Empirical Economics
https://doi.org/10.1007/s00181-021-02178-1

Financial inclusion, financial technology, and economic development: a composite index approach

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Received: 21 October 2020 / Accepted: 22 November 2021

Abstract

Financial inclusion is recognized by policy makers as one of the main tools of promoting household income and economic development. Recently, increasing attention has been focused on proposing reliable indicators to quantify financial inclusion by country. In this research, we adopt a composite index approach for that purpose. The main distinguishing feature of our empirical exercise is its data-driven spirit; in particular, we make very few assumptions about the nature of the composite index. Moreover, we define financial inclusion from three main dimensions making use of both demand and supply side data and recognize that financial technology and digital finance are playing an increasing role in boosting financial inclusion. Next, we analyze financial inclusion changes over time by distinguishing between catching-up and environment change effects. The latter allows us to verify whether policy makers have succeeded in creating an environment that has fostered financial inclusion and quantify the scope for policy interventions. Finally, we take the heterogeneity between countries into consideration by partitioning countries into income per capita categories. Our empirical exercise reveals important patterns useful in understanding financial inclusion differences and designing future policy implementations.

Keywords Financial inclusion · Financial technology · Economic development · Composite index · Heterogeneity gaps

We thank participants of the XVI European Workhop on Efficiency and Productivity Analysis held in London for helpful comments. We also thank anonymous referees and editor Bertrand Candelon for insightful suggestions.

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Published online: 04 January 2022

JEL Classification C43 · G00 · G21 · O11 · O16 · O30

1 Introduction

Exclusive financial systems slow economic growth and contribute to income inequality by limiting saving and borrowing opportunities. In 2011, half of the world adult population had no access to formal financial services, while 69% had an account in 2017 (Demirgüç-Kunt et al. 2018). Financial inclusion (FI)[1] has brought roughly 1.2 billion people into the banking system since 2010 (Klapper 2018). By 2015, more than 60 national governments had recognized FI as one of the main tools for promoting economic development (Sahay et al. 2015); dozens have now adopted policies to expand FI (Demirgüç-Kunt et al. 2018). The World Bank promotes the 2020 goal of Universal Financial Access (UFA).[2] FI is also featured as a target in eight of the 17 goals of the United Nations (UN) 2030 Sustainable Development (UNCDF 2018).

Financial technology, including digital payments and mobile money accounts, has played an important role in boosting FI (Dos Santos and Kvangraven 2017; Klapper 2018) and is the key to achieving the UFA goal (World Bank 2018). Currently, 52% of adults, increased by 10 percentage points since 2014, have used digital payments (World Bank 2018). One billion unbanked adults have a mobile phone and 480 million have Internet access. These facts reveal the potential for further financial inclusion (Demirgüç-Kunt et al. 2018).

Access to basic financial services helps households promote income and human capital and leads to economic growth and overall social welfare gains (Dabla-Norris et al. 2015; Demirgüç-Kunt and Klapper 2012; Liu 2018; United Nations 2015). However, 94% of adults in high-income economies have a formal financial institution account, while this number is 63% in developing economies, including some lower-income economies with only 20% on this share in 2017 (Demirgüç-Kunt et al. 2018). In addition, as an example, among 53.21% households who used credit in China, only 19.77 per cent used formal credit (Chen and Jin 2017). Although improving, large gaps in the degree of FI remain across economies. These gaps may arise from various sources of heterogeneity across countries (for example, economic development, financial infrastructure, geographical location, etc.) (Walheer 2019).

Therefore, having an adequate and reliable measure of financial inclusion is crucial for policy makers, the finance industry, and individuals to understand a country's economic progress. Such a measure is not only required to better understand the current state of play, but to better design future financial industry strategies and policies. It is thus not only important to quantify how FI has changed over time between countries, but to investigate the scope for policy intervention. Finally, understanding and quantifying how heterogeneity between countries plays a role in FI differences over time

[1] Financial inclusion is defined as the availability and equality of opportunities to access financial services with the aim of providing affordable and sustainable financial services to unbanked and underbanked individuals (Nanda and Kaur 2016).

[2] 'By 2020, adults who currently are not part of the formal financial system are able to have access to a transaction account to store money, send and receive payments as the basic building block to manage their financial lives.' (World Bank 2017b).

represent additional valuable information for policy makers. These queries represent the main focus of this research.

A growing body of literature has shown that FI can increase savings and the percentage of entrepreneurs, and reduce poverty and income inequality (Allen et al. 2016; Beck et al. 2009; Liu 2018; Park and Mercado 2018), but less effort has been made to provide consistent measurements of FI. A stream of literature measures FI using econometric estimations. Beck et al. (2007) introduce measurements for banking sector outreach through access and usage dimensions. Honohan (2008) uses the percentage of households having access to formal financial services. Allen et al. (2016) define FI through the usage of formal deposit accounts.

In general, econometric estimations provide valuable information about FI, but face difficulties in dealing with FI changes over time (Sarma 2012). A popular alternative is to measure FI using a composite index approach, which measures FI by aggregating normalized indicators using exogenous or endogenous weights. There are several approaches for building a composite index (OECD 2008). Sarma (2008, 2012) uses a multidimensional approach similar to the UN Human Development Index. Chakravarty and Pal (2010) exogenously assign equal weights to variables. Mialou et al. (2017) employ factor analysis to determine which variables to include. The drawback of this methodology is that it cannot fully use available data. Camara and Tuesta (2018) and Park and Mercado (2018) rely on principal component analysis to overcome this drawback.

While these initial attempts clearly highlight the advantages of using a composite index to measure FI, we believe that more can be done. In particular, we adopt a data-driven approach to define the relative importance of the indicators in our FI composite index. Pasha (2017) finds that the equal weighting among dimensions cannot be statistically justified when measuring poverty across countries, while a data-driven approach can be a better alternative approach. We build our model on the benefit-of-the-doubt methodology (Cherchye et al. 2007a, b), which does not require making a choice for the normalization, but rather, is based on endogenous weights (revealing the relative importance of the indicators). This represents an important advantage since there are no guidelines for choosing normalization and weighting procedures in the FI context.

We use a wide range of indicators and include financial technology when constructing our composite index. This contracts with previous studies which rarely consider financial technology. The majority of previous work considers usage and access to formal financial services by using supply-side data (e.g., Beck et al. 2007; Chakravarty and Pal 2010; Honohan 2008; Mialou et al. 2017; Sarma 2008, 2012). Demirgüç-Kunt and Klapper (2013); Demirgüç-Kunt et al. (2015) use demand-side data to assess usage- and barrier-related indicators. Camara and Tuesta (2018) introduce an aggregate index using both demand- and supply-side data for 2011 and 2014. Park and Mercado (2018) also use data in 2017 and add 'mobile money' in the access dimension, but this indicator may overlap the 'account' indicator in the same dimension.[3]

[3] The definition of 'account' is 'the percentage of respondents who report having an account (by themselves or together with someone else) at a bank or another type of financial institution or report personally using a mobile money service in the past 12 months.' A 'mobile money account' is defined as 'the percentage of

We define FI through three main dimensions: access, availability, and usage, by making use of both demand- and supply-side data and include financial technology for each dimension. We avoid overlapping issues when defining three dimensions. For example, we separate the 'account' indicator into two different indicators: financial institution accounts and mobile money accounts.[4]

Next, we analyze how FI has changed over time among countries. We make a distinction between two important effects. First, the catching-up effect that indicates the change in FI over time is analyzed. This allows us to distinguish countries with progress in FI and those that have regressed, and to quantify this change. Second, we analyze the scope for policy interventions by defining an environment effect. This effect measures the shift in best possible performance; that is, it verifies whether policy makers have succeeded in creating an environment that fosters FI and thus allows us to quantify the scope for policy interventions.

Finally, we acknowledge that heterogeneity is present between countries when defining FI behavior. Previous studies have computed composite index averages or conducted regressions when partitioning countries into different income categories and found higher FI in high-income countries than in other countries (Beck et al. 2007; Cull et al. 2013). Financial technology has driven the progress in FI, but the impact varies across countries (Klapper 2018). We follow a different approach, by considering that heterogeneity should be taken into considering when defining the composite index rather than a-posteriori as in previous work. In particular, we innovate by removing the heterogeneity gap from the FI composite index, but also from the catching-up and environment effects as in Walheer (2019). In practice, we follow the World Bank and separate economies into four categories: high-, upper-middle-, lower-middle-, and low-income groups by using income per capita.[5]

The rest of this article unfolds as follows: In Sect. 2, we define our FI composite index, explain how it can be computed in practice, define catching-up and environment effects, and consider heterogeneity among countries. In Sect. 3, we summarize main findings and discuss policy impacts and present our conclusion.

2 Financial inclusion composite index

There are many ways of measuring financial inclusion in the literature, and no universal conceptual definition or measurement method. Beck et al. (2007) consider banking sector outreach through access and usage dimensions. Honohan (2008) measures FI by using the percentage of households having access to formal financial services. Allen et al. (2016) examine the use of formal deposit accounts by including the ownership of

respondents who report personally using a mobile money service in the past 12 months.' When 'account' and 'mobile money account' are both considered in one dimension, an overlap might occur.

[4] The definition of 'financial institution account' is 'the percentage of respondents who report having an account (by themselves or together with someone else) at a bank or another type of financial institution.'

[5] An example of how the World Bank defines countries: 'For the current 2020 fiscal year, low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of \$1025 or less in 2018; lower middle-income economies are those with a GNI per capita between \$1026 and \$3995; upper middle-income economies are those with a GNI per capita between \$3996 and \$12,375; high-income economies are those with a GNI per capita of \$12,376 or more' (World Bank 2020).

an account, use of account to save, and frequent use of the account. Mialou et al. (2017) define FI through three dimensions: outreach, usage, and quality.[6] Ghosh and Vinod (2017) and Grohmann et al. (2018) both focus on access and use of financial services dimensions, but including different indicators. Camara and Tuesta (2018) construct an index via three different dimensions: access, availability, and barriers. Park and Mercado (2018), building on the work of Sarma (2008), include access, availability, and usage of financial services.

