WP/21/167

IMF Working Paper

Is Digital Financial Inclusion Unlocking Growth?

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INTERNATIONAL MONETARY FUND

 WP/21/167

IMF Working Paper

Monetary and Capital Markets Department

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June 2021

Abstract

Digital financial services have been a key driver of financial inclusion in recent years. While there is evidence that financial inclusion through traditional services has a positive impact on economic growth, do the same results carry over for digital financial inclusion? What drives digital financial inclusion? Why does it advance more in some countries but not in others? Using new indices of financial inclusion developed in Khera et. al. (2021), this paper addresses these questions for 52 developing countries. Using cross-sectional instrument variable procedure, we find that the exogenous component of digital financial inclusion is positively associated with growth in GDP per capita during 2011-2018, which suggests that digital financial inclusion can accelerate economic growth. Fractional logit and random effects empirical estimation identifies access to infrastructure, financial and digital literacy, and quality of institutions as key drivers of digital financial inclusion. These findings are then used to help inform policy recommendations in areas related to the digitization of financial services to promote financial inclusion.

JEL Classification Numbers: C33, C36, G10, G20, O30

Keywords: Fintech; digital financial services; financial inclusion

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[1] The authors wish to thank Tobias Adrian, Martin Čihák, Ulric Eriksson von Allmen, Amina Lahreche, Kimberly Beaton, and Majid Bazarbash for their guidance, support and immensely helpful feedback and comments. We'd also like to thank Itai Agur, Patricia Alonso-Gamo, Pelin Berkmen, Nicolas Blancher, Era Dabla-Norris, Bidisha Das, Jennifer Elliot, Federico Grinberg, Dirk Jan Grolleman, Frederic Lambert, Elena Lukoianova, Inutu Lukonga, Jennifer Moyo, Maria Soledad Martinez Peria, Nicolas Racine, Celine Rochon, Kazuko Shirono, Amadou Sy, Jose Torres, Tomohiro Tsuruga, and Hector Carcel Vilanova for their helpful comments; and participants of various seminars and conferences in which we presented the key findings.

Contents

I. INTRODUCTION

Digital financial services (DFSs), enabled by fintech (technological innovation in the financial sector), have become an important driver of financial inclusion in emerging markets and developing economies (EMDEs) in recent years. Country-based case studies (Jack and Suri, 2011; 2014; Tarazi and Breloff, 2010) and regional studies (Sy et. al., 2019; Berkmen et. al., 2019; Loukoianova et al, 2019, Lukonga, 2018, and Blancher et al., 2019) provide anecdotal evidence on how fintech is increasing access to financial services. Adapting the methodology used to measure financial inclusion through traditional financial institutions, Sahay et. al. (2020) and Khera et. al. (2021) quantify the progress in digital financial inclusion. They find that digital financial inclusion has indeed advanced in most of the EMDEs between 2014 and 2017, even where traditional financial inclusion retreated.

There are two key contributions of this paper. First, we conduct a cross-country examination of digital financial inclusion on economic growth, and second, we explore the key drivers of digital financial inclusion. We use new indices developed by Khera et. al. (2021), which are the most comprehensive to date in capturing multiple aspects of digital financial inclusion across 52 EMDEs across time. These indices facilitate cross-country analyses, and allow for more granular understanding of the relative contribution of digitization versus traditional services to economic growth.

There is considerable literature showing the positive impact of financial development on economic growth (Levine, 2005). Several recent papers also find a positive correlation between traditional financial inclusion and economic growth (Sahay et al., 2015a), and also with poverty alleviation at the country level (Beck, Demirguc-Kunt, and Levine, 2007; Honohan 2004; World Bank, 2008). Our paper adds to this literature by exploring the relationship between digital financial inclusion and economic growth. We regress the growth rate of the real per capita gross domestic product (GDP) against the level of usage of DFSs (measured by the digital financial usage index in Khera et. al. (2021)), along with a broad set of variables that serve as conditioning information, including the measure of traditional financial inclusion. Economic activity is assumed to be more directly affected by the actual usage of financial services which allows consumption smoothing and saving, rather than the availability of access.

In order to address potential endogeneity-related issues, we run a cross-country regression for our sample of 52 countries over the period 2011-18 using three approaches: (i) we establish a significantly positive relationship using a cross-country OLS regression of GDP per capita growth indicators (averaged over 2011-18) on digital financial usage index and; (ii) to avoid potential reverse causality associated with (i), we relate digital financial usage in 2011 to subsequent average growth over the period 2011-18; and (iii) to establish causality, we use a cross-country instrument variable estimator to extract the exogenous components of the digital financial usage index. For this purpose, access to mobile money agents and access to the internet are used as instrument variables to control for the simultaneity bias. Results show that the positive link between digital financial usage and growth is not only due to growth influencing digital financial inclusion; the strong positive relationship between digital financial inclusion and long-run growth is at least partly explained by the effect of the exogenous component of digital financial usage on economic growth.

Most previous studies on the drivers of financial inclusion have focused on traditional financial inclusion.[2] The few studies that have attempted to identify drivers of digital financial inclusion largely focus on a specific country or region and/or use data relating to a specific fintech firm (Aron, 2017). In this paper, we conduct a cross-country analysis by identifying both supply and demand side factors. Specifically, we estimate the following: (i) a random effects panel regression model with mobile agents per capita as dependent variables to identify possible supply-side factors driving digital financial inclusion; and (ii) a fractional logit panel regression model with digital usage index as the dependent variable, to identify possible demand-side factors. A broad set of macroeconomic, socio-economic, and financial sector indicators are considered, including access to digital infrastructure, efficiency and level of competition in the financial sector.

Our key findings are that digital financial inclusion is higher where the use of traditional financial services is high, but where the access to these services is limited. In other words, fintech supply (access) is "filling the gap" left by traditional financial institutions, including due to inefficiencies and lack of competition; and, fintech demand (usage) is higher where individuals have higher financial awareness and trust in the financial system. Moreover, access to digital infrastructure (measured by the accessibility to internet services and mobile phone) and inefficiency of traditional financial service providers are also found to be statistically significant drivers.

These findings have important policy implications. Our results suggest that in countries where there are gaps in access to traditional financial institutions, there is scope for fintech to increase financial inclusion through supply-focused policies such as promoting an enabling environment for innovation and competition in the financial sector. However, promoting supply of DFSs is in itself not sufficient to advance financial inclusion, as the gains will be limited unless accompanied by demand-inducing policies. In this regard, financial and digital literacy, consumer protection, and ensuring cybersecurity could promote the trust in financial services and encourage its uptake. At the same time, with the greater use of fintech in financial services, appropriate regulatory responses are needed to help address emerging risks such as those related to financial inclusion itself stemming from a digital divide across the population, data biases, and ensuring competition amongst fintech companies (Sahay et al., 2020).

The remainder of the paper is organized as follows: Section II presents an overview of the financial inclusion indices used for the empirical analyses; Section III reviews the implication of digital financial inclusion on growth; Section IV analyzes the key drivers of traditional and digital financial inclusion; and Section V concludes with key findings and policy implications.

[2] Dabla-Norris et al., 2015, Rojas-Suarez and Amado, 2014; Rojas-Suarez, 2016, Deléchat et al 2018, Loukoianova, Yang et al., 2018, Blancher et al., 2019.

II. New Indices of Financial Inclusion: Stylized Facts

Khera et. al. (2021) constructs enhanced measurement of financial inclusion for 2014 and 2017 covering 52 EMDEs, by incorporating the digital aspects to the measure of financial inclusion through financial institutions such as banks. Following existing literature, the indices consists of indicators on access and usage provided by financial institutions and by DFSs including mobile money operators, fintech companies and other new entrants in the financial sector (Table 1).

A three-stage principal component analysis (PCA) is used to: 1) construct "access" and "usage" sub-indices, to capture supply-side and demand-side aspects of financial inclusion, respectively; 2) combine access and usage sub-indices into "traditional" and "digital" financial inclusion index, to capture financial inclusion through financial institutions and enabled by technology separately; and 3) construct an overall measure of financial inclusion reflecting both traditional and digital aspects ("comprehensive financial inclusion index").

Table 1. Selected Variables for Financial Inclusion Indices

Overall Financial Inclusion Index

Traditional Financial Inclusion Index	Data Source	Weight	Digital Financial Inclusion Index	Data Source	Weight
Access[1]			**Access**		
Access to bank infrastructure		0.25	**Access to digital infrastructure**		0.125
Number of ATMs per 100,000 adults Number of Branches per 100,000 adults	IMF FAS		Mobile subscription per 100 people % of population who has access to internet	ITU	
			Number of registered mobile money agents per 100,000 adults	IMF FAS GSMA Staff est.	0.25
Usage		0.25	**Usage[2]**		0.125
% of adults with a financial institution account % of adults who saves at a financial institution % of adults with debit cards % of adults who receives wages through a financial institution account % of adults who uses a financial institution account for utility	WB Findex		% of adults who has a mobile account % of adults who uses internet to pay % of adults who uses mobile phone to receive salary or wages % of adults who uses mobile phone to make utility payments	WB Findex	

Note: 'Weight' is the weight of the variable in the overall index of financial inclusion

[1] For missing data from IMF's FAS on ATM per 100,000 adults and bank branches per 100,000 adults, we use proxy variables (i.e. ATM per 10,000 km2 and bank branches per 10,000 km2) to interpolate the missing data. When data on proxy variable is also not available, missing data is filled with the general past trend in the variable.

