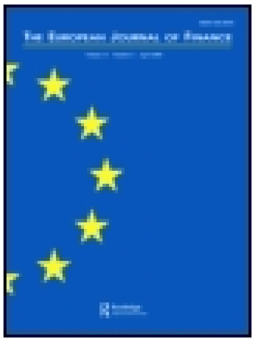

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The diffusion of fintech, financial inclusion and income per capita

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ABSTRACT
Advances in information and communication technology (ICT) have provided a platform for the introduction and diffusion of a range of financial technologies that have transformed the financial sector. This study analyses the diffusion of financial technology (fintech) and its interaction with financial inclusion and living standards (GDP per capita). We consider the determinants and effects of technology diffusion in financial services and identify two possible transmission mechanisms from the financial sector to GDP per capita – a fintech diffusion channel and a financial inclusion channel. We specify the interactions between these two channels and their relationship with income per capita. Our empirical analysis focuses on the diffusion of two enabling fintech innovations: ATMs and associated digital networks; and mobile phones and payments systems. The relationships between fintech diffusion, financial inclusion and GDP per capita are estimated using a panel data set for up to 137 countries over the period 1991–2015 using both cross section and panel techniques, including an error correction model that distinguishes short- and long-run effects. A key finding is that fintech diffusion and financial inclusion have long-run effects on GDP per capita over and above their short-run impact and the effects of investment in fixed and human capital.

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Fintech; financial inclusion; income per capita; growth

1. Introduction

The financial sector has experienced something of a technological revolution over recent decades as information and communication technology (ICT) platforms have facilitated the diffusion of an array of financial technologies (fintech) from automated teller machines (ATMs) and associated digital networks, mobile payments systems, mobile wallets online banking, automated credit scoring techniques (robo advisers) and block-chain technologies.[1] It is only recently that the term fintech[2] has slipped into common usage, however, the emergence of fintech has its roots in the development of ATM networks in the 1980s and 1990s. The digitalisation of financial services and the creation of secure, non-proprietary digital networks enabled the growth of ATM networks and provided a technological platform for further advances in fintech, including internet banking, mobile money and digital payments systems. While the diffusion of fintech has transformed the financial sector, few studies have investigated the effect of technological change in the financial services sector on financial inclusion and living standards. The present paper aims to fill this gap by exploring the factors driving the diffusion of two enabling financial technologies and their impact on financial inclusion and per capita incomes in over 130 countries. In particular, we specify a fintech diffusion channel and a financial inclusion channel to explore how technological change in the financial services sector impacts the real economy.

Fintech diffusion provides an important channel via which financial sector development may permanently raise living standards. This channel is worthy of consideration as it is well known that most of the benefits from innovation flow not from the original production of ideas, or inventions, but from their widespread adoption and use by firms and households (Comin and Hobijn 2010; Stoneman and Battisti 2010). The diffusion of fintech via

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the creation of digital networks, associated ATM networks, mobile money and payments systems, has direct and indirect effects. Digitalisation of financial services and the creation of non-proprietary digital networks can raise productivity and efficiency in the financial services sector itself – where the effects are likely to be strong because of positive network externalities (Hall and Kahn 2003; Scott, Van Reenen, and Zachariadis 2017). In addition, digital networks provide a technological platform on which to expand the reach of financial service providers, thus increasing financial inclusion (Batiz-Lazo 2018), mobilising savings and enhancing both the extent and allocation of investment in the wider economy. Financial technologies, such as, mobile phones, money and payments systems, may also 'enable developing countries to "leapfrog" to more efficient and modern economic systems' (Lashitew, van Tulder, and Liasses 2019, 1201), thus promoting convergence across countries.

This paper extends the existing literatures on fintech diffusion and financial inclusion in the following ways. First, we examine the factors shaping the diffusion of two pervasive fintech products – automated teller machines (ATMs) that exemplify the use of digital networks (Batiz-Lazo 2018), and mobile phones and payments systems. Second, we consider the factors shaping financial inclusion, including the role of ATMs, digital networks and mobile phone and payments systems, as well as socio-economic factors (Graff 2005). Third, we analyse the joint impact of these two effects – fintech diffusion and financial inclusion – on GDP per capita in both the short run and the long run. We also consider the inter-relations between fintech diffusion, financial inclusion and GDP per capita. Our theoretical analysis identifies both a fintech diffusion channel and a financial inclusion channel, thus identifying two transmission mechanisms from the finance sector to the real economy that capture the enabling features of ICT and fintech mentioned by Lashitew, van Tulder, and Liasses (2019), Baldwin (2016) the FSA (2019) and Leong and Sung (2018). The fintech diffusion channel captures the direct and indirect effects of technological progress in financial services on productivity in the financial sector and the wider economy via more efficient provision of financial services to households, business and government. It is distinct from previous work, for example, the 'ideas' production channel identified by Madsen and Ang (2016) since it focuses on the diffusion and use of financial technologies, associated network externalities and knock on effects.[3]

Fourth, in order to capture short and long-run effects, we employ an error correction model that enables us to identify long-run relationships between fintech, financial inclusion and living standards. The model is estimated using a panel data set for up to 137 countries over a 25-year time span (1991–2015). A key finding is that fintech diffusion and financial inclusion have long run effects on GDP per capita over and above their short run impact through capital accumulation.

The remaining sections are organised as follows. Section 2 provides a brief review of the literatures on technology diffusion, financial sector development and growth. Section 3 explains our hypotheses concerning the channels via which key financial technologies may influence financial inclusion and living standards (allowing for the possibility of feedback effects) and describes the derivation and specification of our econometric models. Section 4 provides discussion of our datasets and presents results from our econometric estimations using cross section analysis, including single equation models, three stage least squares and panel data analysis with an error correction model that allows us to identify the short and long-run effects of fintech diffusion and financial inclusion on GDP per capita. The results from our error correction model provide evidence of significant long-run relationships between the extent of diffusion of key financial technologies, financial inclusion and GDP per capita. The final section of the paper draws a number of conclusions for policy makers and identifies areas for further research.

2. Transmission channels in the finance-growth nexus

King and Levine's (1993) seminal paper on financial development and growth starts from the Schumpeterian thesis that finance is essential for innovation and economic development and explores the relationship between various indicators of financial development and growth. The main channels identified by King and Levine stem from the role of financial intermediaries in catalysing savings and investment, and improving the allocation of capital, thus enabling innovation in the wider economy. Notwithstanding their emphasis on Schumpeter's 'finance-innovation-economic development' thesis, there has been relatively little discussion of *how* finance leverages technological change. Rather, the emphasis in much of the finance-growth literature has been on the role of financial sector development on savings, investment and capital allocation, and much empirical analysis has focused on reduced form estimates of relationships between indicators of financial development and growth. The lack of attention to the creation and diffusion of innovations is curious, as a well-known result from growth theory is that while savings and investment may affect growth in the short run, in the long run productivity and growth are determined by technological change.

As Madsen and Ang (2016) note, many studies on the finance-growth nexus utilise cross section or panel data techniques to regress growth, or GDP per capita, on indicators of financial development without exploring the transmission mechanisms from the financial sector to the real economy and few studies (King and Levine 1993; Beck, Levine, and Loayza 2000; Benhabib and Spiegel 2000; Graff 2005; Laeven, Levine, and Michalopoulos 2015; Madsen and Ang 2016; Comin and Nanda 2019 are notable exceptions) have explored the role of finance in shaping total factor productivity growth (TFP) or technological change. Of these, King and Levine (1993) and Beck, Levine, and Loayza (2000) estimate TFP as a residual after accounting for growth in capital and labour inputs and regress estimates of residual TFP on measures of financial intermediation and development. Both studies find that TFP is positively and significantly correlated with financial development.

However, the question of how technological innovations are created and diffused has received little attention in the finance-growth literature. Madsen and Ang (2016) provide new insight into the invention channel linking finance and growth, by explicitly using an 'ideas' production function (Porter and Stern 2000) as a core mechanism via which financial sector development leads to permanent increases in living standards (Madsen and Ang 2016, 552). Using an endogenous growth framework, their results demonstrate the importance of the finance-invention-growth channel (beyond savings, investment and capital allocation) using a specially constructed panel database for 21 OECD countries over the period 1870–2009.

While Madsen and Ang's study finds empirical evidence of a finance-invention-growth channel, their focus is on 'ideas' production in the wider economy, and they do not explicitly consider technological innovation in the financial sector *per se.* Nor do they model the extent of diffusion of financial technologies.[4] Indeed, despite recent interest in fintech, relatively little attention has been devoted to financial innovation as a transmission channel from financial sector development to productivity and growth. An early study by Silber (1983) reviewed 38 financial innovations including ATMs and electronic payments and found that they reduced financial constraints, thus enhancing welfare at the macro level. Similarly, Zilberfarb (1989) found that ATMs increased demand deposits. More recently, Laeven, Levine, and Michalopoulos (2015), Beck et al. (2016), considered the impact of financial innovation on growth and macroeconomic development, while Lashitew, van Tulder, and Liasses (2019) and Jagtiani and Lemieux (2018) explore the effects of mobile phones and fintech on financial inclusion.

The wider literature on innovation and technology diffusion suggests additional channels that may potentially underlie the finance-growth nexus, most notably the adoption and diffusion of financial technologies and their interrelations with financial inclusion and prosperity. While the invention of new products and processes is an important source of productivity growth, it is their diffusion that has the largest impact on the level of economic development and living standards. Comin and Hobijn (2010) estimate that the average time for technologies to diffuse across countries is 45 years, and that differences in the extent of diffusion account for around 25% of the differences in GDP per capita across countries. Yet, the role of technology diffusion generally, and of fintech diffusion in particular, has received little attention in the finance-growth literature to date. Understanding fintech diffusion is important since the omnipresent use of financial services by business, households and government suggests that technology induced productivity gains in the financial sector can have far-reaching effects on the real economy.

The ability of financial systems to mobilise and channel savings to finance both R&D ('ideas' production) and technology diffusion is important in catalysing technological progress and associated improvements in living standards. The extent of financial inclusion plays a critical part in this process. However, standard models often assume that everyone is banked and ignore differences in financial sector coverage associated with the fact that around 1.7 billion people over the age of 15 are excluded from formal financial systems (World Bank 2018). Put differently, formal financial systems are currently unable to mobilise the savings of around 30% of the world's adult population and the extent of financial inclusion varies significantly across countries and over time. Extant empirical research shows that an increase in financial inclusion is associated with an increase in savings, consumption and productive investments (Dupas and Robinson 2013). Given the productivity and equality-enhancing effects of financial inclusion, governments around the world have more inclusive finance as a policy objective as a means of raising savings and investment. Fintech diffusion provides an important transmission mechanism via which productivity gains and increases in financial inclusion raise GDP per capita. It also opens up the possibility of effective policy instruments centred on catalysing technology diffusion and developing fintech infrastructure and support.

In the following section, we set out two specific channels via which financial sector development may influence living standards – the fintech diffusion channel and the financial inclusion channel – and the interactions between them. In particular, we study the diffusion and impact of two key financial technologies that have transformed finance – ATMs and associated digital networks; and mobile phone network payments systems – their interaction with each other and their relationship with financial inclusion and per capita income over time and across countries.

