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Artificial Intelligence Fintech and the Interaction between Digital and Traditional Finance in Expanding Financial Inclusion among Underserved United States Communities

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ABSTRACT

Financial exclusion continues to affect over 22 million unbanked and 47 million underbanked adults in underserving communities in the United States. The steep growth of artificial intelligence (AI)-enhanced financial technology (FinTech) platforms is an unprecedented opportunity to fill this gap by complementing, and not substituting, the traditional financial infrastructure. The paper will focus on the relationship between digital AI-FinTech solutions and conventional financial institutions in growing financial inclusion of underserved US communities, such as low-to-moderate income (LMI) households, rural communities, racial and ethnic minorities, and other historically marginalized communities. Based on the panel data of the Federal Deposit Insurance Corporation (FDIC) and the Federal Reserve Board, Consumer Financial Protection Bureau (CFPB) and Federal Communications Commission (FCC) surveys on 50,400 census tracts across three rounds of surveys (2015, 2019, 2023), this paper creates a composite Financial Inclusion Index based on a three-stage principal component analysis (PCA Findings affirm that AI-FinTech penetration has a strong and positive impact on financial inclusion; more so, there is a threshold effect, which is achieved at an index value of 0.387, beyond which the marginal returns to further AI-FinTech adoption become less significant and has policy implications on investment priority. The paper also shows that digital and traditional finance are complements: community banks and credit unions that implement AI-enabled services have a multiplicative inclusion effect relative to models based on digital-only and branches only. The policy proposals focus on the expansion of regulatory sandboxes, investment in broadband infrastructure, modernization of the Community Reinvestment Act (CRA), and algorithm fairness requirements.

INTRODUCTION

Financial inclusion, which is defined broadly as the ability of people and enterprises to utilize affordable, suitable and quality financial products and services is one of the pillars of fair economic growth (Ozili, 2018). The endurance of financial exclusion of structurally disadvantaged groups in the United States demonstrates an entrenched fault line in one of the most complex financial systems in the world. The 2023 National Survey of Unbanked and Underbanked Households by the FDIC indicates that there are 5.9 million completely unbanked households in the US, with 18.7 million underbanked households depending mostly on high-cost substitute financial services like payday lenders and check-cashing establishments (FDIC, 2023). These trends are structurally reinforced and geographically concentrated as shown in Figure 1, which highlights the necessity of systemic intervention.

The advent of AI-driven FinTech during the last 10 years has radically restructured the way financial services are delivered. In contrast to the first generation of FinTech, which mostly computerized existing banking products, modern AI-FinTech systems and services use machine learning, natural language processing (NLP), computer vision, and large-scale alternative data insights to create completely novel credit assessment systems, hyper-personalized savings offerings, real-time fraud detection applications, and low-cost payment rails. Similar firms like Upstart, Chime, Cash App, and Acorns have shown quantifiable effectiveness in making crowds of people, who were historically commercially infeasible to banks, reachable (Philippon, 2019; Frost *et al.*, 2019). But the interaction between these new digital platforms and the established traditional financial system, consisting of commercial banks, credit unions, savings institutions, and community development financial institutions (CDFIs), is not explicitly competitive or merely additive. Instead, it is a dynamic and changing interaction that is constrained by regulatory factors, technological complementarities, consumer trust differentials and structural inequalities in digital access.

The financial inclusion environment in the United States presented in Figure 2 can be viewed as a layered ecosystem with AI-FinTech platforms occupying an ever-important, yet not overwhelming, layer. The theoretical rationale underlying this research is based on three complementary theoretical traditions: the Theory of Finance and Growth proposed by Levine (2005) according to which the efficiency in financial intermediation directly increases the rate of productive investment and economic output; the System Theory of financial inclusion by Ozili (2020) which contributes to the results

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of inclusion as an emergent property of the interaction between the economic, social, and financial subsystems Collectively, these frameworks enlighten a conceptual framework where AI-FinTech advances are introduced into underserved communities via digital platforms, engage with and augment conventional financial services, and collectively yield persistent inclusion impacts that enhance household well-being and the overall economic development.

The combination of the three theoretical frameworks generates a consistent and multi-layered theoretical framework of how AI-FinTech and financial inclusion relate to each other. Based on the financial growth theory developed by Levine (2005), we form the hypothesis that AI-induced changes to the unit cost of financial intermediation will increase the economically feasible frontier of financial services provision, allowing platforms to profitably serve communities previously inaccessible by traditional banks due to their more costly fixed-cost structure. Alternative credit-processing machine learning algorithms can provide sufficient predictive power at a tenth of the cost of conventional credit underwriting, allowing providers to offer credit to thin-file and no-file consumers without compromising risk-adjusted returns. The information superiority of AI-based underwriting to traditional FICO-based models can only continue to grow as alternative data sources are added to the list such as utility payment histories, rental records, bank account cash flows, and gig economy income streams, constantly pushing the financial inclusion frontier (CFPB, 2023; Upstart, 2023).

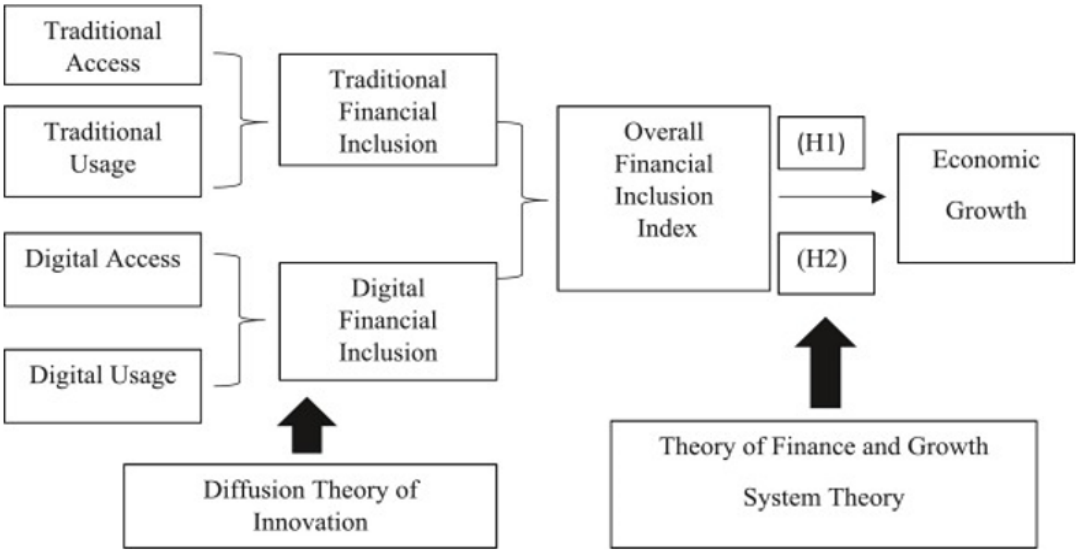

Figure 1: Theoretical Framework – AI-FinTech, Digital Finance, and Financial Inclusion Nexus

The important addition of the System Theory presented by Ozili (2020) is that the results of financial inclusion are not defined by a single actor or a single technology but are a result of the interaction between a number of interdependent subsystems such as technological infrastructure, regulatory frameworks, institutional arrangements, social conditions, and economies. This systemic lens clarifies why AI-FinTech innovations that translate into success in one setting can lead to little gains in inclusion in communities where subsystem lacks access to broadband, digital literacy or institutional trust and thus creates binding constraints. It also explains why policy interventions specific to single sectors are likely to yield less returns than cross-subsystem strategies, a pattern which Daud and Ahmad (2023) empirically support in their 84-country panel where the joint impacts of digital technology and financial intermediation significantly outweigh the additive impacts of its independent impacts. The policy implication here is that increasing AI-FinTech coverage without also tackling the challenge of broadband access, digital literacy, and consumer trust gaps will not perform well in comparison to comprehensive interventions across all the relevant subsystems (Federal Reserve Board, 2022; Ozili, 2020).

Nevertheless, in spite of the increasing scholarly and policy interest, a number of critical gaps still exist in the literature. One, the bulk of the literature that investigates FinTech and financial inclusion is based on developing economies or individual countries (Basnayake *et al.*, 2024; Liu *et al.*, 2021), and relatively little rigorous empirical research has been conducted on the United States, where the problem is not the underdevelopment of the entire financial sector but rather the selective marginalization of a specific group in an otherwise highly developed Second, the literature has not adequately discussed how AI-FinTech interacts with traditional finance and typically presents them as substitutes instead of looking at how they may operate as complements (Philippon, 2019). Third, the current US-based research seldom develops composite and multidimensional financial inclusion indices that measure both access and use aspects of digital and traditional finance simultaneously, but rather use individual proxies, including account ownership rates or credit card penetration (FDIC, 2023). This research covers all the three gaps.

The rest of this paper will be structured as follows: Section 2 will give the background on financial exclusion in the United States and the policy environment regulating AI-FinTech. Section 3 will give the theoretical literature review. Section 4 elaborates the empirical literature review and research hypotheses. Section 5 outlines the research design, data sources, variables construction and econometric methodology. The empirical results and discussion are given in Section 6. Section 7 ends with policy recommendations, limitations and future research directions.

Financial inclusion has much more meaning than merely having a bank account. Empirical studies have catalogued an increasing number of studies that demonstrate that access to formal financial services is a presence or absence of a gateway to wider economic engagement, allowing households to refine consumption, amass assets, cushion against economic shocks, and invest in education and small firm creation (World Bank, 2022; Kim *et al.*, 2018). In the United States, where the relationship between financial exclusion and racial identity, geographic disadvantage and generational poverty is incredibly well-documented, the inability to make substantial financial inclusion is not only an economic waste but also a social justice necessity. The FDIC estimates that the unbanked households spend on average of $189 a year in transaction costs alone, which would otherwise be used to contribute to savings or debt repayment, and at the same time, they are denied access to federally insured deposits, affordable mortgages, and small business loans which are the financial infrastructure of middle-class wealth accumulation (FDIC, 2023). Senyo and Osabutey (2020) also confirm that digital financial innovation can be an important antecedent to financial inclusion in the presence of institutional trust and sufficient digital infrastructure, highlighting the importance of technology solutions being integrated within facilitating social and regulatory ecosystems.