[2] The FAS includes annual data on Mobile Money transactions and volume, but the data is available for only a limited number of countries. These variables are therefore excluded to retain as many countries as possible in our sample.

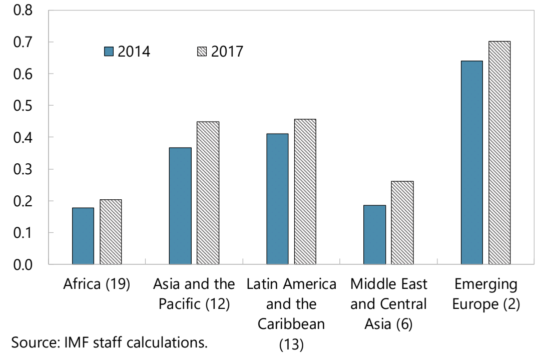
The indices show that:

- **Traditional financial inclusion** is found to be relatively high in countries in Asia and the Pacific, Latin America and the Caribbean, and Emerging Europe (Figure 1). Traditional financial inclusion index remained broadly unchanged between 2014 and 2017, and eight countries experienced a decline.[3]

- **Digital financial inclusion** is found to be relatively high in countries in Africa and Asia and the Pacific regions (Figure 2). Most countries saw an increase in digital financial inclusion index between 2014 and 2017, driven both by access and usage dimensions. The improvement was particularly large in African countries (e.g., Ghana, Benin, and Senegal), while relatively muted in some of the countries in Latin America and the Caribbean, and Middle East and Central Asia.

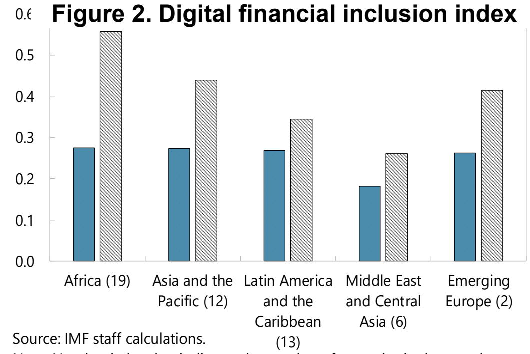
- **Comprehensive financial inclusion** improves significantly for countries with high digital but low traditional inclusion, providing an aggregate measure of differences in financial inclusion across countries (Figure 3). For example, Senegal and Myanmar have similar levels of traditional financial inclusion, but there is a large gap in terms of the comprehensive measure. On the other hand, financial inclusion remain high in China, Turkey and Brazil by both measures, reflecting relatively high levels of financial inclusion both through financial institutions and DFSs. Comprehensive financial inclusion index improved for

Figure 1. Traditional financial inclusion index



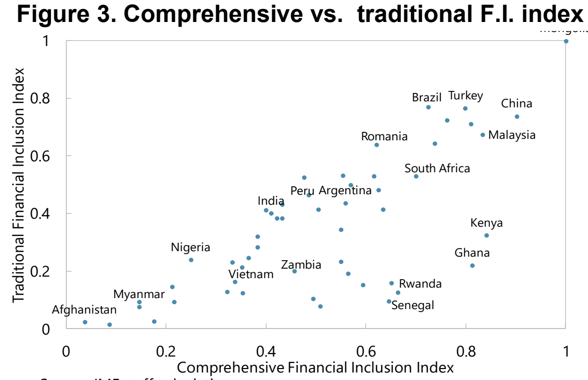
Source: IMF staff calculations.
Note: Number in bracket indicates the number of countries in the sample.

Figure 2. Digital financial inclusion index



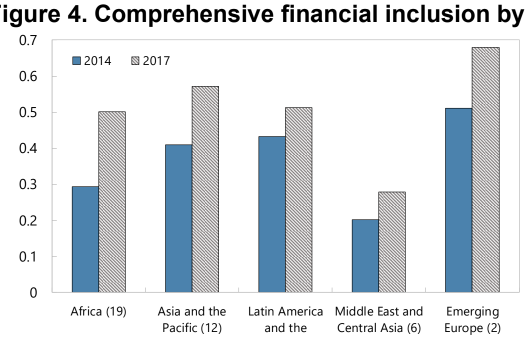
Source: IMF staff calculations.
Note: Number in bracket indicates the number of countries in the sample.

Figure 3. Comprehensive vs. traditional F.I. index



Source: IMF staff calculations.

Figure 4. Comprehensive financial inclusion by region



Source: IMF staff calculations.

[3] Botswana, El Salvador, Mexico, Nigeria, Romania, Rwanda, South Africa, and Zimbabwe.

most countries between 2014 and 2017, most notably in Africa on average.

III. Impact of Financial Inclusion on Macroeconomic Growth

This section adds to the existing body of the finance-growth literature by empirically examining the relationship between digital financial inclusion and economic growth. We resolve concerns about causality by using an instrument variable approach that directly confronts the potential biases induced by simultaneity and omitted variables. The section first reviews the existing literature, discusses the methodology, and then concludes with findings.

A. Literature Review

It is well recognized that financial development is important for economic growth (Levine, 2005). Country and regional-level research has shown that financial development is an integral factor for a country's economic growth and that a positive bidirectional relationship exists between financial development and economic growth. In these studies, the increased scale of the financial sector in the real economy, such as bank credit, bank deposits, and/or monetary aggregates all normalized by the country's gross domestic product (GDP), is considered as "financial deepening".

There are also a number of studies that find a positive impact of greater financial inclusion on growth and reduction of poverty and inequality. Financial inclusion impacts macroeconomic performance through various channels: for instance, access to savings instruments helps households smooth consumption in case of unforeseen shocks; and access to credit enables corporates to improve productivity and competitiveness, and promotes entrepreneurship for individuals. Demirguc-Kunt et al. (2017) discusses benefit of financial inclusion on the reduction of poverty and inequality. Sahay and Čihák (2020) finds that higher financial inclusion in payments is associated with reduction in inequality, particularly for those at the low end of the income distribution and when female financial inclusion is high. On the impact on growth, Sahay et al. (2015) find that, for a country with low levels of financial inclusion (25th percentile), improving financial inclusion to the 75th percentile would lead to a 2-3 percentage point increase in GDP growth on average. Loukoianova et al. (2018) find that a one percent increase in their financial inclusion index (equivalent to an increase from the fourth to the third quartile) is associated with a 0.2 percent cumulative increase in per capita income growth over a five-year period for low income developing countries (and the Asia Pacific region).

Existing studies, however, do not capture the macroeconomic impact of *digital* financial inclusion. For instance, Sahay et al. (2015) and Sahay and Čihák (2020) rely on single measures of financial inclusion/access at the country-level (such as the number of bank accounts per capita), and used these measures to analyze their impact on economic growth. Others such as Dabla-Norris et al. (2015) and Loukoianova et al., (2018) use composite measures instead, but only reflecting indicators of financial inclusion through traditional financial institutions.

While past work shows that the level of financial inclusion is a good predictor of economic growth, these results do not settle the issue of causality (Sahay et al., 2015, Loukoianova et

al., 2018). In cross-country studies of financial development-growth nexus, Levine (1998, 1999) and Levine, Loayza and Beck (2000) use measures of legal origin as instrumental variables for financial development, and find a very strong connection between the exogenous component of financial development and long-run rates of per capita GDP growth. However, these studies are limited to assessing the causal link between financial development and growth. Causal relationship between financial inclusion, and in particular digital financial inclusion and economic outcomes is scarce. This paper's aim is to fill this gap by providing new evidence on the impact of usage of DFSs on economic growth.

The bulk of recent empirical work that assesses the economic impact of digital financial inclusion is based on survey data at the household or firm level for specific countries. They focus on economic benefits of digital financial inclusion (primarily mobile money), including from improved risk sharing, consumption smoothing, and saving. Jack and Suri (2014) finds that consumption of households in Kenya that uses mobile money is unaffected by shocks, while households who do not use mobile money saw a seven percent decline in consumption. Riley (2016) also finds similar results on consumption smoothing by mobile money users after rainfall shocks in Tanzania, while the consumption of non-users from the same village were adversely affected. Demombyne and Thegeya (2012) documents the widespread use of mobile money system for savings in Kenya, and find that mobile money users are 32 percent more likely to have some savings. Mbiti and Weil (2016) finds positive relationship between the adoption of mobile money and frequency of sending and receiving transfers, as well as with bank use, formal savings, and employment.