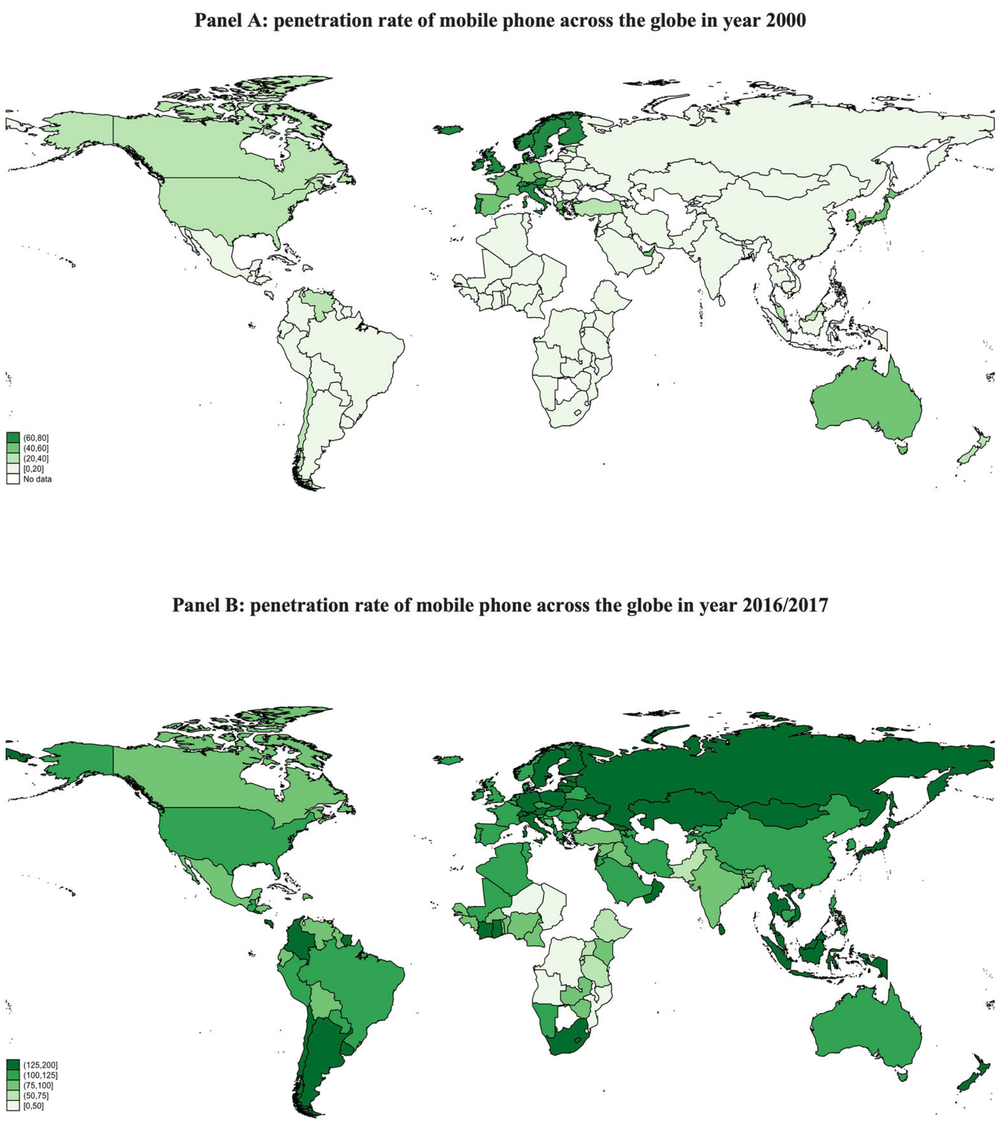

Figure 1. Mobile phone penetration rate (data from World Development Indicators). Source: figures created by the authors.

Note: This figure shows the penetration rate of mobile phone across the globe before 2000. The penetration rate is measured by the number of mobile cellular subscriptions (per 100 people).

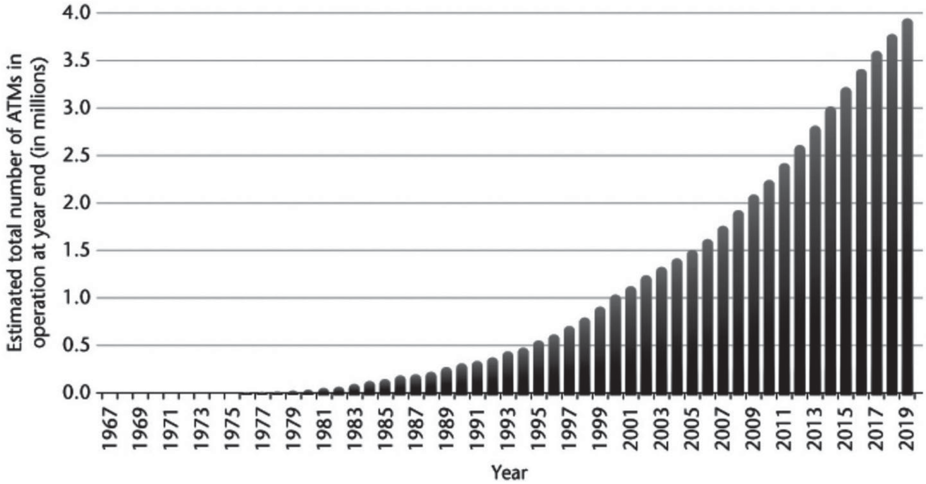

Figure 2. Diffusion of ATMs. Source: Batiz-Lazo (2018).

There is some evidence to suggest that ICT technologies are diffusing more quickly than traditional technologies such as rail, passenger cars and electricity production (Comin and Hobijn 2010), however, Figure 1 shows that fintech diffusion is a slow and variable process across time and countries. Panels A and B illustrate the point with respect to mobile phones: while the extent of diffusion has increased over time, the variability remains high across countries some 40 years after mobile phone technology was initially introduced. Figure 2 shows the adoption of ATMs which has grown significantly since they were first introduced. As Batiz-Lazo (2018) notes, ATMs embody digital networks and markets, interoperability protocols, security software, and card recognition/reading technologies, that are every bit as significant, if not more significant technologically, than the cash machines themselves. There is considerable variation in the extent of diffusion of ATMs, with the number of ATMs per capita varying from zero to 1.88, and much of the growth in the total number of ATMs reflecting catch up by lagging economies driven by growing financial inclusion (Batiz-Lazo 2018).

3. Technology diffusion, financial inclusion and GDP per capita

A variety of approaches have been used in the finance-growth literature. Studies, such as King and Levine (1993) and Beck, Levine, and Loayza (2000) are couched in terms of Solow-type growth models that are used to estimate TFP and seek to endogenise the residual by regressing TFP on finance variables and control variables. Building on this approach, we start from a standard production function (Aghion and Howitt 1998),

$$Y = AK^{\alpha}(hL)^{1-\alpha} \tag{1}$$

where Y is output (GDP), A represents technology and other factors affecting productivity, K is the stock of capital, h is human capital per worker, L is employment and the exponents α and $1\text{-}\alpha$ can be considered as factor shares. Equation (1) can be re-expressed in terms of GDP per capita (Madsen and Ang 2016) to obtain,

$$\frac{Y}{L} = A^{\frac{1}{1-\alpha}}\left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} h \tag{2}$$

When expressed in terms of growth, long-run improvements in GDP per capita depend on improvements in human capital and changes in A or technological progress. In terms of levels of GDP per capita, A is a productivity parameter that represents the extent of technological diffusion (Barro and Sala-i-Martin 1997) and non-technological factors that influence the efficiency of technologies and factors of production, for example, social capital, governance, trust (Graff 2005; Beck, Levine, and Loayza 2000; Comin and Hobijn 2010).

Madsen and Ang (2016) identify an 'ideas' production transmission channel from financial sector development to technological progress, by specifying growth in A as a function of research and development (R&D) intensity, financial development and scale effects. Hence, increases in income per capita are determined in the short run by investment in fixed and human capital, while permanent or long-run increases in productivity are shaped by 'ideas' production facilitated by financial development. Provided there are scale effects, financial sector development has long-run impact on growth and prosperity.

Instead of focusing on R&D and ideas production, we analyse a diffusion transmission mechanism that captures the impact of fintech diffusion on GDP per capita. The extent of technological diffusion is distinct from 'ideas' production or invention, and an important determinant of technological capability and productivity. Moreover, it is the diffusion of technology rather than its invention that has the largest impact on productivity and GDP per capita. Fintech diffusion or the adoption of financial technologies also determines and is determined by, financial inclusion – as mobile payments or digital ATM networks expand, the greater the benefits to individual users from network externalities or scale effects. Non-proprietary digital networks and payments systems that connect customers across many banks, provide platforms for improved financial service provision that enhances financial inclusion. Digital networks and payments systems are subject to positive network externalities or scale effects arising from the greater benefits of using mobile payments systems or ATM machines as the network of users and banks expands.

Numerous studies have confirmed that cross country differences in income per capita are related to cross-country differences in the extent of technological diffusion (e.g. Hall and Kahn 2003; Caselli 2005; Freeman 1989; Hall and Jones 1999; Hsieh and Klenow 2010). In our empirical estimations, we endogenise, A, by specifying it as a function of the extent of the technological diffusion, and non-technological factors, such as, institutional quality (Graff 2005) and financial inclusion. Financial inclusion is also determined by the extent of diffusion of financial technology, since mobile phones and ATMs increase access to financial services, and both variables influence income per capita through A.

Thus, we have a three equation system that we specify econometrically across countries and time, where:

(i) income per capita in country i at time t is determined by capital accumulation, human capital, employment and A_{it}, which is a function of the extent of fintech diffusion, financial inclusion and other variables;
(ii) the extent of fintech diffusion is shaped by financial inclusion and GDP per capita and a number of economic and socio-economic variables (Graff 2005); and
(iii) financial inclusion is determined by GDP per capita, fintech, financial infrastructure, economic structure and socio-economic variables, including political and economic stability and freedom from corruption.

We discuss each of these in turn in Sections 3.1–3.3 below.

3.1. Determinants of the extent of fintech diffusion

In view of the fact that most of the benefits from inventions come not from 'ideas' production or invention but from their widespread adoption and diffusion, our econometric specification lets the productivity or technology parameter, $A_{it,}$ be proxied by the extent of diffusion, D_{ict}(:

$$D_{ict} = \alpha_{it} + \alpha_1 FI_{it} + \alpha_2 y_{it} + \sum_{j=3}^{J} \alpha_j X_{jit} + u_{it} \tag{3}$$

where D_{ict} is the extent of diffusion of technology c in country $i(i = 1, \ldots, N)$, at time t. FI_{it} is the financial inclusion index, y_{it} is the GDP per capita, $X_{1it}, \ldots, X_{Pit}$ are control variables, including trade, which is expected to stimulate innovation diffusion (Eaton and Kortum 1996), urbanisation, and a composite stability index, while u_{it} is a disturbance term.

