Financial inclusion effects of engaging with the fintech ecosystem

Odongo Kodongo

ERSA Working Paper 893

August 2024

Financial inclusion effects of engaging with the fintech ecosystem

Odongo Kodongo[1]

Abstract

Using the FinAccess Kenya Household Survey dataset, we construct a metric of individual engagement with the fintech ecosystem and examine its linkage with consumption of traditional financial products. Deploying a battery of econometric procedures, we document a pervasive gap in the usage of traditional financial products, ranging from 5.3% to 17.5%, between individuals who engage with the fintech ecosystem and those who do not. Treatment-effects procedures yield evidence that engaging with the fintech ecosystem improves individuals' usage of traditional financial products by about 4 percentage points. The positive impact of the fintech ecosystem on the usage of traditional financial products is enabled by fintech mitigating the distance barrier. Interestingly, our findings suggest that the fintech ecosystem does not perform well in addressing financial inclusion inequalities facing young adults, women, the less educated and less wealthy people. We offer policy guides and future research suggestions anchored on these findings.

Keywords: Fintech ecosystem; financial inclusion; financial products; engagement

JEL Classification: G20; G100; J16; O17

[1] Wits Business School, 2 St. David's Place Parktown, Johannesburg 2193. Email: odongo.kodongo@gmail.com

1. Introduction

Consider a self-employed young man living in Nairobi, Kenya. Suppose now that both the young man and his aunt (who lives in a rural village) own and use mobile money accounts (i.e., engage with the fintech ecosystem). Using mobile money services, the young man remits money to his aunt whenever her consumption needs exceed her income. Provided that the young man remains productively employed, their mobile money accounts would help his aunt to smooth her consumption. Thus, due to their ownership and transactional use of mobile money accounts, some studies (e.g., Bollaert et al., 2021; N'dri and Kakinaka, 2020; Shaikh et al., 2023) may infer that both the young man and his aunt are financially included. Yet, questions arise regarding the nature of their inclusion. For example, can the young man access *formal* credit to grow his informal enterprise via his mobile money account? Suppose the young man's enterprise fails, can his aunt rely on her mobile money account for consumption smoothing? That is, is the aunt's mobile money account sufficient to enable her to smooth consumption without her nephew's benevolence?

These questions essentially speak to the difference between formal usage (involving a regulated financial institution) and informal usage (involving only non-regulated institutions) of financial services (Johnen and Mußhoff, 2022). Following Demirgüç-Kunt and Klapper (2013), we argue that although certain types of fintech services usage (e.g., money remittance) are sometimes characterized as financial inclusion (Shaikh et al., 2023) due to their short-term benefits (e.g., consumption smoothing), they may lack the long-term benefits (N'dri and Kakinaka, 2020) often associated with formal financial services usage (e.g., pension). For example, relative to formal credit, informal digital credit is associated with high interest rates[2], which may lead to debt overload (Brailovskaya et al., 2021), and loan amounts that are often too low to foster long-term positive change in users' wellbeing (Johnen, Parlasca, and Mußhoff, 2021). Thus, individuals are considered (effectively) financially included only if they access and use financial services of formal (regulated) institutions and/or markets (Demirgüç-Kunt and Klapper, 2013; Allen et al., 2016).[3]

[2] For example, Kenya's leading mobile service provider, Safaricom's short-term credit service, *Fuliza*, charges a minimum maintenance fee of KES 18 per day on transactions between KES 1001 and 1500, which translates to a 36% monthly interest rate (accessed 03.10.2022).

[3] In this paper, we use the term, "traditional financial products" to refer to usage of formal financial products and services of regulated financial institutions and markets even if the formal products/services are offered on non-conventional platforms (mobile or internet), and even if the institution has partnered with a non-regulated institution for broader reach. Thus, depending on the context, "traditional" and "formal" are used interchangeably. The word "conventional" is used to refer to services and products offered only on traditional platforms such as physical branches of financial institutions or brokerage houses. Further, in many parts of our discussion, we use the short

Consequently, fintech has been criticized as designed to exploit the despair of financially excluded users to satisfy the profiteering incentives of supply-side actors.[4] Such misalignments of incentives between the supply and demand side agents could be mitigated if the fintech ecosystem fostered usage of traditional financial products (in conventional or digital formats) of regulated financial institutions which, additionally, promote responsible financial behavior (e.g., by pegging credit to its affordability to applicants) and avail professional financial advice to consumers.[5] The central theme of this paper, therefore, is to ascertain if engagement with the fintech ecosystem (e.g., ownership of a mobile device *and* using it to consume fintech services) can explain individuals' consumption of formal financial products. That is, we test the implications of Arner et al.'s (2020) contention that the real opportunity afforded by fintech is that it develops an "infrastructure for a *digital* financial *ecosystem* that underpins financial inclusion."

This is important given the burgeoning body of evidence of a close link between the usage of formal financial services and individual welfare (e.g., Chakrabarty and Mukherjee, 2021; N'dri and Kakinaka, 2020). For example, field experiments from African countries such as Kenya (Dupas and Robinson, 2013; Schaner, 2017) and Malawi (Brune et al., 2016) find that addressing barriers to formal savings can lead to large positive effects on household expenditures. Elsewhere, access to banks' savings accounts aids poor households to better manage their resources in Nepal (Prina, 2015), has a positive effect on household income in Sri Lanka (Callen et al., 2019), fosters consumption smoothing in Chile (Pomeranz and Kast, 2022) and India (Somville and Vandewalle, 2023), and improves poor people's wellbeing in 38 countries (Martin and Hill, 2015). The success of financial inclusion should therefore be manifested in its ability to improve the wellbeing of included individuals. And though not conclusive, the foregoing literature appears to infer important implications of consumption of formal financial services on welfare. Thus, it is interesting to ask the question of whether

---

form, "fintech ecosystem" or merely "fintech" to refer to "individuals' engagement with the fintech ecosystem". Finally, the terms, "financial services" and "financial products" are used interchangeably.

[4] Critics such as Natile (2020) argue that that mobile money (specifically m-pesa), although touted as a development agent, focuses on private profit and fails to address the underlying causes of financial exclusion such as lack of resources and irregular or low income. Also critical are Yue et al. (2022), who point out that fintech (typified by digital finance) has created perverse incentives, such as impulsive spending, whose consequence has been an increased debt burden among the newly included financial consumers, which has tended to overshadow the positive benefits of improved access to the credit market. Other critiques such as Gabor and Brooks (2017) aver that fintech thrives on commodification of new financial consumers' personal data and use of data analytics to nudge individual behavior in the direction that promises the largest pecuniary rewards to service providers at the expense of the consumers.

[5] Financial institutions such as unit trusts and mutual funds routinely generate a risk profile of their investors, which they use to advise them (investors) on the most appropriate product portfolios and investment horizons.

individual engagement with the fintech ecosystem fosters their usage of formal financial services.

How, conceptually, is this possible? The modalities of action of the fintech ecosystem in incentivizing formal financial service consumption have been argued in the literature. First, physical access to financial institutions entails large costs (e.g., travel costs, opportunity costs of daily earnings lost) that may discourage consumption of services availed at such institutions (Muralidhar et al., 2019) by individuals with access to them. Because digitalization of services may eliminate some of these costs, fintech may address the problem of financial access without usage. Second, since the consumption of services such as credit is often tied to loan applicants' credit history, an important facilitation role of the fintech ecosystem is that digital transactions leave a transparent electronic trail that facilitates credit evaluation (Philippon, 2019). Third, through big data and analytics offered on the fintech ecosystem, service providers such as fintech start-ups have better appreciation of users' risk profiles (Gabor and Brooks, 2017) which enables them to channel appropriate products to consumers.

Fourth, the literature documents mixed evidence on whether informal finance (where a large part of fintech applications reside) and formal finance are substitutes or complements. Tang (2019) finds that peer-to-peer (P2P) platforms (informal finance) are substitutes for banks (formal finance) because they serve the same borrower population but are compliments to banks in terms of loan size (P2Ps tend to serve small borrowers while banks serve large borrowers). Further, some studies argue that because they are often inadequately capitalized, informal service providers face resource constraints that force them to seek financing from banks (making them complimentary), bridging the gap between informal and formal financial sectors (cf. literature in Madestam, 2014). However, "nested intermediation" of this type is inefficient and may raise the cost of finance to consumers thereby diminishing its potential benefits. For example, although informal financiers may use social networks to mitigate moral hazard problems in their contracts, such information may be costly (tedious process of gathering information from the often-unreliable social networks). Through its flexible features[6] (Karlan et al., 2016) and big data applications, the fintech ecosystem may address the costly information imperfection of nested intermediation and hence more efficiently link informal and formal usages.

Given these compelling reasons, it is straightforward to appreciate why some recent studies (e.g., Demir et al., 2022; Ghosh, 2022; Shaikh et al., 2023) find close linkages between

[6] Karlan et al. (2016) observe that active usage of savings accounts at formal financial institutions can be made easier by enhancing their features to mitigate behavioral biases that disincentivize their use. Because digital platforms can be "configured to create sub-accounts, and to provide real time information", they can more easily enhance such features and foster savings usage.

facets of the fintech ecosystem and financial inclusion. Such studies generally employ unidimensional metrics including mobile money in the contexts of person-to-person transfers (Jack and Suri, 2014) and transaction usage (Demir et al., 2022), government-to-person digital cash transfers (Banerjee, Karlan and Zinman, 2015), and smart cards (Muralidharan, et al, 2016). Studies have also proxied fintech using supply side unidimensional metrics such as biometric identification (e.g., Gine et al., 2012), believed to able to address information asymmetry (Rjoub et al., 2023). Although such studies document valuable insights, the insights are not generalizable across the various facets of the fintech ecosystem, understood as a *multidimensional* network of financial activities underpinned by modern digital technology (Oborn et al., 2019; Chen and Zhang, 2021). Indeed, unidimensional fintech applications do not happen in a vacuum but depend on the well-functioning of the entire system, in which dynamics such as agent behavior, system downtime, and data security, affect consumer experiences (Karanasios, 2018; Lee and Shin, 2018). Thus, individuals who engage more with the fintech ecosystem (e.g., own a digital device, are financially literate, use mobile money, and can resolve supply-side inefficiencies) are better able to ascend to advanced applications such as usage of sophisticated formal financial products like securities investments and insurance.

Therefore, to understand the role of fintech on financial inclusion necessarily requires an appreciation of its multifaceted nature. The multifaceted nature of fintech motivates the need to begin our analysis by proposing a broad-based construct that represents individuals' engagement with the fintech ecosystem, interpreted as the microlevel analog of the fintech ecosystem. A key innovation of this study, the construct is built by operationalizing recent conceptual proposals of Kangwa et al. (2020).[7] We provide a detailed description of the construct in Section 3.1.2. We deploy the new construct to explore the interesting linkage between individuals' engagement with the fintech ecosystem and their usage of financial products of regulated institutions and markets. We examine the linkages using the 2021 FinAccess Kenya Household Survey data.[8] Because the survey was specifically designed to measure financial inclusion, it covers many of its facets including those related to fintech applications. It also provides information on characteristics of individuals which are useful for exploring potential heterogeneities.

---

[7] The proposals, and hence the construct, draw from the understanding of the fintech ecosystem as a subset of the broader digital ecosystem (defined by Barykin et al. (2020) as a "self-organizing, and sustainable network with digital platforms at the base, which forms a single information environment where members of the ecosystem can interact when no hard functional ties exist between them") that exploits technological advances to serve as platforms for provisioning financial services. The readiness for and ability of individuals to access and consume the products and services, and to engage with the associated processes, essentially constitute the fintech ecosystem at the microlevel.

[8] Details on the FinAccess 2021 Kenya Household Survey are provided in Section 3.

Kenya is an appropriate laboratory for testing the implications of the fintech ecosystem for financial inclusion for several reasons. First, Kenya is the pioneer of mobile money technology (Jack and Suri, 2014) and has witnessed notable expansion in the fintech sector in recent years (Bachas et al., 2018), with many innovations around the mobile wallet concept. Second, Kenya ranks first in Africa, and second only to China globally, in mobile payment usage, with mobile wallet and phone transactions amounting to about 87% of its GDP.[9] The fintech ecosystem in Kenya has witnessed remarkable growth since the launch of the revolutionary m-pesa money transfer platform in 2007: the country had at least 385 registered fintech firms as of July 2022, operating in various fintech subspaces such as savings and credit, cryptocurrency and foreign exchange, insurance, and neo-banking.[10] Further, the traditional banking subsector has increasingly become an important player in the country's fintech ecosystem (Bollaert et al., 2021).

Third, Kenya's financial development is considered weak even by Sub-Saharan African standards: IMF data show that Kenya's level of financial development in 2021 was an index value of 0.17 (out of a possible 1.00) compared to countries in the region, such as South Africa (0.55), Mauritius (0.49) and Namibia (0.40). Lower levels of financial development, such as Kenya's, are believed to diminish opportunities for formal financial access especially to low-income individuals who entail higher information asymmetry risks (Madestam, 2014). Because information asymmetry might be easier to address through informal finance (loan sharks, table banking, pawnshops, etc.) due to its superior access to soft information available on social networks (Allen et al., 2021) than through formal finance with its propensity to minimize contracting frictions via techniques such as credit scoring (to mitigate adverse selection) and collateralization (to address moral hazard), informal financial access typically outstrips formal access in less financially developed economies.

With its low level of financial development, therefore, it is logical to expect Kenya's informal access to financial services to outstrip formal access. Interestingly, this is not the case: the 2021 FinAccess data (Figure 1a) show that the country's formal financial access has grown considerably in recent years displacing informal access. The growth in *access* to formal financial services appears to coincide with growth in the consumption of fintech services. The data show an increasing trend in digital finance uptake, with mobile money usage, for example, rising from 27.9% of the population in 2009 to 81.4% in 2021 (Figure 1b). Thus, a close relationship potentially exists between dynamics in the engagement with the fintech ecosystem and financial

[9] This is according to a recent discussion paper by the Boston Consulting Group.
[10] https://tracxn.com/explore/FinTech-Startups-in-Kenya

inclusion. Whether this apparent nexus is indicative of an unequivocal role played by the fintech ecosystem in fostering *usage* of formal financial services is the main empirical question examined in this paper. See Figure 1.

The paper makes several contributions to the literature. Firstly, recent studies employing Kenyan data (e.g., Jack and Suri, 2014; Mbiti and Weil, 2016; Mallinguh et al., 2017) like most others in the literature (e.g., Riley, 2018; Kim, 2020; Dizon et al., 2020; Aziz and Naima, 2021; Morgan, 2022; Shaikh et al., 2023), focus exclusively on variations in one aspect of fintech while neglecting, and hence downplaying the effects of, other important fintech dimensions. We advance the literature on the relationship between fintech and financial inclusion away from this narrow focus by deriving a construct from fintech's multiple facets, which enhances the generalizability of test results. Secondly, many studies argue that fintech can address barriers to financial access such as distance (e.g., Muralidhar et al., 2019) and mitigate factors inhibiting usage such as lack of trust (e.g., Allen et al., 2016) and financial transaction history (e.g., O'Neill et al., 2017; Philippon, 2019). Our study formalizes these conjectures by empirically testing the channels of transmission from engagement with the fintech ecosystem to the usage of formal financial services/products.

Thirdly, to overcome limitations imposed by data paucity, recent studies (e.g., Demir et al., 2022, Hodula, 2022) use panels of many countries to examine relationships of the kind explored in this study. While such research designs may improve external validity, combining countries with different characteristics, even with fixed effects controls, may mask important observed country-level idiosyncrasies, the identification of which may provide useful insights. We address this concern by focusing on one country. This focus enables us to explore previously neglected heterogeneities inherent in the linkages between fintech and formal financial product usage. That is, we test whether the utilization of formal financial products by individuals of differing demographics is equally facilitated by the extent of their engagement with the fintech ecosystem.

We document several interesting findings. First, we provide evidence relating consumers' intensity of engagement with the fintech ecosystem to financial inclusion rather than the supply side as is the norm in the empirical literature (e.g., Aziz and Naima, 2021; Morgan, 2022; Shaikh, Glavee-Geo, Karjaluoto and Hinson, 2023). In this regard, we document a robust positive relationship between individuals' engagement with the fintech ecosystem and the use of traditional financial products. Specifically, the results show that engagement with the fintech ecosystem is associated with an increase in the probability of usage of traditional financial products by at least 0.6 percentage points. These effects remain robust after controlling endogeneity and selection biases and when we employ treatment effects, which allow us to make causal inferences.

