Measuring financial inclusion on time: A multivariate index for Mexican municipalities 2013-2021

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Abstract

Access to financial services varies sharply around the world. In many countries less than half the population has an account with a financial institution, and this lack of access to finance is often the critical mechanism for generating income inequality and uneven growth. This is the case of Mexico, where financial exclusion has often been a critical issue for large shares of the population—mainly in rural and poorer localities. This is an abiding concern for policymakers, given how it thwarts socioeconomic opportunities to families and business alike, hampering economic growth and development. However, evaluating how relevant the issue is requires a careful measurement of financial inclusion which, up to now, has been achieved to a limited extent. We contribute to this literature and in this context by proposing a series of multivariate indices of financial inclusion for Mexico, at the municipal level for the period 2013-2021. The indices encompass different dimensions, including access, and usage, according to what is considered theoretically in the literature, but have been barely considered for the Mexican case. The results indicate that the shares of unbanked population are still large, although it is unevenly distributed in space.

Keywords: bank, financial development, financial inclusion, municipality, state

JEL Classification: G21, G23, G30, O16, R51

1. Introduction

Adequately measuring financial inclusion and identifying geographically financial exclusion is very relevant, recognizing the link of financial inclusion with economic growth and development. Specially in Mexico, in which an important part of the population has very scarce or null access and usage of financial services, mostly in rural and poor localities. In Mexico there is also a lag in financial inclusion for broader segments of population, that do not have an adequate range of financial services. Furthermore, even when there is infrastructure of access, people do not make enough use of the services, or have limitations or barriers for their extended use.

This is a long pending issue in Mexico, limiting socioeconomic opportunities to families and business, and impeding economic growth and development. From the public point of view, there is a perception that access to credit is limited, commissions are high, and the quality of financial services is low. The lack of financial inclusion persists even though it could be considered that the Mexican private banking system has the conditions to improve access, or extend credit. The Mexican banking system is considered solid, with good levels of capitalization and adequate prudential practice, even above international standards. It has good levels of profitability and even has been resilient to the economic contraction experienced as a result of the COVID pandemic. Its legal framework has been modernized in recent years, even though much more has to be done in this respect. Also, a Financial Reform has been undertaken in 2014, to ease restrictions, facilitate the extension of credit, and promote competition.

There are several limitations, barriers, or market failures that have impeded progress in financial inclusion, both from the supply and from the demand side. In fact, the conditions and limitations for financial inclusion in Mexico are very diverse in States, regions and municipalities, where there are municipalities very advanced, and others with severe lags. There are also several different issues of concern in Mexico regarding financial inclusion. To mention some of them, the difficulty of promoting financial inclusion in geographically remote located municipalities, the persistence of cash for many transactions even when access to financial services are available (Del Angel, 2016), and also an important gender gap in financial inclusion (López and CEEY, 2021).

In recent years, progress has been made, and other forms of access, different from more traditional branches or ATMS, have advanced importantly, like correspondents or mobile banking. Nevertheless, these new forms of access or new services could not be adequate or available for some segment of the population. This is the case for municipalities that do not have access to internet connection or do not have smartphones.

Financial inclusion is not simply the opposite of financial exclusion, the concept and concern of financial inclusion is broader. When we refer to financial exclusion we are worried about barriers of poor and disadvantaged social groups from accessing finance. Carbó, Gardener, and Molyneux (2005) define financial exclusion as the inability of some societal groups to access the financial system, particularly the barriers to accessing credit.

Financial inclusion is a broader concept related to access, usage, appropriateness, regulated and even reasonably priced financial services. This is clear from the definitions of financial inclusion that several researchers have stated. Demirguc-Kunt, Klapper, and Singer (2017) defined financial inclusion meaning that adults have access to and can effectively use a range of appropriate financial service. Such services must be provided responsibly and safely to the consumer and sustainably to the provider in a well regulated environment. Beck (2016) considers that financial inclusion is the access by enterprises and households to reasonably priced and appropriate formal financial services that meet their needs.

How to adequately measure financial inclusion?

An important question is how financial inclusion should be measured. With the aim of analysing financial inclusion, several variables or proxies have been proposed, intending to measure different aspects or dimensions of financial inclusion. Some indicators are frequently considered—such as banking infrastructure, or number of accounts—, either separately or jointly. Nevertheless, one indicator could show a contradictory panorama of inclusion when compared with other. For example, in Mexico there are many municipalities without bank branches, but with population holding important number of accounts. But even when they hold accounts, the people in municipalities with no bank branches could be excluded to have basic financial services of credit, savings, insurance, etc., provided with quality and an accessible price. Therefore if we only look at one variable, say accounts, we could arrive to incomplete or incorrect conclusions.

Financial inclusion varies in its dimensions across geographical regions as well as over time. Therefore, from individual indicators or dimensions we can get only partial information on financial inclusion. So, it is evident that financial inclusion is a multidimensional construct and should be measured in a way that gauges adequately the different variables that characterise it. Several researchers have proposed indices of financial inclusion that incorporate various banking sector variables that reflect the level of accessibility, availability and usage of banking services. These are composite indexes that are constructed by aggregating several sub-indices which represent different dimensions of financial inclusion, as considered theoretically in the literature.

Geometric BoD financial inclusion (FI) index

In this article we present a multivariate index of financial inclusion for Mexico, at the municipal level for 2013-2021. The source of the information is the Financial Inclusion Databases published quarterly by CONAIF (Consejo Nacional para la Inclusión Financiera). The indices will have several subdimensions of access and usage, according to what it is considered theoretically in the literature, but multivariate analysis is also conducted to determine the relevant subdimensions that will compose the index. In this way the subdimensions are derived from the data. Researchers construct indices of financial inclusion considering several dimensions that could be outreach, penetration, usage, cost and quality of the financial services. The index uses the dimensions considered previously in the literature, but do not includes dimensions of cost or quality of the financial services because there is no data available to measure this dimension at the municipal level.

The FI index for Mexico could have several applications:

1. As a yardstick to measure performance.
2. To make comparisons across municipalities or countries.
3. To estimate spatial effects in financial inclusion.
4. To evaluate financial inclusion policy measures in time.

We consider that the investigation can have several important contributions:

1. A robust methodology to construct a FI index for municipalities in Mexico is used. As suggested by European Commission and OECD (2008), Nardo et al. (2005), Greco et al. (2019). Conducting multivariate analysis prior to deciding the dimensions of the index, adopting an adequate mathematical formulation to measure financial inclusion, both for weighting and aggregation of the dimensions of the index, and finally conducting robustness analysis.
2. Most of the FI indices are for the country or regional level. Few studies construct indices for subnational levels.
3. The mathematical formulation of the index is innovative and adequate to measure financial inclusion. We propose a geometric mean index with Benefit of the Doubt (BoD) derived weights.To our knowledge this is the first FI Index constructed this way.

2. Theoretical framework

2.1. Financial development, financial inclusion and economic development

Financial inclusion has been seen as a dimension of financial development. Financial inclusion is considered to be associated to some degree with financial depth. As stated by Barajas et al. (2020), if a country mobilises a large amount of funds, it is more likely to provide services to a large percentage of individuals and firms. Financial depth indicators, such as private credit to GDP, could be considered imperfect and incomplete proxies for financial development. As argued by Barajas et al. (2020), it is possible for two countries to have identical levels of banking depth, but with one country allocating the same volume of credit to a handful of large, protected firms, while a second one distributes the funds more broadly across a wide range of firms and individuals. Financial inclusion is a concept related to financial development. It can be measured by specific indicators that researchers have proposed, and in the last decade there has been an effort by regulators and policy makers in many countries of collecting indicators of financial inclusion.

Regarding the link to economic development, there is an extensive literature that has established a positive relationship between financial development, financial depth, and economic growth. Some literature links financial inclusion with variables of financial development. Establishing clear relationships is not always straightforward because there are several channels through which financial inclusion affects different aspects of economic development. It should also be considered that both financial inclusion and economic development are multidimensional concepts. These theoretical links to growth and development establish the importance of studying and measuring financial inclusion.

An article that deals specifically with how financial inclusion can promote developments and specifically can help achieve several of the SDGs, is that of Klapper, El-Zoghbi, and Hess (2016). These authors study the empirical research for several countries in this regard, compile these studies and from there they argue that some objectives are directly promoted by financial inclusion, while, for other objectives, there are theoretical reasons to consider that financial inclusion can help to promote them indirectly, although there is still a lack of studies on this. They argue that financial inclusion can in fact promote most of the SDGs, although empirical evidence is insufficient for some.