Our empirical approach has five main distinguishing features. First, we regroup most of the above indicators together into three dimensions to provide comprehensive coverage of the measurement. We define FI as an economic status in which there is affordable and sustainable access, availability and usage of financial services for all individuals, similar to Sarma (2008) and Park and Mercado (2018), with a richer range of variables involved. Second, financial-technology-related indicators are considered in all three dimensions, as financial technology has been developed and diffused. Third, we make use of a data-driven and flexible methodology in defining and computing our FI composite index. Fourth, we analyze FI changes over time by distinguishing catching-up and environment change effects. The latter allows us to define the scope for policy interventions. Fifth, we recognize that heterogeneity among countries plays a direct role in their FI differences by partitioning countries into different categories using income per capita.

We start by defining our index to capture FI. Next, we show how we constructed the composite index and defined the weights. Then, notions of catching-up and environment change effects are discussed. Finally, we propose a simple and intuitive manner of removing the heterogeneity gap from the catching-up and environment change effects.

2.1 Defining financial inclusion

Assume we observe a panel of N countries during T periods of time. In particular, let us denote the financial inclusion index of country k at time t by FI_{kt}. As explained previously, one distinguishing feature of our approach is to recognize three main dimensions for the FI index: access, availability, and usage. Access (AC) is measured by the ownership of accounts, availability (AV) refers to the supply of financial services, and usage (US) is determined by the users of financial services. We adopt a linear weighting scheme to construct the FI index.[7] That is, for a specific country k at time t, we obtain the following:

$$FI_{kt} = \omega_{kt}^{AC} \times AC_{kt} + \omega_{kt}^{AV} \times AV_{kt} + \omega_{kt}^{US} \times US_{kt}. \tag{1}$$

[6] Their final measure does not include quality due to lack of data.

[7] An alternative is to use a geometric weighting scheme. In general, the (weighted) arithmetic average is more popular for practical work. A formal reason is that it suffices that one dimension equals zero to make the FI index also zero. In our context, the arithmetic average is also preferable since, as explained below, it allows us to endogenously compute the weights. Nevertheless, it should be acknowledged that one advantage of the geometric weighting scheme is that it reduces the compensability issue (that is, greater indicators compensate for lower indicators). Indeed, in general, the arithmetic weighting procedure implies proportional compensability.

The weights reflect the relative importance of each dimension in our index. We highlight that the weights depend on the country and the time period (formally, they depend on k and t). In other words, they are endogenously defined, meaning that we avoid making a subjective judgment. This represents the more general way to define weights in the absence of prior information.[8]

It turns out that to compute our FI index, two elements have to be observed for every country k and time period t: the three sub-indexes (AC_{kt}, AV_{kt}, and US_{kt}), and the weights (ω_{kt}^{AC}, ω_{kt}^{AV}, and ω_{kt}^{US}). We explain in the following how to obtain these measures using observed data only.

2.2 Computing financial inclusion

To obtain a measure for the access, availability, and usage dimensions, we adopt a composite index approach. That is, we use observed indicators to construct a (sub-)index for the three dimensions. In particular, let $\mathbf{x}_{kt}^{CI}$, where $CI = \{AC, AV, US\}$, be a collection of n_{CI} indicators used to construct the composite index for country k and period t. Let δ_{jkt}^{CI} represent weights. Following the spirit of our FI index definition, in (1), we define our composite sub-indexes as weighted averages of the observed indicators:

$$CI_t(\mathbf{x}_{kt}^{CI}) = \sum_{j=1}^{n_{CI}} \delta_{jkt}^{CI} \times \mathbf{x}_{jkt}^{CI}, \tag{5}$$

$$\text{where} \quad 0 \leq \delta_{jkt}^{CI} \leq 1; \text{ for } j = 1, \ldots, n_{CI}, \tag{6}$$

$$\sum_{j=1}^{n_{CI}} \delta_{jkt}^{CI} = 1. \tag{7}$$

The regularity conditions in (6) and (7) are analogous to those defined above in (2) and (3) for the FI index. We use two main sources to obtain data for our indicators: the World Bank Global Findex database and the IMF Financial Access Survey (FAS). Global Findex is a demand-side individual-level database on FI that measures the way adults aged 15+ save, borrow, make payments, and manage risk. It is updated every three years (2011, 2014, 2017), covers 148 economies,[9] and represents more than 97%

[8] We add the following regularity conditions for the weights and sub-indexes:

$$0 \leq \omega_{kt}^{AC} \leq 1; 0 \leq \omega_{kt}^{AV} \leq 1; 0 \leq \omega_{kt}^{US} \leq 1, \tag{2}$$

$$\omega_{kt}^{AC} + \omega_{kt}^{AV} + \omega_{kt}^{US} = 1, \tag{3}$$

$$0 \leq AC_{kt} \leq 100; 0 \leq AV_{kt} \leq 100, 0 \leq US_{kt} \leq 100. \tag{4}$$

The regularity conditions (2) to (4) ensure that the FI index lies in a natural interval; here, between 0 and 100. To ensure this holds, we constrict the three sub-indexes to also between 0 and 100, and the weights to sum to unity and lie in the [0, 1] interval.

[9] We note that 'the term country, used interchangeably with economy, does not imply political independence but refers to any territory for which authorities report separate social or economic statistics' (World Bank, https://datahelpdesk.worldbank.org/knowledgebase/articles/906519).

of the world's adult population. We use the country-level data from this database to construct the access and usage sub-indexes. One specificity of this dataset is that the 2017 survey accounted for the financial technology revolution. Next, IMF-FAS is a supply-side dataset covering 264 economies and used in our availability dimension. We restrict our attention to economies that also appear in the Global Findex dataset, and end with a sample of 130 economies and three periods of time: 2011, 2014, and 2017. Economies are listed in Table 10 in Appendix.

The indicators are summarized in Table 1 and described as follows. Based on Grohmann et al. (2018)[10] and Park and Mercado (2018), the access dimension includes indicators for the percentages of adults with financial accounts and mobile money accounts.[11] We use the percentage of adults with debit and credit cards as a complementary indicator, because those individuals must have a bank account to apply for debit and credit cards.

The availability dimension includes the same indicators as the outreach dimension in Beck et al. (2007) and Mialou et al. (2017): the number of ATMs and the number of financial institution branches per 100,000 adults. Currently, mobile money is available in 90 countries representing 690 million accounts with \$2.4 billion industry revenue in 2017. Also, the percentage of providers who offer mobile money has increased from 56% in 2015 to 73% globally (GSMA 2017). Meanwhile, ATMs and bank branches have been closing down. Including the percentage of financial service providers who offer Internet banking or mobile money services can enhance the measurement of availability because of the trend of financial technology development and digital financial services diffusion. However, due to the lack of data, we choose another indicator that acts as a proxy: secure Internet servers per 1 million people.[12] An additional proxy indicator could include mobile cellular subscription or mobile money agent outlets active per 100,000 adults; however, the sample size is small and does not cover all time periods. To keep the original sample size, we only use Internet services to proxy digital financial services.

For the usage dimension, besides the proportion of adults who borrow and save via a financial institution, we also include the proportion of deposits and withdrawals, as in Allen et al. (2016). We consider 'made or received digital payments' because using digital payments is a common phenomenon nowadays. It turns out that our composite index is more inclusive of financial technology by involving this indicator in the usage dimension. This contrasts with the choice made by Park and Mercado (2018), who consider 'mobile money' in the access dimension only. Finally, we include the private credit-to-GDP ratio as it is one of the most frequently used measures of financial

[10] Grohmann et al. (2018) define the access of finance by using the proportion of the population that has a formal bank account, including mobile money accounts and the proportion of adults that has a debit card.

[11] We treat 'financial institution account' and 'mobile money account' as two indicators. The aim is to assess the effect of mobile money access on the FI level; therefore, we do not use the 'account' indicator, which is defined as the percentage of adults who have an account at a financial institution or using mobile money service.

[12] Secure Internet servers is the number of distinct, publicly trusted TLS/SSL certificates (IMF database). Data are originally from Netcraft Secure Server Survey (http://www.netcraft.com/). Adult population estimates, from the World Bank's World Development Indicators (WDI) dataset, are used to rescale the IMF-FAS raw data for secure Internet servers per 1 million people.

Table 1 Summary of the indicators

Dimension	Indicator	Definition	Data source
AC	Financial institution account (%)	The percentage of adults who report having an account at a bank or another type of financial institution in the past 12 months	Global Findex
	Debit card ownership (%)	The percentage of respondents who report having a debit card	Global Findex
	Credit card ownership (%)	The percentage of respondents who report having a credit card	Global Findex
	Mobile money account (%)	The percentage of adults who report personally using a mobile money service in the past 12 months	Global Findex
AV	ATMs	The number of ATMs per 100,000 population	IMF-FAS
	Bank branches	The number of branches per 100,000 population	IMF-FAS
	Internet service	Secure Internet servers per one million people	IMF, Netcraft and World Bank-WDI
US	Deposit (%)	Among respondents with a financial institution account, the percentage who report one or more deposits into their account in the past 12 months[a]	Global Findex
	Withdraw (%)	Among respondents with a financial institution account, the percentage who report one or more deposits into their account in the past 12 months[b]	Global Findex
	Saved (%)	Saved at a financial institution	Global Findex
	Borrowed (%)	Borrowed from a financial institution or used a credit card[c]	Global Findex
	Digital payments (%)	Made or received digital payments in the past year	Global Findex
	Private credit (% of GDP)	Domestic credit to the private sector	IMF, International Financial Statistics, World Bank & OECD GDP estimates

[a] 'This includes cash or electronic deposits or any time money is transferred into the account by the respondent, an employer, or another person or institution.' (Demirgüç-Kunt et al. 2018)
[b] 'This includes cash or electronic withdrawals or any time money is removed from the account by the respondent, an employer, or another person or institution.' (Demirgüç-Kunt et al. 2018)
[c] We do not include the usage of debit or credit cards because the usage of debit cards is included in 'Withdraw' and the usage of credit cards is included in 'Borrowed' already

Table 2 Averages of the indicators

Dimension	Indicator	2011	2017
AC	Financial institution account (%)	46	58
	Debit card ownership (%)	32	44
	Credit card ownership (%)	17	19
	Mobile money account (%)		15
AV	ATMs (No. per 100,000 adults)	43.47	68.86
	Bank branches (No. per 100,000 adults)	17.39	20.08
	Internet service (No. per 1 million people)	268.57	6070.5
US	Deposit (%)		72
	Withdraw (%)		74
	Saved (%)	18.67	24
	Borrowed (%)	10	12
	Digital payments (%)	26	54
	Private credit (% of GDP)	54.53	57.16

development (Ang and Kumar 2014; Bahadir and Valev 2015; Baltagi et al. 2009; Park and Mercado 2018; Rewilak 2013).[13]

We present the averages of indicators per dimension in Table 2 for our starting and ending periods (2011 and 2017). The average of each indicator has increased for the three dimensions over time. We highlight the important increase of Internet services and digital payments, and the small increase of credit card ownership with respect to debit card ownership.