Second, we find that the distance barrier is as much a disincentive to the use of the fintech ecosystem as it is to access to financial institutions. Nevertheless, the fintech ecosystem tends to address the distance barrier to using formal financial services, perhaps because some of such services are now commonly available in digital formats, which lowers the transaction costs associated with their consumption when supplied via conventional channels. Third, we sought to document the demographic profiles of key beneficiaries of fintech as a financial inclusion enabler. We find that engagement with the fintech ecosystem is associated with an improvement in the consumption of capital market products for older adults (people aged at least 35 years), and more educated individuals (people with secondary and tertiary education). That is, relative to those who do not engage with the fintech ecosystem, fintech facilitates traditionally favored individuals to enjoy higher consumption of securities (e.g., equities and bonds). Importantly, engagement with the fintech ecosystem fails to address inequalities in the consumption of savings, insurance and credit for females, young adults, the less educated, and less wealthy individuals.

The balance of this paper proceeds as follows. We review the literature and state the study's hypotheses in Section 2. Section 3 highlights stylized facts on the fintech ecosystem and financial inclusion in Kenya, describes the data, and addresses measurement issues. The empirical strategy is outlined and executed in Sections 4 and 5 which, additionally, present and discuss the study's tests results. Section 6 concludes and draws policy inferences.

2. Hypotheses development

2.1. Theoretical framework

Economic theory has identified many channels through which the fintech ecosystem may influence the uptake of traditional financial products. First is the transaction cost hypothesis (Mbiti and Weil, 2016; Bachas et al., 2018). Financially included individuals support intertemporal consumption using suitable financial products. However, all else equal, transaction costs reduce the size of the future consumption bundle that can substitute the current consumption bundle, thus diminishing the individual's total consumption opportunity set and limiting the ability of financial products to facilitate consumption smoothing. Transaction costs constitute a range of charges levied by financial institutions such as account opening charges, loan origination fees, and minimum account balances; and access costs such as distance to a financial institution, and opportunity costs, as discussed. The demand for financial services is a function of consumers' desires to attain higher levels of utility through lower transaction costs (Benston and Smith Jr., 1976): accordingly, when a large variety of formal financial products/services can be obtained on a single platform (e.g., fintech spaces) or at a location, the marginal transaction costs for consumers fall considerably, which induces greater consumption of such products and services.

The asymmetric information hypothesis provides the second major channel through which the fintech ecosystem may influence the usage of traditional financial products. Markets may be characterized by discrepancies in information held by counterparties (information asymmetry). Information asymmetry is particularly profound in the financial markets where borrowers often know more about their own moral suasion and industriousness than lenders (Leland and Pyle, 1977). Moreover, because borrowers may be rewarded for overstating their positive traits, it is unrealistic to expect them to be entirely honest about their characteristics. Therefore, lenders must ascertain the true characteristics of their counterparties, which may be costly or unviable. By meticulously documenting people's financial transactions that pass through it, the fintech ecosystem eases information gathering, and lowers the cost of borrowers' credit evaluation, thereby reducing information asymmetry and stimulating financial contracting.

The third theoretical lens for viewing the nexus between fintech and financial inclusion is what we describe, in this paper, as the "trust hypothesis". Gambetta (2000) describes trust as an economic agent's subjective assessment of the odds that another agent will perform a specified action without being monitored. Thus, trust exists if there are reasonable prospects that a party to a contract will take action that is beneficial (or at least not detrimental) to their counterparty. Estimates of expected return in financial contracts are informed by trust amongst counterparties (Xu, 2020): by lowering individuals' assessments of the odds of counterparty dishonesty, trust may improve expected returns (Guiso et al., 2004). In the financial inclusion context, an individual's decision to save at a financial institution, for example, requires the individual's trust that the institution will protect him/her from avoidable loss (Xu, 2020); in same way, the utilization of fintech products is enabled by individual users' trust not just in the fintech infrastructure (Pavlou, 2003) but also in the supply side agents. In the empirical literature, studies highlight the role of (mis)trust in fostering the preference for cash over formal savings in some countries (Stix, 2013).

2.2. Hypotheses

Recent studies employing Kenyan data document a strong role for various aspects of the fintech ecosystem on financial inclusion. For instance, Kim (2020) finds that mobile money has improved the quality of life of the poor in Nairobi by providing a service that enables them not only to save but to do so more frequently. Similarly, Ntwiga (2019) finds that the consumption of credit is explained by source of financial advice, financial literacy, and perceptions on cost and trust, which are positively linked to fintech. Mallinguh et al. (2017) observe that m-pesa ignited a remarkable digital revolution in Kenya, whose result has been the merger of mobile and financial services, which has improved connectivity, expanded financial inclusion, and pressured the government to address cyber-security threats, address the provisioning of relevant infrastructure, and develop an enabling regulatory environment. However, Osoro and Muriithi (2018) call for going beyond the mobile payment services and incorporating "deeper usages" of financial services.

Built on emerging digital technologies, the fintech ecosystem enables supply-side actors to specialize in the provisioning of services in which they have comparative advantage, which lowers the aggregate cost of provisioning of the interrelated services (e.g., Riley, 2018), widens the reach of financial services (World Bank, 2014), and improves trust on the demand and supply sides of the financial services market. Therefore, the specialization may benefit the underprivileged by bringing them into the formal financial system where they can realize welfare gains from increased consumption of financial services.[11] For example, commercial banks could provide services directly (through traditional channels like banking halls) or by partnering with telcos to use mobile service platforms, which foster access to remote locations and lower service provision costs (e.g., by eliminating the need to invest in branches). The resulting lower costs (e.g., lower cost of loan applications) should increase the consumption of formal financial services. Thus, it is sensible to argue that higher usage of traditional financial services (e.g., credit in the foregoing example) can be achieved through greater fintech ecosystem engagement. This is our first hypothesis:

H1: Engagement with the fintech ecosystem increases the consumption of traditional financial products.

In Kenya, where the informal sector creates at least 83% of total employment[12], a large proportion of the active labor force is informally employed, earning daily wages. In such

[11] To illustrate this point, Safaricom (a mobile service provider in Kenya) partnered with Commercial Bank of Africa (now NCBA) in 2012 to operate *m-shwari*, a digital product that enables individuals to save and apply for credit in small denominations via their mobile money accounts.[11] In the context of this study, *m-shwari* can be seen as enabling previously financially excluded individuals to transit from "mere" access to digital remittance services offered on their mobile money accounts to using formal financial services of a regulated financial institution.

[12] In the 2021 Economic Survey, the Kenya National Bureau of Statistics documents that Kenya's informal sector created 14.5 million jobs, accounting for 83.4% of total employment outside of small-scale agriculture.

situations, physical access to financial institutions may entail large costs, including opportunity costs of lost daily wages, travel costs (Muralidhar et al., 2019) plus the standard supply-side levies (see Section 2.1). For such individuals, these costs collectively constitute transaction costs and, considered relative to the value of their financial transaction (typically small in absolute terms), increase the average transaction cost considerably. As explained, the fintech ecosystem may lower transaction costs for such individuals (Mbiti and Weil, 2016; O'Neill et al., 2017) by minimizing travel expenses and lost earnings. This may address the problem of access to formal financial services (e.g., owning a bank account) without usage (e.g., credit). Thus, we state the study's second hypothesis as:

H2: The fintech ecosystem alleviates the distance barrier to the usage of traditional financial products.

For low-income individuals whose earnings and expenditures are largely cash-based, and hence unrecorded, information asymmetry (especially in credit contracting, where financial institutions must work with high default premiums) is an important financial inclusion barrier. In this case, the fintech ecosystem presents the additional benefit of leaving an electronic trail which is not only transparent (Muralidhar et al., 2019), but also establishes a financial history (O'Neill et al., 2017), and plays a crucial facilitation role in credit evaluation (Philippon, 2019). The practicality of using digital transaction records has been demonstrated by institutions, such as Orange Bank Africa, which have adopted innovative ways of credit appraisal that utilize customer data on mobile money transactions.[13] This leads to the third hypothesis of this study:

H3: The fintech ecosystem mitigates the transaction history barrier to the usage of formal financial products.

The effectiveness of financial contracting is informed by the legal enforceability of contracts as well as on the extent to which the counterparties to the contract trust each other (Sapienza and Zingales, 2011). Because personalized, or mutual, trust is developed through repeated interactions, less educated, rural-dwelling, young women (as an example) are likely to self-exclude from financial services if they exhibit low levels of trust towards formal financial services providers, to which they are often less exposed and therefore hardly interact with. Low trust in financial institutions/markets, in part informed by fraud, weak governance, and uncertainty, is regarded as an important demand-side financial inclusion obstacle (Ghosh, 2021) that is difficult to surmount. To illustrate the profound effect of mistrust, Allen et al. (2016) find

[13] This is according to GSMA's 2021 State of the Industry Report on Mobile Money.

that respondents in the former Soviet Union, previously beset by state expropriation of bank assets, were 31% more likely than respondents in other regions to choose, "I don't trust banks" on a questionnaire.

The fintech ecosystem may address the problem of mistrust in many ways. For example, mobile payment systems are built to be proactive: they provide instant evidence that a transaction has been completed; and have inbuilt functionalities to minimize the probability of mistakes, and to ease the resolution of mistakes if made. This potentially explains recent evidence that a fall in the level of trust in financial services incumbents often induces emergence and increased financing of fintech ventures (Cojoianu et al., 2021). Thus, we formulate our fourth hypothesis as follows:

H4: The fintech ecosystem fosters the usage of traditional financial products by promoting trust.

On the supply side, subject to government agencies providing a conducive regulatory environment, innovative fintech start-ups could transform and unbundle traditional financial services to create highly personalized products that target specific consumer preferences and needs (Senyo et al., 2022). Indeed, as Gabor and Brooks (2017) observe, through big data and data analytics, service providers (e.g., fintech start-ups, and banks) have better understanding of the risk profiles of users, which enables them to channel appropriate products to potential consumers.

3. Data

All the data for this study are obtained from the 2021 FinAccess Kenya Household Survey. The sampling frame is drawn from the 5th National Sample Survey and Evaluation Program, which consists of 5,360 clusters stratified into urban and rural areas of each of the 47 counties. Being urban, Nairobi and Mombasa counties are not stratified, putting the number of strata at 92. A three-stage stratified cluster sampling design is then employed. In the first stage, 1000 clusters from NASSEP are selected; in the second stage, systematic random sampling is used, to create a uniform sample of 11 households per cluster. In the third stage, one eligible individual, aged at least 16 years, is selected (sampled without replacement) from a roll of all eligible individuals in each household using the KISH grid. A total of 8669 individuals are interviewed, of which adults (individuals aged 18 years and above) comprise 92.4%. After cleaning and processing, 7230 observations are documented, which are weighted back to the population to be representative at the national and regional levels. This study employs all the 7230 observations.

3.1. Variables and measurement

3.1.1. Financial inclusion

As explained, we use the term financial inclusion to refer to the consumption of traditional (intermediated) financial products of regulated financial institutions and capital markets. Thus, we proxy financial inclusion with savings, credit, and insurance (financial institutions usage) and securities investments (capital markets usage). We omit pensions usage because enrolment into pension and provident funds may sometimes reflect statutory obligations on the part of employers rather than individual choices. We define usage as "currently using" a financial product.[14]

3.1.2. Engagement with the fintech ecosystem

The fintech ecosystem rests on a digital financial infrastructure comprising of four pillars (Arner et al., 2020), namely, (i) digital ID and electronic know-your-customers; (ii) open electronic payment systems, infrastructure, and an enabling regulatory and policy environment; (iii) account opening initiatives and electronic provision of government services; and (iv) digital financial market infrastructure and systems that support value-added financial services and deepen access, usage and stability. The infrastructure serves five broad categories of actors in the fintech space (Lee and Shin, 2018): on the supply side are *fintech startups*, which offer technology-linked payments, financing, wealth management, and other services; *technology developers*, offering services like big data analytics, cryptocurrency, and cloud computing; and *traditional financial institutions* such as banks, insurance firms, and mutual funds; on the demand side are *consumers* of financial services and products. The fifth actor is the government through its financial sector *regulatory agencies*.

The generic identification of actors (Lee and Shin, 2018) and their interconnectedness in an African-country context (Senyo et al., 2022) is the first step toward understanding the fintech ecosystem. More important for this study are the modes of action of the ecosystem in promoting financial inclusion. Kangwa et al. (2020) propose a set of conditions necessary for the fintech ecosystem to facilitate financial inclusion. First, financial-inclusive business models must consider clienteles' *digital consumerism*, especially in Sub-Saharan Africa where there has been a boom in youthful tech-savvy consumers. Digital consumerism is characterized, at the individual level, by ownership of digital devices, social media networking, and ability and

[14] The other options available in the FinAccess questionnaire are "used to use" and "never used". The questionnaire includes follow-up questions for individuals who "used to use" a product to explain why they no longer use the product, but the responses are too few-and-far-between to be useful for the current analyses.

propensity to use digital technologies. Included in our understanding of digital consumerism are fintech start-ups and technology developers, which avail these technologies to digital consumers. The second condition is *financial capability*, which describes the possession by individuals of *functional knowledge* of financial products, as well as behavior and attitude that foster the usage of digital financial services. When operationalizing the financial capability dimension, we are careful not to include any applications that are directly linked to financial institutions such as *m-shwari* and virtual banking, since individuals using them are already using traditional (intermediated) financial services.

Though desirable, digital consumerism may be difficult to achieve as potential financial services consumers often have limited capabilities due, say, to demand-side constraints including inadequate requisite skills such as literacy and computer proficiency (SKOLKOVO, 2015). Thus, the third condition of Kangwa et al. (2020) is *financial literacy*, defined as the possession of skills and knowledge that enable individuals to make informed financial choices. Finally, to develop an encompassing construct that speaks adequately to the utility derived by consumers of services and products offered on the fintech ecosystem, we impose a fourth condition guided by the activity system theory (Karanasios, 2018), according to which *harmony* in an ecosystem may be susceptible to contradictions, manifesting as disputes, breakdowns, and conflicts among agents (individuals, organizations, governments) within the system (Malaurent and Karanasios, 2020).

The four conditions establish the "building blocks" of a metric that describes fintech ecosystem at the micro-level, which we label "engagement with the fintech ecosystem". Table 1 presents a summary of the specific indicators that capture each of the four conditions (or dimensions) of our fintech ecosystem construct. We assume constancy in regulatory quality because, being a single-country study, all respondents experience the same regulatory regime. *Engagement with the fintech ecosystem* is constructed as a score that increases by 1 for every indicator of digital consumerism, financial capability, and financial literacy (all of which increase consumers' utility) to which the respondent answers "Yes". Contrarily, the fintech ecosystem score reduces by one (negative sign) for every "Yes" answer to the indicators that represent ecosystem disharmony, which reduce consumers' utility. See Table 1.

3.1.3. Control variables

The control variables include gender and location of residence, justified by studies in many countries which find that women and rural inhabitants bear a disproportionate burden of financial exclusion (Ghosh and Vinod, 2017; Johnen and Mußhoff, 2022) and are less likely to use fintech services (Ghosh, 2022). We also include age, in years, and age groups (in separate regressions), both of which studies find to be not only important in influencing financial product usage (Allen et al, 2021), but also to act as a critical factor moderating the adoption of digital finance services (Liébana-Cabanillas, Sánchez-Fernández, and Muñoz-Leiva, 2014). The preponderance of the literature suggests that, possibly due to their quickness in adopting new developments in digital technologies, middle-aged individuals have a higher propensity to use fintech services than younger and more elderly individuals. That is, we expect age to have a non-linear relationship with the fintech ecosystem. For financial inclusion regressions, we expect the coefficients of age groups to be broadly positive relative to the 16–17 years age group, which serves as the reference group.

On language, the evidence shows that Kenyans who speak Swahili or English have a higher chance to be financially included than those who cannot communicate in these two languages (Allen et al., 2021). However, this evidence may be circumstantial: Kenyans generally learn English at school and those who have not been to school learn Swahili on the streets in urban areas where it is the language for cross-cultural interaction. Thus, in general, given the confluence between language and both education and urban residence, both of which are known to positively impact financial inclusion (e.g., Liao, Ji and Zhang, 2015), we expect the coefficients of both Swahili and English to be positive. Additionally, the evidence in Liao et al (2015) suggests that the effect of education is *a priori* positive: education provides individuals with better knowledge of financial products and improves their confidence to consume technological innovations.