There are a few papers examining the impact of DFS using macro-data.[4] To the best of our knowledge, there is only one study that measures the macroeconomic growth impact of digital financial inclusion. Based on a general equilibrium macroeconomic model, McKinsey (2016) predicts that digital finance (includes both mobile money and mobile banking) could boost GDP of emerging economies by 6 percent by 2025, informed by field research in seven large countries.[5]

B. Methodology

This paper fills the gap in the existing macro-literature by estimating the impact of digital financial inclusion in payments on growth, and how the relationship differs from that with traditional financial inclusion. We estimate the following regression on a cross-section of 52 countries using the financial inclusion index in Khera et. al. (2021):

$$\dot{y}_i = \beta_0 + \beta_1 (FI_T^u)_i + \beta_2 (FI_F^u)_i + \beta_3 X_i + \varepsilon_i \qquad (1)$$

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[4] See Aron (2018) for a literature survey, which indicates that existing studies concentrate on the impact of mobile money on inflation .

[5] They predict that 1.6 billion unbanked people (more than half of which are women) could gain access to formal financial services; an additional $2.1 trillion of loans to individuals and small businesses could be sustainably extended; governments could gain $110 billion per annum from reduced leakage in public spending and tax collection; and that nearly 95 million new jobs could be created across all sectors.

where i corresponds to the 52 developing and emerging economies in our sample, and ε is the error term. $\dot{y}$ is the per capita GDP growth averaged over 2014 to 2018. FI_T^u and FI_F^u are the traditional and digital financial inclusion usage indices respectively, and X is a vector of control variables that affect growth.[6] We are interested in the sign and significance of the coefficient β_2 which captures the relationship between digital financial inclusion and economic growth, and compare it to β_1 which captures the impact of traditional financial inclusion on economic growth. To take into account a longer time period for growth, we also estimate this regression with per capita GDP growth averaged over 2011 to 2018.

Following the finance and growth literature, the vector of control variables ($X(i)$) include:

i) Level of economic development: log of GDP per capita (source: IMF World Economic Outlook)
ii) Government consumption as a percentage share of GDP (source: World Bank)
iii) Foreign Direct Investment (FDI) as a percentage share of GDP (source: IMF World Economic Outlook)
iv) Level of financial depth: log of private credit as a percentage share of GDP (source: World Bank Development Indicators)
v) Population growth rate (source: IMF World Economic Outlook)
vi) Dummy variables for regional grouping: Asia, Middle East and Central Asia, Latin America, Emerging Europe, Sub-Saharan Africa

To examine the sensitivity of the results, we experiment with different conditioning information sets. We seek to reduce the chances that the cross-country growth regression either omits an important variable or includes a select group of regressors that yields a favored result. Thus, we present the results in a step-wise stage, adding one control variable at a time.

We use instrumental variable approach to assess whether there is a causal relationship between digital financial inclusion and economic growth. Cross-country OLS regressions with the average and initial levels of digital financial inclusion used as explanatory variables indicate economically significant positive relationship with and predictive power of the average growth over 2014-18. Similar results hold true for the regression over 2011-18. However, it does not address the reverse causation nor clarify whether digital financial inclusion may just be a leading indicator as opposed to a fundamental cause of economic growth.[7] To assess whether the digital financial inclusion-growth relationship is driven by simultaneity bias, one needs instrumental variables that explain cross-country differences in

[6] It is the usage of financial services that would have an impact on growth through savings and consumption smoothing rather than merely the access, which is why we only include the measures of financial usage.

[7] See Appendix I for detailed discussion and results of these cross-country OLS regressions.

digital financial usage but are uncorrelated with economic growth beyond their link with digital financial usage and other growth determinants.

We use the initial level of mobile money agents and percent of population who has access to internet as instruments for the digital financial usage index averaged over the respective time periods. The intuitive argument is that some of the variation in using DFSs depends on the access to these services, which is reflected in the access to mobile money agents and internet. Diffusion of mobile money agents and the internet directly influences the usage of financial services by easing the provision of cost-effective financial services, and a key channel through which it contributes to growth. To identify this relationship, we use a regression equation as shown below:

$$\left(\overline{FI_F^u}\right)_i = \alpha_0 + \alpha_1(mma)_i + \alpha_2(internet)_i + \alpha_3 X_i + \mu_i \tag{2}$$

Where *mma* and *internet* represent the initial level of log of mobile money agents per 100,000 adults and percent of population with access to the internet, respectively. Using Equation (2), which yields the relationship between access to mobile money agents and internet with digital financial usage, along with equation (1), which yields the relationship between digital financial usage and economic growth, we estimate the Limited Information Maximum Likelihood (LIML) regression analysis model (Anderson and Rubin, 1949) where digital financial usage is treated as endogenous. The LIML is an instrumental variables estimator, and is a more robust and less biased alternative to a two-stage least squares estimator.[8] For all results employing instrumental variables, tests of instrument strength are reported.

C. Findings

In Table 2 and 3, we report the first-stage relationship between digital usage averaged over 2011-18 and 2014-18 and our instruments, log of mobile money agents and access to the internet. The bottom half of the table shows that there is a significant relationship, with both instruments being statistically significant. The F-statistic for the excluded instruments is higher than Stock and Yogo's (2005) cutoffs for rejecting the null hypothesis of weak instruments, when we restrict the bias of the IV estimator to 15 percent of the OLS bias. In the second stage, the Andersen–Rubin test, which is robust to weak instrument problems and heteroscedasticity, confirms a statistically significant partial correlation between the endogenous variable (digital financial usage) and the outcome (growth). The probability from the Hansen-J overidentification tests – where a significant result (< 10 percent) is ground to reject the null hypothesis that the instruments are valid, meaning that they are uncorrelated with the estimated regression residuals – indicate that this test is passed in all cases.

The LIML model leads to a statistically stronger and larger impact of digital financial usage on GDP per capita growth, in comparison to the OLS estimates discussed in Appendix I. Interpretation of the LIML point estimates for digital financial usage is as follows: from the

[8] The LIML is numerically equivalent to a two-stage least squares where one excluded instrument is employed. However, where the model is not just-identified, as in our model, the LIML estimator is known to be more robust and less biased to the presence of weak instruments (Stock, Wright, & Yogo, 2002).

regression over 2011-18 (Table 2, column 4), a one standard deviation increase in digital financial usage is expected to boost growth by 0.98 standard deviations on average, holding all other variables fixed. In other words, A one standard deviation increase in digital financial usage—equivalent to 0.1205 increase in the index—is expected to boost the annual real GDP growth rate by 1.61 percentage points. The coefficient estimates for other covariates included in the model are plausible. All of these refer to initial conditions and are measured as the value in 2011 and 2014 (or close to 2014), respectively. In the present specification, the estimate on the level of GDP per capita represents a convergence effect—the negative sign indicates that lower income countries grow faster on average. Overall our IV estimation strategy, i.e., instrumenting average of digital usage index with the log of mobile money agents and the access to the internet significantly increases the estimates of the effect of digital financial inclusion on GDP per capita growth.

Table 2. Results: Growth and Digital Financial Inclusion (2011-18)

Second-stage regression						
	Dependent variable: Real GDP growth rate (2011 – 2018)					
Average Digital Usage F.I Index	0.60990**	1.00508***	1.09638***	0.98525***	1.07078***	1.26725***
	(0.3136)	(0.3335)	(0.3562)	(0.3114)	(0.3298)	(0.3663)
Anderson canon. Corr. LM statistic (p value)[1]	0.0121	0.0039	0.0058	0.0014	0.0017	0.0033
Endogenity test (p value)[2]	0.3802	0.0212	0.0172	0.0132	0.0088	0.0021
Overidentification test (p value)[3]	0.5509	0.9916	0.8073	0.9208	0.7632	0.6569
R-squared	58.00%	60.96%	52.30%	61.87%	62.47%	57.51%
First-stage regression						
	Dependent variable: Average digital usage F.I. Index					
Log (Mobile money agents) (2014)	0.02659***	0.02585***	0.02531**	0.02541***	0.02610***	0.02469***
	(0.0090)	(0.0090)	(0.0094)	(0.0087)	(0.0088)	(0.0088)
Internet (2014)	0.00177	0.00251**	0.00226*	0.00306**	0.0026**	0.002786***
	(0.0015)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0013)
R-squared	42.14%	65.71%	61.16%	69.53%	58.65%	57.87%
Observations	43	43	42	43	42	43
	Cragg-Donald Wald statistics[4]					
	4.651†	5.55 ††	4.88†	6.78 ††	6.35 ††	5.41 ††
	Control variables included in first & second stage regressions					
Regional dummies		Yes	Yes	Yes	Yes	Yes
Log (GDP per capita)	-0.0564***	-0.0607***	-0.0679***	-0.0634***	-0.0717***	-0.0876***
	(0.0189)	(0.0193)	(0.0200)	(0.0204)	(0.0215)	(0.0240)
Traditional F.I. index	-0.0319	-0.3155**	-0.3647***	-0.2779*	-0.3065*	-0.2723
	(0.1574)	(0.1600)	(0.1669)	(0.1572)	(0.1609)	(0.1659)
Gov. consumption (% of GDP)	-0.0207***	-0.0136***	-0.0115**	-0.0135***	-0.0108**	-0.0196***
	(0.0043)	(0.0005)	(0.0054)	(0.0049)	(0.0053)	(0.0059)
Population growth	-10.667***	-7.311***	-9.0718***	-7.1186***	-8.9309***	-7.9690***
	(2.4598)	(2.133)	(2.5510)	(2.100)	(2.463)	(2.2530)
Log (credit to GDP)			-0.0013		-0.0078	
			(0.0264)		(0.0298)	
Inflation						-0.0111***
						(0.0022)
FDI (% of GDP)				0.0009	0.0013	0.0009
				(0.0021)	(0.0024)	(0.0021)

[1] The p-value of the Anderson canon. Corr. LM statistic corresponds to a test in which the null hypothesis is that the equation is underidentified.