In practice, three important questions arise when looking at our definition of the financial inclusion composite index: (i) how should we add indicators that have different units? (ii) how can we ensure that the sub-indexes are in the desirable interval (that is, between 0 and 100)? and (iii) how should we compute weights using the data?

We rely on a benefit-of-the-doubt approach (Cherchye et al. 2007a, b) to compute the composite sub-indexes. This method does not require that indicators have the same unit; in other words, it avoids choosing a normalization procedure for the indicator. To define a composite index, it is in general required that the indicators have the same unit. Different options are possible, such as the min–max, the ratio, and the distance to a referent. Clearly, the chosen normalization procedure is not insidious (see Freudenberg (2003) for more discussion about normalization of indicators, and consequences for the composite index). The benefit-of-the-doubt approach naturally gives composite indexes between 0 and 1. (We have modified the programming below to obtain indexes between 0 and 100.) Finally, the weights are endogenously computed using only the data. Roughly speaking, the weights for a particular country and time period are computed using peers at that time period.

[13] Domestic credit to the private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable, that establish a claim for repayment.

Our aim is to investigate how FI has changed between the initial and final time periods (2011 and 2017 in our context). We first explain how to compute the composite index for the initial year, denoted i in the following. Intuitively, since no data are available before that time period, this is computed using data from the base year for the peers. The composite sub-index for the initial period $CI_i(\mathbf{x}_{ki}^{CI})$ for country k is obtained as follows:

$$\begin{aligned} CI_i(\mathbf{x}_{ki}^{CI}) = & \max_{\delta_{jki}^{CI}(j\in\{1,\ldots,n_{CI}\})} \sum_{j=1}^{n_{CI}} \delta_{jki}^{CI} x_{jki}^{CI} \\ s.t. \quad & \sum_{j=1}^{n_{CI}} \delta_{jki}^{CI} x_{jsi}^{CI} \leq 100; \text{ for } s = 1, \ldots, N, \\ & \delta_{jki}^{CI} \geq 0; \text{ for } j = 1, \ldots, n_{CI}. \end{aligned} \tag{8}$$

$CI_i(\mathbf{x}_{ki}^{CI})$ is by definition between 0 and 100. A value of 100 reflects a situation where country k has the optimal value for the composite index at time i; smaller values indicate worse performances. It is important to note that we give full flexibility to the weights in (8); that is, we only require that they are non-negative. We believe it is a reasonable approach when no specific guidance is given to define the three dimensions. Putting this differently, we let the data indicate which indicators are the most important for each dimension.

Next, for the final time period, denoted by f, we suggest using the following programming for every country k:

$$\begin{aligned} CI_f(\mathbf{x}_{kf}^{CI}) = & \max_{\delta_{jkf}^{CI}(j\in\{1,\ldots,n_{CI}\})} \sum_{j=1}^{n_{CI}} \delta_{jkf}^{CI} x_{jkf}^{CI} \\ s.t. \quad & \sum_{j=1}^{n_{CI}} \delta_{jkf}^{CI} x_{js\tau}^{CI} \leq 100; \text{ for } s = 1, \ldots, N \text{ and } i < \tau \leq f, \\ & \delta_{jkf}^{CI} \geq 0; \text{ for } j = 1, \ldots, n_{CI}. \end{aligned} \tag{9}$$

$CI_f(\mathbf{x}_{kf}^{CI})$ has to be interpreted as $CI_i(\mathbf{x}_{ki}^{CI})$: it lies between 0 and 100, where higher values imply better performances. The linear program in (9) looks very similar to that in (10). The subtle but important difference is the added constraint for the time periods (formally captured by $i < \tau \leq f$). In other words, we include all previous observations available at time f, except those of time i, for the peers. Intuitively, this is a way to take what has happened in the past into account; in our context, taking what happened in 2014 into consideration. From a theoretical perspective, we may see this definition as a sequential representation of the composite index.[14]

In practice, these linear programs have to be solved for every country and time period i and f for the three dimensions. Once this is done, a similar approach can be

[14] This representation dates at least to Diewert (1980), who uses it in a production context.

used to find the values of the financial inclusion composite index. In particular, it is given for country k at time $t = \{i, f\}$ as follows:

$$\begin{aligned}
FI_t(\mathbf{x}_{kt}^{FI}) = &\max_{\omega_{kt}^{AC}, \omega_{kt}^{AV}, \omega_{kt}^{US}} \omega_{kt}^{AC} \times AC_{kt}(\mathbf{x}_{kt}^{AC}) + \omega_{kt}^{AV} \times AV_{kt}(\mathbf{x}_{kt}^{AV}) \\
&+ \omega_{kt}^{US} \times US_{kt}(\mathbf{x}_{kt}^{US}) \\
s.t. \quad &\omega_{kt}^{AC} \times AC_{ks}(\mathbf{x}_{ks}^{AC}) + \omega_{kt}^{AV} \times AV_{ks}(\mathbf{x}_{ks}^{AV}) \\
&+ \omega_{kt}^{US} \times US_{ks}(\mathbf{x}_{ks}^{US}) \leq 100; \text{ for } s = 1, \ldots, N, \\
&\omega_{kt}^{AC} \geq 0, \omega_{kt}^{AV} \geq 0, \omega_{kt}^{US} \geq 0,
\end{aligned} \tag{10}$$

where $\mathbf{x}_{kt}^{FI}$ contains all the indicators used to define the access, availability, and usage dimensions. The obtained composite index $FI_t(\mathbf{x}_{kt}^{FI})$ is, by construction, in the desired interval (0 to 100), with smaller values implying less financial inclusion. In that linear program, we do not impose any constraints on the relative importance of the three dimensions in the financial inclusion composite index (formally only non-negativeness is imposed). While this feature is attractive when computing an index for each of the three dimensions in (8) and (9), it is less desirable when computing the financial inclusion composite index. For example, we do not want the financial inclusion composite index to be defined by one dimension exclusively. (The computed weights for the two other dimensions would be zero in that case). To avoid such cases, we add constraints for the relative contributions of the three dimensions. In particular, it is required that the relative contributions lie between two bounds: a lower bound l^- and an upper bound u^+:

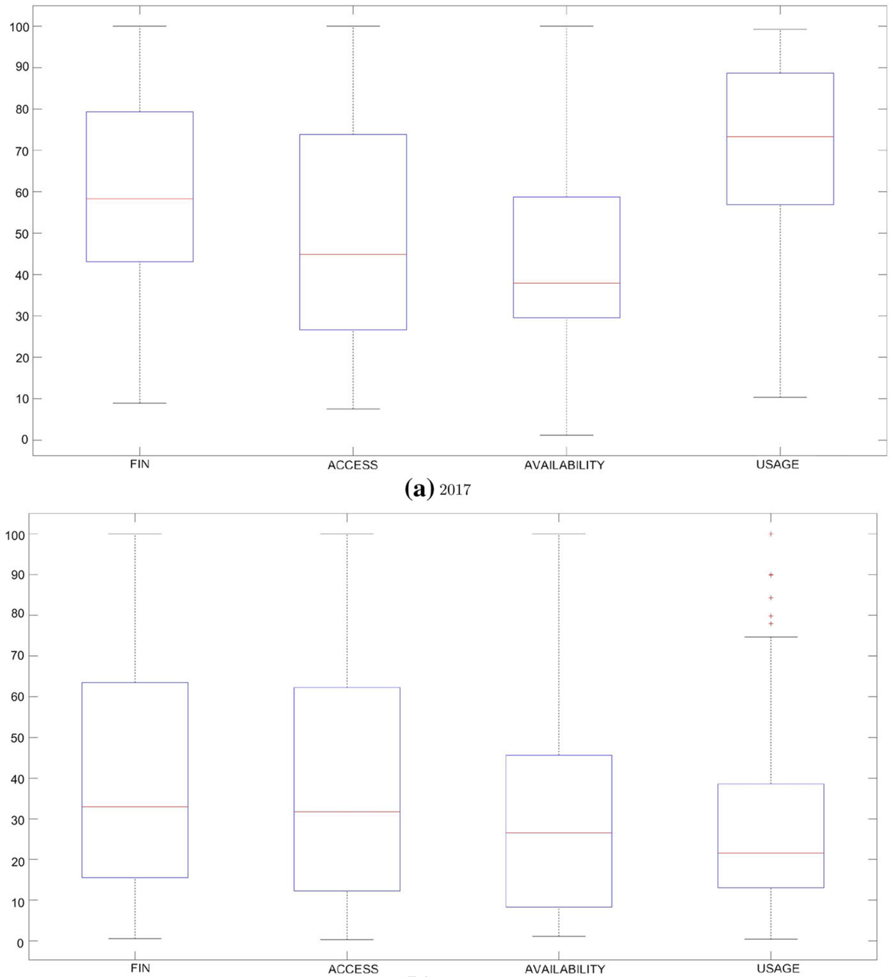
$$\begin{aligned}
&l^- \leq \frac{\omega_{kt}^{AC} \times AC_{kt}(\mathbf{x}_{kt}^{AC})}{\omega_{kt}^{AV} \times AV_{kt}(\mathbf{x}_{kt}^{AV})} \leq u^+, l^- \leq \frac{\omega_{kt}^{AC} \times AC_{kt}(\mathbf{x}_{kt}^{AC})}{\omega_{kt}^{US} \times US_{kt}(\mathbf{x}_{kt}^{US})} \leq u^+, \\
&l^- \leq \frac{\omega_{kt}^{AV} \times AV_{kt}(\mathbf{x}_{kt}^{AV})}{\omega_{kt}^{US} \times US_{kt}(\mathbf{x}_{kt}^{US})} \leq u^+.
\end{aligned} \tag{11}$$

We tested for several specifications of these bounds and chose $l^- = 0.75$ and $u^+ = 1.25$. In other words, the relative contributions of the three dimensions can be 25% lower or larger. Increasing the interval size has little impact on the computed composite indexes.