Other variables that are known to explain financial inclusion, and use of fintech products, include income, which tends to positively affect financial inclusion (Demir, Pesqué-Cela, Altunba, and Murinde, 2022); and income type, whose effect depends on the nature of the individual's occupation (Kodongo, 2018). Studies have also documented close correlation between asset ownership and financial inclusion (e.g., Allen et al., 2021). Thus, we incorporate asset ownership, constructed as a score that increases by 1 for every asset held: the assets included are: television set, radio, fridge, computer (desktop, laptop, tablet), bicycle, motorcycle, and car.

3.2. Cursory relations

Descriptive statistics are shown in Table A1 of the Appendix. The mean value of the fintech ecosystem proxy is 4.517, out of a plausible maximum of 17 with a standard deviation of 2.671, indicating, assuming a normal distribution, that about 68% of the polled individuals score between (approximately) 2 and 7, which are below the conceptual midpoint of 8.5. Thus, despite the reported growth in the consumption of fintech services (Figure 1), the average Kenyan is not yet adequately integrated into the fintech ecosystem. This motivates our tests that seek to establish why Kenyans engage with the fintech ecosystem. The observed minimum and maximum values of the fintech ecosystem construct (not reported in Table A1) are, respectively, –1 and 14. The variable reports a negative (-1) score for 18 individuals out of the 7230 in the sample. When we use the Poisson regression model, which takes the logarithm of the dependent variable, to test some of our hypotheses, we add 1 to every individual's score to meet the necessary condition for logarithmic transformation. Women and rural dwellers constitute about 57% and 68% respectively of the sample; the average respondent is 39 years old; and the bulk (43%) of the respondents are youthful, i.e., aged 18 – 34 years (the 16–17-years age group serves as the reference group).

The table also shows that most of those sampled (about 60%) speak Swahili; that only a small proportion of the respondents (about 11%) have attained or been exposed to some tertiary (university or technical) education; and that a large proportion of the respondents are either casual laborers (39%) or engaged in farming (31%). Asset ownership reports weak performance of an average of 1.30 relative to a plausible maximum of 7, potentially indicating low levels of welfare in the population. It is also interesting to note that the proportion of the low income is high at over 85% of the population, consistent with the low-levels-of-welfare inference made when using asset ownership. Finally, because the sparsely populated and semiarid Northern Kenya region has by far the least developed infrastructure in Kenya, we include a dummy that takes the value of 1 if a respondent is drawn from there and 0 otherwise: about 13% of respondents are from the region.

A notable observation from Table A1 is that there are significant discrepancies in specific attributes (that the literature has associated with financial inclusion) between individuals who engage with the fintech ecosystem and those who do not. For example, the average age of individuals not engaging with the fintech ecosystem (47.5 years) is significantly larger than that of individuals who do (38.5 years), implying that if financial inclusion were to be midwifed by financial technology, age would be an important factor to pay attention to. Similarly, only about 0.3% of individuals who do not engage with fintech have had access to tertiary education while the proportion is much higher at about 11% for individuals who engage with the fintech ecosystem. Other attributes for which the two groups exhibit notable differences include the proportion of individuals in the top 60% of the wealth distribution (63% against 28%); who are functionally numerate (61% against 18%); and who use the internet and mobile money (32% versus 2% and 72% versus 7% respectively). Interestingly, individuals who do not engage with the fintech ecosystem typically live further away from banks and tend to have no records or history of financial transactions and higher levels of mistrust towards established financial structures.

Most importantly, individuals who engage with the fintech ecosystem expectedly appear to enjoy higher consumption of all the traditional financial products of interest to this study relative to those who do not, with the gap being widest for insurance at 17.6% and lowest for security investments (for which non-fintech users report a mean of 0!) at 2.9%. These observations further make it interesting to empirically establish whether engagement with the fintech ecosystem can promote the consumption of traditional financial products.

4. Empirical evidence

4.1. A descriptive study

We begin the analysis with a descriptive study that seeks to empirically establish the existence of an association between fintech ecosystem engagement and the usage of traditional financial products (i.e., we test hypothesis *H1*) using cross-sectional regressions. We estimate the econometric specification in Equation (1) using the logistic regression.

$$Usepdt_i = \gamma_0 + \gamma_1 Finsys_i + \gamma_2' Controls_i + \varepsilon_i \tag{1}$$

where $Usepdt_i$ is an indicator metric of usage of financial products by the ith individual, proxied alternately by savings, credit, insurance, and investments. $Finsys_i$ is constructed as a fintech usage score for the ith individual; and $Controls_i$ represents various characteristics of individuals believed, in the literature, to be able to explain financial inclusion in Kenya as described in Section 3.1.3. For robustness checks, we also run a selection model regression and an instrument variable regression given the possibility of selection biases and endogeneity because use of the fintech ecosystem or financial products may not be a random occurrence. Kenyan counties (administrative units) exhibit a notable disparity in the aggregate income[15], which may also reflect in the extent of financial inclusion of individuals. Therefore, we cluster standard errors by county. ε_i is the mean zero and variance $\sigma^2_{\varepsilon_i}$ random error term.

4.1.1. The basic relationship

The marginal effects from the logistic regression of consumption of various formal products of financial institutions (savings, credit, and insurance) and capital markets (investment in

[15] See, e.g., Kenya National Bureau of Statistics Report (accessed 17.03.2022).

securities such as stocks and bonds, and in investment companies such as unit trusts) against fintech engagement and control variables are reported in Table 2. Broadly, we document strong associations: engagement with the fintech ecosystem potentially betters the probability of usage of traditional financial products by between 0.6% (credit usage) and 2% (insurance usage) among Kenyans.[16] The table, however, reports an insignificant relationship for "investments", which is interesting. Although Kenya's capital market is not young (the Nairobi Securities Exchange was founded in 1954), securities investing is not yet popular among Kenyans, most of whom have only basic knowledge of their functioning: the 2021 FinAccess Survey data show that only about 2.7% of Kenyans have investments in the securities markets (Table A1).

Several other reasons could explain this finding. First, despite the growth in digitalization of services in recent years, the securities market has been based in the country's capital, away from the reach of many less affluent Kenyans and has therefore largely catered to sophisticated and wealthy, mostly Nairobi-based, investors who can access the market, and pay for investment advisory services. Second, except the m-akiba bond that is offered to retail investors on digital platforms, the supply-side of the securities market relies largely on traditional methods of securities issuances, with marketing efforts (usually via conventional outlets like investment banks) typically targeting institutions and sophisticated urban investors. Third, there has been a lull in initial public offerings (IPOs) of stocks since mid-2000s and some oversubscribed IPOs of yesteryears have recorded weak long-term performance (e.g., Kengen) or got delisted (e.g., Access Kenya). While the dearth of IPOs has denied the stock market the necessary publicity that IPOs engender, the weak performance of previous IPOs has discouraged retail investors, some of whom employed leverage in their debut stock purchases, from participating in securities markets.

Most of the control variables, when significant, record coefficient estimates with the expected signs. For example, the consumption of traditional financial products appears to increase with education, women are less likely to use insurance than men, consistent with findings of recent studies (e.g., Johnen and Mußhoff, 2022), but more likely to use financial institutions' credit; and, perhaps due to better earnings, the probability of using formal financial products is higher for individuals in farming than for other examined occupations. Finally, we find, interestingly, that the probability of using traditional financial products generally increases

[16] The marginal effect of an explanatory variable, x, refers to **a very small change** in x. Thus, our results suggest that "a very small change in engagement with the fintech ecosystem" increases the probability of insurance usage by 2 percentage points. The economic effects are consistent with those in the extant literature examining related issues, e.g., Allen et al. (2021)'s findings on the effect of Equity Bank's expansion strategy on financial inclusion in Kenya.

with age and that ability to communicate in English and Swahili is important for credit usage. See Table 2.

We now turn to the diagnostic tests results, reported at the bottom of Table 2. First, we check the goodness of fit of the model using the Pearson test.[17] All four specifications report chi-square p-values exceeding the 10% conventional threshold: thus, we cannot reject the hypothesis that the specifications are well calibrated. Next, we use the link test[18] to check the adequacy of the functional form (logistic distribution) specified, and whether all important explanatory variables are included in the tested specifications. The results show insignificant hats-squared, which affirm the adequacy of the functional forms and empirical specifications. Based on the latter result, the omitted variables problem does not appear to present possible biasing effects on our estimated coefficients. Nonetheless, given the descriptive nature of our findings here, we explore a more rigorous identification of cause-and-effect in the endogenous treatment framework, in Section 4.2.

4.1.2. Addressing possible selection bias

Consumption of formal financial products may not be a random occurrence. For example, individuals may choose to use banking services only if they feel that they have enough income to facilitate opening of an account. Indeed, in the questionnaire, 26% of respondents who do not have a bank account attribute it to lack of income: "I do not have a regular income". This raises the possibility that our estimation results may be driven by selection bias. We attempt to address this econometric concern using a selection model with exogenous treatment. Using an index of wealth reported in the FinAccess 2021 Household Survey dataset, we define the selection variable as a dummy taking the value of 1 if an individual's wealth index is in the top 60% of the wealth distribution and 0 elsewhere. This choice is guided by a recent United Nations Development Program (UNDP) survey[19] which raises concerns about the welfare of "the bottom 40%" in developing countries. Further, we use "numeracy", available in the 2021 FinAccess Kenya Household Survey, as the exogenous treatment variable. Numeracy (really, numerical literacy in our case) is defined as a dummy variable that takes the value of 1 if a respondent answers correctly to the question, "Please read the message that I'm showing you on the screen:[20]

[17] This test compares the observed number of responses to the expected number of responses using cells defined by the covariate patterns. The further away these two are, the higher is the chi-square statistic and the lower its p-value.
[18] The link test is run by re-estimating the model using the predicted value and its square as predictor variables. The predictor variable (hat) should be significant but not its square: if the latter is significant, it may signify the omission of (an) important variable(s) or specification of an inappropriate functional form (Johnen and Mußhoff, 2022).
[19] The inequality gap: the bottom 40 may be further away than we thought.
[20] (Screen): "888YRS Confirmed. KES 370.00 paid to XYZ ABC on 8/9/18 at 4.24PM. Balance is KES 16.51. Cost of transaction: KES 10.00".

what is the transaction cost?", and 0 otherwise. [21] Table 3 reports the results of our selection model tests.

The findings are consistent with those reported in Table 2. The fintech ecosystem is positively associated with individuals' consumption of traditional financial products. Specifically, engagement with the fintech ecosystem increases the probability of usage of traditional financial products by between 1.2% and 1.6% after controlling for various individual-level factors and locational factors typically associated with access and usage of financial products, and potential selection bias. As before, investment usage remains insensitive to fintech ecosystem engagement. It is also important to note that the average treatment effect (numeracy = 1) is indistinguishable from zero in all equations, indicating a robust lack of association between an individual's ability to answer a numeracy question correctly and the individual's consumption of traditional financial products. We explore this point further in the next section.

4.1.3. Are the results driven by endogeneity?

Given that individual decisions to use fintech services and to consume financial products are not randomly occurring, it is possible that the same factors driving financial inclusion may drive fintech ecosystem usage, causing a simultaneity (endogeneity) bias in our tests. For example, the decision to engage with the fintech ecosystem may be correlated with unobservable factors that affect the consumption of traditional financial services. Further, past recipients of remittances might be induced to engage with fintech services to facilitate the receipt of future remittances. Thus, despite the treatment effects used in Section 4.1.2, it is important to have a more rigorous way of dealing with biases emanating from omitted variables and potential simultaneity.

To deal with potential endogeneity, we estimate a linear probability model using the Lewbel (2012) approach[22]. This approach generates internal instruments using heterogeneity in the error term of the first stage regression. The method is convenient when it is difficult to identify external instruments or when external instruments are not available. In our application, we exploit a feature of the method that allows for mixing of the internally generated instruments with external instruments. We estimate the Lewbel model using the two-step Generalized Method of Moments (GMM). The results are reported in Table 4. First, we address the difficult

[21] The other responses in the questionnaire capture reading ability (e.g., "can read screen, but does not get the correct answer", and "cannot read the screen and does not get the correct answer"), which according to Grohmann et al. (2018), cannot pass the instrument test. For further robustness checks, we estimate the equation using distance to the nearest mobile money agent (motivated by Munyegera and Matsumoto, 2016) as an instrument and with both "numeracy and distance to mobile money agent. The results are qualitatively similar.

[22] For robustness, and especially because of the binary nature of the dependent variable, we also estimate the equation using the instrument variable Probit technique. The results are qualitatively similar.

question of identifying appropriate external instruments for our tests. Suggestions have been made in the extant literature that numeracy and language skills directly inform individuals' financial and digital capabilities but do not influence their decisions to consume financial services (Grohmann et al., 2018; Kass-Hanna et al., 2022). Thus, numeracy and language skills affect financial inclusion only through their effect on the engagement with fintech ecosystem. Guided by this literature, therefore, we use numeracy, as defined in Section 4.1.2, as the only external instrument variable. See Table 4.

Results of the relevant supportive diagnostic tests at the bottom of Table 4 give a clean bill of health to our baseline estimations. First, the weak instrument tests report F-statistics above the Stock and Yogo (2005) critical values, confirming that the instruments are suitable. Second, the overidentifying restrictions appear to be met by all specifications, except Insurance: despite its less than perfect performance, however, the estimation results are very consistent with those of the baseline outputs. Overall, the results of the instrument variable regressions confirm that the probability of usage of traditional financial products is higher amongst individuals who engage with the fintech ecosystem. Indeed, relative to the baseline results (Table 2), the findings show that controlling endogeneity marginally improves the magnitudes of our coefficient estimates, implying that failure to do so may slightly underestimate the fintech impact. Finally, we must also note that the results for Investments remain insignificant, consistent with the baseline results.

4.2. Identification

4.2.1. Is there a financial inclusion gap between fintech users and non-users?

We deploy the recentered influence functions (RIF) treatment-effects method (Firpo and Pinto, 2016) to identify inequalities in the consumption of traditional financial products between individuals who engage with the fintech ecosystem and those who do not. The typical treatment-effects procedure begins by defining a joint distribution function $F_{Y_1,Y_0,X,T}(\cdot)$ that characterizes the potential outcomes, Y_1 and Y_0, the exogenous independent variables, X, and a binary treatment variable, T. The realized outcomes, Y, depend on whether the individual is in the treated group or in the untreated group: $Y = TY_1 + (1 - T)Y_0$. Assuming that the distributions of potential outcomes, Y_1 and Y_0, are independent of observed characteristics, X (no confoundedness), and that the number of observations is sufficiently large that there are individuals with similar observed characteristics, X, in both treated and untreated groups (overlapping support), the treatment effects can be estimated using RIF[23] (Firpo and Pinto, 2016) as follows.

$$T \times RIF\left[y, v\left(\hat{F}_{y_1}\right)\right] + (1 - T) \times RIF\left[y, v\left(\hat{F}_{y_0}\right)\right] = b_0 + b_1 T + b_2 X + \varepsilon \quad (2)$$

where v is the distributional statistic of interest (the mean in our case here), $\hat{F}$ are the cumulative distribution functions, estimated separately for the treated (fintech ecosystem users) and untreated groups (non-users). Equation (2) is estimated using the weighted least squares method.[24] The RIF approach has several advantages compared to competing methodologies. First, it is simple to implement; second, it eases the computation of the contributions of individual covariates on the aggregate decomposition, and third, it can be extended to any statistic (other than the mean) for which a RIF can be defined (Rios-Avila, 2020). We implement Equation (2) and interpret our results in accordance with the recommendations of Rios-Avila and de New (2022). See Table 5.