[2] Under the null hypothesis, the specified endogenous regressors can actually be treated as exogenous.

[3] The p-value of the overidentification test refers to the Sargan-Hansen test in which the null hypothesis is that the overidentifying restrictions are valid. Rejection of the null hypothesis mean that the model is misspecified.

[4] Stock-Yogo critical values for weak identification test (used for Cragg-Donald Wald statistics) are 8.68 for 10%, 5.33 for 15% and 4.42 for 20% maximal relative bias. †††, †† and † denote significance at 10%, 15% and 20% respectively according to Stock-Yogo critical values.

Table 3. Results: Growth and Digital Financial Inclusion (2014-18)

Second-stage regression						
	Dependent variable: Real GDP growth rate (2014 – 2018)					
Average Digital Usage F.I Index	0.272	0.715***	0.724**	0.644***	0.675***	0.677***
	(0.248)	(0.268)	(0.282)	(0.230)	(0.250)	(0.223)
Anderson canon. Corr. LM statistic (p value)[1]	0.0295	0.0073	0.0172	0.0054	0.00133	0.0035
Endogenity test (p value)[2]	0.7086	0.0155	0.0123	0.0181	0.0139	0.0079
Overidentification test (p value)[3]	0.1174	0.1573	0.3482	0.2472	0.5025	0.2395
R-squared	53.06%	44.25%	47.07%	53.38%	54.08%	52.30%
First-stage regression						
	Dependent variable: Average digital usage F.I. Index					
Log (Mobile money agents) (2014)	0.0289**	0.0278***	0.0259**	0.0276**	0.0256**	0.0271**
	(0.0109)	(0.0102)	(0.0109)	(0.0102)	(0.0109)	(0.0101)
Internet (2014)	0.00106	0.00239	0.00223	0.00273*	0.00255	0.00314**
	(0.00175)	(0.00146)	(0.00160)	(0.00151)	(0.00164)	(0.00154)
R-squared	41.5%	67.4%	65.6%	68.0%	66.5%	70.2%
Observations	46	46	45	46	45	45
	Cragg-Donald Wald statistics[4]					
	3.53	4.77†	4.98†	3.64	3.8	5.41 ††
	Control variables included in first & second stage regressions					
Regional dummies	No	Yes	Yes	Yes	Yes	Yes
Log (GDP per capita)	-0.0673***	-0.0603***	-0.0622***	-0.0533***	-0.0556***	-0.0496**
	(0.0177)	(0.0207)	(0.0206)	(0.0191)	(0.0192)	(0.0199)
Traditional F.I. index	-0.0151	-0.266**	-0.308**	-0.288***	-0.330***	-0.273**
	(0.102)	(0.118)	(0.122)	(0.111)	(0.117)	(0.107)
Gov. consumption (% of GDP)	-0.0079***	-0.00464*	-0.00381	-0.00388	-0.00309	-0.00465*
	(0.00241)	(0.00272)	(0.00269)	(0.00250)	(0.00253)	(0.00267)
Population growth	-10.09***	-6.743***	-6.025***	-6.176***	-5.610***	-5.613***
	(2.800)	(2.246)	(2.266)	(2.046)	(2.097)	(2.051)
Log (credit to GDP)			0.0200		0.0166	
			(0.0156)		(0.0148)	
Inflation						-0.00479
						(0.00349)
FDI (% of GDP)				0.00485*	0.00480	0.00434
				(0.00293)	(0.00304)	(0.00303)

[1] The p-value of the Anderson canon. Corr. LM statistic corresponds to a test in which the null hypothesis is that the equation is underidentified.

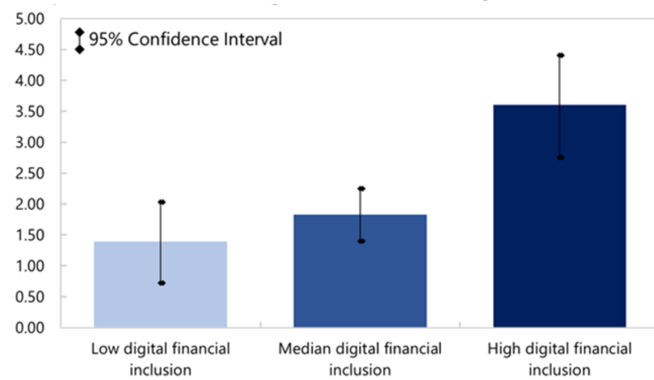
[2] Under the null hypothesis, the specified endogenous regressors can actually be treated as exogenous.

[3] The p-value of the overidentification test refers to the Sargan-Hansen test in which the null hypothesis is that the overidentifying restrictions are valid. Rejection of the null hypothesis mean that the model is misspecified.

[4] Stock-Yogo critical values for weak identification test (used for Cragg-Donald Wald statistics) are 8.68 for 10%, 5.33 for 15% and 4.42 for 20% maximal relative bias. †††, †† and † denote significance at 10%, 15% and 20% respectively according to Stock-Yogo critical values.

The result implies that an increase in digital financial inclusion in payments from the 25th percentile to the 75th percentile is associated with an increase in average economic growth of up to 2.2 percentage points (Figure 5). This increase in growth is likely driven through the consumption channel and through higher formalization. On the other hand, higher initial level of traditional inclusion is found to be associated with slower subsequent growth. This is at odds with the financial inclusion-growth literature that suggests otherwise. However, this could reflect that the impact from traditional financial inclusion has already been reaped prior to period covered in the analysis, and for countries with already high traditional financial inclusion growth benefits might be limited. On the other hand, the benefits of digital financial inclusion have only just started. Given the data constraints, the longest time period we could conduct the analysis on is seven years (2011-18). As a result, the regression may have failed to capture the impact of earlier progresses in traditional financial inclusion.[9] In fact Sahay et al. (2015) finds that the initial levels of various indicators of traditional financial inclusion have a positive impact on 10-year growth between 2004-14. Hence, our finding likely reflects decreasing returns to traditional financial inclusion in the more recent years. On the other hand, digital financial inclusion has expanded rapidly in recent years that would be reflected better in the more recent time period used in this paper. Furthermore, the impact on growth may be underestimated as our analysis only captures payments and does not cover several other components of digital finance (savings, credit, and insurance) that may have more direct impact on consumption smoothing and investment.

Figure 5. Impact of digital financial inclusion on growth
(In percent of annual real GDP growth)



Note: Low, median, and high refers to the average level of fintech-driven financial inclusion at 25th, 50th, and 75th percentile of the sampled countries respectively. The real GDP growth rate is obtained from regression results and it assumed other characteristics of the country are at the median level.

Our robustness checks for the instrument variables estimation are as follows: (i) we use one instrument - log of access to mobile money agents and access to internet as instrument variables individually - as opposed to both of them together; (ii) remove the cyclical effects in GDP: replace the dependent variable with the average of the detrended real GDP growth, by using Hodrick-Prescott (HP) filter to obtain the stationary series; (iii) consider other control variables such as the level of literacy measured by percent of gross secondary school enrollment, using overall financial development measure instead of private credit (% of GDP), which is based on the index computed by Sahay et al. (2015). In all cases, the results are very similar to those in Table 2 and 3. Also, the weak identification statistic shows that when two aggregated instruments are used instead of a single generated instrument, the instrument strength increases.

[9] There also seems to be some scale down of the supply of traditional access, as seen in the decline in the number of branches in some countries.

IV. Drivers of Digital Financial Inclusion

This section empirically analyzes the determinants of digital financial inclusion which helps understand differences across countries in the adoption of DFSs. While previous studies in the literature have identified the determinants of traditional financial inclusion across countries, to the best of our knowledge, this is the first paper that focuses on *drivers* of digital financial inclusion using cross-country empirical analysis. The section first reviews existing literature, some of whose approaches the methodology draws on, and concludes with findings.