2.3 Financial inclusion changes

We start our empirical investigation by showing the boxplots of our financial inclusion composite index and of the three dimensions for 2011 and 2017 in Fig. 1. The boxplots are useful in our case since they provide the medians (more robust than the averages), but also an idea of the dispersion of the composite indexes (given by the lengths of the boxplots).

These boxplots highlight two important stylized facts about FI change between 2011 and 2017. First, there is a clear improvement of FI over time. The median of



(a) 2017

(b) 2011

Fig. 1 Financial inclusion composite index and the three dimensions

the composite index has almost doubled from 2011 (around 30) to 2017 (about 60), evidence that FI has been developed intensively. Second, countries' FI becomes more homogeneous: the length of the boxplots decreases between 2011 and 2017. The sub-indexes of the three dimensions provide more insights. Every dimension presents an improvement from 2011 to 2017; that is, FI improvement is due to improvements in all three dimensions. The medians are comparable in 2011, while the usage dimension presents a higher median in 2017 (almost four times more than in 2011). We may see this result as a consequence of taking digital payments into consideration in our analysis. Also, countries are the most heterogeneous for the access dimension, while there is more homogeneity for the availability dimension over time.

To formally measure how FI has changed between our base and final time periods, we rely on the following ratio to capture the catching-up effect between periods i and f:

$$CU(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = \frac{FI_f(\mathbf{x}_{kf}^{FI})}{FI_i(\mathbf{x}_{ki}^{FI})}. \tag{12}$$

$CU(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ captures the change between the FI index at period i and the FI index at period f. In other words, $CU(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ gives us the catching-up of entity k between the initial and final periods. When $CU(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) > 1\ (< 1)$, $FI_f(\mathbf{x}_{kf}^{FI}) > (<) FI_i(\mathbf{x}_{ki}^{k})$. That is, FI in period f is larger than in period f. A value of 1 implies that there is no change for country k. Clearly, such a ratio can be computed for the sub-indexes. It suffices to replace FI by AC, AV, or US in (12).

Results for the catching-up effects are given in Table 3 and Fig. 2.[15] We present the averages, medians, and the percentages of progress and regress for the FI index and three dimensions. On average, there is a catching-up effect of 2.04, implying that the FI index in 2017 has, on average, increased by 104 per cent with respect to 2011. We find that FI has improved for 84.62% of our 130 countries over the time period. The improvement is confirmed by the median but to a smaller extent, showing that there is heterogeneity between countries in FI (also shown by the length of the boxplots in Fig. 1). This is also clearly confirmed by the results per country in Fig. 2. There, we present the results per country using a world map. Countries in light green indicate a positive catching-up for their FI index. Yellow means the country experienced a more than 100% progress. Countries in dark green have a small scale of regression on catching up in their FI index. Missing data are reported in white.

The dimension-specific catching-up effects confirm the importance of the three dimensions for FI improvement. The usage dimension presents the largest improvement when relying on the median, while the average highlights the access dimension. Around 90% of 130 countries have an improvement for each dimension. This is larger than the percentage progress for the FI catching-up effect. This reveals that some countries have progressed on specific dimensions, but regressed on others. Finally, to verify whether the distribution shifts are statistically true, we make used of the nonparametric Kolmogorov–Smirnov (KS) test.[16] The p-values confirm the overall improvement between the 2 years.

Our results on the improvement of financial inclusion for most of the economies over time are consistent with the findings in Park and Mercado (2018), where they rely on principal component analysis, and with Mialou et al. (2017) who employ factor analysis for different datasets and time periods. Our study provides more comprehensive coverage of the measurement including financial technology indicators and by using both supply- and demand-side data. We also take the heterogeneity among economies into consideration when defining the composite index, which can reduce

[15] We thank an anonymous referee for the idea of including world maps.

[16] H_0: the 2011 and 2017 distributions are equal; H_1: 2017 distribution is larger than the 2011 distribution.

Table 3 Catching-up effects—descriptive statistics

Index	Average	Median	Regress %	Progress %	*p* value
CU	2.04	1.50	13.08	84.62	0.01
ACCESS	2.82	1.39	10.00	88.46	0.02
AVAILABILITY	1.87	1.62	6.47	93.24	0.00
USAGE	2.56	1.85	7.69	91.54	0.00

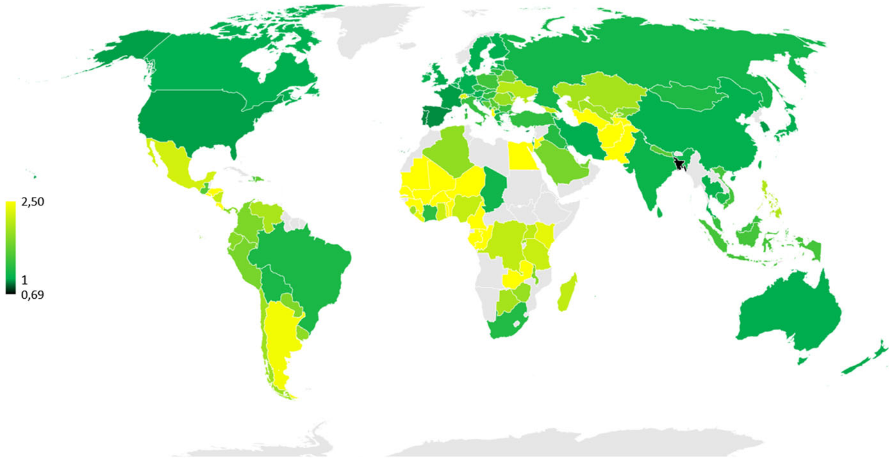


Fig. 2 World map for the catching-up effects

bias in the analysis, rather than a-posteriori as in previous work. We will discuss further in the Heterogeneity Gap section.

2.4 Scope for policy intervention

As explained in the introduction, improving financial inclusion is considered very serious by many national governments and international institutions (for example, World Bank, IMF, UN). It is therefore crucial to have a reliable measurement for FI and to know how FI has changed over time. These two concerns have been addressed in the previous sections. In this section, we provide a complementary tool to measure the environment change effect. This effect measures the shift in the best possible performances between the initial and final time periods. In other words, it verifies whether policy makers have succeeded in creating an environment that fosters FI and allows us to therefore quantify the scope for policy interventions.

The environment change is defined by fixing the evaluated countries at a specific time period and varying the time period for peers. When selecting period i for the evaluated countries, we obtain the following measurement of environment change:

$$EC(\mathbf{x}_{ki}^{FI}) = \frac{FI_i(\mathbf{x}_{ki}^{FI})}{FI_f(\mathbf{x}_{ki}^{FI})}. \tag{13}$$

$EC(\mathbf{x}_{ki}^{FI}) > 1$ when $FI_i(\mathbf{x}_{ki}^{FI}) > FI_f(\mathbf{x}_{ki}^{FI})$. That is, the FI index for country k at period i is higher when peers are those of period i than those of period f. The difference between these indexes reflects a change in the environment; the evaluated countries are fixed. It turns out that there is more scope for performance improvement in period f than in period i. When $EC(\mathbf{x}_{ki}^{FI}) < 1$, the opposite situation prevails: there is a less favorable environment in period f since $FI_i(\mathbf{x}_{ki}^{FI}) < FI_f(\mathbf{x}_{ki}^{FI})$. Policy makers have a direct role to play in that case. A value of one represents the status quo. We remark that $FI_f(\mathbf{x}_{ki}^{FI})$ is a counterfactual composite index where peers and the evaluated country are at two different time periods. It is computed using the linear programs in (9) and (10) by fixing the evaluated countries at time i.

An alternative is to choose period f for the evaluated countries when defining the environment change effect:

$$EC(\mathbf{x}_{kf}^{FI}) = \frac{FI_i(\mathbf{x}_{kf}^{FI})}{FI_f(\mathbf{x}_{kf}^{FI})}. \tag{14}$$

$EC(\mathbf{x}_{kf}^{FI}) < 1$ when $FI_i(\mathbf{x}_{kf}^{FI}) < FI_f(\mathbf{x}_{kf}^{FI})$; that is, when the environment is less favorable under period f and thus more favorable under period i (there is more performance improvement scope in period i than f). When $EC(\mathbf{x}_{kf}^{FI}) > 1$, the environment is more favorable under period f, and thus less favorable under period i. Again, a value of unity indicates the status quo. The counterfactual composite index $FI_i(\mathbf{x}_{kf}^{FI})$ is computed using the linear programs in (8) and (10) by fixing the evaluated countries at time f.