The baseline results of the RIF treatment-effects regressions are presented in Table 5. We report the average treatment effects (ATE) and the average effect of treatment on the treated (ATT).[25] At the outset, it is useful to note that the effect of the fintech ecosystem remains positive and significant in all estimations except credit. Thus, our baseline tests results are robust to alternative estimation methods and conditions. Broadly, the ATE results show that, if every member of the overall population were to engage with the fintech ecosystem, the consumption of traditional financial products would go up by between 1.3% (investments) and 7.7% (insurance). Equally important are the ATT results, which speak directly to the expected causal effects of using the fintech ecosystem on the consumption of traditional financial products for a randomly selected individual who engages with the fintech ecosystem. The results show, for the fintech ecosystem user, that consumption of traditional financial products is between 1.4% and 7.9% higher than that of individuals who do not engage with it. Overall, therefore, despite the visible gains in financial *access* (documented in stylized facts), more needs to be done to bring

[23] The influence function (IF) represents the "influence" of an individual observation on the distributional statistic (e.g., quantile). Adding back the statistic (e.g., quantile) to IF yields the re-centered influence function (RIF). For example, the influence function of the mean, $\mu = E(Y)$ is the demeaned value of the dependent variable, $Y - \mu$, so that the recentered influence function is simply the original values: $Y = \mu + (Y - \mu)$.
[24] The weights for the least squares regression are computed as $\hat{\omega}(x) = T\hat{\omega}_1(x) + (1 - T)\hat{\omega}_0(x)$, where $\hat{\omega}_1(x) = P(T = 1)/P(T = 1|X = x)$ and $\hat{\omega}_0(x) = [1 - P(T = 1)]/[1 - P(T = 1|X = x)]$, such that $P(T = 1)$ is the overall probability that an individual is assigned to the Treatment group and $P(T = 1|X = x)$ is the probability that an individual is assigned to the Treatment group conditional on the observed characteristics (Rios-Avila, 2020). Consistent with the rest of our work, we estimate these probabilities using Probit regression.
[25] The ATT weights are computed as $\hat{\omega}_1(x) = 1$ and $\hat{\omega}_0(x) = [1 - P(T = 1)]/[P(T = 1)] \times [1 - P(T = 1|X)]$.

non-users of fintech products on par with that of fintech users in the consumption of financial services. However, these results may be biased by the fact that users and non-users of fintech draw from sub-populations with different underlying characteristics as documented in Section 3.2. We attempt to address the implications of this possibility using propensity scores matching, explored in Section 5.2.1.

4.2.2. Characterizing the financial inclusion gap

How large is the difference, in traditional financial products consumption, between those who engage with the fintech ecosystem and those who do not? The foregoing analysis indicates a general tendency for fintech non-users to be disfavored in financial inclusion relative to users but falls short of identifying the magnitude of the gap. Thus, we attempt to identify, in this section, the exact difference, between those who engage with the fintech ecosystem and those who do not, in the probability of consumption of each of the major financial products. We deploy RIF of Firpo Fortin and Lemieux (2018) to execute the Oaxaca-Blinder-type identification and decomposition of the gap. As in the foregoing section, we divide the sample into the 'treatment' group (fintech users) and the reference group (fintech non-users) and estimate Equation (3).

$$\Delta v = \left[(\bar{X}^c - \bar{X}^0)'\hat{\beta}_0 + \bar{X}^{c'}\left(\hat{\beta}_c - \hat{\beta}_0\right)\right] + \left[\bar{X}^{1'}\left(\hat{\beta}_1 - \hat{\beta}_c\right) + (\bar{X}^1 - \bar{X}^c)'\hat{\beta}_c\right] \tag{3}$$

where Δv, the gap in the distributional statistics of the treated group (fintech users) and the nontreated group (fintech non-users), is constructed as $RIF\left[y, v\left(\hat{F}_{y_1}\right)\right] - RIF\left[y, v\left(\hat{F}_{y_0}\right)\right]$; "$c$" is the counterfactual; and 1 and 0 respectively denote the treated and nontreated groups. The terms, $(\bar{X}^c - \bar{X}^0)'\hat{\beta}_0$ and $\bar{X}^{1'}\left(\hat{\beta}_1 - \hat{\beta}_c\right)$, are respectively, the "pure" composition (explained) effect and the "pure" unexplained effect components from decomposition; and, $\bar{X}^{c'}\left(\hat{\beta}_c - \hat{\beta}_0\right)$ and $(\bar{X}^1 - \bar{X}^c)'\hat{\beta}_c$ are, respectively, the specification and reweighting errors. A significant and large reweighting error signifies poor identification of the counterfactual and/or poor specification of the model used to estimate the reweighted factors; a significant specification error may indicate that the RIF has incorrectly estimated the distributional statistic (Rios-Avila, 2020). Equation (3) is estimated using weighted least squares. For robustness checks, we later relax the linearity assumption (in Section 5.2.2) and test the same hypotheses using a binary dependent variable decomposition technology attributed to Fairlie (2005). See Table 6.

The "explained" or "composition" effect captures differences in the mean levels of usage of traditional financial products attributed to the observable characteristics or "endowments" (e.g., education, age) of the treated and reference groups, while the "unexplained" effects are attributed to returns on (or benefits of) the observable characteristics. We report the results in Table 6. Due to its low consumption in the broader population, "Investments" is observed too few times compared to other uses and does not realize sufficient degrees of freedom to facilitate this test. Thus, Investments is not included in Table 6. Overall, both the specification and reweighting errors are small in magnitude and statistically insignificant, indicating that the results are free from biasing model misspecification and/or poor-quality reweighting errors. The explanatory variables are grouped by their relatedness to each other: language (English, Swahili), occupation (farming, casual work, and waged), education (primary, secondary, tertiary), and age group (18 years and above) with the excluded categories serving as reference points.

First, consistent with Yang and Zhang (2022) who report improved financial inclusion following fintech adoption, our results here document a perversive gap between fintech users and non-users in the consumption of financial products. Second, the results give an important role to endowments in explaining inequalities in the usage of credit and insurance (generally statistically significant pure composition effect). For example, due to the traditional marginalization of women (e.g., Ghosh, 2022), being female worsens the disadvantages conferred on individuals by their lack of use of the fintech ecosystem in credit consumption. Overall, the advantages that fintech users have over non-users are driven by factors such as education (more education tends to confer privilege in the usage of traditional financial products), asset ownership (owning more assets tends to buttress consumption of financial products amongst individuals who engage with the fintech ecosystem) and men, perhaps due to superior career and income opportunities (Ghosh and Vinod, 2017), have a distinct edge over women in the usage of traditional financial products.

4.3. Heterogeneities in fintech ecosystem's financial inclusion benefits

Section 4.2.2 reports a substantial financial inclusion gap between individuals who engage with the fintech ecosystem and those who do not. However, given the mixed bag of demographic and social characteristics exhibited by financial products consumers, it is interesting to ask the question of which of these characteristics most effectively lend themselves to the mediating role of the fintech ecosystem in fostering financial inclusion. To respond to this question, we estimate a form of Equation (1) that includes the interaction between the fintech ecosystem and the characteristics deemed to describe individuals most likely to engage with the fintech ecosystem (Das and Das, 2020; Gulamhuseinwala et al., 2015), namely, (i) youth (individuals in the age group 18 – 34 years); (ii) males; (iii) higher education (individuals with secondary or tertiary education); and (iv) wealth (individuals in the upper 60% of the wealth distribution). A positive and significant interaction term indicates that the fintech ecosystem benefits individuals of the characteristics represented by 1; a negative and significant effect shows that the profiles denoted by 0 represent the key beneficiaries. We estimate Equation (4):

$$Usepdt_{it} = \gamma_0 + \gamma_1 Finsys_{it} + \gamma_3 Demtic_{ijt} + \gamma_4 Finsys_{it} \times Demtic_{ijt} + \Gamma' X_{it} + \varepsilon_{it} \quad (4)$$

where $Demtic$ is the demographic attributes of interest for our tests and X is the vector of control variables. Considering potential endogeneity, we use the two-step GMM in the linear probability model context. We use numeracy and a set of internal instruments generated through the Lewbel approach, as the instrument variables. The results are reported in Table 7. We find, consistent with earlier findings, that the effect of the fintech ecosystem on investments is largely mute even after we separately account for the demographic characteristics. Similarly, the effect of fintech on the usage of the remaining financial products remains positive and significant. Focusing next on the purpose of this section, the demographic characteristics that lend themselves to the greater exploitation of the fintech ecosystem for financial inclusion, we document interesting findings.

First, when important, the fintech ecosystem appears to foster greater usage of traditional financial products amongst "older adults" with the coefficient for its interaction with "youth" (individuals aged 18 – 34 years) being negative and statistically significant in all specifications. Thus, despite their relatively superior capabilities in adopting technological innovations (Kangwa et al., 2020), the fintech ecosystem does not appear to have amply emancipated younger individuals, who are traditionally marginalized in financial inclusion (Allen et al., 2016), to enjoy greater consumption of traditional financial products. An interesting plausible alternative interpretation of this finding is in the context of the role of the fintech ecosystem in attenuating the financial inclusion gap occasioned by the digital divide (Grishchenko, 2020) between younger adults (generally deemed as more technology savvy) and older adults (deemed more technology shy). That is, benefits such as remote access to one's bank account that the fintech ecosystem provides may incentivize older users not only to adopt digital technologies but, importantly, to utilize them to avail themselves of traditional financial services.

Second, our results show that, when significant (such as for savings, credit and insurance usages), engagement with the fintech ecosystem appears to have unduly "favored" the richer segments of the Kenyan society (individuals in the top 60% wealth) compared to the poor, consistent with the argument of Natile (2020) that despite fintech's ability to accelerate financial *access*, it does not address the underlying vulnerabilities that are responsible for financial exclusion. Neither does the engagement with the fintech ecosystem appear to bridge the education divide in the consumption of traditional financial services: fintech appears to facilitate individuals with higher education (secondary and tertiary) to consume more savings and credit, and to invest more. Finally, the fintech ecosystem does not appear to bridge the gender divide in the use of financial products: the coefficient of the interaction between men and the fintech ecosystem is positive and significant at 10% for savings and credit, and at 5% for insurance.

4.4. Financial inclusion impediments

4.4.1. Does fintech complement or substitute traditional finance?

We attempt to ascertain the possible reasons for individuals' engagement with the fintech ecosystem in Kenya. We conjecture that individuals' consumption of traditional financial products is subject to constraints such as distance to financial institutions (hypothesis *H2*), information asymmetry arising from their lack of or inadequate financial transactions history (*H3*), and lack of trust for formal financial institutions (*H4*). That is, individuals use the fintech ecosystem as a medium that enables them to overcome barriers to formal financial inclusion that they face. To test these hypotheses, we must use the fintech score, a count variable, as our dependent variable. Thus, we estimate equation (5) using the Poisson regression technique.

$$\ln \lambda_i = \delta_0 + \delta_1 Dist_i + \delta_2 Hist_i + \delta_3 Trust_i + \delta_4 NKen_i + \theta' Controls_i + \varepsilon_i \qquad (5)$$

where λ is the expected value of the fintech ecosystem score[26]. The explanatory variables are proxies for "distance to a financial institution" ($Dist$), "lack of a credit history and records of financial transactions" ($Hist$), and "lack of trust for financial institutions and markets" ($Trust$). These variables are constructed from the following information provided by respondents: $Dist$ is proxied by the cost of public transport to the nearest bank being at least KES 200 (US$ 1.30); $Hist$ = "lack of credit history" and "lack of records of financial transactions" in response to the question of why their bank loan application has ever been declined; and $Trust$ is proxied by "I do not trust banks" or "I do not trust capital markets", provided as a reason for not having a bank account and for not using capital markets services. We add a dummy variable ($NKen$) that equals "1" if the respondent hails from Northern Kenya where the infrastructure is relatively less developed, and "0" elsewhere, and the usual $Controls$. Because of the relatively underdeveloped

[26] The Poisson distribution is of the form: $P(Y = y_i) = \left(e^{\lambda_i} \times \lambda_i^{y_i}\right)/y_i!$. We model the expected (mean) count of fintech ecosystem engagement, λ_i, as a function of the explanatory and control variables. Like in the previous estimations, we report marginal effects to ease interpretation.

fintech subsector in Northern Kenya, we expect δ_4 to be negative and significant. On the other hand, δ_x $(x = 1, 2, 3)$ should be positive and significant if fintech products are a substitute for traditional financial products (individuals resort to fintech as a way to overcome formal financial inclusion barriers), and significantly negative if fintech products complement traditional financial products (individuals face similar constraints with fintech as they do with traditional financial products, which are, in this case, perceived as "two sides of a coin").

Table 8 reports the estimation results. As before, standard errors are clustered by the respondents' counties of residence. We begin by examining the diagnostic tests results in column (1). The p-value of the Pearson statistic is greater than the conventional 0.10, indicating that the traditional Poisson model is appropriate. That is, there is no evidence that overdispersion, for example, could bias our estimates. The p-value of the hat-squared test is significant, indicating that the estimated model possibly suffers from potential specification bias arising from, say, an omitted important variable. That is, a variable such as ownership of land, an important store of wealth in Kenya, which are not observed, may drive both engagement with the fintech ecosystem and some control variables such as income. This may cause the estimated errors to be correlated with one or more of the explanatory variables in the estimated model.

Thus, to deal with threats to validity resulting from potential endogeneity, we estimate both the extended Poisson regression model that allows treatment effects and a linear probability model estimated through the two-stage Generalized Method of moments (GMM). Given the discussed weakness of our traditional Poisson estimates, the discussions here are based on the results of the latter two tests. We use income (a dummy variable equal to "0" if the respondent has "no income" and 1 elsewhere) as the treatment variable in treatment effects Poisson regression. The potential outcome mean shows that the average fintech score in the treatment regime (individuals with some income) is about 1.1 times the fintech score in the control regime. Further, we can infer from the average treatment effect on the treated (ATT) that the average income-earning individual engages with the fintech ecosystem about 0.38 times more than their non-income earning counterpart.

Among the explanatory variables, the findings suggest that better educated individuals tend to engage more with the fintech ecosystem. Relatedly, there is a strong association between use of the internet and engagement with the fintech ecosystem: all else equal, internet users engage with the fintech ecosystem by 1.592 (fintech score) higher than non-users. Possession of an identification document (ID) is highly economically significant in informing engagement with the fintech ecosystem, which possibly speaks to the fact that most individuals consume fintech products via mobile phones for which registration for the standard fintech product, mobile money, is conditional on meeting know-your-customer requirements. The results also show, consistent with existing studies on the digital divide (Grishchenko, 2020), that the use of fintech increases with age until some age (negative coefficient estimate for age squared) beyond which it diminishes (i.e., younger individuals are more inclined to using fintech than older individuals); and, expectedly, that higher income promotes fintech usage. Finally, disabled individuals are generally disfavored in the engagement with the fintech ecosystem, consistent with Bin et al. (2023). See Table 8.

Regarding the hypothesized obstacles faced by residents of all regions of the country, and of diverse demographic characteristics, we document surprising findings. The results are surprising because the barrier variables, which are defined from the perspective of financial institutions and hence speak more directly to traditional financial *exclusion*, appear to exhibit a relationship with fintech engagement that is aligned with their desired relationships with financial *inclusion* (usage of traditional financial products). The results are, however, not implausible for several reasons. First, distance to financial institutions, proxied by transport cost to the nearest bank being at least KES 200 (US$ 1.30), is negatively and significantly related to fintech. Thus, contrary to expectations informed by recent studies (Dupas, et al., 2018), distance appears to disincentivize the use of fintech products in much the same way that it does usage of traditional financial services.

As argued, this result is plausible. Take transaction usage of digital money services (e.g., cash withdrawals): this necessarily entails the user interacting with digital money agents, who are typically found in local commercial centers. Similarly, certain mobile money applications, such as buying goods, often require the individual to travel to the locations where the goods are sold (in local commercial centers) to use the seller's till number and to collect the goods, akin to traveling to a bank to withdraw cash prior to shopping. Where the commercial centers referred to in these examples are the same locations in which branches or agents of financial institutions are domiciled, distance entails the exact disincentives (e.g., travel costs and opportunity costs of foregone earnings) to the use of fintech services as it does to physical usage of financial institutions.[27]

Second, we document a negative, but insignificant, relationship between trust and history, both of which are also defined in the context of traditional financial service delivery, and fintech

[27] A recent survey of 400 m-pesa users in Nairobi shows that m-pesa is primarily a payment tool, with the bulk (64%) of its users holding an average monthly balance less than KES 1000 (USD 7.70) and net balance (inflows minus outflows) of only KES 250 (USD 1.90), the results being robust to income levels and employment types. The data are available here. Since withdrawals and deposits must be made through an agent or through an automated teller machine (ATM), distance to the agent/ATM is almost as important as distance to a financial institution.

engagement. Although insignificant, the negative relationships are interesting. For example, from the consumers' perspective, lack of trust for financial service providers is not restricted to products offered on conventional platforms. Rather, it could be worse when the entities offering financial and related products are doing so on technological platforms that are barely understood and not so well regulated as to assure consumers of their data safety (e.g., Zarifis and Cheng, 2022) and safety of their assets entrusted to the platforms. Standard theoretical models indicate that trust is inculcated by individual dispositions and contextual factors (McKnight and Norman, 2001) such as the institutional background, and regulation. This is important in the Kenyan context where, although fintech essentially began with the launch of m-pesa in 2007, specific regulations governing the sub-sector's conduct have not been developed almost two decades later.[28] In such a perceived weak regulatory environment (context), consumers may be positively disposed towards products offered on the fintech space due to their convenience and capabilities, but their full acceptance and adoption hinge on their trust for the technology, and in the providers of the services (Zarifis, Kawalek and Azadegan, 2021).