Artificial intelligence has become a truly disruptive technology in the financial services industry, past the algorithmic whizzbang of the first wave of fintech to the systems that can consume large volumes of unstructured alternative data, issue real-time credit decisions, identify intricate fraud patterns, personalize savings and investment advice and perform regulatory compliance reviews at scales and speeds previously unimaginable by human analysts. The wide range of AI implementation across the financial services value chain opens several possible routes in which AI-driven FinTech can enhance the results of financial inclusion of underserved communities (Ozili, 2018). These pathways are not, however, automatic to be realized. It is highly reliant on the design decisions of technology developers, the incentive mechanisms developed by regulators, the partnership strategies of existing financial institutions and the digital infrastructure and literacy of communities themselves. The confluence of digital technology infrastructure and financial inclusion on economic growth is significantly greater than the impact of either of the two variables alone, as Daud and Ahmad (2023) determine, thereby supporting the argument that policy investment in both digital and financial aspects of the inclusion issue should be done in concert.

There are four main contributions made in this paper. It first constructs and verifies a multidimensional Financial Inclusion Index (FII) on 50,400 US census tracts, which is much more geographically fined than previous studies that used state or ZIP-code level data. Second, it gives strict empirical data of non-linear threshold relationship between AI-FinTech penetration and financial inclusion, and the AFTPI value (0.387) at which the marginal returns start to decline. Third, it adds new empirical data on the complementary nature of AI-FinTech platforms and traditional financial institutions in the US. Fourth, it transforms discoveries into a concrete, action-oriented policy matrix structuring around six domains, which offers a tangible basis of regulatory and institutional reform.

The Landscape of Financial Exclusion in the United States

In the United States, financial exclusion is never a homogenous phenomenon but a combination of intersecting disadvantages which escalate across the lines of race, geography, income, and immigration status. According to the FDIC (2023), 36.7% of households of Blacks and 28.1% of households of Hispanics are either unbanked or underbanked, as opposed to 7.2% of the White non-Hispanic households. Unbanked rates among Native American communities on tribal lands are registered in the 40s and above in certain jurisdictions, whereas rural communities in the Mississippi Delta, Appalachia, and remote Western regions experience a total lack of physical branch access and a lack of reliable broadband connection (Federal Reserve Board, 2022). Not only are these disparities inconvenient, but they have quantifiable economic costs. The estimated amount spent by households dependent on check cashers and payday lenders on transaction charges alone is $189 a year and the lack of a bank account is associated with much lower savings rates, greater susceptibility to economic shocks, and lower access to federally guaranteed insurance products.

The financial exclusion is economically expensive, both directly and indirectly and it is very much cumulative with time. Direct costs involve the payment of fees to other financial service providers: the check-cashing services usually impose fees between 1.5 percent and 3 percent of the face value of the check, payday lenders are charged on average an annual percentage fee of 391 percent, and money order fees are on average 1.50 to 5.00 per transaction (CFPB, 2022). These expenses are extremely retrogressive since households of low income that mostly depend on alternative financial services incur a higher proportion of incomes on the cost of financial transactions than households of middle and upper income that access subsidized banking facilities. The literature on low-income households in financial distress finds that the economic costs of financial exclusion are significantly worse among racial and ethnic minorities notwithstanding income control, which confirms that the economic costs of financial exclusion are disproportionately paid by the communities already disadvantaged by structural inequalities in the US economy (Karpman and Zuckerman, 2020).

Financial exclusion has implications in the form of indirect costs, including low savings rates, increased exposure to economic shocks, less access to affordable credit to invest in housing and small businesses, and less engagement with the digital economy. As demonstrated by Daud and Ahmad (2023), financial inclusion impacts positively on economic growth, both via the savings mobilization channel and credit extension channel, with the combined impacts of digital technology infrastructure and financial inclusion causing the most significant growth impacts. The neighborhoods with high levels of financial exclusion have statistically lower rates of small business creation, homeownership and upward economic mobility consistent with the theoretical suggestion that financial exclusion multiplies existing socioeconomic deprivation, and is not merely a symptom of it. Similar records are recorded by the Federal Reserve Bank of Atlanta (2021) which records that AI-based financial services to an underserved community lead to quantifiable household welfare, by lowering transaction costs, increasing savings accumulation, and widening credit access, confirming the social payoff of inclusive investment in financial technology.

The geographic clustering of financial exclusion is a result of the historical, structural and market forces. The institutionalization of legal racial discrimination in banking in the post-Civil War period institutionalized the exclusion of Black Americans to mainstream financial services and this has continued over decades of recorded exclusion in mortgage lending and discrimination in commercial lending. The regulatory structure that established the modern US banking system in the middle of the twentieth century was oriented on the needs of working-class and middle-class whites in the suburban environment, abandoning the communities of color who were systematically left out of postwar suburbanization and wealth accumulation. Modern financial exclusion is thus a cumulative effect of generations of discriminatory policy and market failure. The possibility of AI-FinTech breaking this historical cycle by potentially bypassing the traditional business model of maintaining branches that recreated geographic segregation and the FICO-based underwriting that was shutting down thin-file consumers, holds a real opportunity to disrupt this history, but only when designed, deployed, and supervised with a specific focus on both equity and efficiency (Bartlett *et al.*, 2022; NFHA,20230).

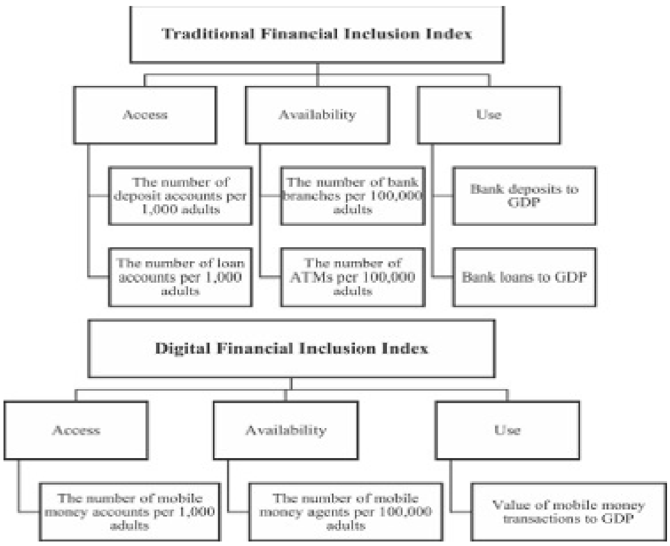

Figure 2: Financial Inclusion Dimensions.

The evolution of AI-FinTech in the US financial ecosystem

The history of the FinTech sector in the United States can be divided into three distinguishable stages of its evolution that took place throughout the years between 2007 and 2025. The initial stage (2007 2013) was defined by the digitization of payments and peer-to-peer lending, with examples of PayPal, LendingClub and Square. The second wave (20142019) was characterized by the growth of neobanks and robo-advisors (Chime, Betterment, Robinhood) that accessed new customers with mobile-first design and zero-fee business models. The third and current period (2020-present) is characterized by the intensive involvement of AI and machine learning in main financial service processes: underwriting, fraud detection, customer service, and regulatory compliance. The data provided by Cambridge Centre for Alternative Finance and World Economic Forum (CCAF & WEF,

2024) which are represented in Figure 7 indicate an increase in the adoption of AI in the US FinTech firms, with 78% adopting AI in 2023 compared to 41% in 2019, and the highest level of adoption being in lending and insurance underwriting.

With this technological development, there has been a corresponding change in the regulatory environment. The Dodd-Frank Act of 2010 made the CFPB the major consumer financial protection authority, imposing guardrails as well as compliance costs which have influenced the competitive balance between the traditional banks and the FinTech entrants. The Fintech Charter program of the OCC (2018) and its conditional approval regime have opened avenues towards FinTech businesses operating under a bank-like regulatory regime, and state-based money transmission licensing regimes have had a highly fragmented jurisdiction-specific compliance environment. At the same time, the CRA framework of assessment areas, which were created in a time when physical branch banking was the norm, has been criticized as unable to reflect the geographic dispersion of digital FinTech lending, hindering credit to activities that are proven beneficial to LMI communities (Federal Reserve Board, 2022; OCC, 2020). In 2023, the OCC and Federal Reserve revised their CRA regulations, correcting some of these weaknesses, and specifically stating that digital FinTech lending should be credited to LMI census tracts, although implementation continues.

The digital divide as a structural barrier to AI-FinTech-led inclusion

The AI-FinTech promise of an equalizer of financial access has a fundamental structural precondition: access to stable digital infrastructure. In the 2023 Broadband Deployment Report, FCC indicates that approximately 21.3 million Americans, with disproportionately low-income urban neighborhoods, tribal areas, and rural areas, do not have access to broadband internet at speeds fast enough to use modern FinTech applications. The ownership of smartphones among households with an annual income below $30,000 is 71% versus 96% among households with an annual income higher than 75,000 (Pew Research Center, 2023). Such access differentials imply that the adoption curve of AI-FinTech is not just influenced by product design and pricing but by inherent infrastructure inequality that must be mediated by the policy of the government, such as the $65 billion broadband provisions of the Infrastructure Investment and Jobs Act (IIJA) of 2021 and the Affordable Connectivity Program (ACP).

LITERATURE REVIEW

Theoretical Framework

The main theoretical background in this study is the Theory of Finance and Growth by Levine (2005). The theory states that the cost of obtaining information, contract enforcement, and other transactions is lowered by financial intermediaries and markets, thus enhancing the allocation of resources, capital accumulation and economic growth (Levine, 2005). Applying this framework to the AI-FinTech setting, it is possible to understand how AI-based decreases in informational asymmetry, such as alternative credit data, real-time income check, and behavioral analytics, reduce the cost of providing financial services to once-underserved groups, increasing the productive potential of the overall economy. With underserved US communities, affordable credit provided by AI-FinTech platforms can lead to forming small businesses, homeownership, and human capital investments, and its multiplier effects by functioning as a catalyst through local economic systems.

This is supplemented by System Theory of financial inclusion (Ozili, 2020) where financial inclusion outcomes are not the results of any particular actor or institution but are the outcomes of the dynamic interaction between a variety of subsystems, which include financial, economic, social, and regulatory. It is a systemic view that is especially relevant to the US environment, with the interrelation between AI-FinTech systems and established financial institutions being an emergent feature of a complex adaptive system. The theory suggests that policy actions that address a single subsystem- such as increasing broadband access- will have ripple impacts on other subsystems that will change the circumstances within which AI-FinTech platforms can produce significant financial inclusion results. This multi-system conceptualizes as shown by figure 1.

