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MULTIDIMENSIONAL INDEX MEASURES OF DIGITAL FINANCIAL INCLUSION IN EMERGING MARKETS: A CASE OF INDIA

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ABSTRACT

The purpose of the study is to measuring with multidimensional index of digital financial inclusion in emerging markets, particularly in aspects of India performance. Despite the promise of digital financial services to reach the unbanked, challenges remain in emerging markets. Digital financial services (DFS) are an effective means of enhancing financial inclusion in emerging markets. There's no doubt the business world is rapidly changing to provide Digital financial services and having significant potential to provide a range of affordable, convenient and secure banking services to poor people in developing countries. In addition to having financial inclusion benefits, they can lower transaction costs for businesses. DFS generally refers to the extensive technologies available to deliver financial services from a broad range of providers to a wide range of recipients using digital remote means (including e-money, mobile money, card payments, and electronic funds transfers). Poor people experience far fewer barriers to accessing digital technology than formal financial services, so delivering financial services digitally should make these services more accessible. The researcher relies on demand and supply-side digital financial services to measure the extent of financial inclusion at country level for Indian states. Researcher postulate that the degree of financial inclusion is determined by three dimensions: usage, barriers and access to financial inclusion. Weights assigned to the dimensions are determined endogenously by employing a two-stage Principal Component Analysis. This composite index offers a comprehensive measure of the degree of financial inclusion, easy to understand and compute and also to provide them with a more reliable, affordable, and accessible way of managing their digital financial inclusion.

Keywords: Digital Financial Services, extensive technologies, Principal Component Analysis, inclusion access, usages, barriers.

JEL: G32, G38, O10, O12, O16, O23

Introduction

Digital financial services (DFS) is transformation the technologies to enable for unbanked people gaining access to financial services through digital channels. These modern times enhancing the Banks, microfinance institutions, mobile operators, and other providers are using mobile phones and point-of-sale devices, along with networks of small-scale agents, to offer basic financial services at greater convenience and lower cost than traditional banking allows. Also referred to as branchless banking, these digital services offer great promise for better serving poor customers (Xavier Faz, Kabir Kumar, Steve Rasmussen, 2016)

Digital Financial Services (DFS) can be implemented in several ways. In the emerging markets the most widely used method is bank-led branchless banking. This typically involves banks taking responsibility for the storage of funds, marketing, branding, and managing customer relations, as well as compliance and engagement with financial regulators. Under this model, banks leverage telecommunications services and agents to enlarge their customer base and increase their market share. A model like this not only provides the benefit of advancing nationwide financial inclusion, but also reduces transaction costs for businesses and their suppliers in rural and remote areas. Bank- led branchless banking in the Pacific was pioneered by Nationwide Microbank (now trading as MiBank) in Papua New Guinea (PNG).MiBank's MiCash mobile wallet and bank account product use the Digicel mobile phone network to bring banking services to rural and remote communities(Banthia, 2013)

Background of the Study

The challenges of Digital financial services for financial inclusion are to deliver at a cost affordable to the unbanked people particular low-income groups through technology. If unbanked people does not have awareness on utilize the technology, not able affordable and there are no suitable relent financial products for unbanked groups. They are also raising important new regulatory issues for policy makers seeking to ensure these services are significant numbers of poor and low-income customers are not able to transfer funds and not

able to store value via digital transactional platforms accessed through mobile phones or other low-cost digital communications infrastructure in India. The problem of assess to finance is a complex for unbanked people and they faced various type of problems. There is a wide disparity across the nation. The six largest cities in India have 11% of the country's bank branches. Meanwhile, the 50 poorest districts have 4,068 loan accounts per 100,000 people, compared with the national average of 11,680. These districts have just 3 branches per 100,000 people, which are less than half the all India average of 7.6 (Amarante Consulting, 2014).

The multidimensional measurement of digital financial inclusion is important in several aspects. First, a measure that aggregates several indicators into a single index aids in summarizing the complex nature of digital financial inclusion and helps to monitor its evolution. A good index is better at extracting information. Second, a better measure of digital financial inclusion may allow us to study the relationship between digital financial inclusion and other macroeconomic variables of interest. Third, information by dimension helps to better understand the problem of digital financial inclusion. It can be a useful tool for policy making and policy evaluation.

On the other side lack of usage of the formal financial service by individuals, due to lack of knowledge, awareness, financial products and lack of financial literacy. The demand side problem is the accurate data is not available from unbanked population from Indian states. The barriers to financial inclusion, perceived by unbanked individuals, provide information about the obstacles that prevent them from using formal financial services. The lack of a harmonized measure that collects multidimensional information to define digital financial inclusion is a pitfall that complicates the understanding of several related problems. There is nobody measures the multidimensional aspects of financial inclusion up to now. Hence there is measurement gap of status of digital financial inclusion (Cámara, 2016).