A. Literature Review

Existing empirical studies on macroeconomic factors and policies driving financial inclusion focus on drivers of traditional financial inclusion. In a regional study (Latin America), Rojas-Suarez and Amado (2014) and Rojas-Suarez (2016) find institutional quality to play an important role in determining financial inclusion gaps, measured by the account ownership at a formal financial institution. Dabla-Norris et. al. (2015) finds that borrowing costs, regulatory environment, and the efficiency and stability of banks are associated with financial inclusion gaps (measured by a composite financial inclusion index). Allen et. al. (2016) examines the individual and country characteristics that are associated with financial inclusion and finds that lower account costs, greater proximity to financial intermediaries, stronger legal rights, and more politically stable environments to be relevant. Blancher et al. (2019) focuses on SME financial inclusion in Middle East and Central Asia, and identifies the role of public sector in the economy, macroeconomic stability, financial sector soundness, competition, and quality of institution as important factors. Deléchat et al. (2018) find structural country characteristics and policies to be significantly related to financial inclusion (measured by a composite financial inclusion index), and that social norms and legal restrictions are strongly related to women's use of financial services.

While there are more recent and growing stuides that attempt to identify drivers of digital financial inclusion, they largely focus on a specific country and/or firm. These studies often rely on survey-based data, and on a single aspect of financial inclusion. Aker and Mbiti (2010) note the rapid adoption of mobile phones across demographics in Kenya, Uganda and Tanzania based on firm-level and household survey data. It discusses potential mechanisms through which mobile phones could provide economic benefits, including improved markets and productive efficiency of firms, job creation, increased resilience of households to shocks, and innovation in delivering financial and other services.. Weil et al. (2012) finds that the adopters of mobile money in East Africa tend to be younger, wealthier, better educated and urban residents.[10] Zeinab (2019) conduct a cross-country study that analyzes the determinants of mobile money adoption using data across seven African countries between 2013-17. They use registered subscriber ratio and active subscriber ratio as the proxies for usage of mobile money adoption, in separate regressions. Using least squares estimation, this study finds that number of mobile money agents, strength of mobile money regulations, banking penetration, and level of education, all have a positive impact on mobile money adoption. However, this

[10] See Aron (2017) for a comprehensive review of literature and methodology used.

study has some limitations: i) size of the sample of countries is small and concentrated in Africa; ii) does not address potential reverse causality mobile money adoption to some of the predictor variables (GDP, number of service providers among others). Based on the analysis of frameworks adopted by 10 countries in Africa and Asia, Staschen and Meagher (2018) identify four basic regulatory enablers for DFSs, namely nonbank e-money issuance, use of agents, risk-based customer due diligence, and customer protection.

B. Methodology

Using the digital financial inclusion index in Khera et. al. (2021) as the dependent variable, we test a broad set of country-level characteristics and policies as possible determinants of digital financial inclusion. We run separate regressions to identify factors affecting supply and demand of DFSs, using mobile money agent and digital usage index as dependent variables, respectively.

The baseline regression for digital payments access is estimated using a random effects regression:

$$mma_{it} = \alpha_0 + \gamma_t + \alpha_1(FI_F^u)_{i,t-3} + \alpha_2(FI_T^a)_{i,t-3} + \alpha_3(FI_T^u)_{i,t-3} + \sum_{k=1}^{n} \beta_k \boldsymbol{X}_{k,i,t-1} + \varepsilon_{it} \qquad (3)$$

where mobile money agents, per 100,000 adults (mma_{it}) in country *i,* at time *t* is used as a proxy for supply of DFSs. Note that we choose to focus on drivers of mobile money agents only as it caters exclusively to providing financial services, as opposed to other measures of digital access, i.e. access to mobile phones and the internet, which cater to a wide range of functionalities. $\boldsymbol{X}_k$ is a vector of other determinants to digital financial access (discussed below). γ_t is the time fixed effect to control for factors that affect all countries in the same way.

To explore the potential substitutability/ complementarity between digital and traditional financial inclusion, we also include traditional access (FI_T^a) and usage (FI_T^u) indices as explanatory variables. A positive coefficient (i.e. positive α_2 and α_3) indicates complementarities whereas a negative coefficient implies that the two are substitutable. No significance would imply that the two types of financial inclusion are independent. Moreover, since the access and usage of DFSs go hand-in-hand, we use the digital usage index (FI_F^u) as a determinant of the access to fintech services.

The sample consists of 52 low income and developing economies for which we compute the financial inclusion index and t refers to 2014 and 2017. Given the limited time dimension of the data,[11] we choose to run the random effect estimator (though this estimator relies on the strong assumption of exogenous country-specific effects), which is estimated using the feasible generalized least squares method. The Hausman test and the Lagrange Multiplier (LM) test (Breusch and Pagan, 1980) confirm that there are significant random effects.

The fractional logit regression (Papke and Wooldridge, 1996) is used to estimate the determinants of digital payments usage, which accounts for the fractional nature of the

[11] We lose a lot of degrees of freedom in a fixed effects model as we only have two time periods.

dependent variable (the financial usage index falls in the unit interval [0,1]), and is capable of handling the extreme values of 0 and 1 without having to manipulate the data. The regression equation estimated is:

$$(FI_F^u)_{i,t} = \theta_0 + \partial_t + \theta_1(mma_{i,t}) + \theta_2(FI_F^a)_{i,t-3} + \theta_3(FI_T^a)_{i,t-3} + \theta_4(FI_T^u)_{i,t-3} + \sum_{k=1}^{n} \delta_k \boldsymbol{X}_{k,i,t-1} + v_{i,t} \quad (4)$$

where FI_F^u is the digital payments usage index for country *i,* at time *t.* $\boldsymbol{X}_{ki}$ is a vector of other determinants of digital financial usage (discussed below) and ∂_t is the time fixed effect. As discussed above, we also include the traditional financial inclusion sub-indices, as well as the digital access indices (mobile money agents and digital infrastructure) to the set of determinants.

A wide range of explanatory variables are considered to capture various aspects of country characteristics. Six financial, macro and socio-economic factors are considered, drawing on Rojas-Suarez and Amado (2014) and Rojas-Suarez (2016):

i) *Level of macroeconomic development:* log of GDP per capita (source: IMF World Economic Outlook);
ii) *Financial sector efficiency:* overhead costs to assets (source: World Bank Finstat);
iii) *Level of competition in the financial sector*: bank concentration defined as a share of assets of three largest commercial banks to total commercial banking assets (source: World Bank Finstat);
iv) *Financial stability:* log of NPL as a share of total gross loans (source: IMF Financial Soundness Indicators);
v) *Governance/institutional quality*: rule of law, scaled from 0 to 1 with 1 signifying strongest rule of law, as an indicator of the perception of confidence in the rules of the society used as a proxy (data source: World Justice Project); and,
vi) Socio-*economic factor:* the share of urban population (source: World Bank Development Indicator.

One-period lagged values for all the explanatory variables are used to avoid reverse causality. The financial inclusion indices used as regressors are lagged by three periods given that they only cover 2014 and 2017.[12][13] Multicollinearity tests suggest high correlation between NPL ratio and GDP per capita – which are included in the regression one at a time.

[12] Note that for t=2014, we use the 2011 values of the financial inclusion indices, which mobile money agents are computed using the same methodology as in Appendix II in Khera et. al. (2021). For the explanatory variables in the traditional financial inclusion index, data for 2011 is available. However, for the digital financial inclusion related underlying variables, while the data on share of population with access to the internet and mobile phone is available for 2011, the data on the usage-related sub-indices are missing. Hence, for the latter we assume that the relative ranking/ scoring of the digital usage index across the countries in 2011 is the same as 2014.

[13] Most of the underlying socio-economic and macroeconomic factors are common determinants for both means of financial inclusion—through traditional financial institutions and through technology—therefore, traditional access and usage indices were used as explanatory variables to capture those elements as well. The three period

(continued…)

C. Findings

Overall, we find that the usage of digital payment services is higher where there already exists a culture of using financial services (proxied by the traditional usage index), but where the access to traditional financial institutions is constrained. We also find that greater competition amongst traditional providers (financial institutions) and inefficiencies in bank operations are positively associated with the supply of mobile money services

Table 4 summarizes the results of the drivers of digital payments usage. Traditional access index has a negative and statistically significant impact on the usage of digital payments services, while high levels of usage of traditional financial services has a positive impact. These two results combined indicate that the gap left by the limited supply of traditional financial services is being filled by digital financial services in countries where the population is already familiar with using traditional financial services —either due to higher financial literacy or trust in the financial system in general. Supply of DFSs (mobile money agents per population) and better access to digital infrastructure (digital access index), not surprisingly, have positive and statistically significant impacts in most specifications.[14] On the other hand, financial sector efficiency and quality of institution do not have a statistically significant impact on the usage.

Table 5 indicates that high bank concentration is negatively associated with lower number of mobile agents. This implies that presence of big dominant banks could hinder the development of mobile money (fintech) providers. On the other hand, high overhead cost of banks is associated with a higher number of mobile agents, implying inefficiencies in banks operations create gaps in providing financial services to wider population. This is consistent with the finding that lower levels of access to traditional financial institutions is associated with a higher number of mobile money agents. Higher quality of institutions also has a positive impact. Enabling environment for competition and inefficiencies in the traditional financial institutions would provide profitable opportunity for fintech companies to enter. The existence of demand for DFSs, on the other hand, appears to be a less important factor—digital usage index is only found to have a positive and statistically significant impact on the supply when variables for financial system competition and institutional quality are not added to the regression.