2.2. Financial inclusion measures and indices in the literature

Importance of measuring financial inclusion and broad approaches

Financial inclusion is important in the policy agenda worldwide, for in stance, G20 leaders have committed in efforts to meet the challenge of promoting financial inclusion around the world (Allen et al., 2016). It is specially relevant in development countries and crucial in Mexico where lags that impede growth and development are extended. Even though it has not been explicitly stated as a SDG, it has been recognized that is key to the advance in all of the SDGs.[1]

To proper diagnosis, analysis and evaluation policies, appropriate measurement of financial inclusion is crucial. With this aim, researchers and policy makers have used several variables or proxies intended to measure and study different aspects or dimensions of financial inclusion. Some indicators are frequently considered -as banking infrastructure, or number of accounts-, either separately or jointly. Nevertheless, one indicator could show a contradictory panorama of inclusion when compared with other. Researchers have pro-

[1]Klapper, El-Zoghbi, and Hess (2016) compile studies that prove the relation of financial inclusion with SDGs.

posed several methods to measure financial inclusion. Beck, Demirguc-Kunt, and Martinez Peria (2007) were the first to measure a country's access to the financial sector through the design new indicators on banking access for three types of services including deposits, lending, and payments using two dimensions: access and use of financial services. The indicators were constructed on the basis of aggregated banking data provided by bank regulators. Worldwide, in recent years many indicators and information have been gathered by national authorities and supervisors of the financial system. It is considered that over the past decade, enormous progress has been made in measuring financial inclusion across the globe (Beck, 2016). In Mexico, the Data Base of Financial Inclusion, published quarterly by the CONAIF (Consejo Nacional para la Inclusión Financiera), has condensed financial inclusion indicators from 2008 to 2021.

There are two different approaches in a broad sense when measuring of financial inclusion. One approach that some researchers have followed is to evaluate only one or a few financial services that are considered key to inclusion. In some cases it has been due to the availability of only some data, or because some of the inclusion indicators can make comparisons easier when studies are carried out from different countries. For example Allen et al. (2016). Another approach is to build multivariate composite indices that include several financial service indicators, and in this way cover several dimensions of inclusion, reducing them to a number for all dimensions, or to indices for each dimension. The greater availability of data in many cases makes this option possible and appropriate.

There are several reasons for considering important to build a multivariate indicator. On the one hand it is recognized that financial inclusion is a multidimensional concept, for this reason comprising several variables could be a more adequate approach. On the other hand, it is possible that different indicators when considered alone, yield different conclusions about financial inclusion of the same country or region. For example, the infrastructure indicators on the one hand, and the number of accounts on the other. Or that a single indicator gives only partial information of inclusion. For a more complete view, it is important to construct a multivariate index. The financial inclusion index could be used as a yardstick to measure performance, and also useful to make comparisons across countries or regions. Most of the indices constructed in the literature are for the country level. For example the indices of Sarma (2015) for 100 countries; Arora (2014) for 98 countries; Gupte, Venkataramani, and Gupta (2012) for 139 countries; Cámara and Tuesta (2018) for 82 countries; and Tram, Lai, and Nguyen (2022) for 41 countries. Some studies construct indices for subnational levels, for example, Chakravarty and Pal (2013) construct indices for 17 major states in India. The important contribution of our research is a robust methodology to construct financial inclusion indexes for municipalities in Mexico.

Revision of the literature on financial inclusion indices

With the aim of analysing financial inclusion, researchers and policy makers have used several variables or proxies intended to measure and study different aspects or dimensions of financial inclusion. Some indicators are frequently considered -as banking infrastructure, or number of accounts-, either separately or jointly. Nevertheless, one indicator could show a contradictory panorama of inclusion when compared with other. For example, in Mexico there are many municipalities without bank branches, but with population holding accounts. Even when they hold accounts, the people in municipalities with no bank branches could be excluded to have basic financial services of credit, savings, insurance, etc., provided with quality and an accessible price.

There is a consensus that financial inclusion comprises access, usage, and quality of the financial services. These three broad aspects include within many dimensions to measure. Also, financial inclusion varies in its dimensions across geographical regions as well as over time. Therefore, from individual dimensions one can get only partial information on financial inclusion. So, it is evident that financial inclusion is a multidimensional construct and should be measured in a way that gauges adequately the different variables that characterise it.

Several researchers have proposed indices of financial inclusion that incorporate various banking sector variables. Most indices are built following a sequence that consists of:

1. Normalization of variables
2. Determination of dimensional sub-indices
3. Weighting of sub-indices
4. Aggregation of sub-indices

Sarma (2015) has proposed an index of financial inclusion incorporating various banking sector variables to reflect the level of accessibility, availability and usage of banking services. Their index of financial inclusion uses the UNDP approach. The index of financial inclusion is computed as an average distance from an ideal and a worst outcome. Therefore, a high value of the index of financial inclusion would indicate low distance from the ideal and high distance from the worst outcome. Indexes were calculated for 45 countries for which data on all three dimensions was available and 81 countries for which data on only two dimensions are available. Depending on the value of IFI, countries are categorized as high financial inclusion, medium financial inclusion and low financial inclusion.

Chakravarty and Pal (2013) has also developed a calculation method for a financial inclusion index, and as the index of Sarma (2015), follows the way in which human development index is calculated. Chakravarty and Pal (2013) improves upon the financial inclusion index proposed by Sarma (2015) because it allows the percentage contributions of different dimensions to be calculated. Chakravarty and Pal (2013) proposal relies on an axiomatic approach defining postulates of an index.

Gupte, Venkataramani, and Gupta (2012) propose an index of financial inclusion improving the quantity of dimensions and indicators considered by previous indices, by trying to involve all the indicators that other scholars have considered.

Arora (2014) has calculated the index of financial inclusion using the same reasoning as Sarma (2015) for 98 countries for which data was available. Arora (2014) has included more variables in the outreach dimension, capturing not just the demographic penetration but also geographic penetration. This author also adds the dimensions of ease and cost of transactions, not included by Sarma (2015).

Cámara and Tuesta (2018) use demand and supply-side information to measure the extent of financial inclusion at country level for eighty-two developed and less-developed countries. They 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.

Aslan et al. (2017) construct indices of the intensity of financial inclusion at the individual and country level, using a micro-dataset covering 146,000 individuals in over 140 countries. Because the data used is categorical, the authors used Joint Correspondence Analysis to construct their indexes, which is the equivalent to Principal Component Analysis for categorical data.

Koomson, Villano, and Hadley (2020) investigate the effect of FI on poverty and vulnerability to poverty using the index of financial inclusion generated by Aslan et al. (2017) from 15 indicators that cover the dimensions of ownership and use of financial products; including insurance and mobile money, access to credit and receipt of remittances.

Mialou, Amidzic, and Massara (2017) use the IMFs Financial Access Survey database to construct a new composite index of financial inclusion. Their index addresses the issue of weighting whose absence has been the most persistent of the criticisms of previous indices. For normalization of the variables the authors use the distance to a reference method. As a weighting methodology for variables and dimensions, Mialou, Amidzic, and Massara (2017) use factor analysis. They consider that because of the difficulty of assigning weights, many previous indices assign equal weights to all variables and dimensions. This is the case not only for most of the UNDPs indices but also for the composite indices proposed by Sarma (2015) as well as Chakravarty and Pal (2013). Assigning equal weights to all variables and dimensions imply that all individual variables contribute equally to the index, and this is not the case for financial inclusion, in which some variables could be more important than others in explaining one dimension and in the overall financial inclusion measure.

As an aggregator Mialou, Amidzic, and Massara (2017) use the weighted geometric mean, to calculate both the intermediate dimensional variables and the cross-dimension composite index. They choose the weighted geometric mean because it addresses in a satisfactory manner the issue of perfect substitutability between variables within a dimension and between dimensions. Being this the main drawback of the versions of the HDI prior to 2010 that used the arithmetic mean. In general, using a linear formulation implies considering the variables as perfect substitutes of each other. The authors consider that perfect substitutability is not a relevant assumption in the particular case of financial inclusion, so the use of a non-linear function is adequate.

Tram, Lai, and Nguyen (2022) construct measures financial inclusion for 41 developing countries. They consider three dimensions: penetration, availability, and use of financial services. They add “mobile money”–related indicators to the three dimensions to correspond to the degree of financial inclusion in these economies. The measure of financial inclusion is constructed using a two-stage principal component analysis (PCA) method by assigning weights endogenously.