The important implication of our findings here, particularly on distance, is that the fintech ecosystem is a possible important alternative avenue (as a complement of conventional financial products) for promoting financial inclusion in Kenya. That is, traditional financial product concepts can be built onto fintech platforms to increase their appeal to those who were hitherto disinterested and to reach those who were hitherto excluded.

4.4.2. Can fintech mitigate financial inclusion impediments?

The special agent theory (Ozili, 2020) argues that complex issues relating to the nature of a population, characteristics of its people, and geography, may impede the provisioning of financial services to a section of the population. To mitigate such impediments, specialized agents (e.g., fintech startups and technology firms) may be required to more effectively reach those who are financially excluded.[29] To be effective, the specialized agent(s) must understand the peculiarities of those who are excluded (in the fintech ecosystem, this could be achieved through big data); devise ways of integrating the informal financial system into the formal financial system (e.g., using formal digital savings products); and identify modalities of

[28] Operations of firms in the sector fall under many disparate laws such as the Data Protection Act, Electronic Transactions Act, Banking Act, Insurance Act, and so on, which does not necessarily inspire trust amongst users.

[29] In some cases, the specialized agent may be created by a principal (e.g., government) specifically to facilitate financial inclusion: for example, the Indian government's 2016 *Jan Dhan Yojana* program to encourage bank account ownership (Demirguc-Kunt, et al., 2017) and the more recent *India Stack*, whose purpose was to bring India's population into the digital age (Das and Das, 2020), have ushered millions of hitherto excluded Indians into the formal financial system. In other cases, the specialized agent may emerge organically through "normal" product innovation to claim a place in the financial inclusion space (e.g., m-pesa in Kenya).

intervention (e.g., product innovation). The modalities of intervention (mechanisms of action) are the issues of concern in this section.

Understanding the mechanisms of action is important because it informs our appreciation of how the fintech ecosystem works and generates policy insights. The fintech ecosystem should promote financial inclusion by mitigating its impediments, which may be price- or non-price-related. Price-related barriers include inadequate or no income to maintain a financial institution account, and cost of financial services (e.g., loan origination fees); while non-price-related barriers include distance from financial institutions (e.g., Bachas et al., 2018; Jack and Suri, 2014), mistrust of financial institutions (Ghosh, 2021; Allen et al., 2021), psychological fear of traditional financial institutions, and financial illiteracy. For example, some studies argue that exclusion of individuals who have no financial transactions history can be addressed by gaining better insights about them to reduce information asymmetry using appropriate fintech tools (Daniel and Grissen, 2015; Jagtiani and Lemieux, 2018).

The results in Section 4.4.1 show that hypothesized financial inclusion barriers such as distance entail similar disincentives to fintech usage. However, it is interesting, given the fast-paced growth in the fintech ecosystem over the last few years (Senyo et al., 2022), to establish whether, consistent with arguments advanced in the foregoing paragraph, fintech addresses, even if partly, the effect of some of these barriers on access to and consumption of traditional financial products. Thus, we examine the role of the fintech ecosystem in the possible attenuation of the major reasons (barriers) that unbanked individuals give for not using traditional financial services. We implement these reasons by interacting them with the fintech ecosystem construct (i.e., using them as moderating variables), consistent with the implications of the special agent theory. Incorporating controls, we estimate the resulting Equation (6):

$$Usepdt_i = \gamma_0 + \gamma_1 Finsys_i + \gamma_2' Chan_i + \gamma_3' Finsys_i \times Chan_i + \Gamma' Controls_i + \varepsilon_i \qquad (6)$$

where $Chan$ are respondents' reasons for not using traditional financial products such as distance from the bank, which Osoro and Muriithi (2018) find to be directly associated with usage of banking services in Kenya; lack of trust for financial institutions, and history of transactions, as discussed in Section 4.4.1. The results, displayed in Table 9, do not document systematic evidence that the fintech ecosystem may intervene effectively regarding history and trust. This is expected given the findings in Section 4.1.1 that history and trust do not constitute a significant barrier to financial inclusion that is addressed by fintech. When significant however (e.g., in the Insurance equation), the fintech ecosystem accentuates potential discriminating effects of history on traditional financial services usage. This finding resonates with recent developments in Kenya's insurance subsector where, despite empirical evidence of weak demand for microinsurance (Platteau, De Bock and Gelade, 2017), many insurance firms have adopted a digital microinsurance strategy that targets low-income populations, a development with the potential, if the weak demand were to be overcome, to build microinsurance as a distinct tech-driven market segment that competes directly with traditional insurance products. Like history, the evidence on trust is weak, with only credit usage reporting a significant negative effect. See Table 9.

The results for distance are, however, consistent with expectations. Findings indicate that distance is predominantly negatively related to financial inclusion. If the fintech ecosystem mitigates the constraints to financial product consumption imposed on individuals by distance (Dupas et al., 2018), the interaction between "fintech ecosystem" and "distance" should be positive. Our results support the positive "distance effect" hypothesis, particularly for savings, credit, and insurance for which fintech usage "reverses" the distance disadvantage by at least 0.7 percentage points. Thus, we infer that engagement with the fintech ecosystem attenuates the distance barrier and hence complements efforts by traditional financial institutions and regulatory authorities to encourage usage of intermediated financial services.[30]

5. Additional tests and robustness

5.1. Alternative construction of the fintech ecosystem

To check for the robustness of engagement with the fintech ecosystem construct, we use two alternative constructs. First, we formulate a synthetic index using standard deviation weights on each variable, i, in the sample: $w_i = (1/\sigma_i)/(1/\sum_i \sigma_i)$. In the second instance, we define the fintech ecosystem as a dummy variable equal to 1 for individuals with a fintech score different from naught and 0 otherwise. We then estimate Equation (1) using the logistic regression technique and the same controls as in the baseline tests. The results (not reported, but available upon request) are qualitatively similar to those reported in Table 2; they document an unambiguous role for the fintech ecosystem in explaining the various forms of formal financial product usage.

[30] The results reported in Table 9 are generated by estimating Equation (5) using logistic regression. As discussed in previous sections, these results might be affected by endogeneity arising from the omitted variables problem. Indeed, when we estimate the equation through the instrument variables Probit regression, the "distance effect" appears to wane as the interaction terms are insignificant. We revisit this issue in Section 5.3.

5.2. A closer look at causal effects

5.2.1. Propensity score matching

The results in Section 4.2.1 are obtained from the RIF regression technique, which assumes that users and non-users of the fintech ecosystem are drawn from identical distributions. This assumption may be incorrect, and the two groups may differ in respect of attributes such as asset ownership, education, and income. Indeed, as discussed in Section 3.2, Table A1 documents significant differences in the mean levels of covariates for the treated (fintech engagers) and control (fintech non-engagers) groups. To achieve identicality regarding the fundamental attributes that define both groups, we use propensity score matching. We evaluate the success of the matching exercise by examining the similarity of the covariates collectively before and after the matching. The results, reported in Figure 2, show that the control and treatment groups reflect discernible dissimilarity prior to the matching, but are similar after matching. Consistent with the baseline results, findings of both the average treatment effects and average effects of treatment on the treated (not tabulated but available from authors upon request) support the hypothesis that fintech engagement supports greater consumption of traditional financial products. See Figure 2.

5.2.2. Relaxing the linearity assumption

To further test the robustness of our cause-and-effect findings in Section 4.2.2, we deploy the Fairlie decomposition (Fairlie, 2005), which uses estimation techniques that account for the binary nature of our dependent variables. In our application, and consistent with our other tests, we use logistic regression. We run the tests with 500 bootstrap replications and, as before, cluster standard errors by county. For brevity, we cluster observed characteristics according to their relatedness (e.g., "occupation" captures the effects of "waged", "business", and "casual" employments). Results (not reported but are available from authors upon request) document strong supporting evidence of disparity in financial inclusion between individuals using and those not using the fintech ecosystem, with similar probabilities as those of RIF estimation results.

5.3. Exogenous variation in mobile money usage

As argued, the need for a broader, more representative, construct is motivated by the multifaceted nature of the fintech ecosystem that goes beyond mobile money and recognizes its various dimensions such as system disruptions, and individuals' abilities to use the system and its offerings. However, a potential issue of concern is whether the fintech ecosystem construct that we evolve represents a valid measure of fintech engagement relative to more established individual proxies such as mobile money usage (e.g., Jack and Suri, 2014) or smart cards (Muralidharan, et al, 2016). To address this concern, we conduct further robustness checks using exogenous variations in mobile money usage. For this purpose, we deploy a binary variable, obtained from the FinAccess database, that takes a value of 1 for individuals who "used a mobile money account for a financial transaction in the past three months" and 0 otherwise.

Using this variable, we first estimate a selection model with exogenous treatment effects (with numeracy as the treatment variable) similar to the one reported in Section 4.1.2. Consistent with the baseline findings, the results reported in Table 10 show that mobile money usage is closely associated with the consumption of traditional financial products. Second, we estimate the recentered influence function regression to test the veracity of the causal inferences made in Section 4.2.2: results, reported in Table 11, again demonstrate that the mobile money users, like the broader engagement with the fintech ecosystem, enjoy superior consumption of traditional financial products relative to non-users. Thus, the mobile money component of the fintech ecosystem behaves the same way as the broader fintech construct in incentivizing financial products usage. Third, we test the channels of transmission of mobile money usage to traditional financial products usage using, for additional robustness checks, the instrument variable Probit regression: consistent with the results in Section 4.4.2, the findings in Table 12 document strong support for the distance channel hypothesis. See Tables 10, 11 and Table 12.

5.4. Fintech ecosystem sub-constructs

Further to the tests with mobile money usage, we evaluate the effect of three of the fintech ecosystem's sub-constructs, namely digital consumerism, financial capability, and financial literacy, on individuals' usage of traditional financial products.[31] We present the results of these tests on Table 13. The results are consistent with those of the baseline tests (Table 2). The additional insight is that the three sub-constructs differ in their effects on financial inclusion with digital consumerism expectedly having the highest impact followed by financial literacy. This is sensible: one needs to have access to digital platforms and be financially literate if they are to enjoy formal financial services/products, when the access to and usage of such services/products are facilitated by digital platforms. In sum, our fintech engagement construct is robust: it speaks

[31] We are indebted to an anonymous referee for suggesting this need. The correlation coefficients between the sub-constructs and the fintech ecosystem construct are included in Table A1. The results show a close association between the sub-constructs and the construct.

broadly to its sub-constructs and micro-constituents such as mobile money usage. See table 13 below.

6. Conclusions and policy implications

Kenya has a reputation as a fintech leader, with high growth in mobile money transactions in recent years. Similarly, the country has made big strides in financial inclusion recording a steep growth in access to financial services between 2016 and 2021. This makes it likely that the expansion of the fintech ecosystem and usage of fintech services have played a role in the growth in financial inclusion. We examine this question and document several interesting findings. First, we demonstrate empirically that by facilitating reach beyond traditional markets, the fintech ecosystem mitigates the distance barrier to financial inclusion. Second, we document a robust positive relationship between the use of traditional products of regulated financial institutions and markets and the fintech ecosystem: individuals who engage with the fintech ecosystem enjoy higher consumption of such products after controlling various socio-demographic factors, locational bottlenecks (e.g., rural residence) and potential endogeneity. Third, we find a discernible gap in the consumption of traditional financial products among those who do not use fintech services, which could potentially be partly addressed by availing fintech services to those currently not engaging with it. Finally, we document that the fintech ecosystem fails to address consumption inequalities for women, young adults, the less educated, and less wealthy individuals in Kenya.

Several policy implications can be drawn from these findings. First, "investments" does not appear to respond with as high economic importance to the fintech "intervention" as do the other uses of financial products. This could possibly reflect low levels of awareness of and access to opportunities available in the capital market which can be addressed from a policy perspective through education. Although Central Bank of Kenya has over the years sponsored or directly participated in efforts to provide financial education to the Kenyan masses, these efforts could be intensified to rope more individuals in the ranks of the financial literate. Secondly, given our finding that the engagement with the fintech ecosystem could promote financial inclusion, availing securities through the fintech space (e.g., buying shares digitally and through mobile money wallets) could partly address market frictions such as transaction costs and promote uptake of securities.

Second, the data show a close association between wealth/income, education, age, location of residence and ability to speak in English on the one hand and engagement with the fintech ecosystem on the other. Because, per our empirical findings, the latter promotes financial inclusion, policymakers need to promote fintech consumption. This could be achieved in many ways. For example, in the Finance Act[32] of 2023, the government increased excise duty on mobile money transactions from 12% to 15% of the transaction value. Such policy actions increase transaction costs and disincentivize consumption of fintech products and should be rethought. If already in place, or if important for government's domestic resource mobilization, policy makers would be advised to consider counter-policy measures, such as judicious application of tax reliefs, that could vitiate their distorting effects on consumer choices.

Finally, we identify opportunities for further studies. For example, besides the fact that the microlevel fintech ecosystem construct is novel and needs to be tested in different circumstances and contexts, the finding that the fintech ecosystem is unable to address financial consumption inequalities is potentially contentious and deserves a follow-up study. Such a study or series of studies could consider zeroing-in on each of the disfavored groups (women, youth, the less wealthy and the less educated) at a time, possibly starting with available Kenyan data.

References

1. Allen, F., Carletti, E., Cull, R., Qian, J. Q. J., Senbet, L., and Valenzuela, P., 2021. Improving access to banking: evidence from Kenya. *Review of Finance*, *25*(2), 403–447.

2. Allen, F., Demirguc-Kunt, A., Klapper, L., and Martinez Peria, M. S., 2016. The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation*, *27*, 1–30.

3. Arner, D. W., Buckley, R. P., Zetzsche, D. A., and Veidt, R., 2020. Sustainability, fintech and financial inclusion. *European Business Organization Law Review*, *21*(1), 7–35.

4. Aziz, A. and Naima, U., 2021. Rethinking digital financial inclusion: Evidence from Bangladesh. *Technology in Society*, *64*, 101509.

5. Bachas, P., Gertler, P., Higgins, S., and Seira, E., 2018. Digital financial services go a long way: Transaction costs and financial inclusion. *AEA Papers and Proceedings*, *108* (May), 444–448.

6. Banerjee, A., Karlan, D. and Zinman, J., 2015. Six randomized evaluations of microcredit: Introduction and further steps. *American Economic Journal: Applied Economics*, *7*(1): 1–21.

7. Barykin, S. Y., Kapustina, I. V., Kirillova, T. V., Yadykin, V. K., and Konnikov, Y. A., 2020. Economics of digital ecosystems. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 1–16.

[32] A copy of the Finance Bill 2023 can be downloaded from the parliamentary website.

8. Benston, G. J. and Smith, Jr., C. W., 1976. A transactions cost approach to the theory of financial intermediation. *Journal of Finance*, *31*(2), 215–231.

9. Bollaert, H., Lopez-de-Silanes, F., and Schwienbacher, A., 2021. Fintech and access to finance. *Journal of Corporate Finance*, *68*, 101941.

10. Brailovskaya, V., Dupas, P., and Robinson, J., 2021. Digital credit: Filling a hole, or digging a hole? Evidence from Malawi. *NBER Working Paper No. 29573*.

11. Brune, L., Giné, X., Goldberg, J. and Yang, D., 2016. Facilitating savings for agriculture: Field experimental evidence from Malawi. *Economic Development and Cultural Change*, *64*, 187–220.