We conducted additional sensitivity analyses to gauge the robustness of these findings. Equation (4) was also estimated using the random effects regression. Results shown in Appendix II confirm our baseline findings. In addition, we conducted the following robustness checks: we used pooled OLS estimation instead of random effects for Equation (3), and tested the relevance of additional explanatory variables for both equations. These include a measure of the extent to which the regulatory environment enables mobile money

lags helps avoid the issue of multicollinearity between the financial inclusion sub-indices and the other explanatory variables.

[14] The coefficient on the access to digital infrastructure variable becomes smaller and insignificant once we control for aggregate trends over time.

developments, i.e. the GSMA mobile money regulatory index;[15] internet costs measured by fixed broadband internet monthly subscription rate; and the level of literacy measured by the percent of gross secondary school enrollment—all these variables are found to have an insignificant impact on adoption of DFSs. This may reflect the early and varying stage of the development of regulatory framework and the predominant use of mobile phone rather than computer in accessing internet in EMDEs. Furthermore, the level of literacy are shown to have effects on the use of traditional financial services, which is already included in the baseline regressions. The results did not change substantially under these alternative specifications, and were aligned with our baseline estimates. The coefficients also remain significant when regional dummies are included, and we find that on an average, countries in Africa have significantly higher usage of DFSs in comparison to other regions.

[15] The GSMA Mobile Money Regulatory Index scores countries on the scale of 0 to 100 based on the extent to which their regulatory framework enables widespread mobile money adoption. The index is comprised of 27 individual indicators, which are aggregated into six dimensions (such as authorization, consumer protection, and agent network), which in turn are aggregated into the overall index. A higher score is associated with a more enabling regulatory framework for mobile money adoption. See https://www.gsma.com/mobilefordevelopment/resources/the-mobile-money-regulatory-index/ for details.

Table 4. Baseline: Determinants of digital payments usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Fractional logit estimation: Digital usage financial inclusion index (t)													
Trad. access	-3.658***	-2.418**	-4.266***	-4.181***	-4.205***	-4.006***	-4.008***	-3.909***	-2.030*	-1.912*	-1.980*	-1.996*	-2.300**	-2.228**
FI Index (t-3)	(1.359)	(1.171)	(1.369)	(1.317)	(1.299)	(1.319)	(1.279)	(1.299)	(1.103)	(1.118)	(1.131)	(1.139)	(1.071)	(1.084)
Trad. usage	4.692***	4.449***	5.092***	5.388***	5.654***	5.660***	5.346***	5.354***	4.956***	5.199***	5.311***	5.322***	4.935***	4.882***
FI Index (t-3)	(0.870)	(0.925)	(1.011)	(1.021)	(1.179)	(1.165)	(1.204)	(1.193)	(0.959)	(0.922)	(0.961)	(0.979)	(0.929)	(0.937)
Digital infrastructure		0.211	1.236	1.165	1.425*	1.814**	0.374	0.607	1.354*	1.534**	1.669**	1.658**	-0.272	-0.229
access (t-3)		(0.721)	(0.933)	(0.825)	(0.843)	(0.852)	(0.923)	(0.995)	(0.710)	(0.779)	(0.802)	(0.784)	(0.955)	(0.939)
Mobile money		0.00302***	0.00201***	0.00170***	0.00184***	0.00169***	0.00114*	0.00107*	0.00264***	0.00235***	0.00248***	0.00249***	0.00170**	0.00166**
Agents (t-1)		(0.00061)	(0.00063)	(0.00066)	(0.00063)	(0.00059)	(0.00068)	(0.00063)	(0.000604)	(0.000632)	(0.000659)	(0.000649)	(0.000679)	(0.000665)
Log (NPL)			0.501**	0.470**	0.511**	0.481**	0.330	0.320						
(t-1)			(0.206)	(0.200)	(0.226)	(0.231)	(0.237)	(0.239)						
Log (GDP									-0.538**	-0.578**	-0.563**	-0.571**	-0.135	-0.0975
per capita) (t-1)									(0.221)	(0.229)	(0.237)	(0.279)	(0.291)	(0.330)
Overhead cost				0.0979	0.0923	0.122*	0.112	0.127*		0.0898	0.0808	0.0794	0.102	0.108*
to assets (t-1)				(0.0719)	(0.0700)	(0.0720)	(0.0689)	(0.0713)		(0.0695)	(0.0679)	(0.0658)	(0.0653)	(0.0625)
Rule of law					-0.0122	-0.0135	0.000135	-0.000901			-0.00716	-0.00710	0.00307	0.00284
(t-1)					(0.0145)	(0.0147)	(0.0147)	(0.0147)			(0.0123)	(0.0123)	(0.0114)	(0.0114)
Urban						-0.00780		-0.00410				0.000578		-0.00276
Population (t-1)						(0.00821)		(0.00905)				(0.00885)		(0.0101)
_cons	-2.215***	-2.918***	-3.901***	-4.301***	-3.998***	-3.805***	-4.182***	-4.076***	0.675	0.474	0.610	0.648	-2.758	-2.946
	(0.233)	(0.211)	(0.394)	(0.508)	(0.511)	(0.578)	(0.483)	(0.578)	(1.480)	(1.618)	(1.629)	(1.758)	(2.118)	(2.224)
Year fixed effect	No	No	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
N	96	96	80	79	79	79	79	79	95	95	95	95	95	95

Note: Robust standard errors are in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% level. 'Trad.' is traditional financial inclusion and digital infrastructure access index is composed of share of population with access to internet and mobile phone.

Table 5. Baseline: Determinants of fintech access

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Random effects estimation: Mobile money agents (t)													
Trad. access	-508.6**	-310.4	-374.0	-365.6	-357.0	-244.4	-254.9	-240.4	-256.1	56.40	56.54	103.1	34.90	86.37
FI Index (t-3)	(206.7)	(224.7)	(235.9)	(231.0)	(224.2)	(242.3)	(234.8)	(235.7)	(226.0)	(226.2)	(233.4)	(215.1)	(224.9)	(207.4)
Trad. usage	134.7	-76.39	52.82	93.50	111.3	164.8	76.16	-10.70	-135.2	165.0	171.1	83.98	-62.81	-115.3
FI Index (t-3)	(166.4)	(193.2)	(187.7)	(185.8)	(180.3)	(185.5)	(192.1)	(190.3)	(196.7)	(189.7)	(194.3)	(184.4)	(198.3)	(186.5)
Digital usage		488.0**	379.0	311.9	233.3	161.5	126.1	270.7	225.7	267.9	301.5	226.4	397.3*	309.2
FI Index (t-3)		(246.4)	(234.7)	(231.7)	(225.3)	(233.7)	(227.0)	(230.7)	(221.0)	(230.3)	(245.3)	(225.0)	(238.2)	(218.6)
Log (NPL)			95.25***	90.93***	81.08**	67.76*	57.52	47.62	33.88					
(t-1)			(33.61)	(33.82)	(33.84)	(35.63)	(35.29)	(35.30)	(34.74)					
Log(GDP										-121.6***	-144.1***	-165.6***	-83.59	-114.6**
per capita) (t-1)										(35.95)	(54.19)	(51.70)	(55.36)	(52.23)
Overhead cost				20.95	35.19**	40.13**	43.98***	38.78**	43.43***	24.15*	20.67	32.29**	22.53*	33.56***
to assets (t-1)				(14.17)	(15.20)	(15.86)	(15.52)	(15.36)	(14.87)	(12.97)	(13.70)	(12.99)	(13.19)	(12.52)
Bank					-3.333**	-2.883*	-2.807*	-3.632**	-3.534**	-3.345**	-3.716**	-3.558**	-3.411**	-3.284**
concentration (t-1)					(1.648)	(1.686)	(1.644)	(1.658)	(1.596)	(1.429)	(1.598)	(1.486)	(1.535)	(1.430)
Urban						-2.164	-2.551	-1.649	-2.143		1.200	0.827	-0.110	-0.279
Population (t-1)						(1.700)	(1.658)	(1.663)	(1.601)		(2.283)	(2.095)	(2.243)	(2.055)
Rule of law							3.294		4.505*			5.886***		5.897***
(t-1)							(2.419)		(2.364)			(2.210)		(2.135)
_cons	212.3***	185.0***	30.61	-50.52	86.51	145.9	45.58	183.8	42.71	1127.4***	1271.8***	1171.1***	843.6**	801.8**
	(44.90)	(45.76)	(72.55)	(90.06)	(117.2)	(126.6)	(144.4)	(123.6)	(138.9)	(284.7)	(374.3)	(347.5)	(383.9)	(354.1)
Year fixed effect	No	No	No	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes
N	96	96	80	79	78	78	78	78	78	94	94	94	94	94

Note: Robust standard errors are in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% level. 'Trad.' is traditional financial inclusion and digital infrastructure access index is composed of share of population with access to internet and mobile phone.