We proxy the extent of fintech diffusion by ATM networks and mobile phone usage. ATM networks incorporate sophisticated digital networks and security technology, while mobile phones, wallets and associated payments systems rely on complex digital networks and security protocols. Both are subject to positive network externalities because the utility of these technologies increases, as the number of banks, payments system agents, firms, and retail customers connected to the respective networks, increases. We therefore expect financial inclusion to have a positive effect on fintech diffusion. This direct transmission mechanism from financial inclusion to fintech diffusion stems fundamentally from positive network externalities and is in addition to the positive effect that financial inclusion may have on income per capita via savings and capital investment, which is specified in Equation (5) below.

3.2. Effect of fintech diffusion on financial inclusion

Financial inclusion is determined by financial technologies that facilitate efficient access to banking services, human capital (Grohmann, Klühs, and Menkhoff 2018) socio-economic variables and financial and political stability (Graff 2005). Hence, we specify the following econometric model:

$$FI_{it} = \lambda_0 + \sum_{c=1}^{2} \lambda_c D_{ict} + \lambda_3 H_{it} + \sum_{k=1}^{K} \lambda_{k+3} Z_{kit} + \mu_{it} \tag{4}$$

where the dependent variable (FI_{it}) represents the financial inclusion index of country $i(i = 1, \ldots, N)$ at time t, D_{ict} is the extent of diffusion of technological innovation, H_{it} is a human capital indicator, $Z_{1it}, \ldots, Z_{Kit}$ are control variables, including absence of corruption (Clausen, Kraay, and Nyiri 2011), government spending as a Keynesian demand side factor, socio-economic and political factors identified by Graff (2005) and μ_i is an error term.

We use two indicators of financial inclusion: the first is the percentage of respondents who report having an account at a bank or another type of financial institution.[5] This variable comes from the Global Findex database.[6] This indicator is a direct measure of the access dimension of financial inclusion (see, Allen et al. 2016). The second indicator is the overall financial development index and three of its sub-components (financial institutions depth, financial institutions access, and financial institutions efficiency) proposed by Svirydzenka (2016).

3.3. Effects of fintech diffusion and financial inclusion on GDP per capita

The effects of financial inclusion and technology diffusion on living standards are captured by the following specification of Equation (2),

$$y_{it} = b_0 + b_1 FI_{it} + \sum_{c=1}^{2} b_{c+1} D_{ict} + b_4 K_{it} + b_5 H_{it} + \sum_{j=1}^{J} b_{6+j} W_{jit} + v_{it} \tag{5}$$

where y_{it} is the log of per capita income of the country $i(i = 1, \ldots, N)$, at time t, H_{it} is a human capital indicator, K_{it} is investment in fixed capital, and $W_{1it}, \ldots, W_{Jit}$ are controls, including population growth, which may encourage greater investment (Becker, Glaeser, and Murphy 1999), composite stability, as a measure of socio-economic and political factors (Graff 2005), and a disturbance term, v_{it}. In this specification, the productivity parameter is captured by the extent of fintech diffusion (D_{ict}) and the state of financial inclusion (FI_{it}).

4. Estimation results

Our empirical strategy is based on three steps. In the first step, we follow the existing literature that uses cross-country regression for Equations (3)–(5). This enables us to have the widest country coverage and make use of available measures of financial inclusion that are not available for the whole time period 1991–2015 (for example, data for holding an account at a formal financial institution and using a mobile money service cover only 3 years, 2011, 2014, 2017). In the second step, we estimate our three-equation model using 3-stage least squares to pick

Table 1. Description of the variables and data sources.

Variables	Definition	Sources
Mobile phone	Extent of diffusion – mobile subscriptions per 100 people	WDI
Account	Proportion of adult population with an account at a formal financial institution	GFD
ATM	Number of ATMs per 100,000 people	WDI
Financial development index (FD)	Overall index of financial development. It includes two categories with three sub-indices in each category: financial institutions (depth, access, efficiency) and financial market (depth, access, efficiency).	Svirydzenka (2016)
Financial institutions depth (FID)	A synthetic index composed of (i) Private sector credit to GDP, (ii) Pension fund assets to GDP, (iii) Mutual fund assets to GDP, and (iv) Insurance premiums (life + non-life) to GDP.	Svirydzenka (2016)
Financial institutions access (FIA)	A synthetic index builds by using number of bank branches and number of ATM.	Svirydzenka (2016)
Financial institutions efficiency (FIE)	A synthetic index composed of (i) Net interest margin, (ii) Lending-deposits spread, (iii) Non-interest income to total income, (iv) Overhead costs to total assets, (v) Return on assets, and (vi) Return on equity.	Svirydzenka (2016)
GDP/N	log of per capita income	WDI
Human capital index	The index proxies the average years of schooling	PWT
Primary school	Proportion of population who completed at least primary school	WDI
Lower secondary school	Proportion of population who completed at least lower secondary school	WDI
Upper secondary school	Proportion of population who completed at least upper secondary school	WDI
Capital	Log of the capital stock at constant 2011 national prices (in mil. 2011US$). The measure of capital that we use is cumulated from series on investment in buildings and different types of machinery (Feenstra, Inklaar, and Timmer 2015).	PWT
Population growth	Growth rate of the population.	WDI
Trade	Trade (% of GDP). Average over the period 1990–2017	WDI
Government spending	General government final consumption expenditure (% of GDP)	WDI
Urbanisation	Urban population (% of total)	WDI
Absence of corruption	This indicator assesses the degree of corruption within the political system.	PRS
Composite stability	It is a composite Political, Financial, Economic Risk Rating	PRS
Political stability	Assessment of the political stability of a country.	PRS
Shadow Economy	Estimation of the shadow economy (% of the GDP). It includes all economic activities which are hidden from official authorities for monetary, regulatory, and institutional reasons	Medina and Schneider (2018)
FDI inflow in ICT/Investment	FDI inflow in ICT sector divided by total investment. Investment is measured by the total gross fixed capital formation	FT and WDI
Legal origin UK	Dummy variable: British legal origin	La Porta et al. (1998)

Note: This table presents the dependent variables and the explanatory variables that we used in the paper, their definitions the abbreviations used in empirical results, and sources of observed data. WDI stands for World Development Indicators, PWT is Penn World Table (PWT), GFD stands for Global Findex database, FT is Financial Times and PRS stands for Political Risk Service Group.

up simultaneities between fintech diffusion, financial inclusion and GDP per capita. For the analysis in steps one and two, we capture time effects by taking the average of existing variables from 2013 to the latest available observation. Therefore, in Table 2, the number of observations equals the number of countries. At step three, we complement the cross section analysis by estimating an error correction model using panel data regression – this enables us to isolate short run and long-run effects of fintech diffusion and financial inclusion.

To explore the effects of fintech diffusion we sought to construct a panel dataset for the widest coverage of countries and longest time period available. The financial inclusion indices are from Svirydzenka (2016) and cover the period 1991–2015. Data were available for a total of 137 countries as listed in Appendix 2. The choice and the construction of the main variables builds on those used in previous studies on financial innovation (see, e.g. Laeven, Levine, and Michalopoulos 2015) and financial inclusion (e.g. Allen et al. 2016) and its impact on growth (e.g. Kim, Yu, and Hassan 2018). Table 1 lists the variables used, their abbreviated names, their definitions and the sources of data.

Table 2. Descriptive statistics.

	Obs.	Mean	Std. Dev.	Min	Max
GDP/N (log)	137	8.84	1.47	5.64	12.02
Account	125	0.59	0.29	0.07	1.00
ATM per capita	132	0.42	0.38	0.00	1.88
Mobile phone per capita	137	1.09	0.33	0.29	1.97
Trade	133	0.89	0.54	0.25	3.95
Government spending	132	0.17	0.05	0.05	0.36
Primary school	125	0.76	0.26	0.08	1
Lower secondary school	136	0.62	0.29	0.06	1
Upper secondary school	133	0.48	0.27	0.03	0.92
Human capital index	118	2.64	0.68	1.18	3.72
Population growth	137	1.30	1.29	−2.23	5.83
Urbanisation	137	0.61	0.23	0.12	1
Number of bank branches	130	0.19	0.22	0.01	2.04
Capital	131	12.92	1.96	8.48	17.81
FDI inflow in ICT/Investment	125	0.02	0.03	0.00	0.23
Shadow economy rate	130	0.27	0.12	0.07	0.65
Absence of corruption	115	2.82	1.21	1.00	5.50
Political risk	115	0.66	0.12	0.38	0.88
Composite risk	115	0.70	0.09	0.42	0.891
Financial development index (FD)	129	0.37	0.23	0.05	0.93
Financial institutions depth (FID)	129	0.33	0.28	0.02	1
Financial institutions access (FIA)	129	0.41	0.27	0.01	1
Financial institutions efficiency (FIE)	129	0.68	0.14	0.25	0.90

Note: This table presents the summary statistics for the dependent and explanatory variables used in this paper. Std. Dev. is the standard deviation of each variable for a panel of 137 countries for 2013–2017. Mean, Min and Max are the average, the minimum and the maximum of each variable in our sample. Obs. is the number of countries. The variables are defined in Table 1.

4.1. Descriptive statistics

The descriptive statistics for all variables used in this study are shown in Table 2. On average, 59% of the population has an account at a formal financial institution. This proportion varies from 7% in Niger and Burundi to almost 100% in Australia, Canada, Denmark, Finland, Netherlands, Norway, New Zealand and Sweden. Over the last five years, the average penetration rate of mobile phone was 109% and varies from 28.72% (Cuba) to 197% (United Arab Emirates). The ATM penetration rate is very low compared to that of the mobile phone. It varies from 0.14 per 100,000 inhabitants in Ethiopia to 188 per 100,000 inhabitants in Korea.

Table 3 reports the correlation matrix. Per capita income is highly and positively correlated with stability indicators (composite or global and political stability), human capital variables (human capital index, primary and secondary school) and financial inclusion – proxied by having an account (correlation greater than 0.7).

Financial inclusion – measured by 'having an account' and the financial development index and its sub-indices – is also positively correlated with human capital variables and stability indices.

Fintech diffusion (ATM and digital networks, and mobile phones and payments) is positively correlated with the proportion of the population leaving the urban area, GDP per capita, stability indices and human capital variables. There is also a positive correlation between financial inclusion and fintech diffusion. These preliminary results indicate that fintech diffusion, financial inclusion, and economic performance are inter-related. We take these inter-relations into account by estimating our three equations as a system in step two of our empirical analysis. The correlation matrix shows that some variables are highly correlated (correlation greater than 0.7). These variables are therefore not included in the regressions at the same time to limit multicollinearity issues.

4.2. Diffusion of technological innovation across countries: cross section analysis

We first focus on mobile phone and ATM technologies and estimate Equation (3). The main results of the estimates are reported in Table 4. The dependent variables are the number of ATMs per capita and mobile phone subscriptions per capita.