In the literature indicates that lack of a harmonized measure that collects multidimensional information to define digital financial inclusion is a pitfall that complicates the understanding of several related problems. The multidimensional measurement of digital financial inclusion is important in several aspects. These are measuring the aggregates several indicators into a single index aids in summarizing the complex nature of digital financial inclusion and helps to monitor its evolution. And also measuring the digital financial inclusion may allow us to study the relationship between digital financial inclusion and other macroeconomic variables of interest. Moreover, information by dimension helps to

better understand the problem of digital financial inclusion. It can be a useful tool for policy making and policy evaluation.

The paper is organized as follows: section two reviews the related literature and find the gap of those studies. Section three, will describes the methodology for constructing our composite index from multi-dimensional data and the results of the sub-indices as well as the composite digital financial inclusion index. Finally, analyses the robustness of our index and conclusion.

Literature Reviews:

AurélieLarquemin(2016) indicated that despite conclusive proof of positive outcomes of older and more recent initiatives towards financial inclusion, Indian authorities and financial inclusion actors lack measurement and knowledge of the outcomes and impact of these past and actual initiatives. It is commonly acknowledge than the shift in the financial inclusion efforts, as illustrated in the PradhanMantri Jan- DhanYojana (PMJDY) policies and recent schemes like the DBT program, are a move in the right direction. However evidence are lacking to establish correlation or causality between specific policies and the financial inclusion situation in India, and to design the next phases.

Manoj Sharma, AnurodhGiri and SakshiChadha(2016),Conduct behavioural economics research to reduce prevalent customer account dormancy - 28% of the PMJDY accounts are dormant. Also 28.88% of the customer accounts are zero or nil balance accounts. Behavioural economics-based research is needed to better understand reasons for customer dormancy and product preferences to drive usage of these accounts for real savings.

Shweta S. Banerjee (2015) Concluded that Global literature on government-to-person (G2P) payments suggests that although digitizing government flows has led to efficiencies for the system, the direct positive impact on financial inclusion is unclear. One of the reasons is that the policy experts designing electronic payment channels are working separately from those designing financial inclusion policies. There is also a matter of sequence. If the digital plumbing is already in place - such as a branchless banking network, a system of agents, or a robust authentication system - then the government can leverage that network for disbursing payments. Pakistan is illustrative of this. Easy Paisa agents, for example, are used to disbursing the Benazir Income Support funds to some of the poorest women in the country – but those agents already were in place and providing financial services.

World Bank Group (2015) reported conclude that the Account ownership at a bank or other financial institution, or through a mobile money or other type of e-money account has

increased among men and women across the globe. However, the 2014 Global Findex database shows that women in developing countries are less likely to have an account than men, even after control ling for income and other individual characteristics worldwide are 7 percentage points more likely than women to own an account. The gender gap in developing economies is 9 percentage points. The gap is largest in South Asia, where only 37 percent of women have an account compared with 55 percent of men.

Methodology

Researchers will use the methodology focus on basic digital financial services, as these services typically constitute the entry point and are the area of greatest immediate need for individuals whose prior engagement with the formal financial sector has been limited, s digital financial service offerings particularly those accessible through mobile telephones mature and become more readily available to the underserved (and consequently, as data associated with these offerings become more widely available), researcher will expand our consideration of financial service offerings to include a broader scope of financial services (e.g., micro insurance and microcredit).

Digital financial inclusion is a broader term that can encompass access to non-financial information and services based on secondary data to estimate the Multidimensional Digital Financial Inclusion Index (MDFII) covering all over Indian states for the year 2010 to 2016. The weights of the index are obtained from a two-stage Principal Component Analysis (PCA) for the estimation of a latent variable. First, researcher applies PCA to estimate a group of three (access, usage and barriers) sub-indices representative of digital financial inclusion. Principal Component Analysis (PCA) to estimate the overall digital financial inclusion index by using the previous sub-indices as causal variables. Researcher will use a parametric method that avoids the problem of weight assignment. Second, researcher offer a harmonized measure of digital financial inclusion for a larger set of Indian states that allows comparisons across states and over time.

In this paper the researcher will construct the Multidimensional Digital Financial Inclusion Index (MDFII) covering 29 Indian states for the year 2010 to 2016 March. The weights of the index are obtained from a two-stage ***Principal Component Analysis (PCA)*** for the estimation of a latent variable. First, researcher applies PCA to estimate a group of three sub-indices representative of digital financial inclusion. Second, researcher applies again PCA to estimate the overall digital financial inclusion index by using the previous sub-indices as causal variables. This index improves existing digital financial inclusion indices in

several ways. On the other side, researcher uses a parametric method that avoids the problem of weight assignment and offers a harmonized measure of digital financial inclusion for a larger set of Indian states that allows comparisons across Indian states since 2010 to 2016.