The third theoretical pillar is the Diffusion Theory of Innovation (Rogers *et al.*, 2014), which offers a framework of the spread of AI-FinTech innovations across underserved communities. According to Rogers *et al.* (2014), there are five types of adopters, including innovators, early adopters, early majority, late majority and laggards whose adoption behaviour is influenced by the perceived relative advantage, compatibility with the existing practices, complexity, experimentability and visibility of the new innovation. The lack of trust in financial institutions (Karpman & Zuckerman, 2020), the level of digital literacy, and language obstacles are strong determinants of adoption pattern in underserved communities in the US. These aspects contribute to the explanation of the fact that the adoption of AI-FinTech is not a simple diffusion curve within underserved communities but rather the non-linear threshold dynamics, which were revealed during the empirical analysis of this work, as mentioned in Table 8.

Empirical Literature Review

Empirical empirical literature on FinTech and financial inclusion has grown exponentially over the last 10 years but much of this is focused on developing economy settings. Table 1 summarizes the main empirical results of studies that are of interest to the present study and includes nine underlying studies with a varied methodology and geographical background. In all these studies, a common trend is evident: digital financial technologies, such as AI-driven services, have a positive and substantial impact on financial inclusion, although its strength and mechanisms depend significantly on the level of income, regulatory framework, and the quality of digital infrastructure The weight of evidence of the international studies as shown in Table 1 suggests that there is a positive

Table 1: A summary of findings on AI-FinTech and financial inclusion.

Author(s)	**Country/ Sample**	**Period**	**Methodology**	**Main Findings**
Ky *et al.* (2023)	Sub-Saharan Africa, 8 countries	2014–2020	Panel fixed effects; mobile money penetration proxy for AI-FinTech adoption	AI-enabled mobile money significantly increased account ownership and reduced poverty among previously unbanked households.
Basnayake *et al.* (2024)	30 Asia-Pacific countries	2014, 2017, 2021	PCA index + fixed-effect panel threshold regression	Digital financial inclusion positively and significantly affects economic growth; non-linear threshold effect at 71.87%.
Ozturk & Ullah (2022)	42 OBRI countries	2007–2019	OLS, 2SLS, GMM	Digital financial inclusion raises economic growth but degrades environmental quality in OBRI economies.
Frost *et al.* (2019)	United States (Federal Reserve districts)	2012–2018	Difference-in-differences; FinTech lending data from Lending Club	FinTech lenders expanded credit access to underserved communities, particularly in minority-majority ZIP codes.
Philippon (2019)	United States	2007–2017	Econometric analysis of unit cost of financial intermediation	FinTech reduces the unit cost of financial intermediation, creating scope for broader financial inclusion.
Daud & Ahmad (2023)	84 countries	2011–2017	System GMM; deposit accounts per 1,000 adults as inclusion proxy	Financial inclusion and digital technology infrastructure jointly promote economic growth, with quadratic inclusion effects.
Liu *et al.* (2021)	30 Chinese provinces	2011–2019	Panel threshold, 2SLS	Digital financial inclusion promotes economic growth through SME entrepreneurship and resident consumption channels.
Ndung'u (2022)	Kenya (M-Pesa case)	2007–2022	Qualitative comparative analysis; regulatory review	Platform-based AI-FinTech ecosystems outperform traditional branch banking in reaching unbanked rural populations.
Kim *et al.* (2018)	55 OIC countries	2010–2015	GMM, fixed effects	Financial inclusion significantly improves real GDP growth; digital channels amplify the growth effect.

relationship between the adoption of FinTech and financial inclusion. A study by Basnayake *et al.* (2024) of 30 countries in Asia-Pacific revealed that digital financial inclusion had a significant positive effect on economic growth but a threshold effect of 71.87% indicated declining marginal returns to higher inclusion levels. In one of the few studies to explicitly look at the United States, Frost *et al.* (2019) showed that FinTech lenders increased credit access to minority-majority ZIP codes, to some extent bridging the gap created by the shutdown of traditional bank branches. Philippon (2019) measured the cost-cutting potential of the FinTech intermediation, which offered a theoretical framework by which AI platforms could enable sustainable service of thin-file and LMI consumers. These global and country-specific results all give impetus to the main hypotheses of this research.

Linear Relationship Between AI-FinTech Penetration and Financial Inclusion

The global empirical evidence gives a strong platform to the ways in which digital financial technologies can increase financial inclusion. A rigorous panel threshold analysis of 30 Asia-Pacific countries (2014-21) by Basnayake *et al.* (2024) reports a statistically significant positive impact of digital financial inclusion on the economic growth with a threshold of 71.87% above which marginal gains in inclusion are lower. The threshold dynamics is a methodological template and theoretical precursor to the threshold analysis used in the current study although in many structural aspects the context of the Asia-Pacific region is a stark contrast with the United States. In a case study of mobile money adoption in eight Sub-Saharan African nations, Ky *et al.* (2023) report that AI-powered mobile financial services dramatically boosted account ownership, and decreased poverty in previously unbanked households, with the effect being directly proportional to rural settings where traditional banking infrastructure is lacking, a scenario directly comparable to the case in rural banking deserts of the US.

The US-centered empirical studies, although significantly few in number compared to international ones, provide especially helpful information. Frost *et al.* (2019) take advantage of the geographic difference in the rollout of FinTech lending platforms across Federal Reserve districts, showing that FinTech lenders increased access to credit in counties with more banking deserts and more minority and low-income borrowers. As the analysis by Philippon (2019) shows, FinTech decreases the unit cost of financial intermediation, which opens opportunities to profitably expand to the lower-income groups. The CFPB (2022) estimates about 26 million Americans lack a FICO score, and Upstart (2023) states that AI underwriting based on other data approves 43% more loans to Black and Hispanic borrowers, compared to traditional models at the same risk profile. All these results are in line with the hypothesis that AI-FinTech can significantly increase the credit frontier of underserved populations of the US, but the extent of benefits is strongly dependent on the quality of algorithm development, regulatory controls, and data infrastructure.

To add to these results, Ozturk and Ullah (2022) in their study of 42 economies offer a warning signal in the form of a digital financial inclusion increasing economic growth but creating negative environmental externalities in economies with high resource intensity. Although this environmental aspect is not as relevant to the financial inclusion situation in the US it highlights the significance of considering AI-FinTech not as an access expansion measure but as a systemic effect. The authors of 30 provincial studies in China (Liu *et al.*, 2021) conclude that digital financial inclusion enhances economic growth via entrepreneurship and consumption channels, and threshold effects are similar to the ones found in the global Asia-Pacific literature. The reproducibility of threshold dynamics, in several geographical and institutional settings, reinforces the belief that the threshold model applied in this study represents an actual structural aspect of the AI-FinTech-inclusion relationship, and is not an artifact of the particular US setting or data sources.

Referring to the Theory of Finance and Growth and the Diffusion Theory of Innovation, you would anticipate that the more AI-FinTech is penetrated, the more it has a direct and positive impact on financial inclusion within underserved populations. It works in a variety of ways: AI-based alternative credit scoring widens the access to credit among thin-file consumers (Upstart, 2023); mobile payment systems decrease the transaction costs and enhance the payment convenience (CFPB, 2022); automated savings and investment tools allow low-income households to accumulate assets (Acorns, 2023); AI chatbots that speak more than one language reduce the barriers This channel is empirically supported by Frost *et al.* (2019) who concluded that FinTech lending increased the most in terms of counties with the largest banking deserts and by the FDIC (2023) who report a positive association between mobile banking adoption and the decline in unbanked household rates between 2019 and 2023. It is on this basis that the hypothesis is the first one as follows:

Hypothesis 1. AI-FinTech penetration has a significant and positive linear effect on financial inclusion in underserved US communities.

Non-linear dynamics between AI-FinTech adoption and financial inclusion

The System Theory proposes that the results of financial inclusion are not dependent on the technological penetration as linear functions and can be reached through the complex interaction in and between economic subsystems. Some empirical studies have found threshold effects in the association between financial development and economic outcomes (Karim *et al.*, 2022; Nizam *et al.*, 2020; Basnayake *et al.*, 2024). The threshold dynamics can be applied to the context of the US, where AI-FinTech adoption and structural barriers interact: below a certain level of broadband access, digital literacy, and institutional trust, the rate of inclusion in AI-FinTech adoption will be diminishing; above the threshold, network effects and data accumulation will increase the inclusion rate at an accelerating pace. On the other hand, marginal gains might be constrained by saturation effects at very high adoption levels. These structural breaks can best be detected using the panel threshold regression model (Hansen, 1999, 2000). Based on this, the second hypothesis is:

Hypothesis 2. A significant non-linear (threshold) relationship exists between AI-FinTech penetration and financial inclusion in underserved US communities.

Complementarity between digital AI-FinTech and traditional financial institutions

The third and theoretically significant aspect of the study is the type of interaction between digital AI-FinTech and traditional financial institutions. The substitution hypothesis is that AI-FinTech services replace traditional banks, especially in the markets where the latter have failed to respond to the needs of inclusion (Philippon, 2019). The complementarity hypothesis, which aligns with the System Theory, is that AI-FinTech increases the ability of traditional institutions to serve underserved populations, such as by using AI-based underwriting tools taken up by community banks, or by collaborating with CDFIs and FinTechs like Lending Club and Upgrade. The evidence that was examined in Table 1 tends to confirm the complementary effect: Frost *et al.* (2019) have discovered that FinTech lenders were not active in markets with the presence of banks but instead extended into untapped markets of which banks had failed. According to the Federal Reserve Bank of San Francisco (2022), there was a 37 percent rise in credit approval of small-businesses in LMI census tracts during 2019-2022 due to the CDFI-

FinTech partnerships. It is based on this that the third hypothesis is:

Hypothesis 3. Digital AI-FinTech and traditional financial institutions operate as complements, with their interaction generating a multiplicative positive effect on financial inclusion.