It turns out that we obtain two different measurements of environment change: $EC(\mathbf{x}_{ki}^{FI})$ and $EC(\mathbf{x}_{kf}^{FI})$. Both give us the change in environment between time periods i and f; the only difference between the change measurements is the time period of the evaluated countries. That is, $EC(\mathbf{x}_{ki}^{FI})$ and $EC(\mathbf{x}_{kf}^{FI})$ are time-dependent. In general, choosing between periods i and f for the evaluated country k represents a subjective question. Moreover, it is preferable to define the environment change effect in such a manner that it does not depend on the time period chosen. A commonly agreed procedure to define a time-independent index change is to take the geometric average of the time-dependent change indexes $EC_i(\mathbf{x}_{kf}^{FI})$ and $EC_f(\mathbf{x}_{kf}^{FI})$ (Cherchye et al. 2007a, b). For country k, this is as follows:

$$EC(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = \left[EC(\mathbf{x}_{ki}^{FI}) \times EC(\mathbf{x}_{kf}^{FI})\right]^{1/2}. \tag{15}$$

$EC(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ has to be interpreted as $EC(\mathbf{x}_{ki}^{FI})$ and $EC(\mathbf{x}_{kf}^{FI})$: greater (smaller) than one implies an improvement (regression) of the environment change effect for country k between periods i and f. Clearly, such a ratio can be computed for the sub-indexes. It suffices to replace *FI* by *AC*, *AV*, or *US* in (15). Descriptive statistics are given in Table 4.

Table 4 Environment effects—descriptive statistics

Index	Average	Median	Regress %	Progress %	p value
EC	1.19	1.10	17.69	81.54	0.00
ACCESS	1.15	1.06	28.46	70.23	0.01
AVAILABILITY	1.32	1.18	26.15	71.54	0.01
USAGE	1.41	1.53	7.19	92.31	0.00

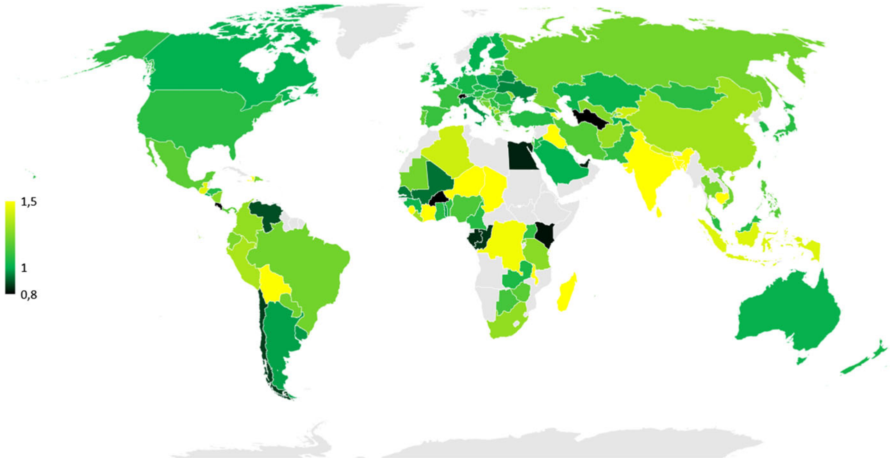


Fig. 3 World map for the environment effects

The results in Table 4 and Fig. 3 indicate that policy makers have succeeded in creating an environment that fosters FI. This is captured by averages and medians that are larger than one. Nevertheless, this is not true for every country, since slightly fewer than 20% of these experienced a regression in their environment. Policy makers should thus target these countries first. As shown in Fig. 3, countries in light green and yellow have progressed in their environment that promotes FI. Some countries in Africa and South America, showing in dark green and black, experienced a regression in their environment. These conclusions hold true for the three dimensions. We note that more than 90% of our 130 countries experienced an improvement of their environment effect on the usage dimension and more than 70% for the two other dimensions. Finally, the p-values of the KS tests confirm our findings of policy improvement.

It is also useful to compare the amplitude of the catching-up and environment change effects. Overall, the environment effects are of a lesser magnitude than the catching-up effects (note that it is statistically verified), which indicates that, while policy makers have succeeded in creating an environment that fosters FI, it is not the main reason explaining the better FI worldwide. The main reason is instead a catching-up effect, probably attributable to country-specific reasons. Nevertheless, it is important to highlight that both effects have contributed to FI.

2.5 Heterogeneity gaps

Our previous results show that economies have made substantial efforts to improve financial inclusion and policy makers have played a positive role in that improvement. In this last section, we propose a simple and intuitive way to take the heterogeneity between countries into consideration. A major difference with the previous work is that we propose an a-priori approach (that is, before evaluating FI of countries), rather than considering heterogeneity a-posteriori (that is, once FI has been computed). In the latter case, averages per category or regressions are usually used.

Previous studies have highlighted that income per capita accounts for the major variation of FI across economies (Demirgüç-Kunt and Klapper 2013; Mialou et al. 2017; Park and Mercado 2018). The presence of heterogeneity in our analysis may have a direct impact on the computed composite indexes, which are implicitly based on the assumption of country homogeneity (formally, all peers are used when computing the composite indexes in the linear programs). In the worst case, this might create bias in our analysis (Walheer 2019). It is thus important to revisit our results when acknowledging the presence of heterogeneity between countries. By doing so, we obtain a bipartite decomposition of the catching-up and environment effects: a pure effect and a heterogeneity gap change. Identifying heterogeneity gaps is of great interest for policy makers, since they can then act to reduce heterogeneity.

In practice, we distinguish economies with respect to their income (per capita) level. We follow the World Bank country categories, in which economies are separated into four groups: high-income, upper-middle-income, lower-middle-income, and low-income economies. The categories are defined by gross national income per capita calculated using the World Bank Atlas method, with thresholds determined by the World Bank, and updated annually with an adjustment for inflation.[17] See Table 10 for more details about the categories.

We start by providing descriptive statistics of our indicators per category for the initial and final year in Table 5. Table 5 demonstrates huge differences among country income groups for most indicators, and the growing role of financial technology as a signification tool for promoting FI. High-income economies are the most likely to be highly FI. For example, the average percentage of adults in high-income economies with a financial institution account was 84% in 2011, while it was only 14% for low-income economies. This is consistent with the finding that higher-income economies have higher participation in formal financial activities (e.g., Demirgüç-Kunt and Klapper 2013).

Mobile banking plays different roles depending on the income level. For high-income economies, mobile banking can be a new product enriching financial services. However, for low-income economies, it is the major financial service used. The average percentage of adults who have a financial institution account and a mobile money account were 92% and 17% in 2017 for high-income economies and 22% and 22% for low-income economies. The lower the income level of an economy, the mobile banking plays a more important role in providing access to financial services. In

[17] Another option would be to categorize countries by region. While this partitioning seems natural, it lacks economic intuition and has not been reported in the previous work.

Table 5 Averages of the indicators per income category

Income group	Dimension	Indicator	2011	2017
High	AC	Financial institution account %	84	92
		Debit card ownership %	64	82
		Credit card ownership %	41	44
		Mobile money account %		17
	AV	ATMs	86.93	87.49
		Bank branches	28.88	24.08
		Internet service	837.56	17243
	US	Deposit %		89
		Withdraw %		91
		Saved %	38	47
		Borrowed %	13	17
		Digital payments %	54	87
		Private credit	98.94	88.14
Upper-middle	AC	Financial institution account %	45	60
		Debit card ownership %	30	44
		Credit card ownership %	12	15
		Mobile money account %		13
	AV	ATMs	48.32	72.35
		Bank branches	19.06	21.13
		Internet service	36.99	2722.6
	US	Deposit %		72
		Withdraw %		75
		Saved %	13	17
		Borrowed %	10	11
		Digital payments %	35	52
		Private credit	50	51.76
Lower-middle	AC	Financial institution account %	24	40
		Debit card ownership %	24	23
		Credit card ownership %	13	5
		Mobile money account %	4	11
	AV	ATMs	16.36	37.73
		Bank branches	12.1	14.02
		Internet service	2.38	452.66
	US	Deposit %		63
		Withdraw %		64
		Saved %	9	12
		Borrowed %	9	11
		Digital payments %	23	34
		Private credit	31.4	41.17

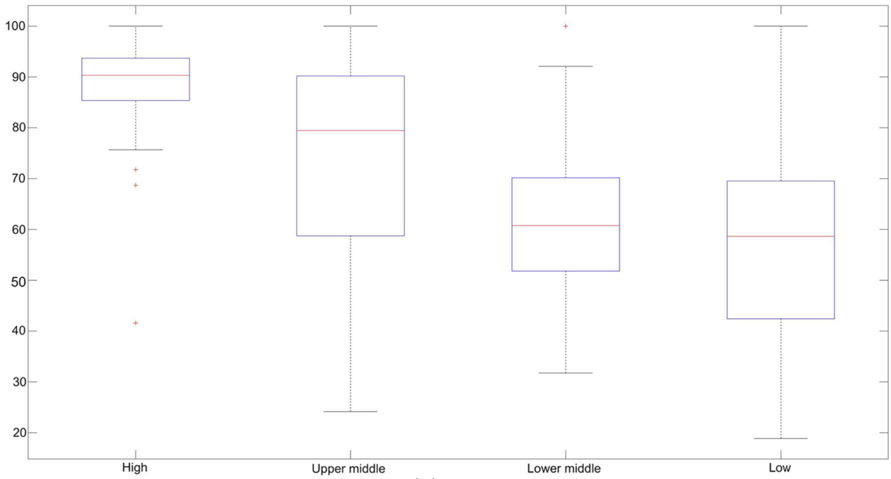
Table 5 continued

Income group	Dimension	Indicator	2011	2017
Low	AC	Financial institution account %	14	22
		Debit card ownership %	14	9
		Credit card ownership %	5	3
		Mobile money account %	2	22
	AV	ATMs	2.6	4.14
		Bank branches	2.8	3.22
		Internet service	0.51	14.29
	US	Deposit %		54
		Withdraw%		53
		Saved %	8	9
		Borrowed %	5	7
		Digital payments %	10	26
		Private credit	16.12	23.99