Finally, researcher provides a comprehensive definition of digital financial inclusion combining information from a large set of indicators from both demand and supply-side data sets, and from two perspectives: banked and unbanked population. It is the first time that a composite index uses a demand-side data set at individual level to measure the level of digital financial inclusion across Indian states. Researcher identifies two problems in the current digital financial inclusion indices. First, existing attempts to build digital financial inclusion indices rely only on supply-side country level data and come up with inaccurate readings of digital financial inclusion due to the existence of measurement errors in the usage indicators. Supply-side indicators, particularly the number of accounts or loans, can overestimate the inclusiveness of financial systems since unbanked population in India does not have even single account. Second, assigning exogenous weights to indicators is often criticized for lack of scientific rigour because exogenous information is imposed.

There are two commonly used approaches to constructing composite indices: non-parametric and parametric methods. Non-parametric methods assign the importance of indicators by choosing the weighs exogenously. There is evidence that indices are sensitive to subjective weight assignment, since a slight change in weights can alter the results dramatically (Lockwood, 2004)Sarma (2008, 2012) and Chakravarty and Pal (2010) are examples of digital financial inclusion indices that apply this methodology to usage and access indicators from supply-side country level data sets. Parametric methods sustain that there exists a latent structure behind the variation of a set of correlated indicators so that the importance of indicators (weights) in the overall index can be determined endogenously through the conversation between the indicators on each dimension of the structure. In brief, weights are determined by the information of sample indicators. There are two parametric analyses commonly used for indexing: PCA and Common Factor Analysis. (Amidzic, 2014). However, the indicators used to digital financial inclusion only include limited supply-side information at country level. What is more, from an empirical point of view, PCA is preferred over Common Factor Analysis as an indexing strategy because it is not necessary to make assumptions on the raw data, such as selecting the underlying number of common factors (Steiger, 1979)

Dimensions of Digital Financial Inclusion and Data Sources

Researcher mainly approached by the usage and access to the formal financial services by using supply-side aggregate data (e.g. Honohan (2007); Sarma (2008, 2012); Chakravarty and Pal (2010) and Amid_zi_c et al. (2014). The only work that relies on demand-side data, at individual level, focuses on several usage and barriers-related indicators individually (Demirg uc-Kunt and Klapper, 2013). However, monitoring different indicators individually, although useful, does not offer a comprehensive understanding of the level of digital financial inclusion across Indian states. On the other hand, as mentioned, the few attempts to measure digital financial inclusion through composite indices are incomplete and subject to methodological problems and measurement errors.

On the other hand, to measure digital financial inclusion through composite indices are incomplete and subject to methodological problems and measurement errors. High usage levels of formal financial services or a broad availability of points of access do not mean necessarily that a system is inclusive. The usage of formal financial services can be conditioned by other socio-economic factors such as GDP per capita, human capital, legal framework, cultural habits or development status that make individuals use these kinds of services in a particular manner. Researcher considers the use of formal financial services as an output of digital financial inclusion rather than a measure of the inclusiveness of a financial system in itself. Likewise, the availability of infrastructure, ATMs and bank branches, captures the extent of accessibility to the formal financial system only partially. Since we do not have information about location or concentration of these points of service, it is not accurate to assert that higher measured levels of these indicators represent a more inclusive financial system.

This paper considers that access and usage are both necessary but not sufficient conditions for measuring the inclusiveness of a financial system. Our hypothesis is that focusing only on usage and access leads to limited measurement of digital financial inclusion. In this context, demand-side individual surveys that gather information on the perceived reasons why people fail to use formal financial services add significant information about.

Principal Component Analysis for Digital Financial Inclusion

Digital Financial inclusion is an abstract concept which cannot be measured quantitatively

in a straightforward way. However this variable is supposed to be determined by the interaction of a number of causal variables. Researcher will assume that behind a set of correlated variables we can and an underlying latent structure that can be identified with a latent variable as is the case of digital financial inclusion. Two important issues arise in the estimate of any latent variable: the selection of relevant variables and the estimation of parameters (weights).Regarding the first issue, it is not possible to rely on standard reduction of information criterion approaches for the selection of variables. For the second, since digital financial inclusion is unobserved, standard regression techniques are also unfeasible to estimate the parameters.

This is a preferred strategy because empirical evidence supports that PCA is biased towards the weights of indicators which are highly correlated with each other (Mishra,2007). Researcher minimizes this problem by applying two-stage PCA (Nagar and Basu, 2004). In the first stage, we estimate the three sub-indices: usage, barriers and access, which defined digital financial inclusion. In the second stage, Researcher estimates the dimension weights and the overall financial inclusion index by using the dimensions as explanatory variables.