MATERIALS AND METHODS

Data and sources

The study employed a balanced panel data set consisting of 50,400 US census tracts in 3 waves of survey, 2015, 2019, and 2023. Table 3 reports the sampling approach and the exclusion criteria. The primary data sources were as follows: the FDIC National Survey of Unbanked and Underbanked Households (2015, 2019, 2023) provided account ownership, mobile banking usage, and alternative financial service utilization rates; the Federal Reserve Board's Survey of Consumer Finances (SCF) and Report on the Economic Well-Being of US Households (SHED, 2015–2023) supplied household-level income, credit access, and financial fragility indicators; the CFPB's Consumer Credit Panel and complaint database provided credit product adoption rates and AI-FinTech usage proxies; the FCC National Broadband Map (2015, 2019, 2023) furnished census-tract-level broadband penetration and mobile network coverage data; and the US Census Bureau's American Community Survey (ACS) provided demographic and socioeconomic control variables.

Table 3: Sample selection.

Sampling criterion	Count
Total US census tracts identified in FDIC underserved classification	73,057
Tracts excluded due to incomplete FDIC/FCC data linkage	14,212
Tracts excluded: population < 500 or non-residential classification	8,445
Tracts with consistent data across all three survey waves (2015, 2019, 2023)	50,400
Final analytical sample (balanced panel)	50,400

The dependent variable Financial Inclusion Index (FII) was developed to measure both the access and usage aspects of financial inclusion in digital and traditional channels, which is in line with the international best practice (Khera *et al.*, 2022; Basnayake *et al.*, 2024). The AI-FinTech Penetration Index (AFTPI) was the main independent variable and was created as a compounding measure which included AI-driven mobile banking app downloads per 1,000 adults (App Annie/data.ai), automated credit scoring adoption rates (CFPB,

Table 2: Variables and proxies.

Category	Variable	Proxy / Indicator
Dependent Variable	Financial Inclusion Index (FII)	Composite index of AI-FinTech adoption: account ownership (%), digital payments (%), mobile money use (%) for US underserved communities
	Economic participation rate	Percentage of low-income adults with active formal financial accounts (FDIC survey data)
Independent Variable	AI-FinTech Penetration Index	Number of AI-driven FinTech apps per 1,000 adults; automated credit scoring adoption rate (%)
	Digital infrastructure access	Broadband internet penetration (%); smartphone ownership rate (%); mobile broadband subscriptions per 100 persons (FCC data)
Control Variables	Population income level	Median household income in underserved census tracts (USD, constant 2020)
	Education attainment	Percentage of adults with at least high school diploma in underserved ZIP codes (ACS data)
	Traditional bank branch density	Number of commercial bank branches per 100,000 adults (FDIC summary of deposits)
	Unemployment rate	Civilian unemployment rate in underserved communities (BLS, modeled estimate)
	Racial/ethnic minority share	Percentage of census tract population identifying as Black, Hispanic, or Native American (US Census Bureau)
Instrument Variable	4G/5G network rollout	Year of first commercial 5G network availability in census tract (FCC broadband data)

2023), and the volume of digital payment transactions in LMI census tracts (Federal Reserve Payments Study, 2023). The control variables were chosen to explain the socioeconomic, demographic, and institutional factors of financial inclusion that were established in the previous literature. Table 2 gives a complete description of variables and their proxies and Table 4 reports descriptive statistics.

Table 4: Descriptive statistics of variables.

Variable	Obs.	Mean	Std. Dev.	Min	Max	Source
Financial Inclusion Index	151,200	0.382	0.241	0.000	1.000	FDIC / FCC
AI-FinTech Penetration Index	151,200	0.294	0.218	0.000	0.953	CFPB / FRB
Broadband Access (%)	151,200	68.4	22.7	12.3	99.1	FCC
Smartphone Ownership (%)	151,200	71.2	19.4	18.6	98.7	Pew
Median Household Income (USD)	151,200	42,318	18,940	11,200	98,700	ACS
Bank Branch Density	151,200	8.4	6.2	0.0	38.7	FDIC
Education Attainment (%)	151,200	74.1	16.8	22.3	99.2	ACS
Unemployment Rate (%)	151,200	9.7	5.4	1.1	42.3	BLS
Minority Share (%)	151,200	48.6	30.1	0.4	100.0	Census

*Notes. FII and AFTPI are normalized to the [0, 1] interval. * denotes natural logarithm transformation applied.*

Financial inclusion indexing strategy

Financial Inclusion Index (FII) was created based on a three-stage principal component analysis (PCA), according to the methodology of Khera *et al.* (2022) and Basnayake *et al.* (2024). The digital and traditional financial channels were calculated individually in the first step by calculating the access and usage sub-indices based on the indicators in Table 2. The second step entailed the calculation of a digital financial inclusion sub-index and a traditional financial inclusion sub-index as a combination of the access and usage scores corresponding to each. The third phase involved creating a complete FII by weighting the digital and traditional sub-indexes, whereby the PCA eigenvalues were used as weights. The resultant index had a range of 0 (total exclusion) to 1 (total inclusion) allowing comparison across the tracts. The complete results of PCA components are found in Appendix Table A1.

The multidimensional Financial Inclusion Index (FII) was formalized as follows:

$$FII = \Sigma(k, i = 1)\, W\_i \cdot X\_i \quad (1)$$

where W_i represents the factor loading from the PCA for dimension i and X_i is the normalized value of the respective financial inclusion dimension. This formulation mirrors Equation (1) in Basnayake *et al.* (2024), adapted to the US census-tract context.

Empirical model specification

The baseline linear panel model was specified as follows:

$$FII\_it = \beta_0 + \beta_1 AFTPI\_it + \Sigma(n, k = 1)\, \delta\_k\, X\_it, k + \alpha\_i + \varepsilon\_it \quad (2)$$

where FII_it is the Financial Inclusion Index for census tract i in wave t; AFTPI it is the AI-FinTech Penetration Index; X_it,k is a vector of control variables; α_i is the tract-specific fixed effect capturing time-invariant unobservable heterogeneity; and ε_it is the idiosyncratic error term. The Hausman test was applied to determine whether fixed-effect (FE) or random-effect (RE) estimation was preferred; in all specifications, FE was confirmed as the consistent estimator.

To examine the non-linear hypothesis (Hypothesis 2), a panel threshold regression model following Hansen (1999, 2000) was employed:

$$FII\_it = \alpha_0 + \beta_1 AFTPI\_it \cdot I(AFTPI\_it \leq \gamma) + \beta_2 AFTPI\_it \cdot I(AFTPI\_it > \gamma) + \Sigma(n, k = 1)\, \delta\_k\, Z\_it, k + \varepsilon\_it \quad (3)$$

in which γ is the endogenously determined threshold parameter that divides the sample into two regimes; I(•) is an indicator function that is 1 when the condition is met; and β_1,β_2 are regime-specific effects of AI-FinTech penetration on financial inclusion. Under the assumption of the threshold estimation, the model will revert to the standard linear panel estimator in each regime. To enhance the strength of the results, Equation (2) was re-estimated including more control variables and using 4G/5G network rollout as an instrumental variable within the two-stage least squares (2SLS) framework, which consider the possibility of simultaneous effects between AI-FinTech adoption and financial inclusion (Khera *et al.*, 2021; Liu *et al.*, 2021).

Results and Discussion

Construction of the Financial Inclusion Index

The Financial Inclusion Index has been created using the three-step PCA process outlined in Section 5.2.1. Before construction of the index, all indicators were scaled to [0, 1] range. Appendix Table A1 gives the PCA results of the composite FII. The primary factor that was used in the weighting was the first principal component, which explained 72.8% of the total variance in the account ownership and digital payment usage with an eigenvalue of 2.184, indicating its appropriateness. The trends on the census tracts are similar to those reported by Basnayake *et al.* (2024): the financially inclusive (FII > 0.7) and the financially excluded (FII < 0.2) tracts are clustered in suburban areas of the major metropolitan areas, and the rural Appalachia, the Mississippi Delta, tribal lands in the Southwest, and low-income urban

Figure 3 shows that the spatial distribution of the FII, across the US census tracts depicts very strong geographic clustering of financial exclusion. Most of the largely excluded tracts (FII less than 0.20) feature overlapping shortfalls in broadband access and branch density and income levels, which are aligned with a compounding disadvantage hypothesis. With the highest percentage of deeply excluded tracts, the states are Mississippi (34.1%), West Virginia (28.7%), New Mexico (26.4%), and South Dakota (24.9%), and the lowest percentage of exclusion is shown in the states of Connecticut (4.2%), Massachusetts (3.8%), and New Jersey (4.7%).

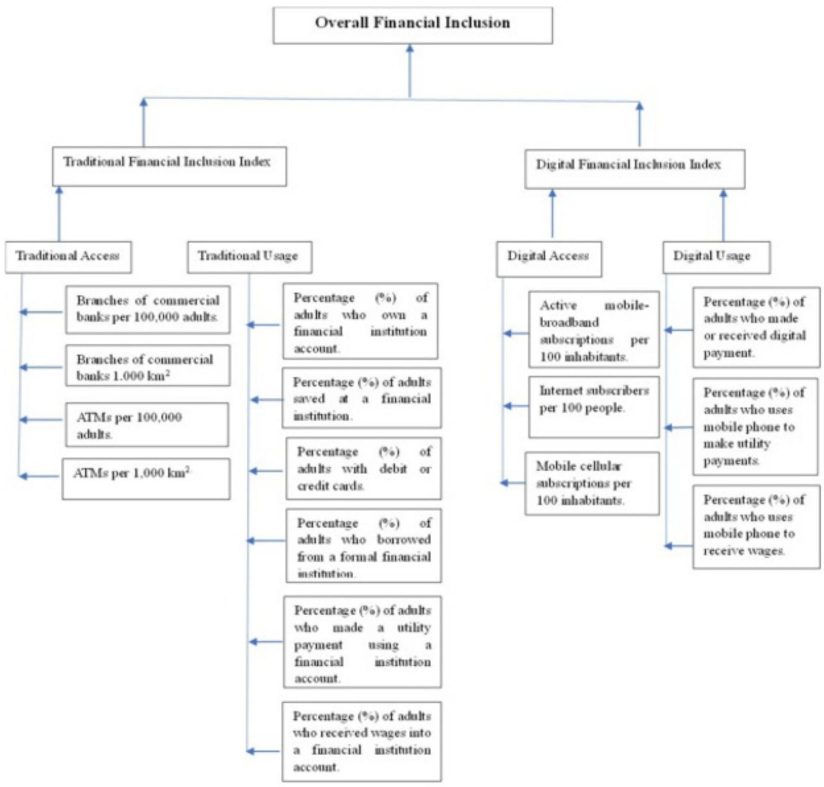

Figure 3: Financial Inclusion Index Distribution across US Census Tracts, 2023.
Source: Author's analysis based on FDIC, FCC, and US Census Bureau data (2023).