Previous financial inclusion indices for Mexico

Zulaica Piñeyro (2013) constructed an index of financial inclusion for Mexico with data from CONAIF of 2011, and calculated it for regions, States and municipalities. The index is constructed using principal component analysis on variables related to the measurement of five dimensions: the levels of access and usage of financial services, financial education, consumer protection and social development. Subsequently, all municipalities are ranked by degree of inclusion performing hierarchical cluster analysis. In this way, 20 indicators were built for each of the municipalities of Mexico, the States, and five geographical regions.

More recently, Citibanamex has also estimated indexes of financial inclusion for Mexican States and Municipalities for 2018, 2019 and 2020, which synthetize the joint influence of 14 variables or access and use of the financial system in Mexico. The methodology for constructing the indexes is also principal component analysis. The source of the data is CONAIF (CONAIF, March, June, Sept, December/ 2011).

A summary of the methodology followed to construct previous indices of financial inclusion is presented in the following table.

2.3. Contrast of methodology of previous FI indices for Mexico and the Geometric mean Index

The indexes constructed by Zulaica Piñeyro (2013) and Citibanamex (2018); Citibanamex (2019) are used to rank municipalities with a multidimensional measure of financial inclusion. In the case of Citibanamex who constructed indices for 2018 and 2019, it is possible to compare if some municipalities have advanced or fell in the ranking in those years, because weights are fixed for the years estimated, from the first component extracted by principal component analysis of 2018.

Nevertheless it has been considered by various researchers that there are some drawbacks of principal component as a weighting technique:

- The standard procedure in using PCA is to use the factor loadings of the first component. However, sometimes the first component alone is not adequate to explain a large portion of the variance of the indicators.
- Low interpretability of principal components.
- Loss of information, when using only one component.
- The weights are always the same for all countries in the sample.

In constrast, this Financial Inclusion Index for Mexico could be used not only to rank municipalities, but also:

- To study dimensions of financial inclusion geographically and their evolution in time
- Variables of the microcredit institutions are used which are important for FI in Mexico.
- Variables of geographic penetration are considered.

The formulation and mathematical framework that used in this Financial Inclusion Index will be presented in the next section.

2.4. Geometric mean index with BoD weights for the estimation of financial inclusion

Initially, several methodological options for the construction of the FI index were considered, pondering cons and pros. The Benefit-of-the-Doubt (BoD) weighting technique has

Table 1: FI Index in literature

Author	Dimensions	Data	Computation of the dimensions	Computation of the FI	Improvements
Sarma (2015)	Banking penetration (1) Availability of banking services (1) Usage (1)		$d_i = \frac{(A-m_i)}{(M_i-m_i)}$	$IFI = 1 - \sqrt{\frac{(1-p_i)^2+(1-a_i)^2+(1-u_i)^2}{3}}$	
Arora (2014)	Outreach (4) Ease(12) Cost(6)	World Bank (2007), 98 countries. CGAP (2009) 22 variables in total	For each variable: $d_i = \frac{(A_i-m_i)}{(M_i-m_i)}$ For each dimension: $D_i = \frac{(d_i 1+m_i)}{(M_i-m_i)}$ where A_i = Actual value , m_i= minimum value, M_i= maximum value	$FAI = D_i I * w_i + D_i II * w_i i + D_i III * w_i ii$ A higher weight to outreach is assigned (2 to outreach and 1 each to ease and cost of transactions)	Multiple indicator approach in contrast to single indicator in each dimension
Chakravarty and Pal (2013)	Geographic penetration; Demographic penetration; Credit account per thousand pop.; Deposit account per thousand pop.; Credit–income ratio; Deposit–income ratio (one indicator for each dimension)	17 states in India (1972–2009)	$A_r = \frac{(x_i-m_i)}{(M_i-m_i)}^r$	$I_r(A_r) = \frac{1}{k}\sum_{i=1}^{k} \frac{(x_i-m_i)}{(M_i-m_i)}^r$	First, an axiomatic structure. Second, the overall index can be broken down into dimension-wise components.
Gupte et.al.(2012)	Outreach (5); Usage (1); Ease of transactions (12); Cost of transactions (6). A total of 24 indicators.	139 countries	For each variable: $d_i = \frac{(A-m_i)}{(M_i-m_i)}$ For each dimension: $D_j = \sum \frac{d_i}{n}$	$FII = D1^{1/5} * D2^{1/5} * D3A^{1/5} * D3B^{1/5} * D4^{1/5}$ $D3A$ Ease of transaction direct relationship $D3B$ Ease of transaction inverse relationship	1) FI Index as a geometric mean: imperfect substitutability across dimensions. 2) More variables for each dimension, the FII is considered more robust.
Camara and Tuesta (2014)	Usage (3) Access (4) Barriers (3) In total 10 indicators	82 countries (2011) Global Findex and IMF	PCA to estimate 3 sub-indices of FI	As a second step apply again PCA to estimate the dimension weights and the overall FI index using the previous sub-indices as causal variables. $FI_i = \frac{\sum_{j=1}^{3} \lambda_j(\phi_{j1} Y_i^u + \phi_{j2} Y_i^b + \phi_{j3} Y_i^a)}{x}$	1) Computation of the sub-indices to estimate dimensions: useful information when designing FI strategies. 2) Weights determined endogeonously by information of sample indicators.

Source: Own elaboration.

been chosen because it is a data-driven technique increasingly used in many applications for estimating composite indices in various areas. The principle of weighting ensures the more optimistic weights, because each entity will chose its weights. In the study of financial inclusion, it is adequate not to have a priori established the importance and trade-offs of the variables, but rather let the data decide, via BoD.

BoD is based in the DEA (Data Envelop Analysis) formulation. DEA uses mathematical programming to measure the relative performance of several units, based on a 'efficiency' score. This score is obtained by a ratio (the weighted sum of outputs to the weighted sum of inputs) that is computed for every unit under a minimisation/maximisation function set by the researcher. From this linear programming formulation, a set of weights (one for each unit) is endogenously determined in such a way as to maximise their 'efficiency' under some given constraints (Greco et al., 2019).

In the context of composite indicators, the classic DEA formulation is adjusted, as usually all the indicators are treated as outputs, thereby considering no inputs. This model is generally referred to as the classic 'benefit-of-the-doubt' approach. The classic BoD model constructs composite indices as weighted arithmetic averages. There are also several proposals of geometric BoD indices, some of these alternatives are described in Rogge (2018).

The methodological choice for the construction of the financial inclusion index for Mexican Municipalities will be a mean geometric aggregated index, with weights derived from a linear BoD model. This approach follows the formulation of Van Puyenbroeck and Rogge (2017), inspired by the literature on index number theory. This type of index is chosen because it has several desirable mathematical properties for a multivariate indicator, as considered by Van Puyenbroeck and Rogge (2017). The authors also extend the basic formulation of the index to provide transitive indicator orderings that allow to compare entities. Finally, the authors propose a formulation to explain the intertemporal evolution of each entity of the analysis.

In the first section, the basic formulation of the index of Van Puyenbroeck and Rogge (2017) is presented in detail. In the following section, one of the extensions of the model is chosen, that will be used to make the indices transitive. In the next section, the formulation for the intertemporal evolution is presented.

Basic formulation of the Geometric BoD Composite Indicator

Van Puyenbroeck and Rogge (2017) propose a formulation of a Geometric Benefit of the Doubt Mean Composite Indicator, that uses "quantity relatives", that is, each subindicator is expressed relative to some base performance standard. Aggregating such relatives is in fact also done with some price and quantity indices. Quantity indices inspire the formulation of Van Puyenbroeck and Rogge (2017), two examples of this group of indices are Geometric versions of Laspeyres and Paasche indices.

Following recent composite indicator literature, multiplicative aggregation has been considered by many researchers as superior over the arithmetic weighted average. There are several reasons for this, as explained by Rogge (2018). First, if subindicators are measured on a ratio-scale and are strictly positive, a weighted geometric average results in an ordering that is independent of the exact scaling of the subindicator. Such invariance results are far more limited in the case of linear aggregation. Second, a geometric aggregation ensures that the marginal returns to an increase in a subindicator value are diminishing rather than constant. Finally, a weighted geometric average penalizes inequality among subindicators.