Let us postulate that the latent variable financial inclusion is linearly determined as follows:

$$FI_i = w_1\, y_i^u + w_2 y_i^b + w_3 y_i^a + e_i \qquad (1)$$

where subscript i denotes the country, and (y_i^u, y_i^b, y_i^a) capture the usage, barriers and access dimension respectively. Thus, the total variation in financial inclusion is represented by two orthogonal parts: variation due to causal variables and variation due to error (ei). If the model is well specified, including an adequate number of explanatory variables, we can reasonably assume that the total variation in financial inclusion can be largely explained by the variation in the causal variables[1]

First Stage of Principal Component Analysis

First Stage PCA: The first stage aims to estimate the dimensions, that is, the three unobserved endogenous variablesy_i^u, y_i^b, y_i^a and the parameters in the following system of equations

$$y_i^u = \beta_1\, accpimt_i + \beta_2\, savings_i + \beta_3\, loan_i + u_i \qquad (2)$$

$$y_i^b = \theta_1\, distance_i + \theta_2\, affordability_i + \theta_3\, docu, emts_i + \theta_4 trust_i + \varepsilon_i \quad (3)$$

$$y_i^a = \gamma_1\, ATM_{popi} + \gamma_2\, branch_{popi} + \gamma_3\, ATM_{km^2 i} + \gamma_4\, branch_{km^2 i} + u_i \qquad (4)$$

(5)

[1] If the model is well specified, E(e) = 0 and the variance of the error term is relatively small compared to the variance of the latent variable, financial inclusion.

Where account is a variable that represents the individuals, who have at least one of the financial products and savings and loan represent individuals who save and have a loan in the formal financial system. Hence, the three dimensions are also indices that estimate by principal components as linear functions of the explanatory variables described in Table 1.

Descriptive statistics					
Variable	Obs	Mean	Std.Dev.	Min	Max
Usage					
Account	29	57	28	6	100
Loan	29	10.6	5.75	1.52	26.83
Savings	29	20.46	17.82	0.82	65.84
Access					
ATM/100,00 pop	29	56.18	52.46	0.49	270.13
Branches/100,000pop	29	20.82	17.91	0.66	89.73
ATM/100,00 km^2	29	53.38	136.73	0.03	1136.25
Branches/100,000km^2	29	17.38	26.51	0.03	131.74
Barriers					
Distance	29	17.06	11.65	0	49.16
Affordability	29	26.32	14.59	0	59.81
Documentation	29	18.6	11.98	0	49.47
Lack of trus	29	18.83	12.1		57.45

(Note that the endogenous variables are unobserved so we need to estimated them jointly with the unknown parameters: β, ∅and .Let Rp; (pxp) define the correlation matrix of the p standardize indicators for each dimension)

We denote λ_j (j= 1,…., p) as the j-th eigenvalue, subscript j refers to the number of principal components that also coincides with the number of indicators or sub-indices, p . $\varphi_j(px1)$ is the eigenvector of the correlation matrix. We assume that $\lambda_1 > \lambda_2 > \ldots\ldots\ldots > \lambda_p$(and denote P_k (k = 1, …., p) as the *k-th* principal component. We get the corresponding estimator of each dimension according to the following weighted averages:

$$y_i^u = \frac{\sum_{j,\ k=1}^{p} \lambda_i^u\ p_{ki}^u}{\sum_{j=1}^{p} \lambda_j^u} \qquad (6)$$

$$y_i^b = \frac{\sum_{j,\ k=1}^{p} \lambda_i^b\ p_{ki}^b}{\sum_{j=1}^{p} \lambda_j^b} \qquad (7)$$

$$y_i^a = \frac{\sum_{j,\ k=1}^{p} \lambda_i^a\ p_{ki}^a}{\sum_{j=1}^{p} \lambda_j^a} \qquad (8)$$

Where P_k = X λ_j. λ_j represents the variance of the k^{th} principal component (weights) and X is the indicators matrix. The weights given to each component are decreasing, so that the larger proportion of the variation in each dimension is explained by the first principal

component and so on. Following this order, the p^{th} principal component is a linear combination of the indicators that accounts for the smallest variance. In brief, this method represents a p-dimensional dataset of correlated variables by p orthogonal principal components, with the first principal component explaining the largest amount of information from the initial data. One issue using principal component analysis is to decide how many components to retain. Although a common practice is to replace the whole set of causal variables by only the first few principal components, which account for a substantial proportion of the total variation in all the sample variables, we consider as many components as the number of explanatory variables. Our concern is to estimate accurately financial inclusion rather than reducing the data dimensionality so, in order to avoid discarding information that could affect our estimates, we account for 100 per cent of the total variation in our database.