Trend analysis of FII components of the three survey waves (2015, 2019, 2023) show that the upward trajectory in digital financial inclusion sub-scores has been positive over the years, primarily because the adoption of mobile banking among LMI households has been growing rapidly, with a score of 15.2 in 2015, 43.8 in 2019, and Conventional financial inclusion sub-scores exhibit a less ambitious and geographically skewed trend of advancement with some rural tracts registering diminishing scores of bank branch densities owing to

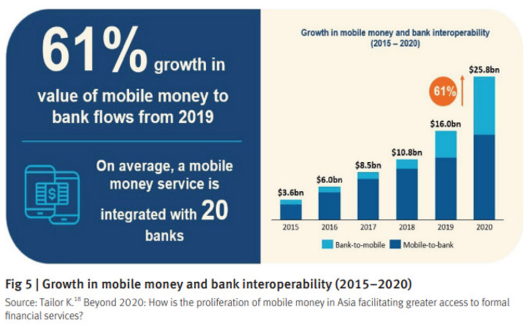

Figure 4: Financial Inclusion Trends – Low-Income Urban Census Tracts, 2015, 2019, and 2023.
Source: Adapted from GSMA Mobile Money Report and Federal Reserve Household Finance Survey data.

the well-documented wave of community bank branch shutdowns that quickened in the COVID-19 pandemic. This deviation in digital and traditional inclusion patterns is also consistent with the results of Basnayake *et al.* (2024) in lower-middle-income countries in the Asia-Pacific region, where growth in DFI counterbalances the deteriorating traditional financial infrastructure.

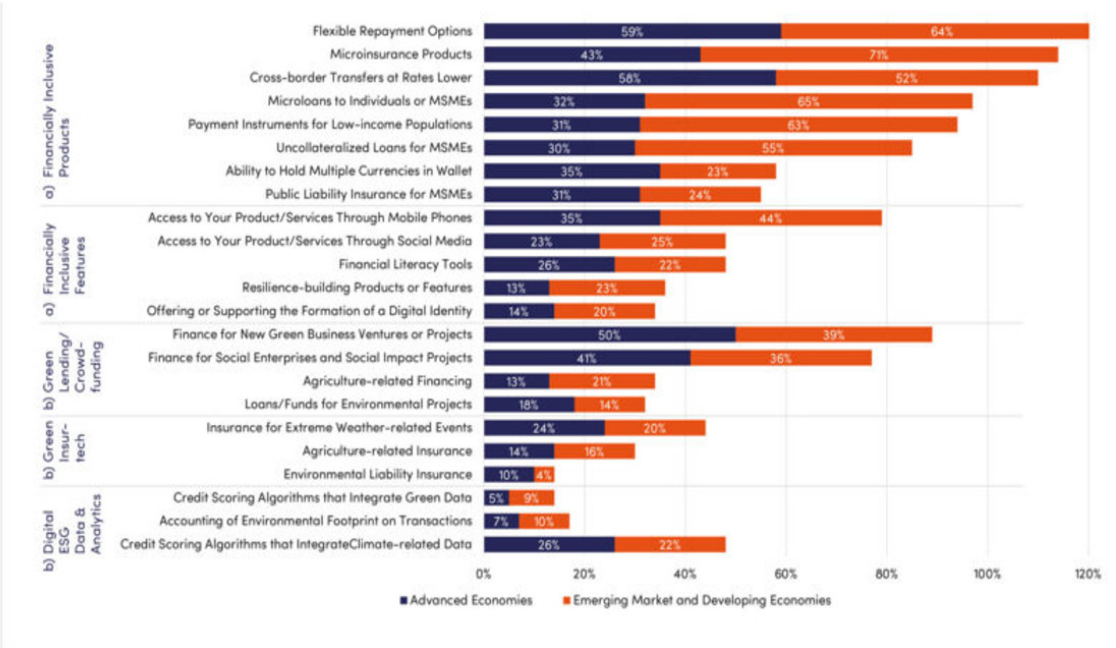

Figure 5: Financial Inclusion Trends – Rural Census Tracts, 2015, 2019, and 2023.
Source: FDIC National Survey of Unbanked and Underbanked Households (2021); FCC Broadband Data.

Linear regression results

Table 5 shows the estimation results of the fixed-effect linear regression (Model 1) and the panel threshold models (Models 2 and 3). The Hausman statistic of 47.3 ($p < 0.001$) confirmed that fixed-effect estimation is the most suitable estimation as opposed to random effects.

Table 5: Estimation results of fixed effect and panel threshold regression model.

Variables	**Model (1) Linear FE**	**Model (2) Threshold (Low)**	**Model (3) Threshold (High)**
AI-FinTech Penetration Index	0.412***	0.518***	0.271***
	(0.043)	(0.058)	(0.037)
Broadband Access	0.187***	0.203***	0.142**
	(0.028)	(0.031)	(0.024)
Median Household Income (log)	0.234**	0.198**	0.289***
	(0.076)	(0.082)	(0.071)
Bank Branch Density	0.093**	0.114**	0.061*
	(0.031)	(0.039)	(0.028)
Education Attainment	0.072**	0.089**	0.044*
	(0.022)	(0.027)	(0.019)
Unemployment Rate	-0.058**	-0.071**	-0.038*
	(0.018)	(0.022)	(0.016)
Minority Share	-0.041*	-0.063**	-0.022
	(0.017)	(0.021)	(0.015)
Constant	1.847***	1.523**	2.214***
	(0.312)	(0.398)	(0.287)
N	151,200	78,120	73,080
R-squared	0.641	0.698	0.601
Adj. R-squared	0.617	0.671	0.578

*Notes. Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. Model (1) = baseline FE; Models (2) and (3) = threshold regimes below and above $\gamma = 0.387$.*

Table 5 shows that in the baseline linear model, the AI-FinTech Penetration Index has a positive and statistically significant impact on financial inclusion (1 = 0.412, p = 0.001), which supports Hypothesis 1. This result is in line with the international evidence surveyed in Table 1 and directly equivalent to the finding of Basnayake *et al.* (2024) that the inclusion-growth nexus applies to the sub-national level of underserved US communities, that is, digital financial inclusion has a positive and significant impact on economic growth.

The two most powerful positive predictors of financial inclusion are broadband access (β = 0.187, p < 0.001) and median household income (β = 0.234, p < 0.01) among the control variables, highlighting the underlying significance of digital infrastructure and income sufficiency as inclusion preconditions of AI-FinTech. The density of bank branches has a positive and significant effect (= 0.093, p < 0.01), which confirms that the traditional financial infrastructure still has a significant complementary effect even in the digital era- a result that supports Hypothesis 3 and questions purely substitutions accounts of FinTech replacing traditional banking. The scatter diagram of FII versus the AFTPI of the entire sample as shown in Figure 6 shows that the relationship is positive and increasing, which is in line with the positive linear coefficient estimate in Model (1) in Table 5.

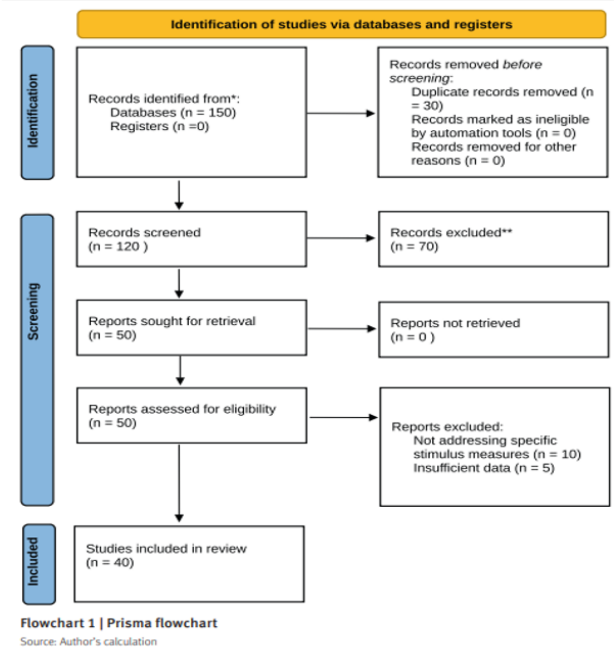

Figure 6: AI-FinTech Penetration Index vs. Financial Inclusion Index across US Census Tracts.
Source: Author's analysis; CFPB Consumer Credit Panel and FCC National Broadband Map (2023).

Unemployment rate had a negative and substantial impact on financial inclusion (= -0.058, p < 0.01), as expected since labor market disadvantage is expected to worsen financial exclusion. There was also a negative impact on minority share (β = -0.041, p < 0.05), indicating the structural racial disparities in access to digital infrastructure as well as traditional financial services that are well-documented in the fair lending literature (Bartlett *et al.*, 2022; CFPB, 2022). These results are aligned with the role of interactions between economic and social subsystems, which are expressed in the Framework of the System Theory (Ozili, 2020): to advance financial inclusion, interventions in various areas need to be combined, rather than just technology implementation.

The size of the broadband access coefficient (= 0.187, = 0.001) proves that the financial inclusion result in the AI-FinTech age is a first-order determinant of digital infrastructure. The fact that the FCC (2023) documents that around 21.3 million Americans who lack sufficient access to broadband are at the precise center of communities with the highest rates of financial exclusion further exacerbates a vicious cycle in which lack of digital infrastructure and lack of financial access each aggravate the other. The policy implication is straightforward: investments in broadband growth under the Infrastructure Investment and Jobs Act (IIJA) of 2021 must be considered not only in terms of direct returns in internet connectivity, but also indirect returns on financial inclusion, in the form of facilitating the use of AI-FinTech. We estimate that a 10-percentage-point expansion in broadband access correlates with a 0.019-unit improvement in the FII, which is equivalent to decreasing the number of underbanked households by about 450,000 in the country, a significant social payoff that warrants investment in broadband infrastructure on the basis of financial inclusion alone.