Van Puyenbroeck and Rogge (2017) propose a methodology for constructing a Geometric Benefit of the Doubt Mean Composite Indicator, in two stages.

First stage: linear BoD estimation

In the first stage, a specific set of base performance indicators relevant for the analysis needs to be selected, and appropriate weights should be attached to each of them.

This set of base indicators are named y_{rB}. Van Puyenbroeck and Rogge (2017) propose to endogenously derive weights from a linear aggregated BoD-model, which is the traditional formulation of the BoD model. These weights are instrumental to a second stage of the construction of the composite indicator. In our estimation, for each municipality i the following model will be solved, as a linear aggregated BoD model:

$$max_{w_{1i} \dots w_{si}} \sum_{r=1}^{s} w_{ri} y_{ri} \tag{1}$$

s.t. $\sum_{r=1}^{s} w_{ri} y_{ri} \leq 1$ $\quad$ N constraints, one for each municipality j=1,. . . ,N

(***Normalisation constraint***)

$w_{ri} \geq 0$ $\quad$ s constraints, one for each weight r =1,. . . ,s

(Positive weights constraint)

In this case, the objective function of linear programming problem of equation (1) provides only an intermediate result, that will be used to compute BoD sub-indicator shares that will be the weights for the geometric index, as follows:

$$\omega_{ri}^{*} = \frac{w_{ri}^{*} y_{ri}}{\sum_{r=1}^{s} w_{ri}^{*} y_{ri}} \tag{2}$$

where $\sum_{r} \omega_{r}^{*} = 1$.

Restriction of weights

To deal with multiple equilibra, it is necessary to restrict weights to avoid coinciding zero and one weight values of variables of several municipalities. Following Van Puyenbroeck and Rogge (2017) we can use a "minimalist position" considering that optimal indicator weights estimated by linear BoD should be at least 5 percent (i.e. $0.05 \leq \omega_{r}^{*}$). This approach implies that the composite index cannot be constructed while disregarding at least one of its constituent sub-indicators. The underlying idea is that all dimensions are considered as providing at least some valuable information. There are several methods of restricting weights, for example specified by consulting experts and assigning a "budget" to them, but Van Puyenbroeck and Rogge (2017) consider that practical experience shows that strong consent is difficult to reach. Following Van Puyenbroeck and Rogge (2017), establishing that weights should be at least 5 percent gives the optimization of weights considerable flexibility, however, not so much as to enable zero weights being attributed to one or more dimensions.

Second stage: geometric composite index

As a second stage of the estimation, a geometric composite index is constructed, with this formulation:

$$C_i^i(y_i, y_B, \omega_i^*) = \prod_{r=1}^{s} (\frac{y_{ri}}{y_{rB}})^{\omega_{ri}^*} \tag{3}$$

Extensions of the geometric index for transitive cross-section comparisons

Van Puyenbroeck and Rogge (2017) propose several extensions to the model to render the geometric indices transitive among entities. BoD weights are specific of each entity, given the nature of BoD optimization in which each entity selects its own weights. For this reason this type of indices are not transitive for cross-section comparisons, in this case we need to arrive at common weights for each entity. One of the extensions proposed by Van Puyenbroeck and Rogge (2017), is to include the base indicator data, B in the first step linear BoD, 1, so that this BoD weights, $w_r B^*$ can be used as common exponents for all countries. The formulation for this extension will then be:

$$CI_i^B(y_i, y_B, \omega_B^*) = \prod_{r=1}^{s} (\frac{y_{ri}}{y_{rB}})^{\omega_{rB}^*} \tag{4}$$

where ω_B^* is obtained as in 2. Van Puyenbroeck and Rogge (2017) consider this a simple way to create a transitive index formula, that can be applied to complete multilateral country comparisons and rankings. In fact, as noted by 2, in any pairwise index comparison between countries i, j, the performance values cancel out, so that we can obtain direct bilateral indices consistent with 4:

$$\frac{CI_i^B}{CI_j^B} = \frac{CI_i^B(y_i, y_B, \omega_B^*)}{CI_j^B(y_j, y_B, \omega_B^*)} = \prod_{r=1}^{s} (\frac{y_{ri}}{y_{rj}})^{\omega_B^*} \tag{5}$$

To make the indices transitive, Van Puyenbroeck and Rogge (2017) propose several alternatives. We will use a benchmark municipality, San Pedro Garza García, of the State of Nuevo León. This municipality was the first of the rank in the initial step of linear Benefit of the Doubt estimation. So we are using the formulation of 4, with the weights obtained by 2 for San Pedro Garza García:

$$CI_i^{SPG}(y_i, y_B, \omega^*_{SPG}) = \prod_{r=1}^{s} (\frac{y_{ri}}{y_{rSPG}})^{\omega^*_{rSPG}} \tag{6}$$

3. Construction of a financial inclusion index for Mexican Municipalities, 2020

In the first subsection, the database and its statistical characteristics are presented. In the second subsection, multivariate analysis is conducted, prior to the estimation of the indices. Exploratory factor analysis and cluster analysis has been done to analyse its statistical properties, for variable reduction, and for deciding on dimensions to consider for aggregation of variables. Finally, in the following subsection, the geometric mean index of financial inclusion for Mexican municipalities is calculated.

3.1. Database, descriptive statistics and correlations of variables

Databases

- Quarterly financial inclusion databases from CONAIF[2].
- Information of the area in km^2 of the municipalities, from *Base de Datos de Inclusión Financiera 2015*.

Preparation of the database

- Quarterly data bases were merged and averaged for 03, 06, 09 and 12 of 2013-2021.
- The variables considered are classified in *Access* and *Usage*, as a first approximation of two broad dimensions of financial inclusion.

[2](CONAIF, March, June, Sept, December/ 2013; CONAIF, March, June, Sept, December/ 2014; CONAIF, March, June, Sept, December/ 2015; CONAIF, March, June, Sept, December/ 2016; CONAIF, March, June, Sept, December/ 2017; CONAIF, March, June, Sept, December/ 2018; CONAIF, March, June, Sept, December/ 2019; CONAIF, March, June, Sept, December/ 2020; CONAIF, March, June, Sept, December/ 2021)

- Demographic variables are used, i.e. variables per 10,000 inhabitants.
- Database consists of 2,458 observations, of several financial inclusion variables of all Mexican municipalities.
- Some variables were added to create new variables:
  - Transaction accounts: Sum of transaction accounts level 1, level 2, and level 3.
  - *"Branches micro"*: Sum of development bank branches, Socap (Cajas) and Sofipo (Popular banks) branches.
- Geographic variables were created dividing the variables by 1,000 km^2.

Variables considered

In total, 32 variables were considered initially for the construction of the Financial Inclusion Index, 10 for Access Dimension and 22 for Usage Dimension, as showed in the following table.

Table 2: Variables considered

No.	Access Variables	Description
1	Branches	Bank Branches
2	Corresp	Correspondents
3	ATMs	Automatic Teller Machines
4	POS	Points of service
5	Mobile B	Mobile banking accounts
6	Branches micro	Branches of development banks and microcredit entities
7	Branches geog	Bank branches in 1,000 km^2
8	Corresp geog	Correspondents in 1,000 km^2
9	ATMs geog	ATMs in 1,000 km^2
10	POS geog	POS in 1,000 km^2
No.	**Usage Variables**	**Description**
11	Transac accounts	Transaction accounts
12	Trad accounts	Traditional accounts
13	Savings	Saving accounts
14	Term deposits	Term deposit accounts
15	Debit accounts	Debit accounts
16	Savings micro	Saving accounts of develop. banks and microcredit entit.
17	Demand deposits	Demand deposit accounts
18	Term dep micro	Term deposit accounts of develop. and microcred.
19	Debit acc micro	Debit accounts of dev. and microcredit
20	Credit accounts	Credit accounts
21	Mortgages	Mortgage credits
22	Group credits	Group credits
23	Personal credits	Personal credits
24	Payroll credits	Payroll credits
25	Automotive credit	Automotive credits
26	Durable goods	Durable goods credits
27	Consump cred micro	Consumption credits of devel. and microcred.
28	Mortg cred micro	Mortgage credits of dev. and microcred.
29	POS trans	POS transactions
30	ATMs trans	ATMs transactions
31	POS trans micro	POS transactions of dev. and microcred.
32	ATMs trans micro	ATMs transactions of dev. and microcred.

Note: All variables are demographic(per 10,000 inhabitants), except when specified as per 1000 km^2.
Source: CONAIF, quarterly databases from 2013 to 2021.