Table 3. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Mobile phone (1)	1														
ATM (2)	0.41***	1													
Urbanisation (3)	0.48***	0.57***	1												
Trade (4)	0.34***	0.12	0.21**	1											
GDP/N (5)	0.57***	0.71***	0.77***	0.33***	1										
Political stability (6)	0.52***	0.61***	0.59***	0.41***	0.83***	1									
Composite stability (7)	0.55***	0.58***	0.59***	0.39***	0.83***	0.91***	1								
Primary school (8)	0.49***	0.60***	0.63***	0.25***	0.74***	0.62***	0.55***	1							
Lower sec. school (9)	0.47***	0.60***	0.53***	0.32***	0.71***	0.64***	0.62***	0.92***	1						
Upper sec. school (10)	0.45***	0.62***	0.50***	0.28***	0.67***	0.64***	0.60***	0.86***	0.93***	1					
Human (11)	0.51***	0.67***	0.62***	0.31***	0.79***	0.75***	0.70***	0.92***	0.92***	0.90***	1				
FDI ICT/Investment (12)	−0.18**	−0.19**	−0.30***	0.09	−0.28***	−0.03	−0.08	−0.27***	−0.22**	−0.21**	−0.23**	1			
Account (13)	0.55***	0.72***	0.65***	0.34***	0.88***	0.82***	0.77***	0.70***	0.68***	0.67***	0.76***	−0.29***	1		
FD (14)	0.43***	0.78***	0.64***	0.20**	0.83***	0.76***	0.76***	0.58***	0.57***	0.55***	0.67***	−0.22**	0.83***	1	
No. of bank branches (15)	0.21**	0.36***	0.34***	0.11	0.36***	0.29***	0.26***	0.32***	0.30***	0.28***	0.28***	−0.13	0.34***	0.26***	1

Note: This table presents the Pearson correlation coefficients between dependent and explanatory variables. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

Table 4. Determinants of the diffusion of mobile phone and ATMs.

	Mobile Phone				ATM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP/N	0.120***				0.175***	0.083***		
	(0.015)				(0.021)	(0.025)		
Trade	0.095**		0.087**	0.073*				
	(0.046)		(0.041)	(0.038)				
Urbanisation			0.544***	0.439***			0.247**	0.197
			(0.129)	(0.142)			(0.109)	(0.122)
Account		0.595***	0.264***	0.130		0.534***	0.773***	0.721***
		(0.078)	(0.096)	(0.110)		(0.136)	(0.114)	(0.137)
Upper secondary school				0.321***				0.289***
				(0.095)				(0.104)
Bank branches					0.212	0.183	0.188	0.157
					(0.189)	(0.148)	(0.153)	(0.139)
Constant	−0.044	0.754***	0.538***	0.462***	−1.158***	−0.657***	−0.220***	−0.277***
	(0.131)	(0.056)	(0.067)	(0.073)	(0.150)	(0.161)	(0.049)	(0.052)
Observations	133	125	124	114	130	123	123	113
Adj. R2	0.361	0.300	0.398	0.423	0.504	0.537	0.526	0.525

Note: This table reports the OLS estimation results of Equation (1). The dependent variables are the number of mobile phone subscription per inhabitant (1–4) and the number of ATM per inhabitant (5–8). Robust standard errors in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

First, we find that a high level of income per capita is associated with a high level of mobile phone adoption. This is consistent with the literature which finds that the likelihood of having a mobile phone is positively associated with economic development (Buys et al. 2009). Second, the higher the proportion of the population that is financially included, the higher the diffusion of mobile phones. Third, composite stability (comprising political, economic and financial stability) tends to enhance the diffusion of innovation. Fourth, a low level of urbanisation decreases the diffusion of innovation.

Focusing on the diffusion of ATMs, the results indicate that GDP per capita and financial inclusion (measured by having an account at a formal institution) are determinants of the diffusion of ATMs. As in the case of mobile phones, the level of urbanisation is also an important determinant of ATM diffusion, as are human capital variables. The number of bank branches does not seem to affect the number of ATMs. This may be due to the sample period (2013–2017). In most countries, the number of ATMs is not necessarily correlated with the number of bank branches since ATMs can be found in train and gas stations, airports, supermarkets, etc.

Fifth, the results indicate that trade is a vehicle for technology diffusion. Our result is consistent with the existing literature which shows that the diffusion of new technologies across countries may take place through international trade in intermediate goods (Eaton and Kortum 1999, 2002; Rivera-Batiz and Romer 1991).

Finally, we analyse the effect of human capital on fintech diffusion. We find that human capital variables (the human capital index, primary and secondary school) are positively and significantly related to the diffusion of technology. This last result indicates that learning and absorptive capacity, captured by human capital, are drivers of technological diffusion. The development of human capital – through education – facilitates the adoption of new technology.

4.3. Financial inclusion and the diffusion of technological innovation

We estimate Equation (4) to understand the determinants of financial inclusion. The results of the estimates are reported in Table 5. Firstly, as expected, GDP per capita and government spending are positively associated with the access to an account at a formal financial institution as demand for financial services from previously unbanked customers increases as incomes rise, and government transfers and expenditure on services, such as, education further stimulate awareness of, and new demand for, financial services.

Table 5. Determinants of having an account at a financial institution.

	(1)	(2)	(3)	(4)	(5)	(6)
Shadow	-1.238^{***}	-0.376^{**}	-0.567^{**}	-0.595^{***}	-0.847^{***}	-0.795^{***}
	(0.169)	(0.148)	(0.232)	(0.185)	(0.145)	(0.167)
Bank branches	0.187	0.013	0.056	0.056	0.031	0.070
	(0.182)	(0.080)	(0.097)	(0.096)	(0.083)	(0.102)
Government spending	0.834^{**}	0.362^{*}	0.508	0.733^{**}	0.525^{*}	0.511
	(0.420)	(0.213)	(0.341)	(0.335)	(0.268)	(0.316)
Mobile phone	0.298^{***}		0.151^{***}	0.090^{*}	0.090^{*}	0.097^{**}
	(0.055)		(0.048)	(0.052)	(0.049)	(0.048)
ATM		0.130^{***}	0.256^{***}	0.232^{***}	0.208^{***}	0.193^{***}
		(0.035)	(0.044)	(0.046)	(0.048)	(0.052)
GDP/N		0.126^{***}				
		(0.014)				
Absence of corruption			0.067^{***}			
			(0.022)			
Composite stability				1.067^{***}		
				(0.290)		
Upper secondary school					0.252^{***}	
					(0.080)	
Human capital index						0.135^{***}
						(0.030)
Constant	0.423^{***}	-0.531^{***}	0.198	-0.307	0.265^{***}	0.168
	(0.105)	(0.150)	(0.135)	(0.225)	(0.080)	(0.119)
Observations	120	120	106	106	110	111
Adj. R2	0.593	0.804	0.714	0.724	0.746	0.730

Note: This table reports the OLS estimation results of Equation (2). The dependent variable is financial inclusion measured by having an account at a formal financial institution. Robust standard errors in parentheses.
$^{***}p < 0.01$.
$^{**}p < 0.05$.
$^{*}p < 0.1$.

Secondly, the size of the shadow economy impairs financial inclusion. By definition, 'the shadow economy includes all economic activities which are hidden from official authorities for monetary (avoid taxes payment), regulatory (avoid governmental bureaucracy or the burden of regulatory framework), and institutional reasons' (Medina and Schneider 2018). High levels of shadow economy activity involve financial transactions outside the formal financial system. Thirdly, on average, the technology diffusion (mobile phone and ATM) boosts financial inclusion, i.e. increases the proportion of the population financially included in the formal system. Fourthly, we find that financial inclusion is positively associated with political and composite stability and good governance (absence of corruption). The political and global environment (stability and governance) spur financial inclusion as in Allen et al. (2014). Fifthly, human capital is also a determinant of financial inclusion. Increases in the human capital index or primary, lower and upper secondary educational attainment increase the level of financial inclusion in the economy probability through financial literacy (Grohmann, Klühs, and Menkhoff 2018).

4.4. The impact of fintech diffusion and financial inclusion on income per capita

In order to assess the effects of fintech diffusion on living standards, we estimate Equation (5). The dependent variable is the log of per capita income. Column (1) of Table 6 reports the estimates of Equation (3) by considering only three inputs (human capital, physical capital and labour) in a production function. In column (2), we add the financial inclusion variable. Financial inclusion positively contributes to income per capita. In columns (3) and (4), we add two fintech diffusion variables and show that the diffusion of technology increases living standards.

This analysis shows that, in addition to traditional factors entering the production function (human capital and physical capital), financial inclusion, technology diffusion and stability are key factors that can increase per capita income. At the same time, GDP per capita is positively associated with financial inclusion and the diffusion of innovation. The results remain significant after controlling for other factors.

Table 6. The determinants of income per capita.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Human capital index	1.644***	0.789***	1.371***	1.370***	0.637***	0.613***	0.583***
	(0.171)	(0.164)	(0.161)	(0.191)	(0.156)	(0.139)	(0.154)
Capital	0.196***	0.117***	0.183***	0.130***	0.099***	0.093**	0.082**
	(0.049)	(0.035)	(0.042)	(0.048)	(0.036)	(0.038)	(0.039)
Population growth	0.122	0.162**	0.169*	0.141	0.194***	0.158**	0.132*
	(0.106)	(0.076)	(0.086)	(0.094)	(0.068)	(0.069)	(0.077)
ATM				0.943**	0.199	0.178	0.146
				(0.363)	(0.217)	(0.167)	(0.196)
Account		3.043***			2.702***	1.814***	1.865***
		(0.380)			(0.397)	(0.406)	(0.442)
Mobile phone			1.425***		0.961***	0.965***	0.758***
			(0.253)		(0.215)	(0.218)	(0.226)
Absence of corruption						0.255***	
						(0.071)	
Composite stability							3.877**
							(1.705)
Constant	1.771***	3.146***	1.004**	2.919***	2.787***	2.856***	1.347
	(0.651)	(0.511)	(0.501)	(0.746)	(0.515)	(0.567)	(0.888)
Observations	118	115	118	118	115	105	105
Adj. R2	0.667	0.830	0.730	0.692	0.855	0.868	0.864

Note: This table presents ordinary least squares OLS estimates of Equation (3). The dependent variable is log of the per capita income. Robust standard errors in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

To gauge the robustness of our findings we extend the analysis by 3-stage least squares to capture simultaneous effects between our three variables – fintech diffusion, financial inclusion and GDP per capita and panel data regressions to distinguish short run and long run effects.

4.5. Systems estimation of fintech diffusion, financial inclusion and GDP per capita

Previously, we found that fintech diffusion can be partly explained by financial inclusion. In addition, fintech diffusion explains financial inclusion and GDP per capita. Moreover, greater financial inclusion also leads to a high level of per capita income. Therefore, all three variables are jointly determined and the estimates attained may be biased. To address this issue of reverse causality, we use three-stage least squares (3SLS) to estimate a series of systems of three equations.[7]

Table 7 reports the results of the estimates. We estimate two different systems of equations. In the first system (Equations (1)–(3)) of Table 7, the variables: mobile phone penetration rate, ATM penetration rate, having an account, GDP per capita and the composite stability index are considered as endogenous.