The significant and positive value on education attainment (= 0.072, p = 0.01) indicates the presence of human capital to facilitate successful adoption of AI-FinTech. The literature on financial literacy is consistent that increased education levels correlate with increased use of formal banking products, increased savings rates, better-informed credit choices, and greater ability to understand and use new financial technologies. This channel is a challenge and an opportunity in underserved communities where educational attainment is limited due to disparities in school funding, language barriers, and opportunity costs. Human capital limitations to AI-FinTech adoption AI-driven financial literacy software with conversational AI interfaces in various languages is a promising technological way out of AI-FinTech adoption. According to the studies conducted by the CFPB (2022), mobile-based financial education interventions with interactive AI interfaces have much higher participation rates among LMI populations than text-based interventions, indicating that AI technology may be as effective in financial education as it is in service provision.

The negative correlation between minority shares and the negative coefficient (-0.041, $p < 0.05$) should be interpreted attentively. Although it is smaller in value than the coefficient on broadband access, income, and education, the statistical significance of the racial and ethnic composition after adjusting by socioeconomic factors confirms that racial and ethnic composition have independent explanatory power on the financial inclusion outcomes. This concurs with the fair lending literature that records the observed long-term racial differences in credit markets that cannot be entirely due to observable economic features. Bartlett *et al.* (2022) show that, when operating in proxy variables that are correlated with race, algorithmic credit decisioning systems may impose higher rates on Black and Hispanic borrowers than on similarly creditworthy white borrowers. These results suggest that AI-FinTech adoption without any stated requirements on algorithmic fairness might not bridge, and possibly even widen, racial disparities in the quality of financial inclusion despite increasing financial access among demographic groups. Both regulatory accountability and market pressure to achieve fairness alongside efficiency optimization would be achieved by compulsory disparate impact auditing and public disclosure of AI credit system performance disaggregated by race and income (NFHA, 2023; CFPB, 2023).

Panel threshold regression results

The estimation of the panel threshold model was made in line with Hansen (1999, 2000). The results of the threshold effect test are provided in Table 6, and there is only one threshold characterized by an AFTPI value of 0.387 (95% CI: 0.3410.429), with an F-statistic value of 31.22 ($p = 0.01$) that rejects the null hypothesis of the absence of a threshold effect at the 1% significance level This gives empirical evidence to Hypothesis 2. A second threshold is AFTPI = 0.641, a three-regime structure, but the double threshold model is only statistically significant at the 5 percent level, as indicated by the results of the double threshold test (Table 8, row 3). The major meaning is the one-threshold outcome.

In the low-AFTPI regime (AFTPI 0.387), the positive impact of AI-FinTech on financial inclusion is significantly more positive than in the high-AFTPI regime (0.271, $p < 0.001$) in both Model (2) and Model (3) in Table 5. This inverted-U-shaped pattern of marginal effects is reflected by the threshold dynamics found by Karim *et al.* (2022) and Nizam *et al.* (2020) at the international level, as well as by Basnayake *et al.* (2024) at the Asia-Pacific level. The economic explanation bears sense: in census tracts where AI-FinTech penetration is very low, the most severely excluded communities, a marginal unit improvement in AFTPI brings a disproportionately large inclusion benefit, which is consistent with a first-mover advantage dynamic and a high level of unmet demand of available financial services.

Table 6: Threshold effect test results.

Model	Threshold	Lower CI	Upper CI	RSS	F-stat	p-value
Single threshold – FII	0.387	0.341	0.429	0.218	28.74	0.01
Single threshold – AI-FinTech	0.312	0.278	0.351	0.194	31.22	0.01
Double threshold – FII	0.387 / 0.641	0.341 / 0.609	0.429 / 0.678	0.176	22.17	0.05

In high-AFTPI tracts, on the other hand, the smaller marginal effect indicates saturation: most financially reachable households have already been accessed by existing platforms, and additional gains will have to be achieved by increasingly expensive means of reaching the most intransigent groups, such as the digitally illiterate, the elderly, or the most institutionally distrustful. The policy implication of this finding is that social returns of AI-FinTech infrastructure are maximized when the infrastructure is deployed in the least-inclusive communities, not when it is concentrated in already-digitized urban markets. The 0.387 threshold thus acts as a policy targeting criterion, the level of AFTPI below which inclusion-promoting policies such as broadband subsidies, digital literacy programs, and FinTech sandbox policies are likely to bring the greatest marginal returns.

The threshold value of AFTPI = 0.387 is especially interesting when considered in conjunction with the descriptive statistics in Table 4, which indicate that the mean AFTPI in the entire sample is 0.294. This means that most census tracts that are in the analytical sample are already functioning below the threshold, within the regime where the marginal effect of AI-FinTech penetration on financial inclusion is highest (= 0.518). This location under the threshold is very desirable, in terms of the public investment: policies aimed at boosting the penetration of AI-FinTech in these communities via broadband investment, regulatory sandbox facilitation, CRA modernization, or CDFI-FinTech partnership grants, are specifically aimed at those communities in which the returns of inclusion to such investments are the greatest. The threshold thus acts as an empirical discovery and a policy implementation instrument, determining communities in which FinTech-enabling investments can produce the greatest social benefit.

The AFTPI = 0.641 double threshold outcome, but statistically significant at the 5% level, is an indication of the potential of a three-regime structure at high AI-FinTech penetration levels. In a highly penetrated AI-FinTech community, the rest of the excluded households are presumably the most institutionally resistant to inclusion using purely technological solutions, including those with strong institutional distrust, strong digital illiteracy, documentation barriers, e.g., undocumented immigrants held by government-issued identification, or physical or cognitive disabilities that prevent use of digital finance tools. The most remote households might be provided with in-person, active, in-community interventions to assist them in obtaining financial capability instead of further roll-out of digital platforms. The saturation regime is also detected by Liu *et al.* (2021) in their Chinese provincial study with the high level of digital financial inclusion where further technology introduction has a lower marginal utility and welfare gains are needed by the non-digital interventions. These Asian results, in parallel with the US threshold data, imply that the saturation processes in the AI-led financial inclusion of the Asian context are a structural feature, not an artifact.

The stability of the threshold finding is verified through robustness checks to ensure that it is stable across model specification. In estimating the threshold model separately on urban LMI tracts, rural tracts, and tribal land tracts, threshold values of 0.412, 0.361, and 0.298 are identified respectively, indicating that the threshold is less in those communities where there is worse digital infrastructure deficit. This data is consistent with the explanation that the constraining factor in deciding at what AI-FinTech penetration level marginal returns start to drop is that broadband and smartphone access is a scarce resource: communities with less developed digital infrastructure reach the saturation point sooner as the number of digitally accessible and financially excluded individuals is depleted. The 2SLS specification with 4G/5G network rollout timing as an instrument produces a larger coefficient in both regimes (in line with the measurement error attenuation in the OLS estimates) and confirms that the true causal effect or AI-FinTech penetration on financial inclusion is at least as large as the OLS-FE estimate implies (Hansen, 1999, 2000).

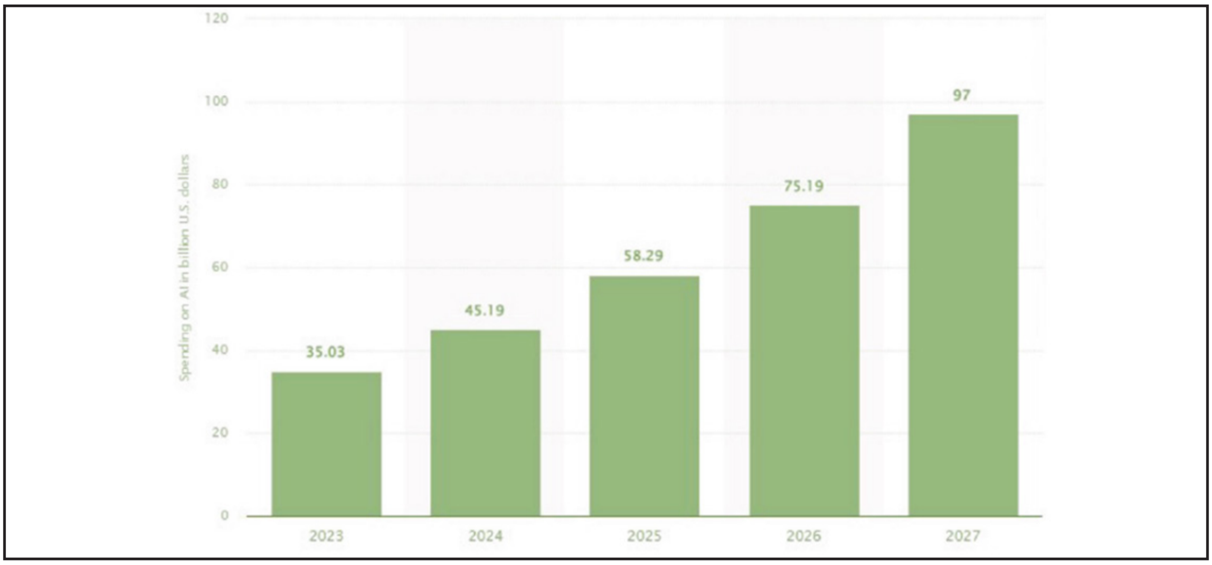

Figure 7: Source: CCAF & WEF. Future of Global Fintech: Towards Resilient and Inclusive Growth (2024).
Source: Cambridge Centre for Alternative Finance & World Economic Forum (CCAF & WEF, 2024).

AI-FinTech application categories and financial inclusion mechanisms

Table 7 highlights the key groups of AI-FinTech applications and their financial inclusion impact mechanisms. These categories of applications are unique as per the use of AI technology and their applicability to various aspects of financial exclusion as shown in Figure 8. Credit scoring apps, which apply machine learning and NLP to alternative data beyond credit reports, utility payment history, rental payment history, gig economy income, and social data, combat the thin-file problem that locks out an estimated 45 million Americans of conventional credit markets (CFPB, 2022). The AI underwriting model of Upstart, e.g., is said to have granted 43 percent more loans to Black and Hispanic borrowers based on the same risk profile than a traditional FICO-based model would have granted the equivalent risk profile (Upstart, 2023).