The 3 maximum value observations were substituted by the *4th* value, so that extreme values do not affect multivariate analysis and the estimation of composite indices. Normalisation of the data base was done by *min-max scaling* method to render indicators comparable. Descriptive statistics of non-normalised variables are presented for *Access* and *Usage*.

Table 3: Summary Statistics for Access Dimension

Variable	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Branches	0.5	0.7	0	0	0.8	3.2
Correspondents	3.4	3.3	0	0	5.1	15.7
ATMs	2.1	3	0	0	3.1	17.1
POS	34.1	58.2	0	3.5	37.1	358
Mobile_banking	2142.4	1554.4	229.7	881.2	3012	7280.4
Branches_micro	0.5	0.9	0	0	0.6	5
Branches_geog	20.3	93.3	0	0	3.7	743.6
Correspond_geog	83.6	293.5	0	0	33.4	2118.3
ATMs_geog	86	396.3	0	0	17	3152.4
POS_geog	1730.6	8160.6	0	5.1	247.8	65862.4

Number of observations: 2458 municipalities.

Source: Own estimation with data of CONAIF (March, June, Sept, December/ 2020).

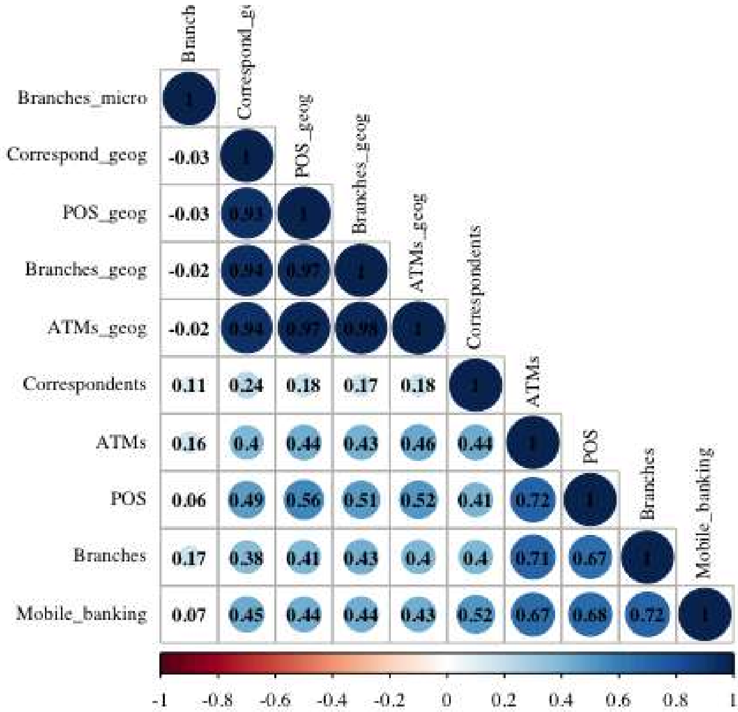
Table 4: Summary Statistics for Usage Dimension

Variable	Mean	Sd	Min	Pctile[25]	Pctile[75]	Max
Transaction_acc	825.2	1044.5	7.1	155.5	1095.8	6357.1
Traditional_acc	2219.1	3677.3	0	0	3335	16750.7
Term_deposit	115	236.2	0	0	131.8	1376
Debit_acc	4311.9	6443.4	30.6	202.3	6644.8	30713.3
Saving_micro	1258	1811.6	0	102.3	1599.3	9536.6
Demand_dep_micro	1110.1	1542.2	0	174.4	1321.6	8621.9
Term_dep_micro	182.3	314.7	0	16.8	192.5	1951.1
Debit_micro	31	103	0	0	11.9	732
Credit_acc	803.9	1156.7	4.2	104.7	935.5	5587.4
Mortgages	39.6	90	0	0.8	30.9	616.9
Group_credits	283	268.2	0	71.6	414.5	1262.4
Personal_credits	940.6	719.6	5.2	251.7	1447.1	3044.3
Payroll_credits	250.9	207.5	0	89.3	364.7	928
Automot_credits	33.2	36.7	0	9.5	43	193.1
Durable_goods_cred	240.6	235.4	0	28.4	373.7	995
Consump_cred_micro	348.2	513.4	0	31.1	418.3	2744.1
Transacc_POS	3833.5	7120.8	0	4.4	4122.2	39521.5
Transacc_ATM	5114.9	7402.6	0	0	7801.4	32480.8

Number of observations: 2458 municipalities.

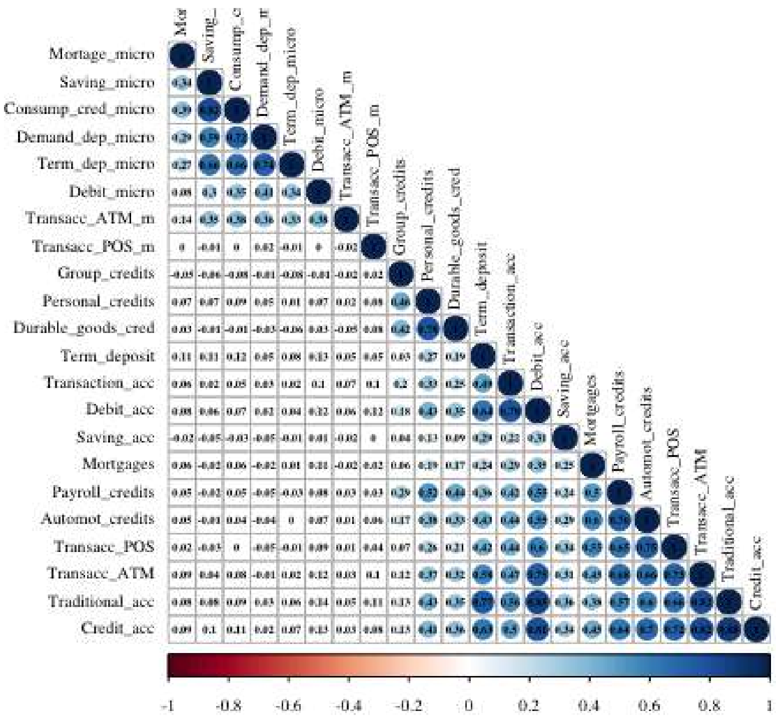
Source: CONAIF (March, June, Sept, December/ 2020).

Figure 1: Correlation matrix of *Access* variables



Own elaboration.

Figure 2: Correlation matrix of *Usage* variables



3.2. Multivariate analysis: Exploratory factor analysis

Multivariate analysis is conducted in the database of 2020, following European Commission and OECD (2008) with the aim of studying the multivariate statistical characteristics of the data, reduction of variables, formal descriptive purposes.

It is considered important that the index has dimensions of financial inclusion. To make the decision of dimensions statistically grounded, exploratory factor analysis is used to investigate the multivariate relationships without making any assumptions about which manifest variables are related to which factors. (Everitt and Hothorn (2011)) This analysis identifies groups of variables that are highly correlated with each other -called factors- and separates them from less correlated groups. (Backhaus et al. (2021))

Following literature, two broad classification of variables of financial inclusion is considered: access and usage of the financial services. Within these two broad categories, exploratory factor analysis is conducted for determining relevant dimensions. Variables will be grouped with high factor loadings in the corresponding factor, meaning that they share a higher affinity with a specific factor into the same dimension.

To assess the suitability of the database before conducting factor analysis, two tests were evaluated: Kaiser-Meyer-Olkin Measure of Sampling Adequacy, and Bartlett's test of sphericity. For both access and usage variables, the KMO-Criterion was 0.86, and the p-value of Bartlett's test was much less than 0.05. Therefore it is concluded that the data is suitable for factor analysis.

Factor analysis for Access

According to literature two types of variables of access will be explored. One demographic, and the other divided by km^2. Researchers that consider geographic indicators on their indices are Arora (2014); Aslan et al. (2017); Cámara and Tuesta (2014); Chakravarty and Pal (2013); Gupte, Venkataramani, and Gupta (2012) and Mialou, Amidzic, and Massara (2017).

Exploratory factor analysis was conducted for 10 *Access* variables, with Varimax rotation.The results of the analysis show variables grouped in two factors, consequently considered as two dimensions of access for explaining financial inclusion. One demographic, and the other geographic. The variable *Branches micro* will be taken off the analysis because the loading is very low. So 9 variables of access are retained, statistically grouped in two factors considered as two dimensions of Access. Factor analysis shows that the two factors together explain 0.683 of the variance, and the test of the hypothesis is satisfied that two factors are sufficient.