Before interpreting the results, we discuss the identification of the systems of equations and provide the appropriate diagnostic statistics for this purpose. First, the systems are overidentified. There are five endogenous variables (mobile phone penetration rate, ATM penetration rate, having an account, GDP per capita and the composite stability index) in the first system and six endogenous variables (mobile phone penetration rate, ATM penetration rate, having an account, GDP per capita, human capital index, and stock of capital) in the second system. In terms of exogenous variables, there are eight exogenous variables in the first system and six in the second system. In addition, we use the political stability index as an instrument in the ATM equation (the correlation between the ATM penetration rate and the political stability index is 0.61). Moreover, the absolute latitude of each country is used as instrument in the second system of equations. Therefore, the number of exogenous variables (including instruments) is greater than the number of endogenous variables in each system. Second, the Hansen J statistic is calculated to determine the validity of the overidentifying restrictions because the system is overidentified.[8] The null hypothesis is that the overidentification restriction is valid. The *p-value* associated with *Hansen's J* statistic should be greater than 0.10 in all cases for the null hypothesis to be accepted and the system to be overidentified. The last row of the Table 7 reports the *Hansen's J* statistic and the associated

Table 7. Results of the 3SLS estimations of the system of Equations (1)–(3).

	Mobile phone (1)	Account (2)	GDP/N (3)	Mobile phone (4)	Account (5)	GDP/N (6)
Mobile phone		0.336**	3.244***		0.505***	3.429***
		(0.147)	(0.525)		(0.177)	(0.749)
ATM		0.451***			0.355**	
		(0.110)			(0.166)	
Account			1.554**	0.370**		1.519**
			(0.679)	(0.154)		(0.764)
Shadow economy rate		−0.572***			−0.507***	
		(0.184)			(0.181)	
Bank branches		−0.017			0.006	
		(0.076)			(0.071)	
Government spending		0.489			0.331	
		(0.394)			(0.296)	
Urbanisation	0.653***			0.392***		
	(0.095)			(0.138)		
Trade	0.042*			0.078*		
	(0.024)			(0.040)		
Human capital index	0.100***					0.644*
	(0.031)					(0.346)
Capital			0.062*			0.164**
			(0.036)			(0.066)
Composite stability index			4.439***			
			(1.653)			
Population growth						0.223***
						(0.069)
Constant	0.402***	0.108	0.386	0.578***	−0.034	−0.071
	(0.093)	(0.162)	(1.120)	(0.069)	(0.168)	(1.041)
Observations	101	101	101	111	111	111
R-squared	0.419	0.610	0.676	0.381	0.582	0.672
Hansen Statistics (*p*-value)		16.566(0.167)			12.656(0.124)	

Note: This table presents 3SLS estimates of the system of Equations (1)–(3). In the first system (models (1)–(3)), mobile phone penetration rate, ATM penetration rate, having an account, GDP per capita and composite stability index are considered as endogenous. Political stability index is used as instrument in addition to the other exogenous variables of the system. In the second system (models (4)–(6)), mobile phone penetration rate, ATM penetration rate, having an account, GDP per capita, human capital index, and stock of capital are considered as endogenous. Absolute latitude of each country is used as instrument in addition to the other exogenous variables of the system. Robust standard errors in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

p-value. There is no evidence against the null of overidentifying restriction hypothesis at 10% level. Finally, we provide evidence for limited risk of weak instruments in the two systems by using the F-statistics calculated after the first stage of the estimation. All F-statistics are greater than 10 (see footnote 8), except the first stage estimation of the mobile phone penetration rate for which this statistic is 9.15. These results indicate that the system is identified and the following paragraphs discuss the main findings.

Fintech diffusion and financial inclusion are two significant determinants of income per capita consistent with our previous findings. Columns (1)–(3) show that the diffusion of innovation enhances financial inclusion and, ultimately GDP per capita through financial inclusion. The second system of equations (columns (4)–(6)) shows the feedback effects from financial inclusion to fintech diffusion (including network externalities) and economic prosperity.

Overall, these new findings do not invalidate our previous results. This indicates limited endogeneity bias in our previous findings.

4.5.1. Panel estimation for up to 137 countries from 1991–2015

In the previous sections, we use cross-section analysis. Therefore, it was not possible to account for country-specific effects nor time dynamics. The main reason why we use cross-section analysis is that the measure of financial inclusion is available only in 2011, 2014 and 2017. To overcome this limitation, we use the financial development database by Svirydzenka (2016). This dataset runs from 1980 to 2015 and covers 137 countries.[9] We restrict our analysis to the period 1991–2015 because data on the shadow economy are not available for later years. We use four indicators to proxy financial inclusion from the financial development database: the financial development index (FD), financial institutions depth (FID), financial institutions access (FIA) and financial institutions efficiency (FIE). Table C1 reports descriptive statistics and Table C2 provides the matrix of Pearson's correlation coefficients. Stationarity tests were carried out and Table C3 reports panel unit root tests. We find that the dependent variables (except for FD and FIE) are integrated of order one, as are some explanatory variables. This opens up the possibility for cointegration analysis. We perform the Kao (1999), Pedroni (1999, 2004), and Westerlund (2005) tests of cointegration on our panel dataset and the presence of cointegration is not rejected.[10] We therefore estimate a dynamic panel model using a dynamic fixed effects technique. The general form of the error-correction equation estimated is,[11]

$$\Delta g_{it} = \alpha_i + \phi\left(g_{i,t-1} - \sum_{k=1}^{K}\theta_k X_{k,i,t-1}\right) + \sum_{k=1}^{K}\gamma_k \Delta X_{k,i,t} + \varepsilon_{it} \tag{6}$$

where Δ denotes the first difference operator, g_{it} is the dependent variable (diffusion of innovation or financial inclusion or GDP per capita), $X_{1it}, \ldots, X_{Kit}$ is a set of control variables, ϕ is the error-correcting speed of adjustment term, α_i are country-fixed effects and ε_{it} is an error term. If $\phi = 0$, there is no evidence of a long-run relationship. If this parameter, which should lie between 0 and -1 for stability, is significant, then the results provide confirmation of a stable long-run relationship.

In what follows, we report the error correction term (ϕ) and the long-run parameters ($\theta_1, \ldots, \theta_K$) for our different models that are estimated using dynamic fixed effects.

4.6. Fintech diffusion

Equation (3) is estimated using the extent of ATM and mobile phone diffusion as dependent variables. The results of the estimates are reported in Tables 8 and 9. The error correction terms are negative and significant at the 1% level in almost all the estimates, except three (columns 5, 6 and 7 of Table 9). This provides evidence of long-run relationships between fintech diffusion, financial inclusion and GDP per capita and the control variables used in the regressions.

More specifically, we find that GDP per capita, urbanisation, trade and financial inclusion – measured by financial development index – are robust determinants of the diffusion of mobile phone technology (Table 8). Financial institutional efficiency and, to a lesser extent, financial institutional depth are two critical aspects of financial inclusion that affect the adoption of mobile phone technology. Other important determinants are human capital (measured by human capital index), political and composite stability and FDI inflow in the ICT sector.

Analysis of ATM diffusion shows that financial institution depth is a determinant of ATMs diffusion (at the 10% level). GDP per capita and measures of stability are also determinants of the diffusion of ATMs (Table 9). The results are consistent with our previous findings based on cross-sectional analysis. In addition, they provide evidence of the long-run effects of fintech diffusion and financial inclusion on GDP per capita.

To test for possibility of different slopes for developed and developing countries, countries are classified into low (low to lower-middle) and high (upper-middle and high) income groups. We run the regressions for these two groups and compare the error correction terms by using the following statistics (see Equation (4) in Paternoster et al. (1998)):

$$Z = \frac{ec_1 - ec_2}{\sqrt{(se(ec_1))^2 + (se(ec_2))^2}}$$

We find[12] that the error correction terms are significantly different at the 5% level between the two groups for the diffusion of mobile phone but not after controlling for composite stability and changing the measure of financial inclusion. Regarding the diffusion of ATMs, generally, we find no significant difference between the speed of adjustment to long-run equilibrium between the two groups.

Table 8. Determinants of mobile phone diffusion (long-run relationships).

	(1)	(2)	(3)	(4)	(5)	(6)	(8)
Financial Development index	2.693***	3.014***	2.250***	0.815*			
	(0.389)	(0.505)	(0.412)	(0.432)			
Financial depth index					1.080*		
					(0.655)		
Financial access index						0.213	
						(0.450)	
Financial efficiency index							1.091***
							(0.358)
GDP/N	0.651***	0.420***	0.534***	0.452***	0.796***	0.827***	0.765***
	(0.056)	(0.088)	(0.092)	(0.075)	(0.065)	(0.093)	(0.076)
Trade	0.350***	0.390**	0.299*	−0.063	0.456***	0.554***	0.499***
	(0.135)	(0.166)	(0.165)	(0.158)	(0.175)	(0.192)	(0.181)
Urbanisation	4.245***	5.866***	3.706**	2.437*	5.339***	5.828***	6.246***
	(1.066)	(1.498)	(1.471)	(1.384)	(1.314)	(1.300)	(1.322)
Composite stability		2.532***					
		(0.932)					
Human capital index			0.935***				
			(0.343)				
FDI inflow in ICT/Investment				2.315**			
				(0.952)			
Error correction term	−0.082***	−0.071***	−0.079***	−0.206***	−0.068***	−0.063***	−0.064***
	(0.010)	(0.011)	(0.012)	(0.022)	(0.008)	(0.008)	(0.008)
Observations	3,144	2,779	2,832	1,121	3,144	3,144	3,144

Note: This table reports the dynamic fixed effects estimation results of Equation (4). The dependent variable is mobile phone subscription per inhabitant. Robust standard errors in parentheses.
$^{***}p < 0.01$.
$^{**}p < 0.05$.
$^{*}p < 0.1$.

Table 9. Determinants of mobile ATM diffusion (long-run relationships).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP/N	0.356**	0.363**	0.313**	0.321**	0.278*	0.250*	0.305*
	(0.146)	(0.164)	(0.132)	(0.148)	(0.152)	(0.140)	(0.183)
urbanisation	−1.823	−1.547	−2.223	−1.964	−3.967	−3.112	−2.414
	(1.562)	(1.603)	(1.660)	(1.689)	(4.536)	(3.595)	(3.629)
Number of bank branches	0.236	0.289	0.251	0.311	0.117	0.094	0.121
	(0.233)	(0.265)	(0.247)	(0.280)	(0.123)	(0.110)	(0.126)
Financial depth index	0.917*		0.979*		1.417		
	(0.476)		(0.508)		(1.352)		
Financial efficiency index		0.297		0.283		1.223	1.254
		(0.426)		(0.434)		(1.174)	(1.353)
Political stability	1.672**	1.751*					
	(0.848)	(0.949)					
Composite stability			1.180*	1.105			
			(0.700)	(0.759)			
Lower secondary school					−0.098	−0.015	
					(0.652)	(0.548)	
Upper secondary school							−0.649
							(0.576)
Error correction term	−0.106***	−0.097***	−0.105***	−0.097***	−0.165*	−0.168*	−0.147*
	(0.037)	(0.035)	(0.037)	(0.035)	(0.095)	(0.090)	(0.089)
Observations	1,304	1,304	1,304	1,304	424	424	451

Note: This table reports the dynamic fixed effects estimation results of Equation (4). The dependent variable is number of ATM per inhabitant. Robust standard errors in parentheses.
$^{***}p < 0.01$.
$^{**}p < 0.05$.
$^{*}p < 0.1$.