V. Conclusion and Policy Implications

This paper builds on a new measure of digital financial inclusion introduced by Khera et. al. (2021) to examine impact on economic growth from digital financial inclusion, and drivers of digital financial inclusion across EMDEs.

Over the recent past, digital financial inclusion is found to have had a positive impact on economic growth. A cross-sectional instrument variable analysis confirms that the exogenous component of digital financial inclusion is positively associated with economic growth; specifically, the large, positive link between digital financial inclusion and economic growth is unlikely due to potential biases induced by omitted variables, simultaneity or reverse causation. Increasing digital financial inclusion in payments is found to boost annual economic growth by up to 2.2 percentage points. Taking into account the impact on investment spurred by fintech credit—which we were unable to conduct due to lack of cross-country data—would likely lead to larger estimated gains. In fact, some fintech companies are expanding into the provision of fintech credit, and there is some evidence that higher digital financial inclusion in payments goes hand in hand with higher fintech consumer financing.

Empirical analysis of drivers indicate that digital financial inclusion tends to be higher where demand for financial services exists, but there are gaps in supply of traditional financial services. Drivers of digital financial access and usage are estimated separately. Other key factors that play a major role in facilitating usage of digital financial inclusion include access to foundational infrastructure (mobile phones, mobile data services, broadband internet), and financial literacy/ familiarity. On the supply side, higher competition, inefficiencies in financial institutions and rule of law are found to be important.

The findings emphasize the importance of taking into account the individual country circumstances in determining policy priorities in promoting financial inclusion. For countries with already high traditional usage but low access, encouraging technological innovation in the payments landscape could fill the gap in bank infrastructure. Given the existing familiarity with using financial services, these countries could have the highest potential to spur financial inclusion through fintech. Even when financial inclusion is already relatively high, policies may be needed to close inclusion gaps within the country (e.g., rural and low-income population) and to ensure a competitive landscape. On the other hand, addressing root causes of high voluntary financial exclusion would be priority for countries with high traditional access but low usage. There, policy could prioritize on improving financial literacy and/ or trust in the financial system in general, and addressing other social barriers including high informality. This would have a positive spillover on the usage of traditional financial services as well and could improve the overall financial inclusion outcome. Countries where both voluntary and involuntary exclusion is high, policies need to tackle both social and economic barriers to the usage as well as encourage competition and promote opportunities for fintech new entrants. Efforts to address inequality in access to technology (e.g., mobile phone, the internet, electricity and digital ID) is key to prevent digital divide within and across countries.

At the same time, the benefits of financial inclusion come with new challenges. While stronger consumer protection and safety net arrangements tend to be associated with higher levels of digital financial inclusion, we also find that some countries are seeing expansion of DFSs without consumer protection rules or crisis management tools. Households in many countries are using mobile money or e-wallets as naturally as cash, assuming digital cash would continue to serve as a medium of exchange, and their wallets are deposits. Fintech companies are often dependent on traditional banks to store customer funds. These could be compromised if the bank that hosts the cash balances of mobile money users became insolvent. Customers funds could also be at risk from insufficient protection and/or failure of the service providers to manage the entrusted funds prudently (see Adrian and Mancini-Griffoli 2019). This could undermine digital financial inclusion particularly in countries where customers have low financial and digital literacy. As the application of technology expands from payments to digital credit and other aspects of financial services, filling the gaps in existing regulatory frameworks becomes increasingly more important to contain potential social and financial stability risks. Regulatory frameworks need to adapt to potential risks related to fintech, including cyber security risks, risk of misuse of new payments channels for illicit activities – money laundering and terrorist financing, as well as liquidity risks.[16]

[16] See Khiaonarong and Goh (2020) and Taylor et al (2019) for more detailed discussions on fintech regulation and supervision.

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Appendix I. Digital Financial Inclusion and Growth

We use a cross-country ordinary least square (OLS) estimation, relating our indices of financial inclusion—traditional and digital indices— at one point in time to subsequent average growth over the periods 2011-17 and 2014-17. The baseline estimation equation is as follows:

$$\dot{y}_i = \beta_0 + \beta_1(FI_T^u)_i + \beta_2(FI_F^u)_i + \beta_3 X_i + \varepsilon(i) \qquad (1)$$

where i corresponds to the 52 developing and emerging economies in our sample, and ε is the error term. $\dot{y}$ is the per capita GDP growth averaged over 2014 to 2018. FI_T and FI_F are the traditional and digital financial inclusion usage indices respectively, and X is a vector of control variables that affect growth.[17] We are interested in the sign and significance of the coefficient β_2 which captures the relationship between digital financial inclusion and economic growth, and compare it to β_1 which captures the impact of traditional financial inclusion on economic growth. To take into account a longer time period for growth, we also estimate this regression with per capita GDP growth averaged over 2011 to 2018.

Following the finance and growth literature, the vector of control variables ($X(i)$) include:

- Level of economic development: log of GDP per capita (source: IMF World Economic Outlook)
- Government consumption as a percentage share of GDP (source: World Bank)
- Foreign Direct Investment (FDI) as a percentage share of GDP (source: IMF World Economic Outlook)
- Level of financial depth: log of private credit as a percentage share of GDP (source: World Bank Development Indicators)
- Population growth rate (source: IMF World Economic Outlook)
- Dummy variables for regional grouping: Asia, Middle East and Central Asia, Latin America, Emerging Europe, Sub-Saharan Africa

We employ the following two approaches:
1) **Cross-country OLS regression with the financial inclusion measures averaged over the period 2014-18:** we assess the empirical relationship between digital financial inclusion averaged over the period 2014-18 and growth also averaged over the 2014-18 period.[18] Appendix Table I.1 indicates that there is a significant positive relationship between usage of DFSs and economic growth, and also holds true for the estimation over 2011-18. Note that for the regression over 2011-18, while we could extend the traditional financial inclusion index back to 2011, due to unavailability of sufficient data we assume that that the

[17] It is the usage of financial services that would have an impact on growth through savings and consumption smoothing rather than merely the access, which is why we only include the measures of financial usage.

[18] All the other regressors in X as well as FI_T are also averaged over the same time period.

relative measure of digital financial inclusion across countries did not change dramatically over time between 2011 and 2014.[19]

While this approach is useful in establishing an economically significant positive relationship, it does not address the reverse causation from GDP per capita growth to digital financial inclusion.

2) **Cross-country OLS regression with financial inclusion measures in the initial period:** To avoid potential reverse causality, we relate our indices of financial inclusion—traditional and digital— at one point in time to subsequent average growth over the period 2014-18 as well as 2011-18. The other regressors also refer to the initial conditions. Appendix Table I.2 indicates that usage of DFSs is a statistically significant predictor of subsequent rates of economic growth in the regression over 2014-18, but that this relationship is not significant in the case of estimation over 2011-18.

In any case, these results do not settle the issue of causality. It may simply be the case that digital financial services may develop in anticipation of future economic activity. Thus, financial inclusion may be a leading indicator rather than a fundamental cause.

Appendix Table I.1. Results: Growth and Digital Financial Inclusion (Approach 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS estimation: Real GDP per capita growth rate (2011 – 2018)						**OLS estimation: Real GDP per capita growth rate (2014 – 2018)**					
Log(GDP per capita)	-0.0418	-0.0518*	-0.0755***	-0.0726***	-0.0733***	-0.0524*	-0.0194	-0.0314	-0.0531***	-0.0542***	-0.0478**	-0.0349
	(0.0254)	(0.0258)	(0.0231)	(0.0239)	(0.0242)	(0.0266)	(0.0192)	(0.0189)	(0.0171)	(0.0178)	(0.0194)	(0.0212)
Trad. F.I. Index	0.330**	0.243	0.185	0.160	0.158	-0.0435	0.140	0.103	0.0691	0.0486	0.0122	-0.144
	(0.138)	(0.157)	(0.128)	(0.142)	(0.144)	(0.161)	(0.0856)	(0.0903)	(0.0735)	(0.0809)	(0.0920)	(0.105)
Digital usage F.I Index	0.0855	0.0670	0.228**	0.187*	0.188*	0.216*	0.0462	0.0523	0.130**	0.115*	0.111*	0.164**
	(0.109)	(0.107)	(0.0939)	(0.102)	(0.104)	(0.113)	(0.0658)	(0.0628)	(0.0536)	(0.0580)	(0.0583)	(0.0668)
Gov. consumption (% of GDP)	-0.0187***	-0.0181***	-0.0185***	-0.0179***	-0.0178***	-0.0107*	-0.0112***	-0.0120***	-0.0115***	-0.0114***	-0.0111***	-0.00661**
	(0.00456)	(0.00537)	(0.00419)	(0.00479)	(0.00485)	(0.00579)	(0.00270)	(0.00283)	(0.00227)	(0.00250)	(0.00252)	(0.00318)
Log (credit as a % Of GDP)		0.0449		0.0116	0.0149	0.0138		0.0315*		0.0164	0.0154	0.0199
		(0.0274)		(0.0265)	(0.0276)	(0.0324)		(0.0164)		(0.0151)	(0.0152)	(0.0162)
Inflation		-0.0102	-0.0101*	-0.00852	-0.00859	-0.00580		-0.00830**	-0.00652**	-0.00582*	-0.00562*	-0.00377
		(0.00690)	(0.00559)	(0.00617)	(0.00624)	(0.00617)		(0.00337)	(0.00282)	(0.00305)	(0.00307)	(0.00301)
Population growth			-8.758***	-8.431***	-8.366***	-4.801			-6.693***	-6.212***	-6.299***	-3.977**
			(2.302)	(2.632)	(2.663)	(3.022)			(1.618)	(1.778)	(1.788)	(1.872)
FDI (% of GDP)					-0.00207	-0.000855					0.00249	0.00343
					(0.00416)	(0.00421)					(0.00297)	(0.00287)
_cons	0.660***	0.655***	1.142***	1.072***	1.058***	0.866***	0.338**	0.380**	0.757***	0.705***	0.674***	0.541***
	(0.179)	(0.225)	(0.192)	(0.239)	(0.244)	(0.261)	(0.134)	(0.144)	(0.137)	(0.157)	(0.162)	(0.168)
N	47	43	46	43	43	43	49	45	48	45	45	45
Regional *f.e.*	No	No	No	No	No	Yes	No	No	No	No	No	Yes
adj. *R*2	0.297	0.307	0.508	0.448	0.436	0.476	0.249	0.378	0.538	0.520	0.516	0.572