Second Stage PCA

The second stage of the principal component analysis computes the overall digital financial inclusion index by replacing y_i^u y_i^b and y_i^a in Eq. (1) and applying a similar procedure to the described in the first stage (to estimate the vectors of parametersλ). This produces the following estimator of the financial inclusion index:

$$FI_j = \frac{\sum_{j,\ k=1}^{p} \lambda_j \, p_{ki}}{\sum_{j=1}^{p} \lambda_j} \qquad (9)$$

The highest weight λ_1 is attached to the first principal component because it accounts for the largest proportion of the total variation in all causal variables. Similarly, the second highest weight λ_2 is attached to the second principal component and so on. After some algebra, we can write each component, p_{ki} of (9) as a linear combination of the three Sub-indices (p = 3) and the eigenvectors of the respective correlation matrices represented by $\emptyset$

$$p_{1i} = \emptyset_{11}\, y_i^u + \emptyset_{12}\, y_i^b + \emptyset_{13}\, y_i^a \qquad (10)$$

$$p_{2i} = \emptyset_{21}\, y_i^u + \emptyset_{22}\, y_i^b + \emptyset_{23}\, y_i^a \qquad (11)$$

$$p_{3i} = \emptyset_{31}\, y_i^u + \emptyset_{32}\, y_i^b + \emptyset_{33}\, y_i^a \qquad (12)$$

So that the financial inclusion index can be expressed as:

$$FI_i = \frac{\sum_{j=1,}^{3} \lambda_j (\emptyset_{j1}\, y_i^u + \emptyset_{j2} y_i^b + \emptyset_{j3} y_i^a}{\sum_{j=1}^{3} \lambda_j} \qquad (13)$$

Rearranging terms, we can express the overall financial inclusion index as a weighted average of the dimensions as in Eq. (1):

$$FI_i = w_1 y_i^u + w_2 y_i^b + w_3 y_i^a + e_i$$

where the relative weights (importance) of each dimension, w_k, in the final index are computed as[2] :

$$w_k = \frac{\sum_{j=1}^{3} \lambda_j\, \emptyset_{jk}}{\sum_{j=1}^{3} \lambda_j} \text{ k= 1,2,3.} \qquad (14)$$

In this section researcher present the estimated financial inclusion indices for 29 Indian states PCA for the year 2016 March. The correlation matrix for the causal variables used to measure digital financial inclusion is reported[3]. See the table below

Table 2
Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Account	1	-	-	-	-	-	-	-	-	-	-
Loan	0.53	1	-	-	-	-	-	-	-	-	-
Savings	0.81	0.57	1	-	-	-	-	-	-	-	-
ATMs=100,000 pop.	0.68	0.33	0.54	1	-	-	-	-	-	-	-
Branches=100,000 pop.	0.55	0.25	0.31	0.56	1	-	-	-	-	-	-
ATMs=1,000 Km2	0.35	0.11	0.34	0.60	0.20	1	-	-	-	-	-
Branches=1,000 Km2	0.44	0.00	0.35	0.45	0.56	0.64	1	-	-	-	-
Distance	-0.45	-0.25	-0.27	-0.39	-0.43	-0.21	-0.40	1	-	-	-
High cost	-0.43	-0.29	-0.28	-0.34	-0.26	-0.26	-0.30	0.55	1	-	-
Documentation	-0.31	-0.23	-0.16	-0.31	-0.28	-0.05	-0.13	0.49	0.39	1	-
Lack of trust	-0.18	-0.05	-0.30	0.01	0.08	-0.21	-0.26	0.03	0.31	-0.07	1

First Stage Empirical Results

In the first stage, researcher computes the weights for the causal variables for each sub-index and estimates the latent variables: usage, barriers and access that represent the

[2] In general the sum of the weights expressed by the formula above does not necessarily have to equal 1 due to the fact that principal component methodology normalizes the mode of each eigenvector to 1. The weights therefore could be very close to but not always equal to 1.

[3] Although the Global Findex reports reliable data for 123 countries, the lack of data to measure access in some of these countries and the tax haven status of others require us to reduce our sample size to 82 countries.

dimensions of financial inclusion. Since we construct the sub-indices as weighted averages of the principal components, it is possible to gather the coefficients for each causal variable. These weights are derived by Eqs. (2-4) and normalized such that their sum is 1.With regard to the weighting scheme, for the usage dimension, the indicator for loans has the highest weight (0.42), followed by having an account and savings, at 0.30 and 0.28 respectively, (see upper panel of Table 3).

Table 3

Principal Components Estimates

Usage					
Variable	PC_1	PC_2	PC_3	PC_4	norm. weight
Account	0.5968	-0.4551	0.6608	-	0.30
Loan	0.5126	0.8499	0.1223	-	0.42
Savings	0.6172	-0.2658	-0.7041	-	0.28
Eigenvalues	2.2617	0.5579	0.1804	-	
Access					
Variable	PC_1	PC_2	PC_3	PC_4	norm. weight
ATMs per 100,000 pop.	0.5204	0.0368	0.7283	-0.4443	0.33
Branches per 100,000 pop.	0.4546	0.7461	-0.0687	0.4816	0.35
ATMs per 1000 Km^2	0.4907	-0.6618	0.0282	0.5661	0.16
Branches per 1000 Km^2	0.5308	-0.0633	-0.6812	-0.5002	0.16
Eigenvalues	2.5050	0.8044	0.5530	0.1377	
Barriers					
Variable	PC_1	**PC2**	PC3	PC4	Norm. weight
Distance	0.5198	-0.3481	-0.2594	0.7358	0.23
Adorability	0.5357	-0.0126	-0.5986	-0.5955	0.24
Documentation	0.5184	-0.3407	0.7373	-0.2676	0.24
Trust	0.4172	0.8733	0.1757	0.1803	0.29
Eigenvalues	3.12863	0.585401	0.150115	0.135852	