Table 5: Exploratory factor analysis access- Loadings

		Factor1	Factor2
1	Branches		0.84
2	Correspondents	-0.118	0.595
3	ATMs		0.834
4	POS	0.149	0.749
5	Mobile_B		0.822
6	Branches_micro	-0.132	0.213
7	Branches_geog	0.979	
8	Corresp_geog	0.941	
9	ATMs_geog	0.981	
10	POS_geog	0.964	

Of the geographic variables only two will be retained: *Branches geog*, *Correspondents geog*. *ATMs geog POS_geog* will not be used, they are considered not necessary because they are very highly correlated with the rest, as shown in the correlation matrix figure of access, so the additional statistical information that they provide is negligible. So finally we will have 7 variables of access.

Factor analysis for *Usage*

Exploratory factor analysis was conducted for 22 *Usage* variables, with Varimax rotation. According to this analysis variables could be statistically grouped in four factors that explain cumulatively 0.564 of the variance of all the data. The SS loadings are above one, so all the factors should be retained.

5 variables are left out , because their factor loadings are low, variables 3, 9, 18, 21 and 22, as showed in the table. So 17 variables are retained for *Usage*. Factor analysis is done again leaving out the 5 variables just mentioned, and with this reduction of variables this time considering three factors. The cumulative variance explained by the three factors is 0.63, the first factor accounting for 35% of the variance.

Table 6: Exploratory factor analysis usage- Variance explained

	Factor1	Factor2	Factor3	Factor4
SS loadings	3.955	3.351	3.137	1.971
Proportion Var	0.180	0.152	0.143	.090
Cumulative Var	0.180	0.332	0.475	.564

Own estimation.

Highlighting the resulting loadings in a table shows which variables are grouped in each factor, as follows:

Table 7: Exploratory factor analysis usage- Loadings

		Factor1	Factor2	Factor3	Factor4
1	Transac_accounts	0.509		0.272	0.169
2	Trad_accounts	0.907		0.338	0.139
3	Savings	0.306		0.231	
4	Term_deposits	0.767	0.115	0.153	
5	Debit_accounts	0.784		0.339	0.184
6	Savings_micro		0.858		
7	Demand_deposits_micro		0.786		
8	Term_dep_micro		0.764		
9	Debit_acc_micro		0.405		
10	Credit_accounts	0.747	0.103	0.522	0.138
11	Mortgages	0.166		0.636	
12	Group_credits				0.504
13	Personal_credits	0.268		0.154	0.884
14	Payroll_credits	0.299		0.715	0.375
15	Automotive_credit	0.332		0.811	0.184
16	Durable_goods	0.209		0.143	0.797
17	Consump_cred_micro		0.926		
18	Mortg_cred_micro		0.395		
19	POS_trans	0.448		0.737	
20	ATMs_trans	0.67		0.556	0.12
21	POS_trans_micro	0.116			
22	ATMs_trans_micro		0.425		

Conclusion of factor analysis

Exploratory factor analysis showed that we can consider two subdimensions in *access*, and four subdimensions in *usage*. And that we can leave out five variables of the analysis, so in total we will consider 26 variables. The dimensions of usage could be named in four categories: Debit accounts of banking institutions, Debit and credit accounts of microcredit institutions, Credit1, and Credit 2. Among the variables we considered transactions in ATMs and transactions in POS. Factor analysis showed us that transactions in ATMs is statistically classified in Debit accounts of banking institutions; and transactions in POS in Credit 1.

Variables of Access retained

The dimensions of Access could be named as *Access Demographic* and *Access Geographic*.

Table 8: Dimensions of Access

	A1: Access Demographic		A2: Access Geographic
1	Branches	6	Branches geog.
2	Correspondents	7	Corresp. geog.
3	ATMs	8	ATMs geog.
4	POS		
5	Mobile Banking		

Variables of Usage retained

The dimensions of *Usage* could be named in four categories: Debit accounts of banking institutions, Debit and credit accounts of microcredit institutions, Credit1, and Credit 2.

Among the variables we considered transactions in ATMs and transactions in POS. Factor analysis showed us that transactions in ATMs is statistically classified in Debit accounts of banking institutions; and transactions in POS in Credit 1. The classification of variables is presented in the following table.

Table 9: Dimensions of Usage

U1	Debit banking	U2	Debit and credit micro.	U3	Credit 1	U4	Credit 2
1	Transaction accounts	7	Saving micro	12	Mortgage	16	Group credits
2	Trad accounts	8	Demand deposits	13	Payroll credits	17	Personal credits
3	Savings	9	Term deposits	14	Automotive	18	Durable goods
4	Term deposits	10	Debit acc micro	15	POS trans		
5	Debit accounts	11	Consump cred micro				
6	ATMs trans						

3.3. Estimation of Geometric BoD FI Index for 2020

Prior to the estimation of indices, variables are aggregated in dimensions according to the categories derived from exploratory factor analysis. Variables normalised by min-max method and multiplied by 10 are used to render the variables comparable in scale. The 0-10 scores are averaged to obtain an aggregate score per dimension. They will be denominated for ***Access***: A1 and A2; and for ***Usage***: U1, U2, U3 and U4. Financial inclusion indices are estimated by the methodology proposed by Van Puyenbroeck and Rogge (2017) described in **??**, consisting in two steps. First, computing DEA Benefit of the doubt, in its standard linear form, and extracting weights that will be used in the second stage of the estimation. In this sense the weights obtained in the estimation are shadow weights. The second stage of the estimation is computing geometric mean indices, pondered by the weights of the first step. To make the indices transitive, Van Puyenbroeck and Rogge (2017) propose several alternatives. We will chose to use a benchmark municipality, San Pedro Garza García, of the State of Nuevo León. This municipality was the first of the rank in the initial step of linear Benefit of the Doubt estimation. So we are using the formulation of 4, with the weights obtained by 2 for San Pedro Garza García:

$$CI_i^{SPG}(y_i, y_B, \omega^*_{SPG}) = \prod_{r=1}^{s} \left(\frac{y_{ri}}{y_{rSPG}}\right)^{\omega^*_{rSPG}} \tag{7}$$

that was the first of the rank in the initial step of linear Benefit of the Doubt estimation. An advantage of the transitive geometric formulation used, is that we can easily see the importance of each dimension, for each municipality.

The top 45 municipalities are presented in the following table, with the ranking, the index number, and also the computation of each dimension.

Table 10: Financial Inclusion Index 2020 with weighted subdimensions
Geometric with BoD weights - Top 50 Municipalities