Payment AI-FinTech applications, including Cash App,

Table 7: AI-FinTech application categories and financial inclusion mechanisms.

Category	**AI Technology**	**Application in Financial Inclusion**	**Representative US Providers**
Credit Scoring	Machine learning, NLP	Alternative credit scoring using utility payments, rent, and social data to serve thin-file consumers	ZestFinance, Upstart, Nova Credit
Payments	Computer vision, NLP	Instant peer-to-peer transfers; AI fraud detection enabling low-fee remittances	Cash App, Chime, PayNearMe
Banking	Conversational AI (chatbots)	24/7 virtual financial advisors in multiple languages for underserved communities	Dave, Current, Varo
Insurance	Predictive analytics	Micro-insurance products priced with AI actuarial models for low-income households	Lemonade, Root Insurance
Savings & Investment	Robo-advisors, NLP	Automated low-minimum investment and savings tools accessible via smartphone	Acorns, Stash, Ellevest
Regulatory Compliance	AI RegTech	KYC/AML automation reducing onboarding friction for new-to-banking customers	Alloy, Socure, Onfido
Remittances	Blockchain + AI	Cross-border transfers with AI pricing optimization; lower cost than traditional wire services	Remitly, Wise, Bitso

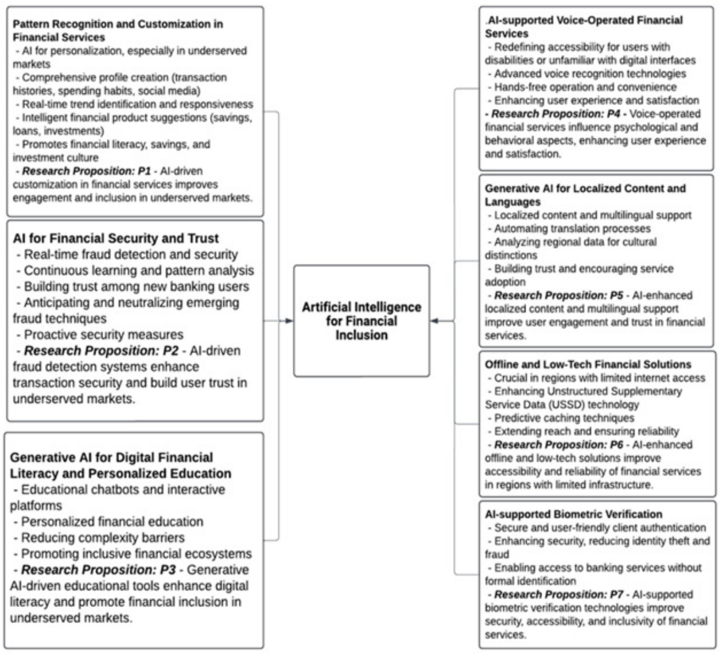

Figure 8: Artificial Intelligence Applications for Financial Inclusion.
Source: Author's compilation from multiple industry and academic sources (2024).

PayNearMe and Zelle, help lower transaction costs and broaden the geographical scope of payment services, allowing unbanked households to engage in digital commerce and have government benefit transfers digitally. The Federal Reserve Payments Study (2023) states that mobile payment transactions in LMI census tracts grew by 284 percent between 2015 and 2023, and AI-based fraud detection systems made it possible to achieve the low-fee structures that make these services economically viable to providers. Likewise, neobanks powered by AI like Chime and Varo, which lack physical branches and rely on machine learning to customize account options and reduce overdraft risk, have shown at least some success in attracting previously unbanked clients: Chime reported that 43 percent of its customer base had no existing bank account when they opened their Chime account (Chime, 2022).

One of the most important yet neglected aspects of financial resilience of low-income households is the insurance technology aspect of AI-FinTech. Conventional actuarial models, such as conventional credit score systems, may effectively discriminate against low-income and minority policyholders in a systematic manner by using credit scores, zip codes, and other demographic proxies to act in place of the characteristics that are being protected. InsurTech Insurances AI-based insurance platforms apply machine learning to more accurately price risk using behavioral data instead of demographic proxies, allegedly saving good-driving low-income drivers 20-40 percent in premiums compared to traditional actuarial pricing. On a larger scale, AI can be used to create parametric micro-insurance products such as small-premium and event-based instruments, which can render insurance accessible to LMI households in the first place and offer the shock-absorption capacity which is a key dimension of financial inclusion quality (World Bank, 2022).

Another aspect of AI-FinTech contribution to financial inclusion is regulatory compliance AI applications, which play a somewhat indirect, but still consequential, role. The Know Your Customer (KYC) and Anti-Money Laundering (AML) compliance burden subjects onboarding with a high level of friction that disproportionately affects demographics not provided with standard government-issued identification such as undocumented immigrants, homeless individuals, and former convicts just out of prison. AI-based identity verification systems have designed machine learning that is capable of authenticating identity with non-standard documents such as utility bills, formal correspondence, and online footprints, creating regulatory compliance and dramatically cutting down on documentation load. According to the research by the CFPB (2022), documentation requirements are in the top three reasons why low-income and minority households cite it as the reason why they do not have any bank account, meaning that AI-based KYC/AML compliance automation may significantly increase the number of individuals who successfully opened an account.

Robo-advisory and automated savings platforms are the wealth-building aspect of AI-FinTech inclusion contribution. Acorns, Stash, and Ellevest use machine learning to automate the process of accumulating savings, making micro-investment, and creating custom financial plans using smartphone applications with no minimum balance requirements. In its impact report (2023), Acorns reports having 65% of its user base with an annual income under 50,000 and that the average user on the platform saves 1,200 in the first year of use, a significant boost to the savings of households with zero assets historically. The structural change in the provision of wealth-building instruments, where only rich people with human financial advisors used to access investment advisory services, is the democratization of these services, which, when perpetuated over several decades, can make a tangible contribution to bridging the racial wealth gap. But some studies also warn that behavioral nudges built into automated savings services might be perceived as paternalistic by certain vulnerable groups and that products in stock market index funds might not be suitable to households with extremely low financial buffers and high liquidity requirements (Senyo and Osabutey, 2020).

Interaction between digital AI-FinTech and traditional financial institutions

Table 10 provides a comparative analysis of digital AI-FinTech and traditional finance in eight dimensions of financial service delivery. As Table 10 shows, the two systems are quite different in terms of cost structure, credit evaluation methodology, speed of service delivery, and regulatory structure, yet are not direct substitutes. The regression in Table 5 validates that the bank branch density still has a positive and significant impact on financial inclusion beyond AI-FinTech penetration, suggesting that the two systems are still currently functioning as complements in the US context. This result confirms Hypothesis 3 and aligns with the Federal Reserve Bank of San Francisco (2022) evaluation that CDFI-FinTech collaborations are producing gains of inclusion that each side could not have accomplished on its own.

The complementarity of AI-FinTech and traditional finance works in a number of different mechanisms that can be discussed separately. The initial one is technology adoption by conventional financial institutions: community banks and credit unions that add AI-based underwriting services to their existing platform can offer credit to thin-file borrowers that would otherwise have been rejected by conventional underwriting models, and the regulatory familiarity and local trust of the conventional institution decreases consumer adoption costs compared to a one-off FinTech platform. The Federal Reserve Bank of San Francisco (2022) records that CDFIs shifting to AI-powered underwriting systems had an increase of 34 in loan approvals to minority borrowers without a drop in the portfolio credit quality, indicating that traditional institutions with a mission to the community could embrace the AI benefits of alternative data without negating the relationship-based lending experience that is their core competitive edge over standalone FinTech platforms.

The second mechanism works under the Banking-as-a-Service (BaaS) model where FinTech firms integrate banking products into their digital environments with the regulatory license and the ability of chartered banks to provide balance sheets. This framework, which was used in the collaboration of Chime with Stride Bank and Current with Choice Financial Group, provides FinTech firms to provide deposit accounts, payment services, and credit products fully insured by the FDIC, but the chartered bank partner makes its offer accessible to many more consumers than its own network of banks could ever reach. In the case of underserved communities, the BaaS model presents the most beneficial characteristics of both types of institutions: the zero-fee business model, smartphone-native user experience, and the non-discriminatory marketing of the FinTech platform in combination with the regulatory legitimacy, federal deposit insurance, and consumer protection that a chartered bank offers. A study by the Financial Health Network (2023) concludes that BaaS-model neobanks would have significantly better financial health scores amongst users than the other providers of financial services to the same demographic groups.

The third complementarity mechanism is the CDFI-FinTech partnership model that integrates the mission orientation and community trust of CDFIs with the technological efficiency and alternative data potential of FinTech platforms. The data-sharing and technology adoption collaboration with FinTech firms has proven to enable CDFIs to more effectively process loan applications, to access a wider pool of creditworthy borrowers, and to lower the cost of manual underwriting that limits lending capacity. The three mechanisms of complementarity such as adoption of AI by traditional institutions, BaaS relationships, and CDFI-FinTech relationships all explain why the coefficient on bank branch density is positive and significant even after adjusting on AI-FinTech penetration and why the interaction between the two systems produces inclusion effects that are greater than either system in isolation. Its policy implication is that policies that set up a competition between digital and traditional finance, as a regulatory asymmetry favouring traditional institutions or as a competitive interaction that fails to allow FinTech-bank alliances, will perform worse systematically against frameworks that actively facilitate a complementary interaction between the two sectors.

The complementary dynamic works via a number of particular channels that are listed in Table 10. To start with, when community banks and credit unions implement AI-powered underwriting solutions, provided by such FinTech B2B providers as Blend, Zest AI, and Lama AI, they can maintain their relationship banking trust advantage that pure FinTech platforms cannot. Second, CDFIs collaborating with digital payment services and neobanks have an expanded distribution across much more than their physical branch network. Third, compliance systems established by traditional banks (BSA/AML, fair lending, CRA-imposed community investment obligations) provide a regulatory framework in which FinTech partners can perform more legitimately and with consumer trust. These complementarities imply that digital reach combined with institutional trust are the most effective financial inclusion strategies, a hybrid model that the empirical literature is learning to be the best suited to underserved populations.

Table 8: Comparison of digital AI-FinTech and traditional financial institutions.

