consumption growth, and export growth, respectively.

A.6 FinTech Growth and the Channel Equations

FinTech development is measured by the growth rate of the Peking University Digital Financial Inclusion Index. Let FTG_{it} denote FinTech growth in province i and year t .

The theoretical discussion above implies that FinTech growth may affect the three observed demand-side channels:

$$\begin{aligned} INVG_{it} &= \alpha_i^I + \delta_t^I + \pi_I FTG_{it} + \varepsilon_{it}^I, \\ RETG_{it} &= \alpha_i^C + \delta_t^C + \pi_C FTG_{it} + \varepsilon_{it}^C, \\ EXPG_{it} &= \alpha_i^X + \delta_t^X + \pi_X FTG_{it} + \varepsilon_{it}^X. \end{aligned}$$

Here, π_I , π_C , and π_X measure the reduced-form association between FinTech growth and each transmission channel. The expected signs are:

$$\pi_I > 0, \pi_C \geq 0, \pi_X \geq 0.$$

The strongest theoretical prediction concerns the investment channel. Because FinTech can relax financing constraints for SMEs and private firms, π_I is expected to be positive and economically meaningful. The consumption channel may also be positive, but its aggregate effect may be smaller if FinTech mainly changes the payment mode rather than total consumption volume. The export channel is expected to be positive but more province-specific and therefore less likely to dominate in a national provincial panel.

A.7 Mapping to the Empirical Growth Regression

The main empirical specification estimates the relationship between FinTech growth, the channel variables, and regional output growth. The full channel specification is:

$$GR_{it} = \alpha_i + \delta_t + \beta_D FTG_{it} + \lambda_I INV_{it} + \lambda_C RETG_{it} + \lambda_X EXP_{it} + u_{it}.$$

Here, GR_{it} is the growth rate of gross regional product per capita. The terms α_i and δ_t are province and year fixed effects. The coefficients λ_I , λ_C , and λ_X measure the conditional association between each channel variable and output growth. The coefficient β_D captures the remaining association between FinTech growth and output growth after controlling for the three observed channels.

The coefficient β_D should be interpreted as a reduced-form direct effect. It may include productivity effects, entrepreneurship effects, financial-deepening effects, digital-infrastructure effects, omitted channels, and residual unobserved factors. It should not be interpreted as a clean structural HANK wedge.

The benchmark total-effect regression excludes the three channel variables:

$$GR_{it} = \alpha_i + \delta_t + \beta_T FTG_{it} + e_{it}.$$

The coefficient β_T measures the total reduced-form association between FinTech growth and regional output growth.

A.8 Channel Decomposition

The empirical decomposition separates the total effect of FinTech growth into direct and indirect components. Combining the output-growth equation with the channel equations gives:

$$\beta_T = \beta_D + \lambda_I \pi_I + \lambda_C \pi_C + \lambda_X \pi_X.$$

For the partial decompositions presented in Tables 5-7, the coefficients λ_j are obtained from separate channel-specific regressions. For the simultaneous decomposition presented in Table 8, however, λ_I , λ_C , and λ_X are estimated jointly in Model D1. Accordingly, the indirect effects reported in Table 8 measure conditional channel contributions that account for correlation among the mediators.

The indirect effect through fixed investment is:

$$Indirect_I = \lambda_I \pi_I.$$

The indirect effect through retail consumption is:

$$Indirect_C = \lambda_C \pi_C.$$

The indirect effect through exports is:

$$Indirect_X = \lambda_X \pi_X.$$

The share of the total effect accounted for by channel j is:

$$Share_j = \frac{\lambda_j \pi_j}{\beta_T}.$$

The direct-effect share is:

$$Share_D = \frac{\beta_D}{\beta_T}.$$

This decomposition is reduced-form rather than structural. It is useful because it quantifies how much of the observed FinTech-growth association is statistically accounted for by the three measured channels. It does not prove that the estimated channel effects are structural causal parameters.

A.9 Interpretation of the Direct Effect

The direct effect β_D captures the part of the FinTech-growth association that remains after controlling for fixed investment growth, retail consumption growth, and export growth. Several mechanisms may be included in this residual component.

First, FinTech may improve productivity by lowering search, transaction, monitoring, and screening costs. Second, it may support entrepreneurship by expanding access to finance for new firms and self-employed workers. Third, it may deepen financial markets by increasing the reach and intensity of formal financial services. Fourth, it may improve resource allocation by directing credit toward higher-return users that were previously underserved by traditional banks.

However, the direct effect may also contain omitted variables, measurement error, or remaining endogeneity. Therefore, the direct effect should be interpreted cautiously as a residual reduced-form association rather than as a separately identified structural mechanism.

A.10 Theoretical Predictions

The framework generates three empirically testable predictions.