12. Callen, M. de Mel, S., McIntosh, C. and Woodruff, C., (2019). What are the headwaters of formal savings? Experimental evidence from Sri Lanka. *Review of Economic Studies*, *86* (6), 2491–2529.

13. Chakrabarty, M., and Mukherjee, S., 2021. Financial inclusion and household welfare: An entropy-based consumption diversification approach. *European Journal of Development Research*, *34*(3), 1486–1521.

14. Chen, S. and Zhang, H., 2021. Does digital finance promote manufacturing servitization: Micro evidence from China. *International Review of Economics and Finance, 76*, 856–869.

15. Cojoianu, T. F., Clark, G. L., and Hoepner, A. G. F., 2021. Fin vs. tech: are trust and knowledge creation key ingredients in fintech start-up emergence and financing? *Small Business Economics*, *57*, 1715–1731.

16. Daniel, B., and Grissen, D., 2015. Behavior revealed in mobile phone usage predict loan repayment (*Department of Economics, Brown University, Working Paper Series*).

17. Das, A., and Das, D., 2020. Perception, adoption, and pattern of usage of fintech services by bank customers: evidence from Hojai District of Assam. *Emerging Economy Studies*, *6* (1), 7–22.

18. Demir, A., Pesqué-Cela, V., Altunba, Y. and Murinde, V., 2022. Fintech, financial inclusion, and income inequality: a quantile regression approach. *European Journal of Finance*, *28*(1), 86–107.

19. Demirgüç-Kunt, A., and Klapper, L., 2013. Measuring financial inclusion: Explaining variation in use of financial services across and within countries. *Brookings Papers on Economic Activity* (1), 279–340.

20. Demirguc-Kunt, A., Klapper, L., Ansar, S., and Jagati, A., 2017. Making it easier to apply for a bank account: A study of the Indian market (*World Bank Policy Research Working Papers No. WPS8205*).

21. Dizon, F., Gong, E., and Jones, K., 2020. The effect of promoting savings on informal risk sharing: experimental evidence from vulnerable women in Kenya. *Journal of Human Resources*, *55*(3), 963–998.

22. Dupas, P. and Robinson, J., 2013. Savings constraints and microenterprise development: Evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics* **5**, 163–192.

23. Dupas, P., Karlan, D., Robinson, J., and Ubfal, D., 2018. Banking the unbanked? Evidence from three countries. *American Economic Journal: Applied Economics*, *10*(2), 257–297.

24. Fairlie, R. W., 2005. An extension of the Blinder-Oaxaca decomposition technique to logit and probit models. *Journal of Economic and Social Measurement*, *30*(4), 305–316.

25. Firpo, S. P., and Pinto, C., 2016. Identification and estimation of distributional impacts of interventions using changes in inequality measures. *Journal of Applied Econometrics*, *31*, 457–486.

26. Firpo, S. P., Fortin, N. M., and Lemieux, T., 2018. Decomposing wage distributions using recentered influence function regressions. *Econometrics*, *6*(2), 1–40.

27. Gambetta, D., 2000. Can we trust trust? In Gambetta, Diego (ed.) *Trust: Making and Breaking Cooperative Relations*, electronic edition, Department of Sociology, University of Oxford, Chapter 13, 213–237.

28. Gabor, D., and Brooks, S., 2017. The digital revolution in financial inclusion: International development in the fintech era. *New Political Economy*, *22*(4), 423–436.

29. Ghosh, S. and Vinod, D., 2017. What constrains financial inclusion for women? Evidence from Indian micro data. *World Development*, *92*, 60–81.

30. Ghosh, S., 2021. How important is trust in driving financial inclusion? *Journal of Behavioral and Experimental Finance*, *30*, 100510

31. Ghosh, S., 2022. Gender and financial inclusion: Does technology make a difference? *Gender, Technology and Development*, 26(2), 195–213.

32. Giné, X., Goldberg, J. and Yang, D., 2012. Credit market consequences of improved personal identification: Field experimental evidence from Malawi. *American Economic Review ,102*(6), 2923–2954.

33. Grishchenko, N., 2020. The gap not only closes: Resistance and reverse shifts in the digital divide in Russia. *Telecommunications Policy*, *44*(8), 102004.

34. Grohmann, A., Klühs, T., and Menkhoff, L., 2018. Does financial literacy improve financial inclusion? Cross country evidence. *World Development*, *111*, 84–96.

35. Gulamhuseinwala, I., Bull, T., and Lewis, S., 2015. FinTech is gaining traction and young, high-income users are the early adopters. *Journal of Financial Perspectives*, *3*(3), 16–23.

36. Hodula, M., 2022. Does fintech credit substitute for traditional credit? Evidence from 78 countries. *Finance Research Letters*, *46*(Part B), 102469.

37. Jack, W., and Suri, T., 2014. Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, *104*(1), 183–223.

38. Jagtiani, J., and Lemieux, C., 2018. *Do fintech lenders penetrate areas that are undeserved by traditional banks?* (Federal Reserve Bank of Philadelphia Working Paper Series). Philadelphia.

39. Johnen, C. and Mußhoff, O., 2022. Digital credit and the gender gap in financial inclusion: Empirical evidence from Kenya. *Journal of International Development, 35*(2), 272 - 295.

40. Johnen, C., Parlasca, M., and Mußhoff, O., 2021. Promises and pitfalls of digital credit: Empirical evidence from Kenya. *Plos One*, *16*(7), e0255215.

41. Kangwa, D., Mwale, J. T., and Junaid, S. M., 2020. Co-evolutionary dynamics of financial inclusion of generation Z in a Sub-Saharan digital financial ecosystem. *Copernican Journal of Finance and Accounting*, *9*(4), 27–50.

42. Karanasios, S., 2018. Toward a unified view of technology and activity: The contribution of activity theory to information systems research. *Information Technology and People*, *31* (1), 134–155.

43. Karlan, D., Kendall, J., Mann, R., Pande, R., Suri, T. and Zinman, J., 2016. Research and impacts of digital financial services. *NBER Working Paper No. 22633* (September).

44. Kass-Hanna, J., Lyons, A. C. and Liu, F., 2022. Building financial resilience through financial and digital literacy in South Asia and Sub-Saharan Africa. *Emerging Markets Review*, *51*(Part A), 2022, 100846.

45. Kim, K. H., 2020. The role of mobile money in improving the financial inclusion of Nairobi's urban poor. *African Journal of Science, Technology, Innovation and Development*, *12* (7), 855–865.

46. Kodongo, O., 2018. Financial regulations, financial literacy, and financial inclusion: Insights from Kenya. *Emerging Markets Finance and Trade*, *54*(12), 2851–2873.

47. Lee, I., and Shin, Y. J., 2018. Fintech: ecosystem, business models, investment decisions, and challenges. *Business Horizons*, *61*(1), 35–46.

48. Leland, H. E. and Pyle, D. H.,1977. The informational asymmetries, financial structure, and financial intermediation. *Journal of Finance*, *32*(2), 371–387.

49. Lewbel, A., 2012. Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business and Economic Statistics*, *30*, 67–80.

50. Liao, L., Ji, L., and Zhang, W., 2015. Education and credit: evidence from P2P lending platform. *Journal of Financial Research*, 3, 146–159.

51. Liébana-Cabanillas, F., Sánchez-Fernández, J., and Muñoz-Leiva, F., 2014. Antecedents of the adoption of the new mobile payment systems: the moderating effect of age. *Computers in Human Behavior*, 35, 464–478.

52. Madestam, A., 2014. Informal finance: A theory of moneylenders. *Journal of Development Economics*, *107*, 157–174.

53. Malaurent, J., and Karanasios, S., 2020. Learning from workaround practices: The challenge of enterprise system implementations in multinational corporations. *Information Systems Journal*, *30*(4), 639–663.

54. Mallinguh, E., Zoltan, Z., and Kecskes, H., 2017. Innovative financial digital ecosystem: an evaluative study of Kenya. In K. Cebeci, A. Pawlicz, and A. Altaher (Eds.), *MIRDEC - 6th International Academic Conference on Social Sciences, Multidisciplinary, Economics, Business and Finance Studies (Global Meeting of Social Science Community)*. Lisbon, Portugal: MIRDEC.

55. Martin, K. D., and Hill, R. P., 2015. Saving and well-being at the base of the pyramid: Implications for transformative financial services delivery. *Journal of Service Research*, *18*(3), 405-421.

56. McKnight, D. H. and Chervany, N. L., 2001., What trust means in e-commerce customer relationships: an interdisciplinary conceptual typology. *International Journal of Electronic Commerce*, *6*(2), 35–59.

57. McKnight, D. H., Cummings, L. L. and Chervany, N. L., 1998. Initial trust formation in new organizational relationships. *Academy of Management Review*, *23*(3), 473–490.

58. Mbiti, I. and Weil, D. N., 2016. The Impact of M-Pesa in Kenya. In S. Edwards, S. Johnson, and D. N. Weil (eds.), *African Successes, Volume III: Modernization and Development*, University of Chicago Press, 247–293.

59. Morgan, P. J., 2022. Fintech and financial inclusion in Southeast Asia and India. *Asian Economic Policy Review*, *17*, 183–208.

60. Munyegera, K. and Matsumoto, T., 2016. Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. *World Development*, *79*, 127–137.

61. Muralidhar, S. H., Bossen, C., and O'Neill, J., 2019. Rethinking financial inclusion: From access to autonomy. *Computer Supported Cooperative Work: An International Journal*, *28*(3–4), 511–547.

62. Muralidharan, K., Niehaus, P., and Sukhtankar, S., 2016. Building state capacity: Evidence from biometric smartcards in India. *American Economic Review*, *106*(10), 2895–2929.

63. N'dri, L. M., and Kakinaka, M., 2020. Financial inclusion, mobile money, and individual welfare: The case of Burkina Faso. *Telecommunications Policy*, *44*(3), 101926.

64. Natile, S., 2020. Digital finance, inclusion, and the mobile money "social" enterprise. *Historical Social Research*, *45*(3), 74–94.

65. Ntwiga, D. B., 2019. Can fintech shape the dynamics of consumer credit usage among the un(der)banked? (*KBA Centre for Research on Financial Markets and Policy Working Paper Series No. WPS/04/19*). Nairobi.

66. O'Neill, J., Dhareshwar, A., and Muralidhar, S. H., 2017. Working digital money into a cash economy: The collaborative work of loan payment. *Computer Supported Cooperative Work: An International Journal*, *26*(4–6), 733–768.

67. Oborn, E., Barrett, M., Orlikowski, W., and Kim, A., 2019. Trajectory dynamics in innovation: developing and transforming a mobile money service across time and place. *Management Science*, *30*(5), 869–1123.

68. Osoro, B. J., and Muriithi, D., 2018. Financial inclusion: how do you know that you are there? (*KBA Centre for Research on Financial Markets and Policy Working Paper Series No. WPS/03/18*). Nairobi.

69. Ozili, P. K., 2020. Theories of financial inclusion. In E. Özen and S. Grima (Eds.), *Uncertainty and Challenges in Contemporary Economic Behavior (Emerald Studies in Finance, Insurance, and Risk Management)* (pp. 89–115). Emerald Publishing Limited.

70. Pavlou, P. A., 2003. Consumer acceptance of electronic commerce: integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134.

71. Philippon, T., 2019. On fintech and financial inclusion. *NBER Working Paper Series*. Cambridge, MA: National Bureau of Economic Research.

72. Platteau, J-P., De Bock, O., and Gelade, W., 2017. The demand for microinsurance: a literature review. *World Development*, *94*, 139-156.

73. Pomeranz, D. and Kast, F., 2022. Savings accounts to borrow less. *Journal of Human Resources*, 0619-10264R3.

74. Prina, S., 2015. Banking the poor via savings accounts: Evidence from a field experiment. *Journal of Development Economics*, *115*, 16–31.

75. Riley, E., 2018. Mobile money and risk sharing against village shocks. *Journal of Development Economics*, *135*(May), 43–58.

76. Rios-Avila, F., 2020. Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. *Stata Journal*, *20*(1), 51–94.

77. Rios-Avila, F. and de New, J., 2022. Marginal unit interpretation of unconditional quantile regression and recentered influence functions using centered regression (July 29, 2022). *Melbourne Institute Working Paper No. 14/22*, http://dx.doi.org/10.2139/ssrn.4175831

78. Rjoub, H. Adedayo, T. S. and Kirikkaleli4, D., 2023. Blockchain technology-based FinTech banking sector involvement using adaptive neuro-fuzzy-based K-nearest neighbors algorithm. *Financial Innovation 9*, 1–23.

79. Sapienza, P. and Zingales, L., 2011. Trust, social capital, and financial development. *The Reporter,* 2 (June).

80. Schaner, S., 2017. The cost of convenience? Transaction costs, bargaining power, and savings account use in Kenya. *Journal of Human Resources*, *52*, 919–945.

81. Senyo, P. K., Karanasios, S., Gozman, D., and Baba, M., 2022. Fintech ecosystem practices shaping financial inclusion: The case of mobile money in Ghana. *European Journal of Information Systems*, *31*(1), 112–127.

82. Shaikh, A. A., Glavee-Geo, R., Karjaluoto, H. and Hinson, R. E., 2023. Mobile money as a driver of digital financial inclusion. *Technology Forecasting and Social Change*, *186*(Part B), 122158.

83. SKOLKOVO., 2015. Digital platforms and the ecosystems of financial inclusion: The Russian experience. Moscow, Russia: *The Moscow School of Management, SKOLKOVO*. Retrieved from https://ssrn.com/abstract=3104644

84. Somville, V. and Vandewalle, L., (2023). Access to banking, savings and consumption smoothing in rural India. *Journal of Public Economics*, *223*, 104900.

85. Stix, H., 2013. Why do people save in cash? Distrust, memories of banking crises, weak institutions and dollarization. *Journal of Banking and Finance, 37*(11), 4087–4106.

86. Stock, J. and Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Andrews D. W. K. (ed.), *Identification and Inference for Econometric Models*. New York: Cambridge University Press. 80–108.

87. Tang, H., 2019. Peer-to-peer lenders versus banks: substitutes or complements? *Review of Financial Studies*, *32*(5), 1900–1938.

88. World Bank., 2014. Financial inclusion (*Global Financial Development Report*). Washington DC: The World Bank Group.

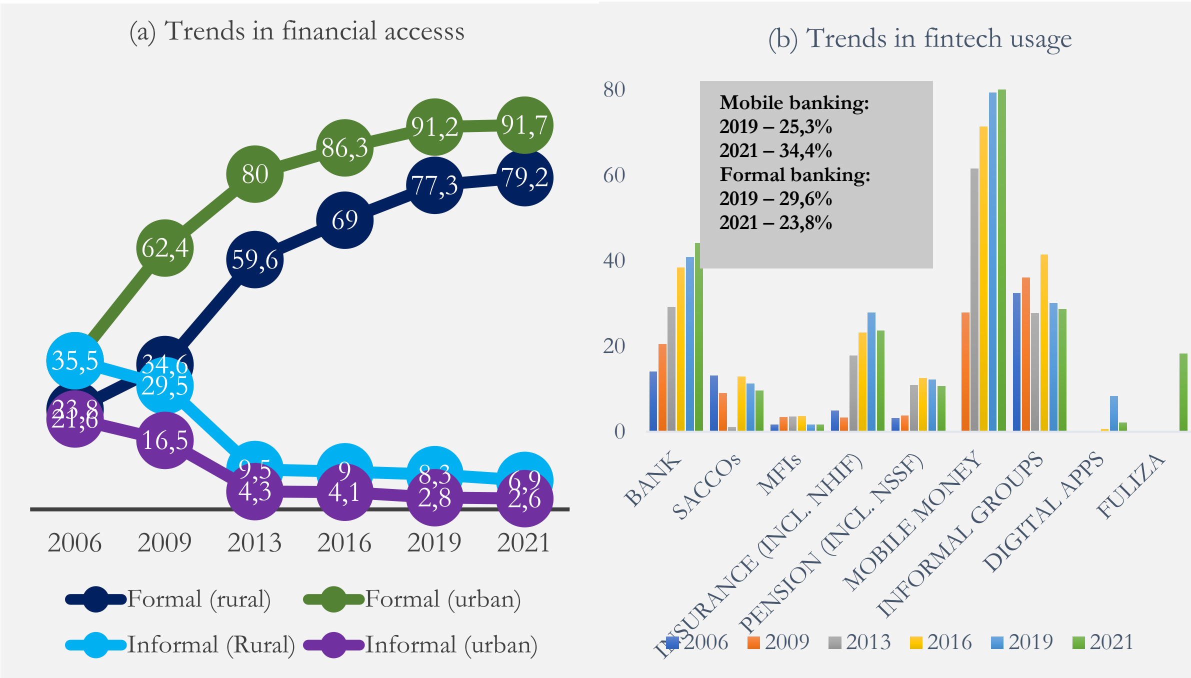
89. Yang, T. and Zhang, X., 2022. FinTech adoption and financial inclusion: Evidence from household consumption in China. *Journal of Banking and Finance*, *145*, 106668.