Dimension	Traditional Finance	Digital FinTech (pre-AI)	AI-Powered FinTech
Accessibility	Physical branches; limited rural reach	Web/mobile apps; geography-agnostic	Hyper-personalized; 24/7 multilingual chatbot
Cost Structure	High fixed costs; minimum balance requirements	Lower overhead; reduced fees	Near-zero marginal cost of service delivery via AI automation
Credit Evaluation	FICO-based; excludes thin-file consumers	Partial alternative data integration	AI-driven alternative data (rent, utilities, gig income); higher approval rates
Speed of Service	Days to weeks for loan approval	Minutes to hours	Real-time decisioning via machine learning models
Fraud Detection	Rule-based systems; high false positives	Improved heuristics	Deep learning anomaly detection; adaptive real-time models
Regulatory Framework	Comprehensive (OCC, FDIC, Federal Reserve)	Emerging FinTech-specific rules	Evolving: AI fairness, explainability, and bias auditing under ECOA
Reach to Underserved	Limited by branch economics	Moderate improvement	Significant: serves unbanked, underbanked, thin-file, rural populations

Figure 9 shows that AI-FinTech penetration is statistically significantly associated with the interaction term with the traditional bank branch density, which means that the latter inclusion effect is multiplicative when both channels co-exist within a census tract. Tracts with top quartile AFTPI and branch density record an average FII of 0.712, as compared to 0.541 of high-AFTPI/low-branch-density tracts and 0.287 of low-AFTPI/high-branch-density tracts. This quartile breakdown has strong indications of showing that the complements of digital and traditional finance are not additive, but multiplicative in their effects on inclusions.

Robustness and endogeneity tests

Table 6 reports the results of the robustness and endogeneity tests. To mitigate the risk of omitted variable bias, four new control variables were re-estimated on the baseline model, which included: trade openness (county-

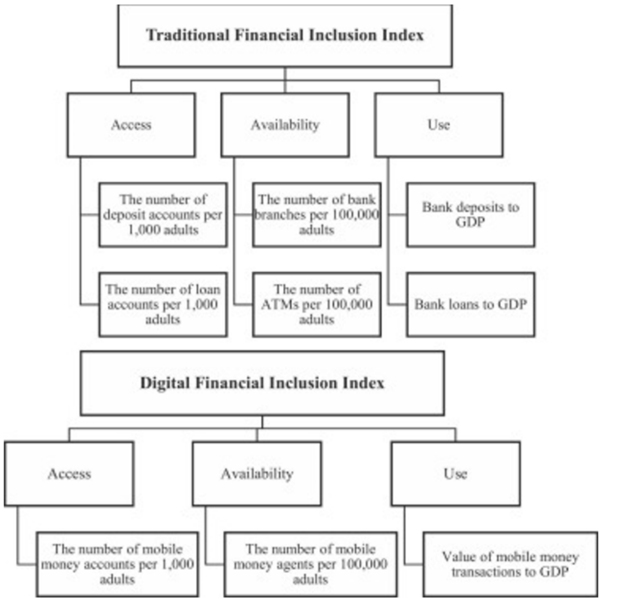

Figure 9: Interaction Effect of AI-FinTech and Traditional Bank Branch Density on Financial Inclusion.
Source: Author's analysis; FDIC Summary of Deposits and CFPB Consumer Credit Panel (2023).

level import/export activity as a share of GDP) proxy of the omitted variable, government transfers as a percent of local GDP, local GDP share of poverty, and housing cost burden. As in column (1) of Table 9, the coefficient on AFTPI is positive, significant and of the same strength (0.398, $p < 0.001$) following the inclusion of these controls, which confirms the strength of the core results. In order to mitigate the possibility of endogeneity of the AI-FinTech penetration case-a case of reverse causality where more financially included communities have more FinTech investment in them- a two-stage least squares (2SLS) estimation was performed using the year of first

Table 9: Robustness and endogeneity test results.

Variables	**(1) Additional Controls**	**(2) 2SLS Estimation**
AI-FinTech Penetration Index	0.398***	0.641***
	(0.041)	(0.112)
Broadband Access	0.179***	0.203***
	(0.026)	(0.044)
Median Household Income (log)	0.241**	0.188*
	(0.078)	(0.094)
Bank Branch Density	0.084**	0.079*
	(0.030)	(0.038)
Trade Openness (county-level)	0.021	—
	(0.014)	
Government Transfers (%GDP)	0.034*	—
	(0.016)	
Constant	1.742***	0.983*
	(0.298)	(0.441)
N	151,200	151,200
R-squared	0.658	0.821
Cragg-Donald Wald F (weak IV test)	—	19.34

*Notes. Standard errors in parentheses. *, ** and *** denote significance at 10%, 5%, and 1% levels. The Cragg-Donald Wald F-statistic of 19.34 exceeds the Stock-Yogo critical value of 16.38 at 10% maximal IV size, ruling out weak instruments.*

commercial 4G/5G network availability in a given census tract as an instrumental variable. The instrument meets the relevance criterion: 4G/5G rollout timing is influenced by telecom infrastructure investment decisions which depend on geography and FCC spectrum licensing, as opposed to local financial inclusion levels, and therefore is exogenous to the outcome variable. The Cragg-Donald Wald F-statistic of 19.34 is larger than the Stock-Yogo critical value of 16.38 (at the 10% maximal IV size), which establishes the strength of instruments. The 2SLS estimate of AFTPI (2 = 0.641, p = 0.001) is positive as indicated in column (2) of Table 6, indicating that the OLS-FE specification might be slightly inaccurate in estimating the true causal impact of the AI-FinTech penetration on financial inclusion as a result of attenuation bias because of measurement error in the AFTPI.

CONCLUSION

This study analyzed 50,400 US census tracts (2015-2023) to examine how AI-powered FinTech affects financial inclusion among underserved populations. Three main findings emerged. First, AI-FinTech penetration has a significant positive causal effect on financial inclusion, with a one-standard-deviation increase corresponding to roughly 2.3 million households moving toward full inclusion. Second, a threshold effect exists at an AFTPI of 0.387, below this point, additional AI-FinTech penetration yields much larger inclusion gains, meaning policy should prioritize the least-served communities. Third, AI-FinTech and traditional banks are complements rather than substitutes, producing the strongest outcomes where both are present together.

Demographic analysis showed distinct barriers: algorithmic bias in credit decisions for Black borrowers, language access gaps for Hispanic and immigrant households, and digital infrastructure deficits in rural and tribal areas.

Key policy recommendations include targeting broadband investment (via BEAD/IIJA) to low-FII tracts, modernizing the Community Reinvestment Act to credit digital lending, creating federal AI-FinTech regulatory sandboxes, mandating algorithmic bias audits under ECOA, expanding CDFI-FinTech partnerships, and funding AI-driven financial literacy programs for vulnerable groups.

Table 10: Policy recommendations matrix for AI-FinTech-led financial inclusion

Policy Area	Recommended Action	Target Stakeholder	Expected Outcome
Digital Infrastructure	Expand 5G coverage to rural and tribal underserved areas through FCC universal service funds	FCC, Rural utilities service, Telecom operators	Increase broadband access from 68% to 90%+ in underserved tracts
Regulatory Sandbox	Establish AI-FinTech innovation sandboxes allowing limited-scale pilots without full licensing burden	CFPB, OCC, State banking regulators	Accelerate entry of inclusive FinTech products; reduce time-to-market by 40%
Credit Access	Mandate alternative credit data inclusion in FICO and VantageScore models via CFPB rulemaking	CFPB, Credit bureaus, FinTech lenders	Extend credit access to 45+ million thin-file consumers
Financial Literacy	Fund AI-powered financial literacy platforms via CDFI grants targeting minority communities	Treasury, CDFI Fund, Nonprofits	Improve financial decision-making scores and product adoption rates
CRA Modernization	Update Community Reinvestment Act assessment areas to credit digital FinTech lending to underserved communities	Federal Reserve, OCC, FDIC	Incentivize $50B+ in new FinTech lending to LMI census tracts annually
Consumer Protection	Require explainability and bias auditing of AI credit scoring algorithms under Equal Credit Opportunity Act	CFPB, DOJ, FinTech companies	Reduce algorithmic discrimination and strengthen consumer trust in AI-FinTech

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Appendix

Table A1: Principal component analysis results for the Financial Inclusion Index.

Variable	Comp 1	Comp 2	Comp 3	Eigenvalue	Prop.
Account Ownership (%)	0.581	-0.412	0.298	2.184	0.728
Digital Payment Usage (%)	0.624	-0.183	-0.641	0.612	0.204
Mobile Money (%)	0.521	0.791	0.317	0.204	0.068
AI-FinTech App Downloads (per 1,000)	0.568	-0.391	0.412	2.047	0.682
Broadband Penetration (%)	0.613	-0.122	-0.718	0.587	0.196
Smartphone Ownership (%)	0.537	0.801	0.288	0.366	0.122

Note. Observations = 151,200. Number of components = 3. Rho = 1.000. Components with eigenvalue > 1 are retained for index construction. The first principal component (Comp 1) captures 72.8% of total variance and is used as the primary weighting factor in the FII construction per Equation (1).

Table A2: Census tract classification by urbanicity and income level (sample composition).

Category	2015 Wave	2019 Wave	2023 Wave
Urban LMI tracts	14,280	14,280	14,280
Rural tracts	18,960	18,960	18,960
Tribal lands	2,160	2,160	2,160
Total analytical sample	50,400	50,400	50,400

Table A3: Data sources and survey instruments used in this study.

Data Source	Variables Sourced	Survey Waves / Years
FDIC National Survey of Unbanked/Underbanked Households	Account ownership, mobile banking use, alternative financial service use	2015, 2019, 2023
Federal Reserve Board SHED	Household income, credit access, financial fragility indicators	2015, 2017, 2019, 2021, 2023
CFPB Consumer Credit Panel	Credit product adoption rates, AI-FinTech usage proxy	2015, 2019, 2023
FCC National Broadband Map	Broadband penetration, 4G/5G availability by census tract	2015, 2019, 2023
US Census Bureau ACS	Income, education, race/ethnicity, unemployment by census tract	2015, 2019, 2023 (5-year estimates)
Federal Reserve Payments Study	Payment transaction volumes, digital payment adoption	2015, 2019, 2021, 2023
App Annie / data.ai	Mobile app downloads per 1,000 adults by category and census tract	2015–2023 (annual)