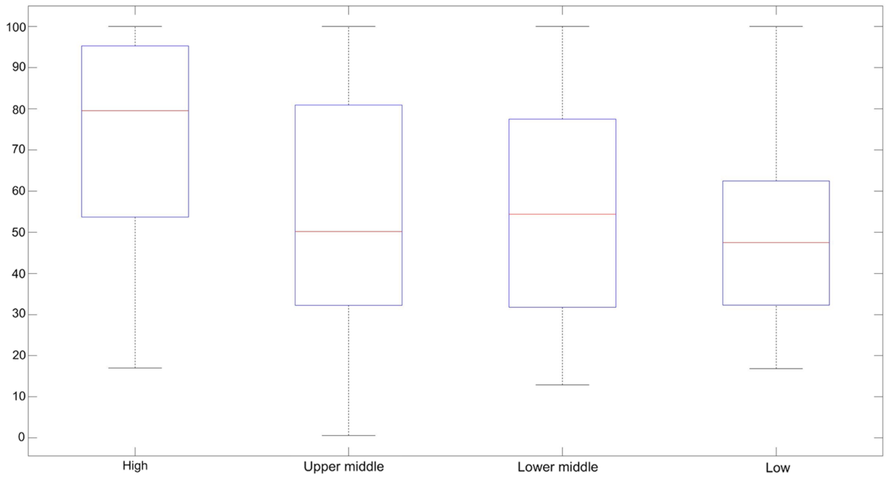
terms of bank branches, high-income economies have shut down branches since 2011. However, there is an increasing tendency for upper-middle-income economies. Lower-middle- and low-income economies had more commercial bank branches in 2017 than in 2011, but this increase was mild. This phenomenon can be indirectly explained by the rise of the importance of mobile banking services among lower-income economies. For all income groups, secure Internet services have increased over time, providing a good foundation for the success of digital finance services. The percentage of adults who have a mobile money account and who made or received digital payments over the past year has increased dramatically, regardless of the country income group.

To remove heterogeneity from our catching-up and environment change effects, we introduce the notion of a category-specific FI composite index. This is labeled for each category c as $FI_t^c(\mathbf{x}_{kt}^{FI})$. It has to be interpreted as $FI_t(\mathbf{x}_{kt}^{FI})$, but when restricting peers to group c. Also, we have that $FI_t^c(\mathbf{x}_{kt}^{FI}) \geq FI_t(\mathbf{x}_{kt}^{FI})$. Intuitively, when considering less (more) peers, this can only increase (decrease) the composite index value. The ratio of both indexes, that is, $\frac{FI_t(\mathbf{x}_{kt}^{FI})}{FI_t^c(\mathbf{x}_{kt}^{FI})}$, gives us a measure of the heterogeneity gap for country k at time t. When $FI_t^c(\mathbf{x}_{kt}^{FI}) = FI_t(\mathbf{x}_{kt}^{FI})$, that is, $\frac{FI_t(\mathbf{x}_{kt}^{FI})}{FI_t^c(\mathbf{x}_{kt}^{FI})} = 1$, there is no gap, while $FI_t^c(\mathbf{x}_{kt}^{FI}) > FI_t(\mathbf{x}_{kt}^{FI})$, that is, $\frac{FI_t(\mathbf{x}_{kt}^{FI})}{FI_t^c(\mathbf{x}_{kt}^{FI})} < 1$, reveals a larger heterogeneity gap. The category-specific FI composite index can also be computed using linear programming. In fact, it suffices to adapt the linear programs in (9), (10), and (11) by replacing N by N_c, where N_c is the number of peers in group c. Boxplots for $FI_t^c(\mathbf{x}_{kt}^{FI})$ are given in Fig. 4.

Figure 4 confirms the dominance of high-income economies, with medians around 80 in 2011 and 90 in 2017. The fastest progress has occurred in the upper-middle-income economies, where the median increased from 50 to 80. Lower-middle- and low-income economies have improved at a similar pace, with roughly 20 degrees of



(a) 2017



(b) 2011

Fig. 4 Category-specific financial inclusion composite index

increase. Moreover, the range of the FI level among economies has shrunk for high-, upper-middle-, and lower-middle-income economies, indicating less difference within each income group. The high-income group had the largest decrease in terms of FI inequality; in other words, high-income economies had a higher similar degree of financial inclusion in 2017 as in 2011.

To better understand the results for the category-specific FI composite index, we provide category-specific boxplots for the three dimensions in Fig. 5. The increase of the category-specific FI composite index for high-income economies is mainly due to the usage dimension (median of 45 in 2011 and 90 in 2017), while the other two dimensions show only mild increases. Also, the usage dimension's range shrunk

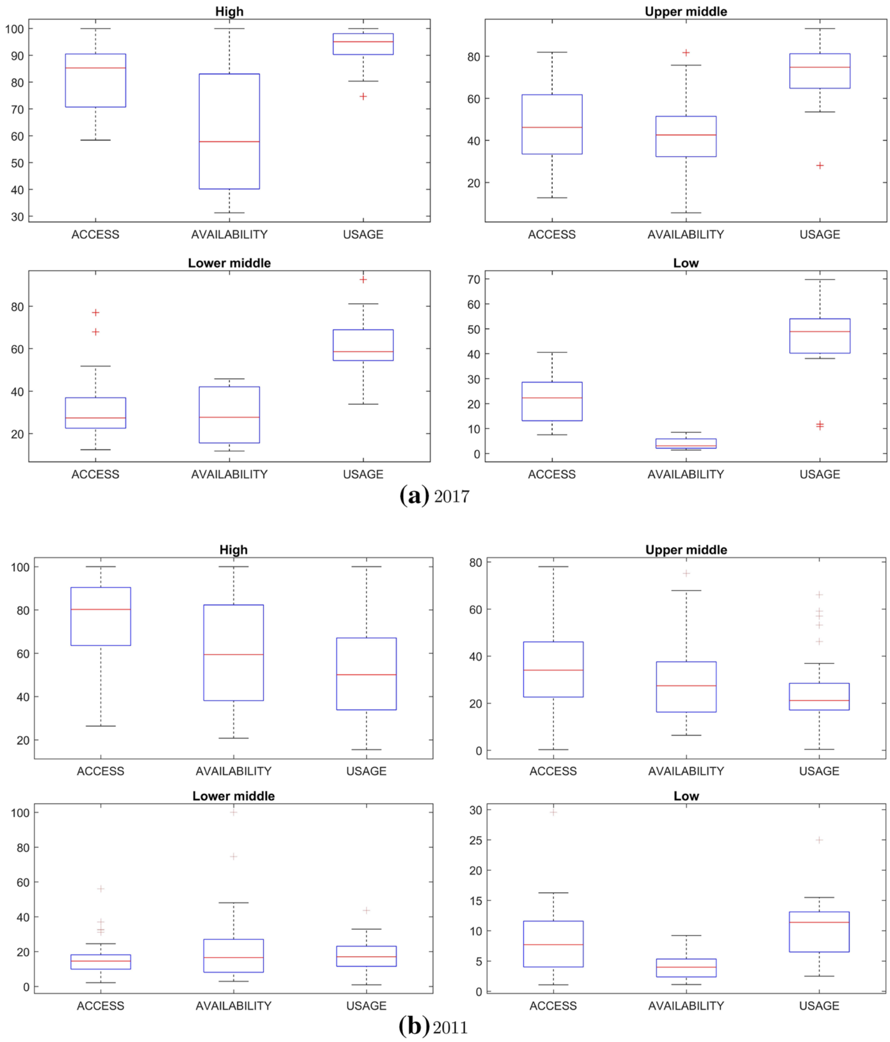


Fig. 5 Dimensions per income category

dramatically, indicating that high-income economies had a close high usage degree in 2017. Similarly, the upper-middle-income economies showed significant progress in the usage dimension and mild improvements in the other two dimensions. The main difference with high-income countries is that the range is larger for each dimension. In 2011, the lower-middle-income group had a low level for the access dimension (below 20); by 2017, this had increased to 30. The median level of the usage dimension increased from below 40 in 2011 to 70 in 2017. Low-income economies experienced significant increases in the access (from roughly 8 to more than 20) and the usage (from 30 to more than 60) dimensions. Overall, all dimensions contributed to the improvement in FI, but the usage dimension comprised the major influence (as in

Table 6 Category-specific catching-up effects—descriptive statistics

Income group	Index	Average	Median	Regress %	Progress %	*p* value
High	*CU*	1.22	1.10	21.95	73.17	0.04
	ACCESS	1.08	1.00	13.66	83.90	0.00
	AVAILABILITY	1.15	1.17	31.71	53.66	0.11
	USAGE	2.04	1.71	1.21	97.56	0.00
Upper-middle	*CU*	1.64	1.24	20.12	77.14	0.00
	ACCESS	1.27	1.26	14.29	85.71	0.00
	AVAILABILITY	0.91	0.90	68.57	22.86	0.21
	USAGE	2.67	2.36	2.86	91.43	0.00
Lower-middle	*CU*	1.95	1.42	12.12	81.82	0.01
	ACCESS	2.05	1.54	1.41	94.87	0.00
	AVAILABILITY	1.23	1.01	45.45	38.48	0.19
	USAGE	2.97	2.30	0.51	96.97	0.00
Low	*CU*	1.40	1.33	14.29	80.95	0.00
	ACCESS	1.94	1.75	19.05	80.95	0.00
	AVAILABILITY	0.93	1.01	42.86	52.38	0.15
	USAGE	2.50	1.86	9.52	85.71	0.00

Fig. 1, which considers all countries together). When considering levels, availability was the highest in 2011. This makes sense: the first step is to make financial services available (high levels in 2011 and 2017) and then promote usage (high increases between 2011 and 2017).