Notes: The weights are normalised add up to 1

It is important to notice that although the weights are not evenly distributed, none of the indicators is dominant; this is a desirable condition for an index. For the access dimension, the ratios of ATMs and branches per adult population have higher weights than these ratios per square kilometer. The weights for the latter are half of the former (see middle panel of Table 3). This means that the indicators relative to population contain more information than the ones relative to area for exploring the access dimension. Finally, the lower panel of table 3 shows the weights for the indicators in the barriers dimension. For the first three indicators (distance, affordability and documentation), the weights are very similar, at 0.23, 0.24 and

0.24 respectively. Lack of trust is the most important indicator in finding the barriers dimension, with a weight of 0.29.

Since weights are obtained from the information in the principal components and the corresponding eigenvalues, it is worth studying the composition of these components to understand the structure of our estimated indices. See the table 4

Table 4

Cumulative Variance Explained by Components

Components	Cumulative variance
	Usage
PC_1	0.7539
PC_2	0.9399
PC_3	1
	Access
PC_1	0.6262
PC_2	0.8273
PC_3	0.9656
PC_4	1
	Barriers
PC_1	0.7822
PC_2	0.9285
PC_3	0.9660
PC_4	1

Table 4 shows, in a cumulative way and by dimensions, the amount of the total variance explained by the different components. For the usage dimension, we observe that the first component, which contains 75% of the total information in this dimension (see Table 4) has an even contribution of the three indicators: account, loan and savings. This suggests that these three indicators measure the same latent structure. However, only the indicator referring to loans adds extra information through the second component. It might indicate that having a loan also represents a stage of greater digital financial inclusion since most people who have a loan already have another financial product, such as a bank account or pay-roll account. As a result, having a loan may be an accurate indicator to identify more consolidated stages of digital financial inclusion. When defining the access dimension, as shown in the middle panel of Table 3, we again and an even contribution of the four indicators to the first principal component since the coefficients in the eigenvector for this component are similar. However, variables related to population are more powerful in measuring access since they add information in the second and third component as well. Finally, for the barriers dimension, we also find that the four indicators

contribute evenly to the first component, which accounts for almost 80 per cent of the total variation in the data. Distance, affordability and documentation have their highest loadings in the first component. Although lack of trust contributes to the first component, it has its highest weighting in the second component, which indicates that this variable also adds extra information in a different structure from the first component. Lack of trust is a structural variable that can be related to not only idiosyncratic financial system issues (efficiency of financial institutions, financial stability, episodes of bank failures, etc.) but also to broader issues beyond the financial markets, such as governance, cultural norms, economic crises or macroeconomic variables such as inflation.

State wise dimensional indices with ranks and Financial Inclusion Index (FII)

Researcher have analysed the ranks of states based on dimensions namely Demand, Supply, and Infrastructure. Researcher computed Digital Financial Inclusion Index (DFII), which is the composite index of all these three dimensions in India. Researchers applied the impact factor of drag, on the Digital Financial Inclusion Index, and have arrived at a final index termed as Comprehensive Financial Inclusion Index (CFII). Researcher compared the CFII results with 1) financial inclusion index developed by CRISIL (2013). Multi-dimensional index indicates that backwardness of States calculated by Rajan Committee Govt. of India (2013). Ranks of states by percentage of poor people and percentage of households having banking facility (Census of India 2011) with Per capita income.

Table: 5

State wise dimensional indices with ranks and Financial Inclusion Index (FII)

S. No	Name of the State	FII(Rank) (Access, Usage, Barriers	Demand Index(Rank) (Access, Usage, Barriers	Supply Index(Rank) (Access, Usage, Barriers	Infra Index (Rank) (Access, Usage, Barriers
1	Kerala	0.4116 (1)	0.4676(5)	0.6155 (2)	0.6263(2)
2	Goa	0.4116 (2)	0.5663 (2)	0.6398 (1)	0.6067(3)
3	Punjab	0.3345 (3)	0.2188 (12)	0.3699 (4)	0.6798(1)
4	West Bengal	0.3279 (4)	0.5216 (4)	0.3858 (3)	0.5233(5)
5	Tamil Nadu	0.3100 (5)	0.2860 (9)	0.3640 (5)	0.5227(6)
6	Andhra Pradesh	0.2763 (6)	0.5402 (3)	0.2831 (7)	0.4471(8)
7	Karnataka	0.2616 (7)	0.1121 (19)	0.2708 (8)	0.5491(4)
8	Telengana	0.2575 (8)	0.2966 (8)	0.3165 (6)	0.3713(11)
9	Uttarkhand	0.2547 (9)	0.4255 (6)	0.2706 (9)	0.3845(10)
10	Himachal Pradesh	0.2342 (10)	0.6566 (1)	0.2461 (10)	0.3548(13)
11	Haryana	0.2313 (11)	0.1686 (14)	0.1787 (15)	0.5119(7)
12	Arunachal Pradesh	0.2295 (12)	0.3038 (7)	0.1897 (12)	0.4205(9)
13	Gujarat	0.1937 (13)	0.1356 (17)	0.1891 (13)	0.3598(12)
14	Odisha	0.1928 (14)	0.2464 (11)	0.2113 (11)	0.2799(15)