We further explore the possibility that fintech diffusion is a function of positive externalities by testing a non-linear relationship between financial inclusion and technology diffusion. Firstly, we regress the diffusion of mobile phones and ATMs on the natural log of the financial development index and find a positive relationship. Secondly, we use the square of financial inclusion and find a U-shaped relationship only for the diffusion of mobile phone and financial inclusion. This second result indicates that financial inclusion drives the diffusion of mobile phones up to a certain threshold above which its contribution declines slightly.

Finally, we consider the possibility that the degree of industrialisation and the level of competition in the banking sector might affect fintech diffusion. Therefore, in addition to the urbanisation variable, we control for the share of the industrial sector in GDP (as a proxy of the level of industrial development) and the concentration of the banking sector measured by the share of the three largest banks (a proxy of competition). We find that these variables are not significantly related to the diffusion of ATMs.

4.7. Financial inclusion

To analyse the determinants of financial inclusion, we estimate Equation (4) using financial institutional depth and access to financial institutions as dependent variables. The results are reported in Table 10. Mobile phone diffusion, the size of the shadow economy and government spending are critical determinants of financial institutional depth. Human capital – measured by a human capital index – and composite stability are also important for the deepening of the financial institutions, and thus inclusion. It is worth noting that the depth of financial institutions is higher in countries where the level of the informal economy is low (a lower value of the *shadow economy rate*). These findings are consistent with our cross section results, but again they provide additional evidence of the long run relationships between financial inclusion, GDP per capital and fintech diffusion.

The analysis of the access dimension of financial inclusion shows that GDP per capita and the size of the informal sector are two main determinants of financial inclusion. Again, a high level of informal economy is associated with a low level of access to financial institutions – measured by the number of bank branches and ATMs. Conversely, higher GDP per capita stimulates access to financial institutions.

Although we find that the diffusion of mobile phones is related to financial inclusion, one important question is the effectiveness of ICT diffusion, that is the number of years of ICT adoption a country needs before there are sustained effects on financial inclusion. To answer this question, we plot the diffusion curve of mobile phones, that is the average mobile phone penetration rate per year (see Figure C1). We also plot the relationship between financial inclusion and the mobile phone penetration rate to obtain the average mobile phone penetration rate at the consolidation point (Figure C2). Based on this information, we estimate the effectiveness of the diffusion

Table 10. Determinants of financial institutional depth and access.

	Financial institutions depth				Financial institutions access			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile phone		0.062***	0.069***	0.036**		0.059	0.076	−0.170
		(0.011)	(0.013)	(0.016)		(0.052)	(0.062)	(0.192)
GDP/N	0.045***				0.151***			
	(0.010)				(0.045)			
Shadow rate	−0.299**	−0.212**	0.054	−0.145	−0.762	−1.932***	−1.290	−5.217*
	(0.117)	(0.087)	(0.128)	(0.090)	(0.554)	(0.695)	(0.872)	(3.152)
Government Spending	0.006***	0.004**	0.006***	0.002*	0.007	0.008	0.008	0.055
	(0.002)	(0.002)	(0.002)	(0.001)	(0.006)	(0.007)	(0.006)	(0.041)
Composite stability		0.313**					1.821**	
		(0.122)					(0.818)	
Lower secondary school								−0.077
								(0.441)
Human capital index				0.122***				−0.077
				(0.040)				(0.441)
Error correction term	−0.151***	−0.162***	−0.162***	−0.180***	−0.064***	−0.051***	−0.044***	−0.098**
	(0.018)	(0.019)	(0.020)	(0.021)	(0.012)	(0.014)	(0.013)	(0.039)
Observations	3,067	2,779	3,067	2,832	3,067	2,779	3,067	2,832

Table 11. Effectiveness of mobile phone penetration rate.

	Inflexion point (mobile phone penetration rate, %)	Number of years	Reference average penetration rate and year
High income	44	10	0.9% in 1990
Upper-middle income	83	12	1% in 1996
Lower-middle income	43	8	1% in 1999
Low income	30	7	0.9% in 2001

Table 12. Determinants of GDP/N (long-run relationships).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Human capital index	1.292***	0.275	1.886***	1.233***	0.685**	2.073***	1.186***	0.695**
	(0.297)	(0.171)	(0.310)	(0.289)	(0.282)	(0.323)	(0.272)	(0.284)
Capital	0.148	0.342**	0.343**	0.186	0.210	0.350**	0.187	0.195
	(0.149)	(0.167)	(0.147)	(0.141)	(0.153)	(0.164)	(0.143)	(0.162)
Population growth	−0.036	−0.013	−0.034	−0.032	−0.044	−0.032	−0.026	−0.046
	(0.035)	(0.012)	(0.034)	(0.031)	(0.031)	(0.041)	(0.033)	(0.032)
Mobile phone	0.505***	0.326***		0.413***	0.575***		0.448***	0.632***
	(0.081)	(0.074)		(0.089)	(0.082)		(0.080)	(0.082)
ATM		0.164*						
		(0.096)						
Financial access index			1.258***	0.655**	0.556**			
			(0.296)	(0.309)	(0.282)			
Financial efficiency Index						1.206**	0.954**	0.345
						(0.503)	(0.405)	(0.390)
Composite stability					4.354***			4.394***
					(0.863)			(0.811)
Error correction term	−0.169***	−0.446***	−0.157***	−0.175***	−0.178***	−0.145***	−0.175***	−0.172***
	(0.022)	(0.031)	(0.020)	(0.023)	(0.020)	(0.015)	(0.020)	(0.018)
Observations	2,832	1,304	2,832	2,832	2,779	2,832	2,832	2,779

Note: This table reports the dynamic fixed effects estimation results of Equation (4). The dependent variable is the GDP per capita. Robust standard errors in parentheses.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

of mobile phones to be 7 years for low income countries, 8 years for lower-middle income countries, 10 years for high income countries and 12 years for upper-middle income countries using references dates (Table 11). This is consistent with the well-known finding that lower income countries can benefit more quickly from technology diffusion and catch-up.

4.8. *GDP per capita*

Finally, we estimate Equation (5) using per capita income. Table 12 reports the estimates. Fintech diffusion (mobile phones and ATMs) is positively associated with per capita income, indicating the long-run impact of diffusion on income per capita. Regarding financial inclusion, the results show that *financial institutions access* and *efficiency* play an important role, while there is no effect (at conventional significant levels) of the *depth* dimension on GDP per capita. Composite stability and human capital, however, do also determine income per capita in the long run.

5. Conclusion

The widespread diffusion of ATMs and the associated development of global inter-bank digital networks and markets (Batiz-Lazo 2018) has transformed financial services over the past 25 years or so. Similarly, mobile phone technology linked with mobile payments systems and digital financial networks is transforming the way banking services are provided across the globe. Despite this transformation, relatively little research has been conducted on the impact of the widespread diffusion of fintech.

Theoretically, the diffusion of new technology in the financial services sector has the potential to enhance financial inclusion and raise living standards in the wider economy. This paper has focused on two possible transmission mechanisms (the fintech diffusion channel and the financial inclusion channel) the interactions between them, and their impact on income per capita. The existence of positive network externalities means that financial inclusion increases the utility of networked financial services, such as, ATMs and mobile money and payments.

Our empirical analysis is based on cross section estimations for up to 137 countries (using the average value of each variable for 2013–2017) and panel data analysis using an error correction model for the period 1991–2015. The cross section estimations show that the extent of fintech diffusion increases with financial inclusion, human capital and GDP per capita. This last result suggests that financial sector development is partly driven by activity in the real economy. We also find that the extent of fintech diffusion (ATMs and mobile phones and payments systems) increases financial inclusion. In addition, our cross section results show that GDP per capita is increased by investment in fixed and human capital, the diffusion of ATMs and mobile phones, as well as socio-economic variables, such as absence of corruption and composite stability (political, economic and financial risk). In light of evidence of endogeneity, we estimate our 3 equations as a system using three stage least squares. The main results are preserved in nature, with limited endogeneity bias.

Due to the fact that the technology diffusion is a long-run process, and because many of the variables in our panel data set are non-stationary, the panel estimations are conducted using an error correction model with country fixed effects. These results provide evidence of long-run relationships between fintech, financial inclusion and income per capita.

The main findings in this paper open up new avenues for policy and future research. Most governments target living standards as a policy variable. More recently, financial inclusion has also been adopted as a target by policy makers. Our results suggest that fintech diffusion has positive effects on both GDP per capita and financial inclusion, and that financial inclusion also drives fintech diffusion and raises GDP per capita. The positive impact of fintech diffusion and its relationship with financial inclusion suggests that governments should look at a wider set of policy variables to increase the performance of the financial sector. In addition to standard policies to reduce corruption, promote political stability, contain economic and financial risks and control shadow banking activities, government policies should also be designed to enhance the extent of fintech diffusion. Potential policy instruments include: standard setting (particularly in ICT, digital networks and security protocols that can enhance network externalities and interoperability), infrastructure development (including fibre optic cable, telecommunications networks that give greater access to financial services and the development of mobile payments systems) and education and training in fintech adoption and use, as a means of leveraging financial inclusion and higher GDP per capita.

The present study has focused on two – albeit pervasive – fintech technologies. Both utilise ICT, digital networks, security protocols and inter-bank operability. There is clearly scope for future research to look at the diffusion of other financial technologies to ascertain their effects on key policy targets such as financial inclusion and GDP per capita.

Notes

1. See Batiz-Lazo (2009, 2018), Konheim (2016), Hall and Kahn (2003), and Scott, Van Reenen, and Zachariadis (2017) for analysis of the introduction and diffusion of ATMs and digital networks; Frame and White 2012 for an overview of financial innovations and their diffusion; and Lashitew, van Tulder, and Liasses (2019) on the diffusion of mobile phones, money and payments technology.
2. The Financial Stability Board (2019, 1) defines fintech as, 'technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services.' Leong and Sung (2018, 75) use a similar definition and identify three stages of fintech development – Fintech Mark 1.0 involved the development of enabling technologies that 'breed related products of financial technology' reflecting the 'platform technology' nature of ATMs, digital networks and security protocols.