90. Yue, P., Korkmaz, A. G., Yin, Z., and Zhou, H., 2022. The rise of digital finance: Financial inclusion or debt trap? *Finance Research Letters*, 102604.

91. Zarifis, A. and Cheng, X., 2022. A model of trust in fintech and trust in insurtech: how artificial intelligence and the context influence it. *Journal of Behavioral and Experimental Finance*, *36*, 100739.

92. Zarifis, A., Kawalek, P. and Azadegan, A., 2021. Evaluating if trust and personal information privacy concerns are barriers to using health insurance that explicitly utilizes AI. *Journal of Internet Commerce*, *20*(1), 66–83.

Figure 1: Access to financial services by location of residence, 2006 – 2021



Source: FinAccess Kenya Financial Inclusion Survey, 2021

Figure 2: Sample attributes before and after matching

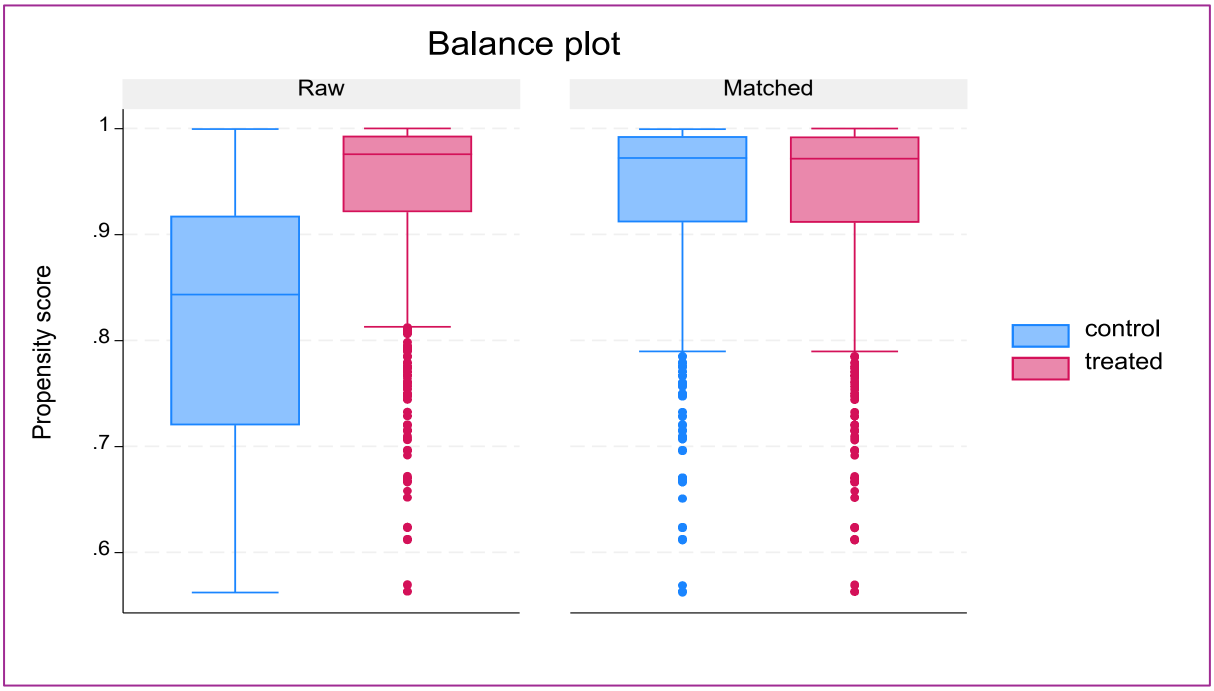


Table 1: Fintech ecosystem indicators

Fintech ecosystem dimension	Specific indicator(s)
Digital consumerism	Currently registered on a mobile money platform
	Owns a mobile phone or has access to someone else's mobile phone
	Mobile phone can access the internet
	Member of the household owns fixed internet at home
Financial capability	Paid monthly bills using a mobile money account
	Paid monthly bills using pay bill/till number on mobile money
	Paid school fees using a mobile money account
	Paid school fees using pay bill/till number on mobile money
	Paid daily expenses using a mobile money account
	Paid daily expenses using pay bill/till number on mobile money
	Sent money inside Kenya using a mobile money account
	Sent money inside Kenya using pay bill/till number on mobile money
	Received money from inside Kenya using a mobile money account
	Received money from inside Kenya using pay bill/till number on mobile money
	Paid a bill for medical treatment using a mobile money account
	Paid a medical bill using pay bill/till number on mobile money
Financial literacy	If you take a loan of KES 10,000 with interest rate of 10% per year, how much more money do you have to pay at the end of the year?
Ecosystem harmony	Mobile money account inability to transact due to system down time
	Mobile money account agent float unavailability
	Mobile money account holder unable to get to an agent
	Mobile money account fraud/attempted fraud (e.g., received less money from agent)

Table 2: Explaining usage of financial products

This table reports the marginal effects (unless otherwise specified) from the Logit regression with various usages of financial products of regulated financial institutions and markets as dependent variables. Robust standard errors (computed using the Delta method) are clustered by county of residence.

	Institutions			Markets
Dependent variable	Savings	Credit	Insurance	Securities
Fintech scores				
Coefficients†	0.147***	0.139***	0.166***	0.136*
	(0.031)	(0.037)	(0.021)	(0.099)
Marginal effects	0.011***	0.006***	0.020***	0.003
	(0.002)	(0.002)	(0.003)	(0.002)
Female	0.009	0.013**	-0.032**	-0.004
	(0.009)	(0.006)	(0.013)	(0.005)
Rural dwelling	-0.018	-0.003	-0.012	-0.008**
	(0.006)	(0.004)	(0.013)	(0.004)
Age group (18 – 24)	0.131	0.506***	0.027	-0.007
	(0.411)	(0.062)	(0.030)	(0.084)
Age group (25 – 34)	0.211	0.571***	0.115***	0.009
	(0.406)	(0.056)	(0.034)	(0.083)
Age group (35 – 44)	0.255	0.611***	0.172***	0.031
	(0.408)	(0.057)	(0.032)	(0.083)
Age group (45 – 54)	0.262	0.614***	0.198***	0.027
	(0.407)	(0.056)	(0.035)	(0.083)
Age group (55 +)	-0.015	0.027***	-0.083***	-0.006
	(0.015)	(0.010)	(0.019)	(0.004)
Language: English	0.301	0.599***	0.334***	0.057
	(0.409)	(0.060)	(0.032)	(0.084)
Language: Swahili	-0.018	0.028*	-0.004	0.009
	(0.027)	(0.017)	(0.027)	(0.047)
Education: Primary	-0.025	0.020	-0.013	0.002
	(0.028)	(0.015)	(0.027)	(0.046)
Education: Secondary	0.076***	0.039***	0.078***	0.028**
	(0.019)	(0.014)	(0.026)	(0.011)
Education: Tertiary	0.110***	0.049***	0.134***	0.043***
	(0.019)	(0.016)	(0.027)	(0.011)
Occupation: Farming	0.151***	0.079***	0.214***	0.059***
	(0.021)	(0.014)	(0.030)	(0.012)
Occupation: Waged	0.064***	0.024***	0.010	0.015***
	(0.014)	(0.008)	(0.015)	(0.005)
Occupation: Casual	0.108***	0.068***	0.181***	0.007
	(0.011)	(0.006)	(0.015)	(0.006)
Asset ownership	0.005	-0.005	-0.003	-0.004
	(0.010)	(0.008)	(0.009)	(0.005)
Constant†	0.017***	0.010***	0.041***	0.008***
	(0.004)	(0.002)	(0.004)	(0.001)
p-value of				
Wald	0.000	0.000	0.000	0.000
Pearson	0.994	0.898	0.201	1.000
Hat	0.000	0.000	0.000	0.000
Hat squared	0.601	0.487	0.135	0.884
# Bootstrap replications	44	37	50	50
# Observations	7230	7230	7230	7230

† indicates that the reported value is from the original logistic regression (i.e., not marginal effect); # denotes "no. of".
***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.10$

Table 3: Selection model with exogenous treatment

This table reports the marginal effects (unless otherwise specified) from the estimation of a selection model with exogenous treatment. Robust standard errors are clustered by county. We use numeracy and wealth respectively as the selection and treatment variables.

	Institutions			Markets
Dependent variable	Savings	Credit	Insurance	Investments
Fintech scores				
Coefficients	0.074*** (0.016)	0.048*** (0.022)	0.062*** (0.014)	0.034 (0.035)
Marginal effects	0.012*** (0.003)	0.003 (0.002)	0.016*** (0.004)	0.001 (0.001)
Average treatment effect	0.017 (0.014)	0.012 (0.009)	0.026 (0.020)	0.004 (0.005)
Controls	Yes	Yes	Yes	Yes
Error correlations	-0.16 [0.30]	0.34 [0.67]	-0.17 [0.15]	0.99 [0.00]
p-value of Wald chi-sq	0.000	0.000	0.000	0.000
Selected	4349	4349	4349	4349
Non-selected	2881	2881	2881	2881
# observations	7230	7230	7230	7230

***, p < 0.01; **, p < 0.05; *, p < 0.10.

Table 4: Lewbel Instrument variables regression

This table reports the coefficient estimates (clustered robust standard errors in parentheses) linear probability model instrument variables regression. The instrument set consists of numeracy and internal instruments constructed using the Lewbel (2012) approach.

	Institutions			Markets
Dependent variables	Savings	Credit	Insurance	Investments
Fintech scores	0.013*** (0.004)	0.007*** (0.002)	0.024*** (0.005)	-0.001 (0.002)
Controls	Yes	Yes	Yes	Yes
Wald [p-value]	66.53 [0.00]	32.94 [0.00]	470.95 [0.00]	15.30 [0.00]
Weak instruments†				
Cragg-Donald	79.83	79.83	79.83	79.83
Kleibergen-Paap	56.17	56.17	56.17	56.17
Overidentification (Hansen)	21.87 [0.15]	13.49 [0.64]	27.82 [0.03]	20.35 [0.21]
# observations	7230	7230	7230	7230

***, p < 0.01; **, p < 0.05; *, p < 0.10. † The highest Stock and Yogo (2005) critical value is 55.15. The null hypothesis of weak instruments is rejected if the computed statistic is higher than the critical values.

Table 5: RIF Treatment effects

This table reports abridged results of the RIF treatment effects regression of fintech ecosystem effects on financial inclusion. ATE is "average treatment effects"; ATT is "average treatment effects on the treated. Robust standard errors cluster by county.

	Savings	Credit	Insurance	Investments
Fintech dummy				
ATE	0.038*** (0.011)	0.015 (0.016)	0.077*** (0.028)	0.013*** (0.004)
ATT	0.040* (0.016)	0.016 (0.015)	0.079** (0.034)	0.014*** (0.004)
Controls	Yes	Yes	Yes	Yes
# bootstrap replications	50	50	50	50
p-value of Wald	0.00	0.00	0.00	0.00
Adjusted R squared	0.13	0.10	0.18	0.05
# observations used	7063	7063	7063	7063

***, p<0.01; **, p<0.05; *, p<0.10

Table 6: Decomposition of the fintech ecosystem usage effects (Oaxaca-Blinder)

This table shows the decomposition of effects on financial products usage for individuals who use the fintech ecosystem vs those who do not. TCE is total composition effect; FEF is total unexplained effect; comp. is "composition"; Spec is "specification"; Rewgt is "reweighting"; p-val is p-value. Variable clusters are formed thus. Language: English, Swahili; Age group: 18–25 years. 26–35 years, 35–45 years, 46–55 years, >55 years; Education: primary, secondary, tertiary; Occupation: waged, farming, casual. Asset ownership is a score as explained.

	Savings		Credit		Insurance	
Fintech non-users	0.026*** (0.009)		0.007* (0.003)		0.052*** (0.012)	
Fintech users	0.114*** (0.012)		0.060*** (0.006)		0.227*** (0.016)	
Difference (gap)	-0.089*** (0.011)		-0.053*** (0.006)		-0.175*** (0.013)	
Decomposition	TCE	FEF	TCE	FEF	TCE	FEF
Spec error [p-val]	0.009 [0.558]		0.007 [0.489]		-0.020 [0.751]	
Rewgt error [p-val]		-0.003 [0.931]		-0.001 [0.966]		-0.008 [0.933]
Pure comp. effect	0.006 (0.005)		-0.012*** (0.004)		-0.022*** (0.008)	
Pure FEF effect		-0.089 (0.074)		-0.047 (0.060)		-0.126 (0.214)
Rural	0.004*** (0.001)	0.004 (0.052)	0.003*** (0.001)	0.000 (0.050)	-0.004*** (0.001)	-0.048 (0.307)
Female	-0.001* (0.001)	0.004 (0.052)	-0.001** (0.000)	-0.006 (0.036)	-0.004** (0.002)	-0.018 (0.177)
Age group	0.018*** (0.002)	-0.077 (0.095)	0.000 (0.001)	-0.014 (0.065)	0.020*** (0.003)	-0.091 (0.271)
Language	0.001 (0.001)	-0.009 (0.121)	-0.001*** (0.000)	-0.009 (0.040)	0.004*** (0.001)	0.011 (0.208)
Education	-0.015*** (0.002)	-0.048 (0.116)	-0.001 (0.001)	-0.020 (0.049)	-0.011*** (0.002)	-0.088 (0.181)
Occupation	-0.013*** (0.005)	-0.010 (0.134)	-0.008** (0.004)	-0.030 (0.037)	-0.014** (0.006)	0.026 (0.212)
Asset ownership	0.000 (0.001)	-0.052 (0.057)	-0.004*** (0.001)	-0.031 (0.035)	-0.013*** (0.003)	-0.051 (0.199)
Constant		0.100 (0.249)		0.063 (0.114)		0.134 (0.429)
# Non-users	582	582	582	582	582	582
# Users	6648	6648	6648	6648	6648	6648

***, p<0.01; **, p<0.05; *, p<0.10.

Table 7: Lewbel IV estimation of beneficiaries of fintech ecosystem

This table reports coefficient estimates (clustered robust standard errors in parentheses) from two-step GMM estimation of a linear probability model. $Youth$ = age group: 18 – 34 years; $Wealth$ represents the three upper wealth quintiles (60% upper wealthy); $HigEd$ is higher education (secondary and tertiary); "# Obs." is number of observations. J is Hansen's J-statistic for testing overidentifying restrictions. F is from the Wald test of goodness of fit.

	Savings				Credit				Insurance				Investments			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	12)	(13)	(14)	(15)	(16)
Fintech	0.02** (0.01)	0.01*** (0.00)	0.004*** (0.00)	0.002* (0.00)	0.02*** (0.01)	0.003** (0.00)	0.004*** (0.00)	0.003*** (0.00)	0.04*** (0.01)	0.01*** (0.00)	0.02** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Youth	0.06*** (0.02)				0.09*** (0.02)				0.10*** (0.03)				0.05*** (0.01)			
Male		-0.00 (0.03)				-0.01** (0.01)				-0.03** (0.01)				0.00 (0.13)		
$HigEd$			-0.01 (0.02)				-0.01 (0.01)				0.10** (0.04)				-0.01 (0.02)	
Wealth				-0.03*** (0.01)				-0.02* (0.01)				0.05*** (0.01)				-0.02 (0.02)
$Fintech \times Youth$	-0.02*** (0.01)				-0.03*** (0.01)				-0.03*** (0.01)				-0.02*** (0.00)			
$Fintech \times Male$		0.004* (0.00)				0.003* (0.00)				0.01*** (0.00)				0.00 (0.00)		
$Fintech \times HigEd$			0.02*** (0.00)				0.01*** (0.00)				0.01 (0.01)				0.01** (0.00)	
$Fintech \times Wealth$				0.01*** (0.00)				0.01*** (0.00)				0.01*** (0.00)				0.00 (0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prob F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Prob J	0.209	0.111	0.413	0.369	0.127	0.155	0.216	0.148	0.782	0.096	0.322	0.101	0.419	0.127	0.127	0.199
# Obs.	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230	7230

***, p<0.01; **, p<0.05; *, p<0.10.

Table 8: Explaining usage of fintech products

This table reports marginal effects outputs for Equation (5) with robust standard errors, clustered by county of residence, for the regression of the fintech ecosystem (dependent variable) against explanatory variables and a set of controls. ID stands for identification document. ATE and ATT respectively denote average treatment effect and average treatment effect on the treated. POM = potential outcome mean.