15	Uttar Pradesh	0.1626(15)	0.2453 (12)	0.2111(14)	0.26653(14)
16	Assam	0.1577 (16)	0.2486 (10)	0.1649 (16)	0.2141(20)
17	Bihar	0.1442(17)	0.1492(16)	0.1195(18)	0.2588(17)
18	Rajasthan	0.1416 (18)	0.0421 (21)	0.09601 (20)	0.2658(16)
19	Chhattisgarh	0.1352 (19)	0.1541 (15)	0.1263 (17)	0.2187(19)
20	Jharkhand	0.1235 (20)	0.1287 (18)	0.0743 (21)	0.2518(18)
21	Jammu & Kashmir	0.1066 (21)	0.1773 (13)	0.1004 (19)	0.2091(21)
22	Madhya Pradesh	0.1057(22)	0.1679(14)	0.1014(20)	0.2187(22)
23	Mizoram	0.10456(23)	0.1563(13)	0.1123(21)	0.2258(23)
24	Nagaland	0.10346(24)	0.1356(14)	0.10564(22)	0.2165(24)
25	Sikkim	0.10258(25)	0.1267(15)	0.10427(23)	0.1892(25)
26	Tripura	0.10154(26)	0.1173(16)	0.10234(24)	0.1748(26)
27	Meghalaya	0.0871(27)	0.1057(17)	0.0862(25)	0.0872(27)
28	Maharashtra	0.0521(28)	0.0631(18)	0.0523(26)	0.0623(28)
29	Manipur	0.342(29)	0.351(19)	0.0425(27)	0.0468(28)

The Digital Financial Inclusive Index (DFII) is a composite index of all three dimensions and emphasizes on uniform development of the states across these three dimensions. It suggests a direction for policymakers to improve the performance. The purpose of this analysis is to find out the dimensions across which a particular state is doing well or is underperforming.

The States having uniform development across at least two dimensions have shown better overall rank e.g. Kerala, Goa and Tamil Nadu. Kerala has secured second rank in Supply and Infrastructure dimensions both. In supply dimension it is observed that the State has highest number of Life Insurance offices and agents in India, area wise. In infrastructure dimension it has highest female literacy and ranks first in health indicator. Goa tops the list as per Supply dimension, as it has highest penetration of bank branches and ATMs in India, geographically as well as demographically. It has second rank in Demand dimension, which is mainly because of first rank in insurance density indicator. Tamil Nadu has shown uniform development accorss all three dimensions.

In Demand dimension, it ranks second in NBFCs, and third in Bank factor. In Infrastructure, it is showing uniform development across all factors. There is a group of states having one of the dimensions as well developed but remaining two are comparatively very poor. These states are Himachal Pradesh, Andhra Pradesh and Gujarat. Himachal Pradesh ranks third in Demand dimension, and seventh and eighth in Supply and Infrastructure dimensions respectively. All factors of Demand dimension namely Bank, NBFCs, and Insurance are comparatively well developed. The State ranks low in transport and irrigation indicators in Infrastructure dimension. Andhra Pradesh tops the list in Demand dimension, and other group comprises states, namely Punjab and Haryana, where poor development in

one dimension has adversely affected their overall ranking. Punjab ranks 12th in Demand dimension, which is getting affected by NBFCs factor. Haryana ranks nineteenth in Demand dimension. In Demand dimension, it is poor in NBFCs and insurance factors.

Second Stage Empirical Results

In the second stage, researcher applies PCA on the three sub-indices (usage, access and barriers) to compute their weights in the overall index. Table 6 presents the composition of the principal components and the normalized weights for each dimension or sub-index.

Table:6 Principal Component Estimates

	Principal Component Estimates			
	Financial Inclusion Index			
Variable	PC_1	PC_2	PC_3	norm. weight
Usage	0.5775	-0.5758	0.5787	0.29
Access	0.5437	0.8001	0.2535	0.42
Barriers	0.609	-0.1682	-0.7752	0.28
Eigenvalues	2.28051	0.485501	0.233989	

Notes: The weights are normalised add up to 1

The last column shows that PCA assigns the highest weight to access (0.42), followed by usage with a weight of 0.29 and barriers at 0.28. Thus, this information reveals that access is the most important dimension for explaining the degree of digital financial inclusion. Supply of formal financial services contributes more than number of users to explain the latent structure behind our pool of indicators, ie, the degree of financial inclusion. Access is a key since it represents a necessary but not sufficient condition for using formal financial services.