3. Madsen and Ang's study provides valuable analysis of the impact of research and development (R&D) on ideas production or invention for 20 OECD countries. However, the measures they use for the knowledge stock and R&D do not fully capture for R&D in financial services as until recently the collection of data via Business R&D surveys did not cover the financial intermediation sector and the proportion of financial innovations that is patented is low (Dal Borgo et al. 2013).
4. The distinction between invention (or 'ideas' production) and diffusion is captured by the 'paradox of patents' (Robinson 1956), i.e. that patents are designed to spur invention by slowing down the rate of diffusion (Rosenberg 1972; MacLeod 1991). Invention and innovation are also distinct; inventions only become innovations when diffusion begins, i.e. an invention becomes an innovation when it starts to be utilised in the economy by firms, consumers or government (OECD, *Oslo Manual*, 2005).
5. Another indicator used in the literature is the percentage of respondents who report personally using a mobile money service in the 12 months preceding the survey (see, Allen et al. 2016). We did not use this indicator due to the limited coverage of this indicator in our dataset.
6. It may be argued that survey respondents are educated people who, on average, have higher income. Thus, using the percentage of respondents who report having an account at a bank or another type of financial institution as indicator of financial inclusion might be biased. However, the Global Findex database is drawn from nationally representative samples using random selection techniques. The target population is the entire civilian, non-institutionalised population age 15 and above without targeting the level of education. Respondents are randomly selected within eligible households by following the Kish grid (eligible households are selected using random technique as well).At present, this is the best source to assess the proportion of the population with a bank account because it is based on the demand side and not collected from suppliers. In developing countries, financial inclusion measured on the supply side is biased due to duplication of the number of bank accounts (the same person has multiple bank accounts in different financial institutions).
7. For a system to be identified, the number of exogenous variables in all the equations, including the instruments (any additional variables), minus the number of exogenous variables in each equation of the system must be greater than or equal to the number of endogenous variables. In other words, there must be at least as many noncollinear exogenous variables in the remaining system as there are endogenous right-hand-side variables in an equation. When the number of exogenous variables is greater than the number of endogenous variables, the system is overidentified and we use the *Hansen's J* statistic to determine the validity of the overidentifying restrictions. Tests of overidentifying restrictions test whether: (i) the instruments are uncorrelated with the error term; and (ii) the equation is mis-specified and one or more of the excluded exogenous variables should in fact be included in the structural equation. The *p-value* associated with the *Hansen's J* statistic should be greater than 0.10 in all cases. In addition, the F-statistics calculated after the first stage of the estimation – and usually used to check whether the estimated models are globally significant – is used to test the existence of weak instruments. These F-statistics are expected to be greater than 10 (see Staiger and Stock 1997).
8. This is preferred to the Sargan test which is not robust to heteroskedasticity.
9. The maximum number of observations is 3,425, i.e. 137 countries over 25 years from 1991 to 2015, but there are missing observations for some countries and years.
10. The results are available upon request from the authors.
11. This equation does not account for country heterogeneity in parameters. Country effects are captured only through the fixed effects. This assumption can be strong, however, the results of the estimates do not invalidate our previous findings based on cross-sectional analysis.
12. The results are available upon request from the authors.

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Appendix 1: Long definitions of some variables taken from PRS Group (2019) List of variables, downloadable from: https://epub.prsgroup.com/list-of-all-variable-definitions

Political risk rating

'A means of assessing the political stability of a country on a comparable basis with other countries by assessing risk points for each of the component factors of government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tensions, law and order, ethnic tensions, democratic accountability, and bureaucracy quality. Risk ratings range from a high of 100 (least risk) to a low of 0 (highest risk), though lowest de facto ratings generally range in the 30s and 40s.'

Corruption

'A measure of corruption within the political system that is a threat to foreign investment by distorting the economic and financial environment, reducing the efficiency of government and business by enabling people to assume positions of power through patronage rather than ability, and introducing inherent instability into the political process. (Refer to ICRG Methodology for maximum points for this variable, as well as for related formulas for calculating risk.)'

Appendix 2: list of countries

This table is sorted by region, income level and country name. EAP stands for Europe & Central Asia, LAC stands for Latin America & Caribbean, MENA is Middle East & North Africa, NA stands for North America, SA is South Asia, SSA is Sub-Saharan Africa.

Table B1. List of the countries used in this paper.

Region	Income	Country	Region	Income	Country
EAP	High income	Australia	LAC	Lower middle income	Honduras
EAP	High income	Japan	LAC	Upper middle income	Belize
EAP	High income	Korea, Rep.	LAC	Upper middle income	Brazil
EAP	High income	New Zealand	LAC	Upper middle income	Colombia
EAP	High income	Palau	LAC	Upper middle income	Costa Rica
EAP	High income	Singapore	LAC	Upper middle income	Cuba
EAP	Lower middle income	Cambodia	LAC	Upper middle income	Dominican Republic
EAP	Lower middle income	Indonesia	LAC	Upper middle income	Ecuador
EAP	Lower middle income	Mongolia	LAC	Upper middle income	Guatemala
EAP	Lower middle income	Philippines	LAC	Upper middle income	Guyana
EAP	Lower middle income	Vietnam	LAC	Upper middle income	Jamaica
EAP	Upper middle income	China	LAC	Upper middle income	Mexico
EAP	Upper middle income	Fiji	LAC	Upper middle income	Paraguay
EAP	Upper middle income	Malaysia	LAC	Upper middle income	Peru
EAP	Upper middle income	Thailand	LAC	Upper middle income	Suriname

(*continued*)

Table B1. Continued.

Region	Income	Country	Region	Income	Country
EAP	Upper middle income	Tuvalu	LAC	Upper middle income	Venezuela, RB
ECA	High income	Andorra	MENA	High income	Israel
ECA	High income	Austria	MENA	High income	Kuwait
ECA	High income	Belgium	MENA	High income	Malta
ECA	High income	Croatia	MENA	High income	Oman
ECA	High income	Cyprus	MENA	High income	Qatar
ECA	High income	Czech Republic	MENA	High income	Saudi Arabia
ECA	High income	Denmark	MENA	High income	United Arab Emirates
ECA	High income	Estonia	MENA	Low income	Syrian Arab Republic
ECA	High income	Finland	MENA	Lower middle income	Tunisia
ECA	High income	France	MENA	Upper middle income	Algeria
ECA	High income	Germany	MENA	Upper middle income	Iran, Islamic Rep.
ECA	High income	Greece	MENA	Upper middle income	Iraq
ECA	High income	Hungary	MENA	Upper middle income	Jordan
ECA	High income	Iceland	MENA	Upper middle income	Lebanon
ECA	High income	Ireland	NA	High income	Canada
ECA	High income	Italy	NA	High income	United States
ECA	High income	Latvia	SA	Low income	Nepal
ECA	High income	Liechtenstein	SA	Lower middle income	Bangladesh
ECA	High income	Lithuania	SA	Lower middle income	Bhutan
ECA	High income	Luxembourg	SA	Lower middle income	India
ECA	High income	Netherlands	SA	Lower middle income	Pakistan
ECA	High income	Norway	SA	Lower middle income	Sri Lanka
ECA	High income	Poland	SA	Upper middle income	Maldives
ECA	High income	Portugal	SSA	Low income	Benin
ECA	High income	Slovak Republic	SSA	Low income	Burkina Faso
ECA	High income	Slovenia	SSA	Low income	Burundi
ECA	High income	Spain	SSA	Low income	Chad
ECA	High income	Sweden	SSA	Low income	Congo, Dem. Rep.
ECA	High income	Switzerland	SSA	Low income	Ethiopia
ECA	High income	United Kingdom	SSA	Low income	Guinea
ECA	Low income	Tajikistan	SSA	Low income	Malawi
ECA	Lower middle income	Georgia	SSA	Low income	Mali
ECA	Lower middle income	Kyrgyz Republic	SSA	Low income	Mozambique
ECA	Lower middle income	Moldova	SSA	Low income	Niger
ECA	Lower middle income	Ukraine	SSA	Low income	Rwanda
ECA	Upper middle income	Albania	SSA	Low income	Senegal
ECA	Upper middle income	Armenia	SSA	Low income	Tanzania
ECA	Upper middle income	Azerbaijan	SSA	Low income	Togo
ECA	Upper middle income	Belarus	SSA	Low income	Uganda
ECA	Upper middle income	Bosnia and Herzegovina	SSA	Low income	Zimbabwe
ECA	Upper middle income	Bulgaria	SSA	Lower middle income	Angola
Region	Income	Country	Region	Income	Country
ECA	Upper middle income	Kazakhstan	SSA	Lower middle income	Cabo Verde
ECA	Upper middle income	Montenegro	SSA	Lower middle income	Cameroon
ECA	Upper middle income	Romania	SSA	Lower middle income	Cote d'Ivoire
ECA	Upper middle income	Russian Federation	SSA	Lower middle income	Ghana
ECA	Upper middle income	Turkey	SSA	Lower middle income	Kenya
LAC	High income	Argentina	SSA	Lower middle income	Lesotho
LAC	High income	Bahamas, The	SSA	Lower middle income	Nigeria
LAC	High income	Chile	SSA	Lower middle income	Zambia
LAC	High income	Trinidad and Tobago	SSA	Upper middle income	Mauritius
LAC	High income	Uruguay	SSA	Upper middle income	Namibia
LAC	Lower middle income	Bolivia	SSA	Upper middle income	South Africa
LAC	Lower middle income	El Salvador			

Appendix 3: additional econometric evidence (panel data results)

The maximum number of observations is 3,425 – i.e. 137 countries over 25 years from 1991–2015 – there are missing observations for some countries and years.

Table C1. Summary statistics (panel data).

Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP/N	3,350	8.20	1.67	4.63	12.10
Financial Development index	3,225	0.33	0.23	0.00	1.00
Financial depth index	3,225	0.27	0.27	0.00	1.00
Financial access index	3,225	0.32	0.28	0.00	1.00
Financial efficiency index	3,225	0.63	0.18	0.00	0.96
Trade	3,167	0.83	0.50	0.00	4.42
Government spending	3,094	15.92	5.81	0.91	76.22
Human capital index	2,832	2.45	0.69	1.03	3.73
Primary school	629	0.81	0.20	0.05	1.00
Lower secondary school	715	0.65	0.26	0.02	1.00
Upper secondary school	721	0.53	0.25	0.00	0.96
Population growth	3,419	1.42	1.57	−6.18	16.33
Urbanisation	3,425	0.57	0.23	0.05	1.00
Density	3,404	4.15	1.37	0.36	8.96
ATM	1,437	0.38	0.38	0.00	1.88
Mobile phone	3,388	0.46	0.49	0.00	2.08
Number of bank branches	1,526	0.19	0.20	0.00	2.58
Capital	3,144	12.55	2.01	7.33	18.03
Shadow rate	3,250	0.31	0.13	0.06	0.72
Absence of corruption	2,793	2.98	1.31	0.00	6.00
Political stability	2,793	0.67	0.13	0.18	0.97
Composite stability	2,793	0.70	0.11	0.23	0.94
FDI inflow in ICT/Investment	1,295	0.02	0.03	0.00	0.34
FDI inflow in ICT/FDI	1,338	0.13	0.17	0.00	1.00
Employment agriculture	3,325	28.93	25.72	0.13	92.84
Exports Agriculture	2,803	1.06	1.90	0.00	19.52