[19] An alternative specification might rank countries as having low, medium or high levels of a given financial inclusion indicator, which is assumed to not change dramatically over time. In this case, the index is interpreted as a ranking rather than an absolute level

Appendix Table I.2. Results: Growth and Digital Financial Inclusion (Approach 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS estimation: Real GDP per capita growth rate (2011 – 2018)						**OLS estimation: Real GDP per capita growth rate (2014 – 2018)**					
Log(GDP per capita)	-0.0427** (0.0248)	-0.0545* (0.0278)	-0.0731*** (0.0250)	-0.0648** (0.0250)	-0.0645** (0.0253)	-0.0501* (0.0251)	-0.0316 (0.0196)	-0.0423** (0.0206)	-0.0633*** (0.0181)	-0.0611*** (0.0180)	-0.0614*** (0.0183)	-0.0463** (0.0184)
Trad. F.I. Index	0.354** (0.149)	0.215 (0.171)	0.191 (0.147)	0.0900 (0.157)	0.0842 (0.161)	-0.0992 (0.163)	0.164* (0.0905)	0.0878 (0.104)	0.104 (0.0815)	0.0405 (0.0887)	0.0436 (0.0913)	-0.0789 (0.0936)
Digital usage F.I Index	0.0693 (0.137)	0.0776 (0.130)	0.180 (0.120)	0.175 (0.120)	0.180 (0.123)	0.196 (0.126)	0.0233 (0.0928)	0.0330 (0.0883)	0.152* (0.0787)	0.135* (0.0785)	0.134 (0.0797)	0.151* (0.0790)
Gov. consumption (% of GDP)	-0.0185***	-0.0200*** (0.00491)	-0.0182*** (0.00449)	-0.0181*** (0.00441)	-0.0182*** (0.00449)	-0.0124** (0.00525)	-0.0110*** (0.00296)	-0.0118*** (0.00300)	-0.0106*** (0.00256)	-0.0105*** (0.00256)	-0.0104*** (0.00261)	-0.00637** (0.00306)
Log (credit as a % of GDP)		0.0610** (0.0262)		0.0299 (0.0251)	0.0306 (0.0257)	0.0223 (0.0272)		0.0464** (0.0187)		0.0279* (0.0164)	0.0274 (0.0168)	0.0273 (0.0170)
Inflation		-0.00243 (0.00542)	-0.00795* (0.00435)	-0.00369 (0.00484)	-0.00391 (0.00501)	-0.00340 (0.00473)		-0.00576 (0.00494)	-0.00692* (0.00408)	-0.00527 (0.00418)	-0.00507 (0.00437)	-0.00440 (0.00424)
Population growth			-7.887*** (2.099)	-7.497*** (2.267)	-7.516*** (2.298)	-5.726** (2.459)			-7.289*** (1.521)	-6.601*** (1.565)	-6.589*** (1.585)	-3.996** (1.873)
FDI (% of GDP)					-0.000878 (0.00410)	-0.00167 (0.00390)					0.000417 (0.00228)	0.000341 (0.00222)
_cons	0.673*** (0.176)	0.630** (0.253)	1.125*** (0.215)	0.945*** (0.244)	0.941*** (0.248)	0.860*** (0.234)	0.434*** (0.138)	0.425** (0.172)	0.846*** (0.150)	0.731*** (0.163)	0.734*** (0.165)	0.599*** (0.160)
N	48	45	46	45	45	45	51	49	50	49	49	49
Regional *f.e.*	No	No	No	No	No	Yes	No	No	No	No	No	Yes
adj. *R*2	0.261	0.352	0.455	0.486	0.473	0.543	0.219	0.308	0.487	0.506	0.494	0.566

Note: Robust standard errors are in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% level.

Appendix II: Robustness checks on Determinants of digital payments usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Random effects estimation: Digital usage financial inclusion index (t)												
Trad. access	-0.527***	-0.373**	-0.618***	-0.607***	-0.615***	-0.565**	-0.547***	-0.517**	-0.237	-0.220	-0.232	-0.249	-0.248
FI Index (t-3)	(0.171)	(0.171)	(0.210)	(0.212)	(0.210)	(0.221)	(0.207)	(0.216)	(0.171)	(0.174)	(0.176)	(0.170)	(0.174)
Trad. usage	0.779***	0.667***	0.738***	0.749***	0.851***	0.853***	0.739***	0.740***	0.773***	0.775***	0.799***	0.679***	0.683***
FI Index (t-3)	(0.139)	(0.131)	(0.137)	(0.138)	(0.149)	(0.153)	(0.152)	(0.157)	(0.132)	(0.133)	(0.138)	(0.141)	(0.147)
Digital infrastructure		0.110	0.255**	0.263**	0.316***	0.385***	0.162	0.207	0.353***	0.368***	0.381***	0.127	0.129
access (t-3)		(0.0958)	(0.116)	(0.117)	(0.120)	(0.135)	(0.133)	(0.152)	(0.117)	(0.119)	(0.121)	(0.152)	(0.153)
Mobile Money		0.000563***	0.000379***	0.000355***	0.000372***	0.000344***	0.000272**	0.000260**	0.000464***	0.000450***	0.000463***	0.000361***	0.000365***
Agents (t-1)		(0.000102)	(0.000112)	(0.000115)	(0.000113)	(0.000115)	(0.000117)	(0.000118)	(0.000102)	(0.000104)	(0.000106)	(0.000109)	(0.000112)
Log (NPL)			0.0757**	0.0734**	0.0827***	0.0779**	0.0572*	0.0556*					
(t-1)			(0.0300)	(0.0308)	(0.0309)	(0.0321)	(0.0318)	(0.0327)					
Log (GDP									-0.125***	-0.126***	-0.121***	-0.0575	-0.0633
per capita) (t-1)									(0.0377)	(0.0382)	(0.0390)	(0.0448)	(0.0536)
Overhead cost				0.0135	0.0123	0.0176	0.0142	0.0172		0.00819	0.00671	0.00907	0.00854
to assets (t-1)				(0.0121)	(0.0120)	(0.0130)	(0.0117)	(0.0127)		(0.0103)	(0.0106)	(0.0103)	(0.0109)
Rule of law					-0.00390*	-0.00412*	-0.00168	-0.00189			-0.00137	-0.0000603	-0.0000588
(t-1)					(0.00223)	(0.00228)	(0.00236)	(0.00242)			(0.00200)	(0.00200)	(0.00202)
Urban population						-0.00162		-0.000940					0.000270
(t-1)						(0.00162)		(0.00161)					(0.00169)
_cons	0.0717*	-0.0410	-0.172**	-0.228***	-0.117	-0.0733	-0.126	-0.0997	0.799***	0.765***	0.781***	0.324	0.356
	(0.0370)	(0.0428)	(0.0680)	(0.0842)	(0.106)	(0.119)	(0.103)	(0.117)	(3.09)	(2.85)	(2.89)	(1.03)	(1.02)
Year fixed effect	No	No	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes
N	96	96	80	79	79	79	79	79	96	95	95	95	95

Note: Robust standard errors are in parentheses. ***, **, * indicate statistical significance at the 1, 5 and 10% level. 'Trad.' is traditional financial inclusion and digital infrastructure access index is composed of share of population with access to internet and mobile phone.