In terms of the principal component structure, Researcher observe that the first and most important component, accounting for 76 per cent of the total variation in the data (see Table 7), has an even contribution of the three dimensions.

Table 7

Cumulative Variance Explained by Components

Components	Cumulative variance
	Financial Inclusion Index
PC_1	0.7602
PC_2	0.9220
PC_3	1

This indicates that the three dimensions measure the same latent structure which is interpreted as the degree of digital financial inclusion. Moreover, unlike usage and barriers,

access allocates part of its information in the second component, so this dimension not only contributes to the overall index through the first principal component, but also adds extra information through the second component and gains importance in explaining the overall index.

Conclusions and policy recommendations

Digital Financial inclusion is an essential ingredient of economic development and poverty reduction and it can also be a way of preventing social exclusion. A person's right to use formal financial services, as a way of preventing social exclusion, must be a priority. However, efforts to measure digital financial inclusion are scarce and incomplete. Digital Financial inclusion is a multidimensional concept that cannot be captured accurately by single indicators on their own, but is determined by a much larger set of indicators than the few considered so far. The nature of the financial systems is complex and heterogeneous. An inclusive financial system needs particularly to encourage usage of its services on the part of society's most vulnerable groups; that is, those most a effected by obstacles to digital financial inclusion.

Digital Financial Inclusion Index was computed, for 29 states using data for indicators of three dimensions namely; Supply, Demand and Infrastructure. After application of impact of Drag factor the Comprehensive Index of Digital Financial Inclusion is arrived at. On the basis of the range of index, states are grouped in four categories namely High, Higher Middle, Lower Middle, and Low.

Kerala tops ranks as per CFII and Manipur comes lowest. Out of 29 States, there are no states under High and Higher Middle category. Kerala and Goa come under lower middle category, and all other States are under low category, indicating the scope for further development

On the other hand, existing composite indices to measure digital financial inclusion, taking arbitrary weights, are questionable. This paper proposes a two-stage PCA to measure the extent of digital financial inclusion for Indian States. This methodology is statistically sound for index construction and robust to high dimensional data. Researcher, measure digital financial inclusion through composite indices for 29 states by using 11 causal variables as digital financial inclusion determinants for 2016. Specially, our index assumes that the degree of digital financial inclusion is determined by the maximization of usage and access to formal financial services, as well as by the minimization of obstacles causing involuntary exclusion.

Demand-side information to assess the usage and barriers dimensions is a key in determining the degree of digital financial inclusion. The dimension of usage measures digital financial inclusion from the banked perspective, and barriers do so from the perspective of the unbanked. Information from excluded people helps to reveal a comprehensive picture of the extent to which a financial system is inclusive. Our major contribution is twofold. First, researcher uses a parametric method to determine the contribution of each indicator in our financial inclusion index. It has the advantage of not employing any exogenous, subjective information. Second, researcher builds a comprehensive index that includes both demand- and supply-side information.

As shown by our estimates, access is the most important dimension for measuring the level of digital financial inclusion. This result suggests that supply of formal financial services is more important than number of users in explaining our index. Access represents a necessary but not sufficient condition for using formal financial services.

Policy makers

Both the Central and State Governments can objectively assess the state wise/area wise digital financial inclusion. They can identify the excluded areas and can design the programme suitable to the respective area. Index is based on three dimensions, and gives equal importance to each of them. By using the results, policymakers should give more resources to the dimension which is least developed. As such the index can be used as an objective tool for resource allocation. They should also try to reduce the impact of drag factors to improve overall situation

Regulators:

Regulators can give a differential treatment to the excluded area identified through this measure. This will encourage the banks to speed up the agenda for digital financial inclusion. This index can be used for shifting the policy focus from sector wise lending to segment wise lending i.e. to those that are truly underserved (Planning commission, Govt. of India, 2009). Regulators can use it for developing an "Information System" dedicated to financial inclusion covering indicators in the index.

Banks:

Banks can use this measure to continuously monitor and evaluate the performance of their area wise financial inclusion plan in digital financial services. We concluded that the degree of financial inclusion is highly correlated with some macroeconomic variables such as GDP per capita, education, efficiency of a financial system and financial stability. A non-remunerative and badly supervised last-mile service delivery system through banking correspondents was one of the key reasons for the flagship financial inclusion scheme failing on these parameters. The creation of such an index is useful to shed some light on the determinants of financial inclusion as well as its contribution to economic growth and development. Also, we believe that desegregated information on the different dimensions will be useful for policy recommendations. Efforts in such direction yield relevant improvements on the analysis of financial inclusion's causes and consequences. In general observation indicates that target-based attempt to open accounts led to confusion among people that the overdraft facility and was unhinged money the government would deposit once the accounts were opened.

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