		FI Index		Weighted subdimensions[1]					
State_name	Municipality_name	FI_Geom	Rank	A1_Dim	A2_Dim	U1_Dim	U2_Dim	U3_Dim	U4_Dim
Ciudad de México	Miguel Hidalgo	1.501	1	1.006	1.286	1.037	1.011	1.052	1.052
Ciudad de México	Benito Juárez	1.246	2	1.032	1.108	1.017	1.010	1.055	1.005
Ciudad de México	Cuauhtémoc	1.171	3	1.060	0.919	1.090	1.001	1.085	1.015
Nuevo León	San Pedro Garza García	1.000	4	1.000	1.000	1.000	1.000	1.000	1.000
Ciudad de México	Álvaro Obregón	0.795	5	0.794	1.007	0.869	1.001	1.109	1.030
Ciudad de México	Cuajimalpa de Morelos	0.761	6	0.990	1.097	0.707	1.005	0.958	1.029
Tamaulipas	Tampico	0.651	7	0.782	1.002	0.824	1.007	0.966	1.036
Nuevo León	Monterrey	0.626	8	0.862	0.930	0.771	1.000	0.999	1.014
Oaxaca	Oaxaca de Juárez	0.621	9	0.823	0.922	0.771	1.017	0.998	1.045
Ciudad de México	Tlalpan	0.618	10	0.669	1.092	0.847	0.990	0.961	1.050
Ciudad de México	Coyoacán	0.607	11	0.740	1.223	0.670	0.995	0.986	1.021
Veracruz	Orizaba	0.590	12	0.803	1.010	0.738	1.004	0.947	1.038
Veracruz	Boca del Río	0.586	13	0.828	0.972	0.710	0.998	0.986	1.043
Jalisco	Guadalajara	0.546	14	0.770	1.047	0.701	1.012	0.942	1.014
Nuevo León	San Nicolás de los Garza	0.524	15	0.764	1.007	0.668	1.000	1.012	1.009
Tlaxcala	Tlaxcala	0.488	16	0.780	0.829	0.751	1.000	0.970	1.035
Hidalgo	Pachuca de Soto	0.467	17	0.806	0.784	0.725	1.000	0.985	1.035
Ciudad de México	Azcapotzalco	0.465	18	0.739	0.917	0.667	0.989	1.017	1.022
México	Metepec	0.450	19	0.751	0.919	0.640	1.007	0.981	1.030
Morelos	Cuernavaca	0.433	20	0.796	0.802	0.686	1.007	0.947	1.037
Veracruz	Xalapa	0.432	21	0.743	0.881	0.672	0.995	0.954	1.034
Tlaxcala	Apizaco	0.418	22	0.760	0.773	0.731	0.995	0.926	1.056
México	Tlalnepantla de Baz	0.415	23	0.688	1.010	0.613	0.989	0.954	1.033
Ciudad de México	Venustiano Carranza	0.415	24	0.734	0.885	0.644	0.991	0.975	1.025
Nuevo León	Guadalupe	0.403	25	0.710	0.949	0.604	1.000	0.973	1.019
Querétaro	Querétaro	0.402	26	0.767	0.742	0.684	1.025	0.982	1.027
Ciudad de México	Iztapalapa	0.393	27	0.592	1.310	0.541	0.985	0.919	1.035
Ciudad de México	Gustavo A. Madero	0.391	28	0.621	1.116	0.580	0.991	0.952	1.029
Veracruz	Antigua, La	0.387	29	0.837	0.595	0.790	0.996	0.928	1.065
Veracruz	Veracruz	0.381	30	0.728	0.865	0.618	0.998	0.942	1.043
México	Naucalpan de Juárez	0.370	31	0.689	0.924	0.612	0.990	0.927	1.034
Puebla	San Andrés Cholula	0.357	32	0.761	0.808	0.604	0.995	0.943	1.025
Tamaulipas	Ciudad Madero	0.351	33	0.673	0.877	0.572	1.005	0.998	1.037
Chiapas	Tuxtla Gutiérrez	0.348	34	0.721	0.767	0.639	0.998	0.951	1.038
Ciudad de México	Iztacalco	0.347	35	0.650	0.888	0.605	0.989	0.976	1.031
Yucatán	Mérida	0.347	36	0.755	0.715	0.637	0.999	0.982	1.030
México	Cuautitlán	0.346	37	0.669	0.907	0.607	0.982	0.920	1.039
Puebla	Puebla	0.346	38	0.699	0.844	0.606	0.997	0.942	1.031
México	Toluca	0.339	39	0.718	0.759	0.639	1.005	0.935	1.037
Veracruz	Poza Rica de Hidalgo	0.338	40	0.741	0.699	0.664	1.005	0.940	1.043
Zacatecas	Zacatecas	0.336	41	0.784	0.587	0.706	1.006	1.006	1.023
Tlaxcala	Apetatitlán de Antonio Carvajal	0.334	42	0.730	0.863	0.542	0.995	0.938	1.048
México	Cuautitlán Izcalli	0.333	43	0.662	0.875	0.587	0.989	0.956	1.033
México	Coacalco de Berriozábal	0.331	44	0.611	0.957	0.568	1.013	0.951	1.036
Quintana Roo	Benito Juárez	0.325	45	0.748	0.738	0.603	0.994	0.956	1.028
Oaxaca	Salina Cruz	0.325	46	0.746	0.666	0.638	1.004	0.967	1.056
Veracruz	Córdoba	0.315	47	0.702	0.748	0.639	1.007	0.890	1.046
Nuevo León	Allende	0.315	48	0.801	0.583	0.727	1.010	0.885	1.037
Nuevo León	Apodaca	0.315	49	0.661	0.860	0.556	0.997	0.978	1.021
Colima	Colima	0.313	50	0.801	0.572	0.704	1.010	0.949	1.012

Note:
Own estimation.
[1] Min-max subdimensions, raised to the power of BoD weights.

Table 11: Geometric BoD Financial Inclusion Index 2020 and Min-Max Subdimensions Top 50 Municipalities

		FI Index		Min-max subdimensions[1]					
State_name	Municipality_name	FI_Geom	Rank	Dim_A1	Dim_A2	Dim_U1	Dim_U2	Dim_U3	Dim_U4
Ciudad de México	Miguel Hidalgo	1.501	1	6.309	9.117	7.618	0.638	4.754	3.962
Ciudad de México	Benito Juárez	1.246	2	6.898	4.273	7.156	0.593	4.854	0.673
Ciudad de México	Cuauhtémoc	1.171	3	7.570	1.651	8.924	0.289	5.780	0.967
Nuevo León	San Pedro Garza García	1.000	4	6.175	2.536	6.782	0.277	3.488	0.550
Ciudad de México	Álvaro Obregón	0.795	5	2.771	2.626	4.347	0.303	6.617	1.738
Ciudad de México	Cuajimalpa de Morelos	0.761	6	5.962	4.061	2.258	0.415	2.675	1.689
Tamaulipas	Tampico	0.651	7	2.623	2.558	3.675	0.468	2.824	2.185
Nuevo León	Monterrey	0.626	8	3.688	1.754	2.979	0.276	3.464	0.933
Oaxaca	Oaxaca de Juárez	0.621	9	3.138	1.681	2.974	1.039	3.443	3.025
Ciudad de México	Tlalpan	0.618	10	1.523	3.959	4.012	0.123	2.722	3.708
Ciudad de México	Coyoacán	0.607	11	2.164	7.049	1.906	0.183	3.201	1.262
Veracruz	Orizaba	0.590	12	2.875	2.667	2.594	0.366	2.490	2.342
Veracruz	Boca del Río	0.586	13	3.200	2.190	2.294	0.230	3.206	2.843
Jalisco	Guadalajara	0.546	14	2.490	3.197	2.196	0.689	2.418	0.938
Nuevo León	San Nicolás de los Garza	0.524	15	2.415	2.626	1.884	0.269	3.755	0.780
Tlaxcala	Tlaxcala	0.488	16	2.601	0.978	2.740	0.284	2.894	2.111
Hidalgo	Pachuca de Soto	0.467	17	2.916	0.737	2.443	0.281	3.187	2.089
Ciudad de México	Azcapotzalco	0.465	18	2.153	1.632	1.882	0.117	3.877	1.290
México	Metepec	0.450	19	2.275	1.649	1.651	0.478	3.095	1.766
Morelos	Cuernavaca	0.433	20	2.793	0.823	2.054	0.489	2.494	2.256
Veracruz	Xalapa	0.432	21	2.190	1.333	1.926	0.180	2.617	2.064
Tlaxcala	Apizaco	0.418	22	2.378	0.686	2.507	0.181	2.169	4.655
México	Tlalnepantla de Baz	0.415	23	1.676	2.666	1.437	0.119	2.606	1.946
Ciudad de México	Venustiano Carranza	0.415	24	2.106	1.364	1.682	0.137	2.980	1.449
Nuevo León	Guadalupe	0.403	25	1.871	1.944	1.370	0.268	2.955	1.129
Querétaro	Querétaro	0.402	26	2.456	0.555	2.032	1.884	3.117	1.579
Ciudad de México	Iztapalapa	0.393	27	0.997	10.000	0.966	0.087	2.068	2.092
Ciudad de México	Gustavo A. Madero	0.391	28	1.176	4.428	1.205	0.142	2.583	1.711
Veracruz	Antigua, La	0.387	29	3.326	0.181	3.211	0.200	2.201	6.428
Veracruz	Veracruz	0.381	30	2.042	1.215	1.472	0.231	2.407	2.896
México	Naucalpan de Juárez	0.370	31	1.687	1.700	1.429	0.125	2.187	2.046
Puebla	San Andrés Cholula	0.357	32	2.386	0.856	1.374	0.193	2.426	1.442
Tamaulipas	Ciudad Madero	0.351	33	1.559	1.301	1.154	0.395	3.441	2.267
Chiapas	Tuxtla Gutiérrez	0.348	34	1.977	0.656	1.638	0.235	2.556	2.368
Ciudad de México	Iztacalco	0.347	35	1.376	1.383	1.379	0.116	3.004	1.838
Yucatán	Mérida	0.347	36	2.324	0.460	1.621	0.259	3.113	1.752
México	Cuautitlán	0.346	37	1.527	1.548	1.394	0.069	2.080	2.422
Puebla	Puebla	0.346	38	1.776	1.071	1.384	0.223	2.406	1.784
México	Toluca	0.339	39	1.948	0.624	1.636	0.414	2.307	2.237
Veracruz	Poza Rica de Hidalgo	0.338	40	2.178	0.409	1.851	0.394	2.377	2.802
Zacatecas	Zacatecas	0.336	41	2.643	0.168	2.254	0.425	3.625	1.328
Tlaxcala	Apetatitlán de Antonio Carvajal	0.334	42	2.067	1.196	0.975	0.189	2.351	3.484
México	Cuautitlán Izcalli	0.333	43	1.470	1.287	1.256	0.118	2.648	1.988
México	Coacalco de Berriozábal	0.331	44	1.112	2.024	1.131	0.745	2.553	2.155
Quintana Roo	Benito Juárez	0.325	45	2.252	0.541	1.362	0.171	2.640	1.637
Oaxaca	Salina Cruz	0.325	46	2.228	0.320	1.632	0.378	2.843	4.565
Veracruz	Córdoba	0.315	47	1.802	0.581	1.641	0.494	1.702	3.164
Nuevo León	Allende	0.315	48	2.857	0.163	2.469	0.597	1.644	2.268
Nuevo León	Apodaca	0.315	49	1.463	1.181	1.053	0.218	3.046	1.227
Colima	Colima	0.313	50	2.853	0.148	2.233	0.618	2.521	0.894