Using our notion of category-specific FI composite index, we obtain a useful decomposition of our catching-up and environment effects into two parts: a category-specific effect and a heterogeneity gap. In other words, we remove heterogeneity from the composite index and thus isolate pure effects. Let us first consider the catching-up effect, which can be decomposed into two parts for every country k as follows:

$$CU(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = CU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) \times GCU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}). \quad (16)$$

$CU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ captures the catch-up effect for country k in group c. In turns out that $CU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ has to be interpreted as $CU(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$, but when peers are restricted to group c (instead of taking all countries into consideration). This means that it provides a less strict measurement since countries are compared with their direct peers. Formally, $CU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = \frac{FI_f^c(\mathbf{x}_{kf}^{FI})}{FI_i^c(\mathbf{x}_{ki}^{FI})}$. Next, $GCU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ captures the heterogeneity gap change for the catching-up effect for country k. Formally, it is defined as: $GCU^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = \frac{FI_f(\mathbf{x}_{kf}^{FI})/FI_f^c(\mathbf{x}_{kf}^{FI})}{FI_i(\mathbf{x}_{ki}^{FI})/FI_i^c(\mathbf{x}_{ki}^{FI})}$. When it is larger (smaller) than unity, this implies that the heterogeneity gap decreases (increases) for the catching-up effect. Results are provided in Table 6 for the category-specific catching-up effects.

As highlighted previously, all categories present an improvement in their FI behavior. Table 6 provides additional relevant information. A larger improvement is found for the lower-middle countries (+95% on average), followed by the upper-middle category (+64% on average), the low-income countries (+40%), and then the high-income countries (+22 per cent). This implies that the middle-income economies are catching-up faster than the other economies on average, and the lower-middle-income economies are catching-up the fastest.

About 73.17% of high-income economies have improved their FI degree. The usage dimension displays the greatest catching-up, increasing by 104% since 2011 with 97.56% of economies in this group making progress. In contrast, the access dimension has only increased by 8%. In addition, the access and availability dimensions both contributed to the high increase in the catching-up effect of the upper-middle-income group, with increases of 198% and 174%, respectively. There is also a higher average increase in this effect (133%) and a higher percentage of economies in this group with an improvement (77.14%) compared with the high-income group. For the lower-middle-income group, the usage dimension caught up the most, with an increase of 197%, followed by the access (154%) and availability (83%) dimensions. Finally, roughly 81% of low-income economies have made positive progress. The usage dimension improved by 150% from 2011 to 2017, followed by the access (94%) and availability (23%) improvements. These results are overall confirmed by the p-values of the KS tests.

We continue our analysis per category by providing heterogeneity gaps for the catching-up effects in Table 7 and Fig. 6. Light green and yellow in Fig. 6 show an economy experienced a decrease in their heterogeneity gap for the catching-up effect on average, while dark green means an economy experienced a small increase in this gap. Recall that the heterogeneity gap for the catching-up effect decreases when the heterogeneity gap change is greater than unity. A first stylized fact is that all heterogeneity gap changes are inversely related to income category: low-income (+15% on average), lower-middle-income (+5% on average), upper-middle-income (−3% on average), and high-income economies (−9% on average). Both low-income and lower-middle-income economies experienced a decrease in their heterogeneity gaps over time for the catching-up effect, while the other two groups had a small increase in this gap on average. Catching-up capacities are therefore more homogeneous for lower-income economies when the evaluation is analyzed within each group instead of across all economies. Moreover, the percentage of progress for low-income (47.25%), lower-middle-income (45.70%), and upper-middle-income (+35.14% on average), and high-income (+18.29%) economies also confirms this path. These improvements are confirmed by the p-values of the KS tests.

Remarkably, the availability dimension presents the largest improvement in both the degree and the number of progressed economies except for the high-income group. The access dimension shows a decrease in heterogeneity gap for the catching-up effect for all income groups. These are why countries become more homogeneous in terms of their catching-up capacities. We also highlight the negative contribution of the usage dimension. This observation is consistent with our suggestions for policy makers to focus more on this dimension. Nevertheless, there remain important differences between the composite and category-specific composite indexes for many countries,

Table 7 Heterogeneity gaps for the catching-up effects—descriptive statistics

Income group	Index	Average	Median	Regress %	Progress %	p value
High	*GCU*	0.91	0.93	69.27	18.29	0.31
	ACCESS	1.02	1.02	24.39	73.17	0.03
	AVAILABILITY	0.96	1.01	29.27	60.98	0.11
	USAGE	0.78	0.81	9.76	90.24	0.00
Upper-middle	*GCU*	0.97	0.85	62.85	35.14	0.33
	ACCESS	1.20	1.11	37.14	62.86	0.09
	AVAILABILITY	1.47	1.35	5.71	92.29	0.00
	USAGE	0.72	0.69	83.74	11.18	0.49
Lower-middle	*GCU*	1.05	0.95	54.30	45.70	0.18
	ACCESS	1.34	1.20	27.27	72.73	0.02
	AVAILABILITY	1.53	1.35	15.15	84.85	0.00
	USAGE	0.84	0.74	92.36	7.64	0.54
Low	*GCU*	1.15	0.98	52.12	47.25	0.14
	ACCESS	1.13	1.14	42.76	57.14	0.12
	AVAILABILITY	2.36	1.40	9.52	90.48	0.00
	USAGE	0.79	0.71	61.62	37.38	0.19

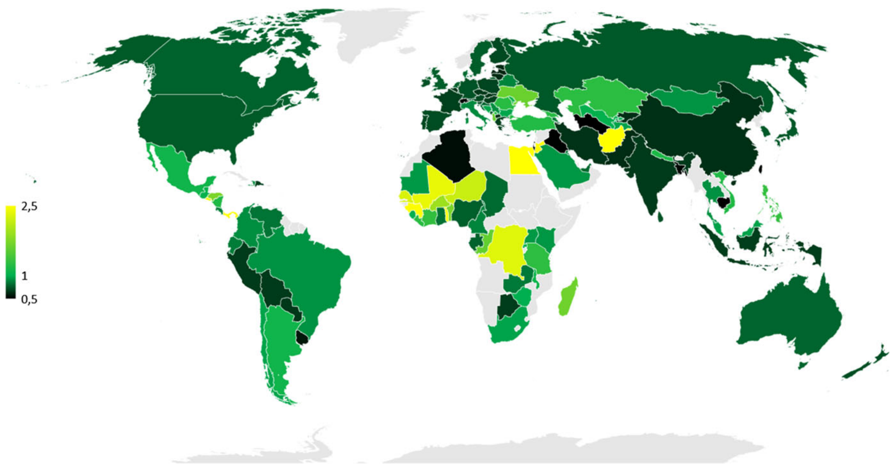


Fig. 6 World map for the heterogeneity gap of catching-up effects

revealing that while heterogeneity gaps have, on average, fallen over time, there is still heterogeneity among countries.

Similar reasoning can be applied to obtain a bipartite decomposition of the environment change effect:

$$EC(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = EC^{c}(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) \times GEC^{k}(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}). \tag{17}$$

Table 8 Category-specific environment effects—descriptive statistics

Income group	Index	Average	Median	Regress %	Progress %	*p* value
High	*EC*	1.05	1.05	4.39	95.87	0.00
	ACCESS	1.15	1.17	1.21	98.98	0.00
	AVAILABILITY	1.14	1.71	31.71	65.85	0.03
	USAGE	1.30	1.24	2.17	94.52	0.00
Upper-middle	*EC*	1.19	1.17	15.71	81.43	0.00
	ACCESS	1.14	1.10	15.14	77.74	0.00
	AVAILABILITY	1.48	1.47	4.74	91.54	0.00
	USAGE	1.25	1.25	7.47	90.74	0.00
Lower-middle	*EC*	1.14	1.15	1.09	94.88	0.00
	ACCESS	1.01	1.01	4.12	94.51	0.00
	AVAILABILITY	1.37	1.35	3.03	96.97	0.00
	USAGE	1.46	1.47	2.14	94.47	0.00
Low	*EC*	1.24	1.27	24.21	75.54	0.00
	ACCESS	1.11	1.07	34.54	57.89	0.06
	AVAILABILITY	1.75	1.02	12.52	78.59	0.00
	USAGE	1.46	1.44	2.32	95.24	0.00

$EC^k(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ captures the environment effect for country k in group c. Formally, $EC^c(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = \left[\frac{FI_i^c(\mathbf{x}_{ki}^{FI})}{FI_f^c(\mathbf{x}_{ki}^{FI})} \times \frac{FI_i^c(\mathbf{x}_{kf}^{FI})}{FI_f^c(\mathbf{x}_{kf}^{FI})}\right]^{1/2}$. Next, $GEC^k(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI})$ reflects the heterogeneity gap change for the environment effect for country k. Formally, it is defined as: $GEC^k(\mathbf{x}_{ki}^{FI}, \mathbf{x}_{kf}^{FI}) = \left[\frac{FI_i(\mathbf{x}_{ki}^{FI})/FI_i^c(\mathbf{x}_{ki}^{FI})}{FI_f(\mathbf{x}_{ki}^{FI})/FI_f^c(\mathbf{x}_{ki}^{FI})} \times \frac{FI_i(\mathbf{x}_{kf}^{FI})/FI_i^c(\mathbf{x}_{kf}^{FI})}{FI_f(\mathbf{x}_{kf}^{FI})/FI_f^c(\mathbf{x}_{kf}^{FI})}\right]^{1/2}$. When it is larger (smaller) than 1, this implies that the heterogeneity gap decreases (increases) for the environment effect. Note that both the category-specific environment effect and the heterogeneity gap change are defined using geometric averages (see our discussion of (15)). Results are given in Table 8 for the category-specific environment effects.