	Traditional Poisson model	Extended (treatment) Poisson	Instrument variable LPM
	(1)	(2)	(3)
Distance to bank	-0.409*** (0.123)	-0.403*** (0.124)	-0.324*** (0.075)
History of transactions	-0.208 (0.204)	-0.235 (0.203)	-0.281 (0.174)
Trust	-0.192 (0.172)	-0.190 (0.171)	-0.143 (0.125)
Northern Kenya	-0.346 (0.266)	-0.361 (0.266)	-0.265 (0.145)
Female	-0.010 (0.050)	-0.011 (0.050)	0.010 (0.043)
Language – English	-0.003 (0.255)	-0.013 (0.253)	0.082 (0.146)
Language – Swahili	0.177 (0.223)	0.161 (0.220)	0.189* (0.105)
Education – primary	1.439*** (0.188)	1.439*** (0.187)	1.031*** (0.096)
Education – secondary	2.235*** (0.199)	2.236*** (0.198)	1.751*** (0.105)
Education – tertiary	2.590*** (0.217)	2.604*** (0.215)	2.502*** (0.131)
Occupation – Farmer	0.146** (0.072)	0.131* (0.070)	0.141** (0.053)
Occupation – Waged	0.428*** (0.084)	0.397*** (0.081)	0.749*** (0.079)
Occupation – Casual	0.181** (0.085)	0.149* (0.084)	0.239*** (0.068)
Age	0.098*** (0.011)	0.099*** (0.011)	0.066*** (0.007)
Age squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Possession of ID	1.850*** (0.132)	1.823*** (0.131)	1.657*** (0.090)
Ownership of assets	0.322*** (0.028)	0.323*** (0.028)	0.360*** (0.025)
Internet use	1.461*** (0.091)	1.463*** (0.090)	1.592*** (0.065)
Disability	-0.483*** (0.111)	-0.487*** (0.112)	-0.396*** (0.079)
Income (mid and upper)	0.123 (0.130)		0.356** (0.136)
Treatment (no income = 0)			
POM		1.072*** (0.029)	
ATE		0.373*** (0.140)	

	Traditional Poisson model	Extended (treatment) Poisson	Instrument variable LPM
	(1)	(2)	(3)
ATT		0.377*** (0.142)	
Constant			0.536*** (0.168)
Pseudo R-squared/Rho	0.132	0.995	0.497
p-value of			
Hat squared	0.000		
Goodness of fit	0.000		0.000
Independence		0.000	
Hansen			0.378
Weak instruments (F-stat) †			
Cragg-Donald			1725
Kleibergen-Paap			523

***, p<0.01; **, p<0.05; *, p<0.10.

† The highest Stock and Yogo (2005) critical value is 55.15. The null hypothesis of weak instruments is rejected if the computed statistic is higher than the critical values.

Table 9: Outputs of interaction regressions

$Dist$ is distance to the nearest bank; $Hist$ is history of financial transactions; and PA is product appropriateness; "app" stands for appropriateness. HL is an abbreviation for the Hosmer-Lemeshow test.

	Savings			Credit			Insurance			Investments		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fintech score	0.009*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.005*** (0.001)	0.006*** (0.002)	0.006*** (0.001)	0.019*** (0.003)	0.020*** (0.003)	0.019*** (0.003)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
Distance	-0.139*** (0.048)			-0.050* (0.026)			-0.056** (0.027)			-0.034 (0.025)		
History		-0.052 (0.138)			-0.033 (0.097)			0.160 (0.117)			0.004 (0.039)	
Trust			-0.054 (0.083)			0.062* (0.034)			-0.131 (0.089)			-0.020 (0.013)
$Fintec \times Dist$	0.014** (0.006)			0.007* (0.004)			0.009** (0.004)			0.004 (0.004)		
$Fintec \times Hist$		0.002 (0.017)			0.004 (0.011)			-0.037* (0.020)			-0.002 (0.006)	
$Fintec \times Trust$			0.009 (0.015)			-0.010** (0.005)			0.019 (0.016)			-0.003 (0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value of												
Wald χ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pearson	0.99	0.99	0.99	0.53	0.98	0.30	0.59	0.40	0.41	0.99	0.99	0.99
Hat-sqd.	0.66	0.63	0.57	0.31	0.43	0.28	0.05	0.15	0.11	0.96	0.89	0.85

***, p<0.01; **, p<0.05; *, p<0.10.

Table 10: Selection model with exogenous treatment for mobile money usage

This table reports the marginal effects (unless otherwise specified) from the estimation of a selection model with exogenous treatment. Robust standard errors are clustered by county. We use numeracy and wealth respectively as the selection and treatment variables.

	Institutions			Markets
Dependent variable	Savings	Credit	Insurance	Investments
$MMuse$				
Coefficients	0.287*** (0.079)	0.262** (0.118)	0.294*** (0.069)	0.195* (0.106)
Marginal effects	0.049*** (0.015)	0.018* (0.010)	0.075*** (0.018)	0.007* (0.004)
Numeracy: ATE	0.220** (0.086)	0.244** (0.114)	0.196** (0.079)	0.177 (0.127)
Controls	Yes	Yes	Yes	Yes
Prob Wald chi sq.	0.00	0.00	0.00	0.00
Selected	4349	4349	4349	4349
Non-selected	2881	2881	2881	2881

***, p < 0.01; **, p < 0.05; *, p < 0.10.

Table 11: Decomposition of the mobile money usage effects (Oaxaca-Blinder)

This table shows the decomposition of effects on financial products usage for individuals who use mobile money vs those who do not. TCE is total composition effect; FEF is total financial inclusion effect; n-users represents "non-users"; comp. is "composition". Spec is "specification"; Rwt is "reweighting".

	Savings		Credit		Insurance		Investments	
MM non-users	0.032*** (0.006)		0.011*** (0.002)		0.081*** (0.010)		0.005*** (0.002)	
MM users	0.144*** (0.014)		0.078*** (0.007)		0.281*** (0.018)		0.038*** (0.006)	
Difference (gap)	-0.112*** (0.010)		-0.067*** (0.007)		-0.200*** (0.018)		-0.033*** (0.005)	
Decomposition	TCE	FEF	TCE	FEF	TCE	FEF	TCE	FEF
Spec error [p-val]	-0.013 [0.676]		-0.053 [0.099]		-0.037 [0.148]		-0.022 [0.489]	
Rwt error [p-val]		0.016 [0.521]		0.043 [0.215]		-0.044 [0.234]		0.017 (0.465)
Pure comp. effect	0.056*** (0.012)		-0.039*** (0.010)		-0.093*** (0.021)		-0.015** (0.006)	
Pure FEE effect		-0.058** (0.026)		-0.019 (0.018)		-0.113*** (0.023)		-0.012 (0.022)
Controls	Yes		Yes		Yes		Yes	

***, p<0.01; **, p<0.05; *, p<0.10. in square brackets are p-values; in braces are standard errors.

Table 12: IV-Probit regression results for mobile money usage

This table reports coefficient estimates from the instrument variable regression of mobile money usage against explanatory variables and a set of controls. $MMuse$ is mobile money usage; $Dist$ is "distance"; $Hist$ is "history of financial transactions"; Exog. is the Wald test for exogeneity of instruments.

	Savings			Credit			Insurance			Investments		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$MMuse$	2.000*** (0.227)	1.990*** (0.171)	1.984*** (0.170)	2.145*** (0.173)	2.036*** (0.158)	2.035*** (0.158)	2.178*** (0.151)	2.057*** (0.156)	2.049*** (0.154)	2.237*** (0.187)	2.123*** (0.200)	2.197*** (0.162)
Distance	-0.181 (0.272)			0.198 (0.239)			0.355** (0.151)			0.139 (0.312)		
History		-0.417 (0.523)			-0.481 (0.634)			0.267 (0.430)			-0.142 (0.507)	
Trust			-0.514 (0.335)			0.246 (0.360)			-0.643** (0.309)			-0.204 (0.178)
$MMuse \times Dist$	-0.055 (0.045)			-0.084** (0.043)			-0.102*** (0.032)			-0.096* (0.054)		
$MMuse \times Hist$		-0.006 (0.072)			0.019 (0.087)			-0.124* (0.075)			-0.036 (0.077)	
$MMuse \times Trust$			0.049 (0.051)			-0.080 (0.055)			0.061 (0.059)			-0.047 (0.036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value:												
Wald χ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Exog.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*, p<0.10; **, p<0.05 and ***, p<0.01

Table 13: Fintech ecosystem sub-constructs

This table reports the marginal effects (unless otherwise specified) from the Logit regression with various usages of financial products of regulated financial institutions and markets as dependent variables. Robust standard errors (computed using the Delta method) are clustered by county of residence. # denotes "no. of". ***, p < 0.01; **, p < 0.05; *, p < 0.10. The number of observations is 7230.

	Institutions			Markets
Dependent variable	Savings	Credit	Insurance	Securities
A. Digital Consumerism				
Digital consumerism				
Coefficients	0.319***	0.322***	0.434***	0.446***
	(0.072)	(0.097)	(0.088)	(0.099)
Marginal effects	0.024***	0.013***	0.053***	0.010***
	(0.008)	(0.004)	(0.011)	(0.003)
p-value of				
Wald	0.000	0.000	0.000	0.000
Pearson	0.997	0.614	0.451	0.999
Hat	0.000	0.000	0.000	0.000
Hat squared	0.378	0.345	0.115	0.766
Bootstrap replications	47	37	50	49
B. Financial Capability				
Digital capability				
Coefficients	0.145***	0.175***	0.167***	0.144*
	(0.037)	(0.035)	(0.030)	(0.088)
Marginal effects	0.011***	0.007***	0.020***	0.003
	(0.003)	(0.001)	(0.003)	(0.002)
p-value of				
Wald	0.000	0.000	0.000	0.000
Pearson	0.417	0.164	0.563	0.998
Hat	0.000	0.000	0.000	0.000
Hat squared	0.352	0.489	0.117	0.924
Bootstrap replications	43	39	50	47
C. Financial Literacy				
Financial literacy				
Coefficients	0.287**	0.298**	0.254***	0.309
	(0.133)	(0.149)	(0.097)	(0.233)
Marginal effects	0.022**	0.012**	0.031**	0.007
	(0.010)	(0.006)	(0.012)	(0.005)
p-value of				
Wald	0.000	0.000	0.000	0.000
Pearson	0.040	0.000	0.174	0.999
Hat	0.000	0.000	0.000	0.000
Hat squared	0.428	0.215	0.085	0.885
Bootstrap replications	40	36	50	50

Appendix

Table A1: Variable construction and summary statistics.

		Full sample			Fintech ecosystem		
					Users (6648)	Non Users (582)	t-test (Are means equal?)
Variable	Construction	Mean	SD	Obs.	Mean	Mean	p-value
Usage of financial products							
Savings	Equals 1 for respondents who currently use Savings from a prudential formal financial institution.	0.107	0.310	7230	0.114	0.026	0.000
Credit	Equals 1 for respondents who currently use Credit from a prudential formal financial institution	0.056	0.229	7230	0.060	0.007	0.000
Insurance	Equals 1 for respondents who currently use Insurance from a prudential formal financial institution	0.215	0.411	7230	0.230	0.053	0.000
Investments	Equals 1 for respondents who currently use Investments in securities markets (stocks, bonds, etc.)	0.027	0.162	7230	0.029	0.000	0.000
Explanatory variable							
Fintech ecosystem	Score of various variables as described in Section 3.1.2	4.517	2.671	7230	4.283	0.000	0.000
Financial inclusion barriers							
Distance	Equals 1 if respondent lives at least KES 200 from the nearest bank	0.169	0.375	7230	0.157	0.299	0.000
History	Equals 1 if respondent has no credit history or record of financial transactions	0.015	0.121	7230	0.016	0.005	0.002
Trust	Equals 1 if respondent answers, “no trust” regarding banks, security markets and brokers	0.023	0.151	7230	0.024	0.010	0.002
Other variables							
Rural dwelling	Equals 1 if an individual lives in rural areas	0.679	0.467	7230	0.662	0.873	0.000
Female	Equals 1 if respondent is of female gender	0.566	0.496	7230	0.562	0.617	0.009
Age	Actual (integer) age, in years, of individual	39.2	18.1	7230	38.5	47.5	0.000
Age (18–24 years)	Equals 1 if age (years) is in the range [18, 24]	0.179	0.383	7230	0.182	0.139	0.004
Age (25–34 years)	Equals 1 if age (years) is in the range [25, 34]	0.251	0.434	7230	0.261	0.131	0.000
Age (35–44 years)	Equals 1 if age (years) is in the range [35, 44]	0.182	0.386	7230	0.188	0.110	0.000

Age (45 – 54 years)	Equals 1 if age (years) is in the range [45, 54]	0.121	0.326	7230	0.122	0.100	0.081
Age (over 55 years)	Equals 1 if age (years) is aged 55 years or more	0.209	0.406	7230	0.096	0.201	0.000
Language: English	Equals 1 if individual speaks English	0.323	0.467	7230	0.330	0.234	0.000
Language: Swahili	Equals 1 if individual speaks Swahili	0.597	0.491	7230	0.595	0.622	0.193
Education: primary	Equals 1 if highest education is “primary”	0.409	0.492	7230	0.411	0.390	0.319
Education: secondary	Equals 1 if highest education is “secondary”	0.289	0.453	7230	0.305	0.112	0.000
Education: tertiary	Equals 1 if highest education is “beyond high school”	0.108	0.310	7230	0.112	0.003	0.000
Occupation: waged	Equals 1 if respondent is wage-employed	0.113	0.317	7230	0.122	0.014	0.000
Occupation: farming	Equals 1 if respondent is farming	0.309	0.462	7230	0.308	0.325	0.410
Occupation: casual	Equals 1 if respondent is casually employed	0.392	0.488	7230	0.402	0.280	0.000
Asset ownership	Score of assets owned	1.272	1.189	7230	1.336	0.531	0.000
Possession of ID	Equals 1 if respondent owns identification document	0.876	0.330	7230	0.885	0.773	0.000
Low income	Equals 1 if respondent earns below KES 30,000	0.863	0.344	7230	0.865	0.837	0.077
Middle income	Equals 1 if respondent earns KES 30,001–200,000	0.023	0.151	7230	0.025	0.000	0.000
North Kenya	Equals 1 if respondent is from Northern Kenya	0.131	0.337	7230	0.122	0.230	0.000
Disability	Equals 1 if respondent has a disability	0.145	0.352	7230	0.134	0.278	0.000
Wealth	Equals 1 if one’s wealth is in the top 60%	0.601	0.489	7230	0.628	0.284	0.000
Youth	Equals 1 if respondent is in age group (18 – 35 years)	0.463	0.499	7230	0.478	0.299	0.000
Numeracy	Equals 1 if respondent answers a numeracy question correctly	0.579	0.494	7230	0.613	0.184	0.000
Uses internet	Equals 1 if respondent used internet in the last year	0.292	0.455	7230	0.316	0.021	0.000
Mobile money user	Equals 1 if respondent used a mobile money account for a financial transaction in past three months	0.671	0.470	7230	0.724	0.070	0.000

Fintech ecosystem sub-constructs		Mean	SD	Obs.	Correlation with fintech ecosystem construct		
Digital consumerism	Score of various variables as described in Table 1	1.873	0.917	7230	0.728	-	-
Digital capability	Score of various variables as described in Table 1	2.020	1.724	7230	-	0.847	-
Financial literacy	Score of various variables as described in Table 1	0.425	0.494	7230	-	-	0.504