Table C2. Pearson correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mobile phone	1								
(1)									
ATM	0.477***	1							
(2)	(0.000)								
Urbanisation	0.362***	0.549***	1						
(3)	(0.000)	(0.000)							
Trade	0.266***	0.063**	0.199***	1					
(4)	(0.000)	(0.018)	(0.000)						
GDP/N	0.581***	0.718***	0.778***	0.255***	1				
(5)	(0.000)	(0.000)	(0.000)	(0.000)					
Political stability	0.317***	0.595***	0.556***	0.315***	0.750***	1			
(6)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Composite stability	0.364***	0.494***	0.580***	0.305***	0.790***	0.903***	1		
(7)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Primary	0.478***	0.509***	0.501***	0.192***	0.670***	0.572***	0.431***	1	
(8)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Lower secondary	0.476***	0.438***	0.423***	0.260***	0.616***	0.542***	0.464***	0.871***	1
(9)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Upper secondary	0.470***	0.406***	0.371***	0.214***	0.586***	0.521***	0.442***	0.809***	0.943***
(10)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Human	0.476***	0.635***	0.655***	0.263***	0.757***	0.689***	0.661***	0.877***	0.910***
(11)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FDI ICT/Investment	−0.136***	−0.197***	−0.183***	0.206***	−0.229***	−0.061**	−0.089***	−0.289***	−0.203***
(12)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.032)	(0.002)	(0.000)	(0.000)
FDI ICT/FDI	−0.002	0.030	−0.016	0.077***	0.044	0.049*	0.033	0.050	0.039
(13)	(0.944)	(0.304)	(0.563)	(0.005)	(0.106)	(0.084)	(0.242)	(0.262)	(0.363)
Employment (agriculture)	−0.441***	−0.585***	−0.833***	−0.272***	−0.863***	−0.644***	−0.675***	−0.666***	−0.577***
(14)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Export Agriculture	−0.137***	−0.129***	−0.197***	0.039**	−0.265***	−0.089***	−0.145***	0.004	−0.048
(15)	(0.000)	(0.000)	(0.000)	(0.040)	(0.000)	(0.000)	(0.000)	(0.925)	(0.211)
Financial Development	0.476***	0.794***	0.625***	0.201***	0.829***	0.735***	0.732***	0.533***	0.512***
(16)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Financial depth	0.382***	0.684***	0.537***	0.241***	0.743***	0.720***	0.692***	0.453***	0.465***
(17)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Financial Access	0.488***	0.850***	0.645***	0.157***	0.828***	0.670***	0.627***	0.600***	0.498***
(18)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Financial efficiency	0.365***	0.405***	0.324***	0.243***	0.533***	0.471***	0.534***	0.305***	0.346***
(19)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table C2. Continued.

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Upper sec	1									
(10)										
Human	0.901***	1								
(11)	(0.000)									
FDI ICT/Investment	−0.191***	−0.155***	1							
(12)	(0.000)	(0.000)								
FDI ICT/FDI	0.079*	0.019	0.507***	1						
(13)	(0.055)	(0.529)	(0.000)							
Employment (agriculture)	−0.554***	−0.729***	0.204***	−0.002	1					
(14)	(0.000)	(0.000)	(0.000)	(0.932)						
Export Agriculture	0.032	−0.196***	0.079***	0.063**	0.196***	1				
(15)	(0.395)	(0.000)	(0.005)	(0.025)	(0.000)					
Financial Development	0.454***	0.662***	−0.169***	0.055**	−0.668***	−0.194***	1			
(16)	(0.000)	(0.000)	(0.000)	(0.047)	(0.000)	(0.000)				
Financial depth	0.432***	0.609***	−0.091***	0.136***	−0.605***	−0.139***	0.891***	1		
(17)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)			
Financial Access	0.448***	0.683***	−0.197***	0.031	−0.687***	−0.208***	0.832***	0.720***	1	
(18)	(0.000)	(0.000)	(0.000)	(0.259)	(0.000)	(0.000)	(0.000)	(0.000)		
Financial efficiency	0.316***	0.278***	−0.122***	0.018	−0.423***	−0.073***	0.615***	0.512***	0.486***	1
(19)	(0.000)	(0.000)	(0.000)	(0.524)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: This table presents the results of unit root tests. The null of all test is 'all panels contain unit roots'. Fisher-Type statistics are the Inverse normal distribution of the Dickey Fuller test. The lag length is selected based on Akaike Information Criteria for Im-Pesaran-Shin (2003) test. Other statistics are based on two lags except for ATM for which the statistics are based on the first lag. *P*-values are in parentheses. The decision is heavily based on Maddala and Wu (1999) or Pesaran (2007) when these statistics are available. Blank cells indicate that we are not able to compute statistics due to insufficient number of observations for some countries of the panel.

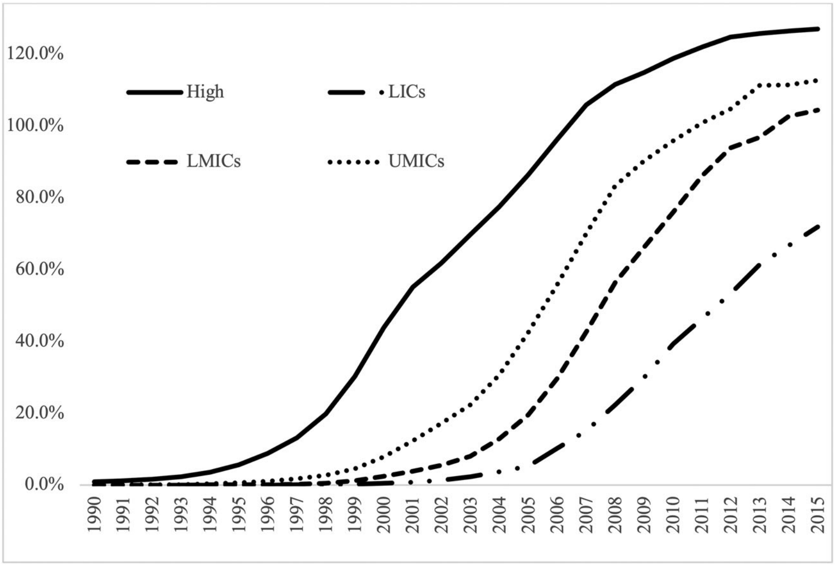

Figure C1. (Average) mobile phone diffusion curve.

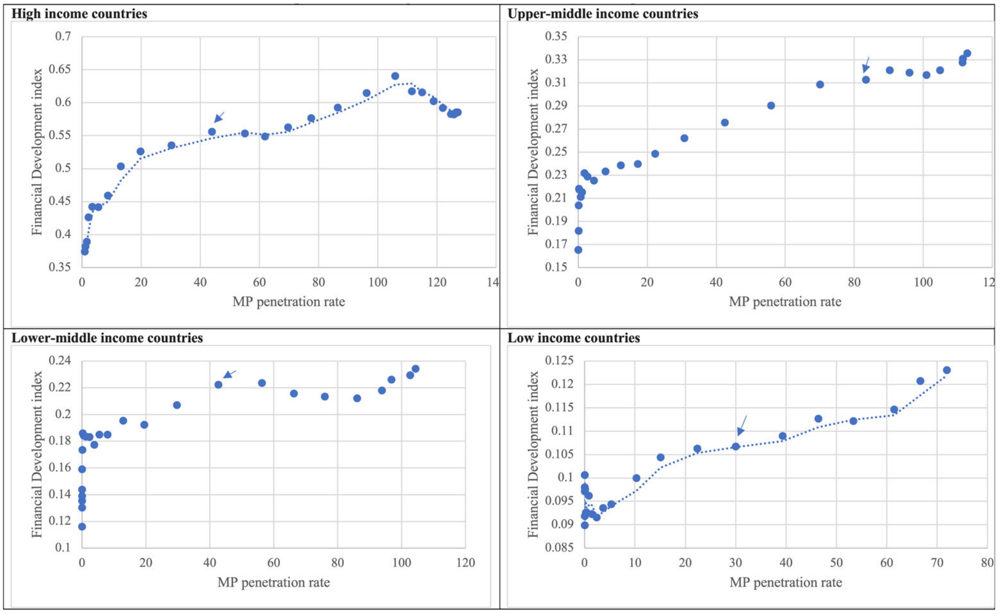

Figure C2. Relationship between financial inclusion and mobile phone diffusion.

Table C3. Unit root tests.

	Im, Pesaran, and Shin (2003)		Fisher-type (Choi 2001)		Maddala and Wu (1999)		Pesaran (2007)		Decision
	without trend	with trend	without trend	with trend	without trend	with trend	without trend	with trend	
Mobile phone	17.79(1.00)	7.22(1.00)	0.52(0.70)	8.45(1.00)	129.24(1.00)	154.48(1.00)	1.91(0.97)	6.59(1.00)	I(1)
ATM			2.39(0.99)	4.70(1.00)					I(1)
GDP/N	7.95(1.00)	1.31(0.91)	0.00(0.50)	0.49(0.69)	121.05(1.00)	212.69(0.98)	−7.79(0.00)	−3.24(0.00)	I(1)
Density	13.20(1.00)	−36.32(0.00)	9.38(1.00)	2.39(0.99)	1,157.57(0.00)	724.12(0.00)	7.38(1.00)	7.65(1.00)	I(1)
Shadow	6.98(1.00)	−5.86(0.00)	1.63(0.95)	−1.28(0.10)	176.64(1.00)	305.34(0.02)	−2.93(0.00)	5.21(1.00)	I(1)
FD	−2.61(0.00)	−5.46(0.00)	−7.81(0.00)	3.64(1.00)	333.76(0.00)	327.17(0.00)	0.67(0.75)	1.74(0.96)	I(0)
FID	4.47(1.00)	−2.19(0.01)	−0.89(0.19)	3.21(1.00)	227.71(0.91)	252.34(0.59)	−1.29(0.10)	2.81(1.00)	I(1)
FIA	15.31(1.00)	8.09(1.00)	4.57(1.00)	3.25(1.00)	240.22(0.78)	267.02(0.34)	2.58(1.00)	4.78(1.00)	I(1)
FIE	−14.11(0.00)	−18.24(0.00)	−7.12(0.00)	−7.44(0.00)	635.04(0.00)	630.97(0.00)	−8.77(0.00)	−2.09(0.02)	I(0)
Trade	−4.49(0.00)		1.14(0.87)	0.53(0.70)					
Urbanisation			4.74(1.00)	1.27(0.90)	404.20(0.00)	313.53(0.01)	6.50(1.00)	17.65(1.00)	I(1)
Human capital index	13.79(1.00)	5.93(1.00)	4.78(1.00)	2.96(1.00)	162.76(1.00)	202.68(0.67)	7.00(1.00)	18.12(1.00)	I(1)
Political stability	−14.15(0.00)	−8.66(0.00)	−12.08(0.00)	−7.19(0.00)	566.39(0.00)	459.88(0.00)	−7.46(0.00)	−3.01(0.00)	I(0)
Composite stability	−14.19(0.00)	−7.97(0.00)	−8.53(0.00)	−4.59(0.00)	540.94(0.00)	393.79(0.00)	−2.80(0.00)	−2.53(0.01)	I(0)
Absence of corruption	−10.05(0.00)	−6.71(0.00)	−6.73(0.00)	−2.46(0.01)					
Capital	14.93(1.00)	3.70(1.00)	6.32(1.00)	7.06(1.00)	136.48(1.00)	169.81(0.99)	6.59(1.00)	7.85(1.00)	I(1)
Population growth	−31.59(0.00)	−43.54(0.00)	−6.40(0.00)	−5.87(0.00)	397.93(0.00)	261.57(0.01)	−1.19(0.12)	1.04(0.85)	I(0)
Number of bank branches			1.91(0.97)	1.34(0.91)					I(1)
Government spending	−7.66(0.00)		−5.21(0.00)	−1.51(0.07)					I(0)
Employment in agriculture	3.38(1.00)	−2.14(0.02)	7.56(1.00)	−2.36(0.01)					I(1)