All groups experienced improvements in FI environment on average. For high-income economies, more than 95% have had a better environment since 2011, with 5% improvement on average. This improvement is 19% when considering all countries instead of only high-income countries (see Table 4). Without controlling for heterogeneity, the improved environment for FI is overestimated for that group. Among the three dimensions, usage had the greatest improvement (30% on average) and availability the lowest (14%). The effect is 41% for usage and 32% for availability when considering all economies, which again is an overestimate. The upper-middle-income group performed better than the high-income group in terms of environment improvement (increase of 19%). In contrast to the high-income group's results, upper-middle-income economies had a large improvement in the availability dimension (48%). Interestingly, compared with the catching-up effect, the increasing level of the pure environment effect is lower for most dimensions. Within the lower-middle-

Table 9 Heterogeneity gaps for the environment effects 2011–2017

Income group	Index	Average	Median	Regress %	Progress %	*p* value
High	*GEC*	1.00	0.99	56.20	42.80	0.11
	ACCESS	0.97	0.97	92.71	68.29	0.08
	AVAILABILITY	1.07	1.08	41.46	56.10	0.13
	USAGE	0.79	1.08	98.57	1.15	0.47
Upper-middle	*GEC*	1.02	1.03	42.57	51.43	0.12
	ACCESS	1.00	1.00	31.43	68.57	0.06
	AVAILABILITY	0.90	0.80	48.57	51.43	0.11
	USAGE	0.78	0.76	91.14	8.57	0.48
Lower-middle	*GEC*	0.89	0.91	87.87	12.12	0.51
	ACCESS	0.98	0.99	77.27	12.73	0.65
	AVAILABILITY	0.77	1.07	21.21	75.76	0.05
	USAGE	1.49	1.47	2.58	94.74	0.00
Low	*GEC*	0.95	0.98	57.47	41.41	0.29
	ACCESS	0.93	0.98	33.33	66.67	0.21
	AVAILABILITY	1.01	1.00	19.05	80.95	0.00
	USAGE	0.97	0.96	85.71	14.29	0.25

income group, the FI environment for the access dimension improved only by 1% on average. The availability and usage environment effects increased by 37% and 46%, respectively. For all dimensions, more than 94% of economies had a positive environment change. The largest environment improvement within groups occurred in the low-income category on all dimensions: +24% for overall environment change, 11% for access, 75% for availability, and 46 per cent for usage. All these are confirmed by the *p*-values of the KS tests. All in all, without controlling for heterogeneity, the environment effects were overestimated for high-income and lower-middle-income economies on average and underestimated for low-income economies, especially for the availability and usage dimensions.

We end our analysis with heterogeneity gap changes for the environment effects. Results are given in Table 9 and Fig. 7. In Fig. 7, green color indicates an economy has no change in heterogeneity gaps for environment effect on average, light green and yellow represent a reduction in the environment heterogeneity gap, and dark green and black mean increases in this gap. High-income economies have no change in heterogeneity gaps on average. That is, the impact of economic development for the environment component on average remained the same over the survey period. The upper-middle-income economies have the largest reduction in environment heterogeneity gap: 51.43% of economies in that group reduced their gap. It indicates that the impact of economic development on the environment effect declines over time for that group. However, a large percentage of lower-middle- and low-income economies show greater gaps. The average heterogeneity gap for the environment effect for these two groups is less than 1, indicating increases in heterogeneity gaps; that is, economic development level plays a more important role in the environment

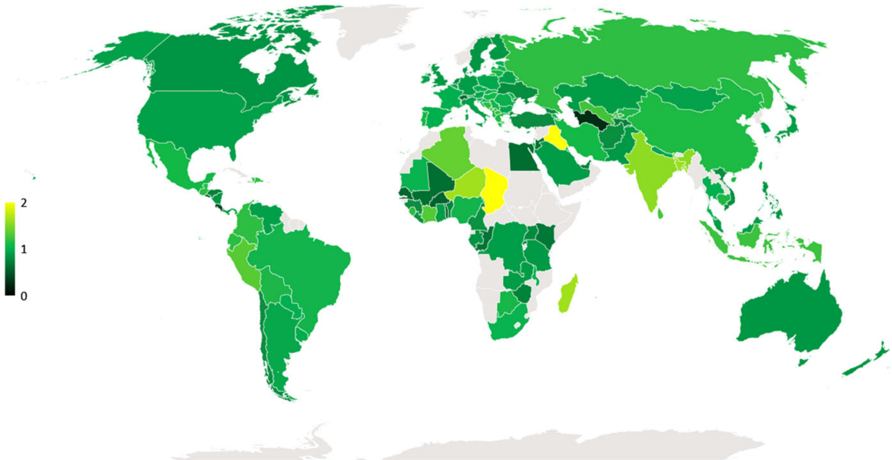


Fig. 7 World map for the heterogeneity gap of the environment effects

change effect. More than half of the economies decreased their gap for at least two dimensions. This is indeed confirmed by the p-values of the KS tests. For example, 94.74% of lower-middle-income economies made progress in decreasing the usage dimension heterogeneity gap and the average gap decreased by 49%. One may interpret our results as success of the World Bank's efforts to reach the UFA goal by 2020. World Bank identified 25 priority countries, which together represent 70 per cent of the unbanked adult population worldwide, to promote financial access, by developing and implementing National FI Strategies in these countries (World Bank 2015). These countries are mainly lower-middle- and low-income economies, and it is for that group that we observe large positive environment change effects. In addition, we find that the impact of economic development level, represented by income per capita, has become more and more important for these two income groups.

3 Conclusion

Financial inclusion (FI) has been developed intensively worldwide due to improvements in the access, availability, and usage of financial services. More than 60 national governments recognize it as one of the main tools for boosting household income and economic development. It has been set as a goal in the UFA by 2020 by the World Bank and the 2030 Sustainable Development by the United Nations. With the Fintech movement, national financial inclusion strategies continue to lean toward digital finance (Kass-Hanna et al. 2021). Therefore, having a reliable measure of FI with digital finance components is crucial for better understanding progress in FI and better designing financial industry strategies and policies.

In this research, we use data from both demand and supply sides and apply a data-driven approach to measure FI of countries. Our FI composite index is based on three dimensions: access, availability, and usage, with digital finance indicators included for each dimension. We observe positive catching-up effects for 84.62 per cent of our 130 countries over the time period 2011 to 2017. Economies with lower initial FI levels have, generally, higher catching-up effects. By measuring the environment change effect, which is used to verify whether policy makers have succeeded in creating an environment that fosters FI, we find that policy makers have succeeded in improving the environment for FI for most of the countries. However, the magnitude is smaller than the catching-up effect. In general, both effects contribute to the FI development.

In addition, we control for economic development heterogeneity and decompose the composite index change into explanatory factors. Commonly, heterogeneity is analyzed after FI is computed, which is used in average comparison and regression analysis. As a result, the FI index fails to capture the pure performance differences due to the bias caused by the heterogeneity. We solve this issue by considering the economic development gap before evaluating FI of each country. We confirm the presence of significant heterogeneity among countries, and that economic development is closely related to FI. We show that catching-up improvement is due to a positive within-group pure performance increase and a decrease of the economic development impact for lower-income groups. For higher-income groups, the catching-up effect is also positive, although the economic development impact becomes slightly larger.

Our findings have several important policy implications. First, we confirm that governments, the private sector, and international institutions have made significant efforts to improve FI. Second, economies with low initial FI levels have experienced substantial catching-up effects, consistent with a strong government push to promote FI. The lower the income level of an economy, the digital finance plays a more important role in providing access to financial services. To continue such positive FI movement, improving financial and technological infrastructure and designing financial and digital education programs can be helpful. Next, although policy makers have succeeded in improving the environment for FI at the overall level, this is not true for all economies or all dimensions. We recommend policy makers target these countries which experienced regression in their environment first in all three dimensions. In particular, the focus is suggested to put on the access dimension for these regressed upper-middle- and low-income economies and on the availability dimension for the regressed high-income economies. In addition, we observe a decrease in heterogeneity gap among economics for the catching-up effect through access and availability dimensions, but a negative contribution of the usage dimension. To reduce such heterogeneity gap, our results suggest that further supports for the usage dimension are needed. In a sense, the first step was to make financial services available; now, it is crucial to promote usage to further increase FI. Finally, policy makers are recommended to make further efforts to improve the financial policy environment, especially for economies with lower FI levels in high- and middle-income economies.

Declarations

Conflict of interest The authors declare that they have no conflict of interests.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Appendix

See Table 10.

Table 10 Income categories

Income group	Economy
High	Australia, Austria, Bahrain, Belgium, Canada, Chile, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong (China), Hungary, Ireland, Israel, Italy, Japan, Korea, Rep., Kuwait, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Poland, Portugal, Saudi Arabia, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan (China), United Arab Emirates, United Kingdom, United States, Uruguay
Upper-middle	Albania, Algeria, Argentina, Azerbaijan, Belarus, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Croatia, Dominican Republic, Ecuador, Gabon, Iran, Iraq, Kazakhstan, Macedonia, Malaysia, Mauritius, Mexico, Montenegro, Panama, Paraguay, Peru, Romania, Russian Federation, Serbia, South Africa, Thailand, Turkey, Turkmenistan, Venezuela
Lower-middle	Bangladesh, Bolivia, Cambodia, Cameroon, Congo, Rep., Cote d'Ivoire, Egypt, El Salvador, Georgia, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Kosovo, Kyrgyz Republic, Mauritania, Moldova, Mongolia, Nicaragua, Nigeria, Pakistan, Philippines, Sri Lanka, Tajikistan, Ukraine, Uzbekistan, Vietnam, West Bank and Gaza, Zambia
Low	Afghanistan, Benin, Burkina Faso, Chad, Congo, Dem. Rep. Guinea, Haiti, Liberia, Madagascar, Malawi, Mali, Nepal, Niger, Rwanda, Senegal, Sierra Leone, Tanzania, Togo, Uganda, Zimbabwe

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