First, the fixed-investment channel is expected to be the strongest observed transmission mechanism. This prediction follows from the idea that FinTech relaxes financing constraints for firms and entrepreneurs, particularly SMEs and private firms with limited collateral or credit histories.

Second, the retail-consumption channel may be positive but weaker. FinTech can improve household liquidity and payment convenience, but its aggregate effect on retail sales may be limited if it mainly changes how transactions are conducted rather than how much households consume.

Third, the export channel is expected to be positive but peripheral. FinTech may reduce trade-finance and payment frictions, but export responses depend heavily on provincial openness, industrial structure, logistics capacity, and exposure to external demand.

Overall, the HANK-motivated framework supports the empirical focus on heterogeneous financial frictions and demand-side channels. It provides a theoretical rationale for examining fixed investment, retail consumption, and exports, while preserving the reduced-form interpretation of the panel estimates.

Appendix B: Response to Potential Methodological Concerns

This appendix addresses several methodological questions that may arise regarding the empirical strategy.

B.1 On the Use of GDP Components as Channel Variables

A potential concern is that using components of GDP growth (investment, retail sales, exports) as channel variables to explain GDP growth constitutes a circular argument grounded in accounting identities. This concern is addressed on three grounds.

First, the national income identity $Y \equiv C + I + G + NX$ constrains only the *sum* of component effects, not their individual magnitudes, signs, or statistical significance. Finding that FinTech increases GDP entirely through investment with zero effect on consumption — as the present study documents — is genuinely informative and cannot be deduced from the identity alone.

Second, the use of growth-rate specifications breaks the exact additive identity constraint. The growth rate of a sum is not equal to the sum of the growth rates of its components; rather,

$$g_Y \approx (C/Y)g_C + (I/Y)g_I + (G/Y)g_G + (NX/Y)g_{NX}.$$

This share-weighted relationship means that individual channel regression coefficients carry independent information and are not mechanically constrained to sum to the total GDP growth coefficient.

Third, the channel equations (Models E1–E3) regress each component's growth rate on FinTech growth *independently* of the main growth equation. The estimated channel slopes (π_I, π_C, π_X) measure the association between FinTech and each demand component, not the accounting relationship between the component and GDP. The decomposition then combines these independent estimates with the multiplier estimates from the growth equation, providing a two-step procedure that is conceptually distinct from the accounting identity.

B.2 On Identification Without Instrumental Variables

The present study relies on two-way fixed effects with a lagged-variable robustness check rather than formal instrumental variable estimation. This choice reflects both practical constraints (the difficulty of finding valid province-level instruments for FinTech growth in a short panel) and the judgment that two-way fixed effects, combined with the growth-rate specification and lagged-variable check, provide a credible identification strategy for the research question at hand.

The two-way fixed effects absorb (i) all time-invariant provincial characteristics (geography, institutional quality, historical economic structure, cultural factors) and (ii) all common year-specific shocks (national policy changes, global cycles, technology diffusion trends). The identifying variation is therefore within-province, within-year changes in FinTech growth that deviate from both the province's own average and the national year average. Reverse causality would require that province-specific, time-varying demand

shocks (after removing province and year means) causally accelerate FinTech adoption within the same year. The lagged specification further mitigates this concern by ensuring that the FinTech measure is predetermined.

This identification strategy is consistent with the approach used in the foundational finance–growth panel literature (Beck, Levine, & Loayza, 2000; Levine, Loayza, & Beck, 2000) and in the recent applied FinTech–growth literature using Chinese provincial data. The results should be interpreted as documenting a robust conditional association between FinTech growth and regional output growth, with the lagged specification providing suggestive evidence on direction, rather than as definitive causal identification.

B.3 On the Growth-Rate Specification

The use of growth rates rather than levels of the FinTech index is motivated by stationarity considerations. Panel unit root tests (Table 2 of the main text) confirm that all growth-rate variables reject the unit root null, while the level of the PKU-DFIIC exhibits strong trending behavior consistent with non-stationarity. Regressing non-stationary level variables can produce spuriously significant results (Granger & Newbold, 1974; Kao, 1999). The growth-rate specification ensures valid statistical inference and is consistent with the growth regression tradition in the finance–growth literature (Beck et al., 2000; King & Levine, 1993; Levine et al., 2000).

A secondary advantage is that growth rates simultaneously remove entity-specific fixed effects and linear trends. If $y_{i,t} = \alpha_i + \delta_i t + u_{i,t}$, then $\Delta y_{i,t} = \delta_i + \Delta u_{i,t}$ — the entity-specific intercept drops out, providing identification benefits similar to within-transformation but additionally eliminating deterministic trends that might bias level regressions.

The main trade-off is that first-differencing can amplify measurement error (Griliches & Hausman, 1986), potentially attenuating estimated coefficients toward zero. If measurement error is a concern, the estimated FinTech effect of 0.022 should be interpreted as a conservative lower bound.