Note:
Own estimation.
[1] Min-max subdimensions, not weighted.

Kernel distribution of the FI Index

The kernel distribution of the calculated index is presented in the following figure where we observe that the index is highly concentrated in values between a and .3, and a few municipalities with respect to the total of them have values between .3 and 1.5. This reflects that most municipalities in Mexico present very low levels of financial inclusion. When we look at kernel distributions of the index by regions, we see that the municipalities of Ciudad de México (formally named "Delegaciones") have very differing levels of the FI Index, while the other regions, specially the "Sur" region (south), are concentrated mainly at very low levels, near zero.

Figure 3: Kernel distribution of the FI Index 2020

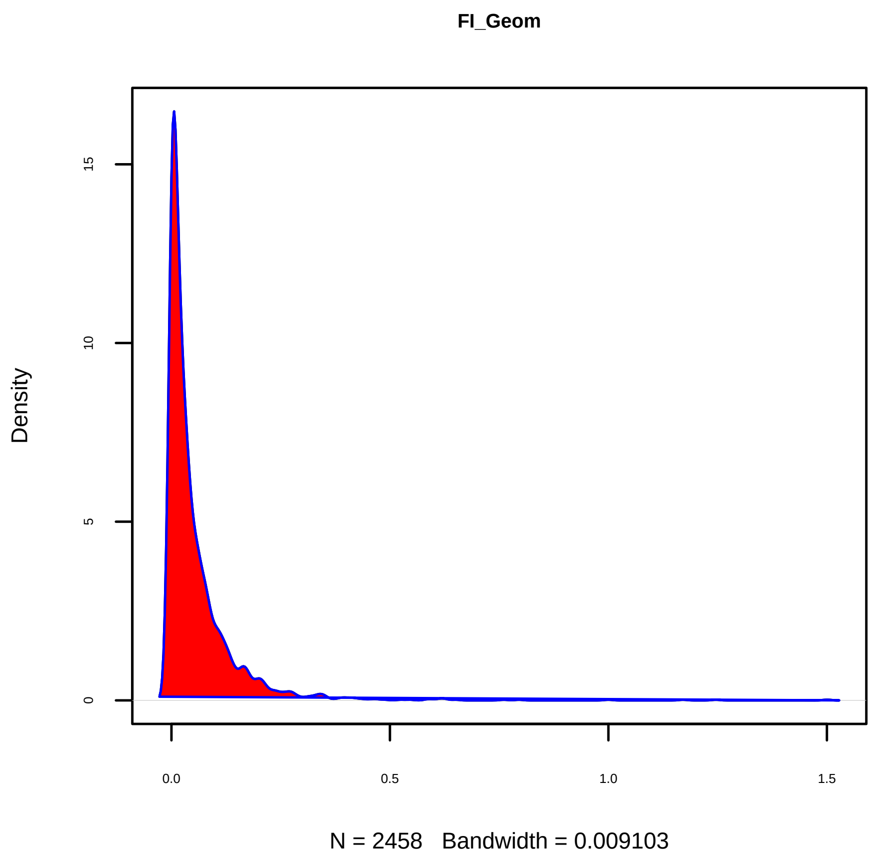


Figure 4: Kernel distribution of the FI Index 2020, by regions

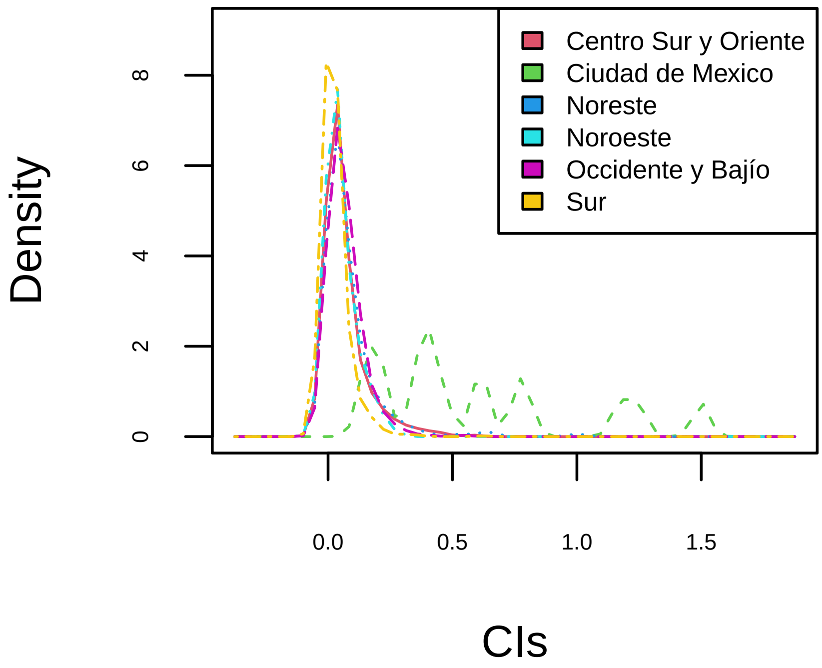
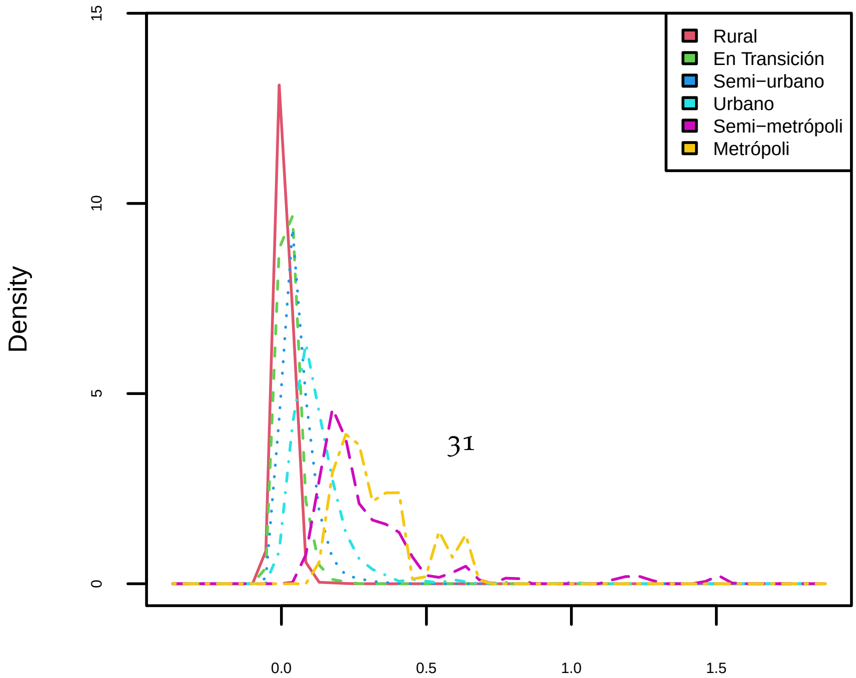


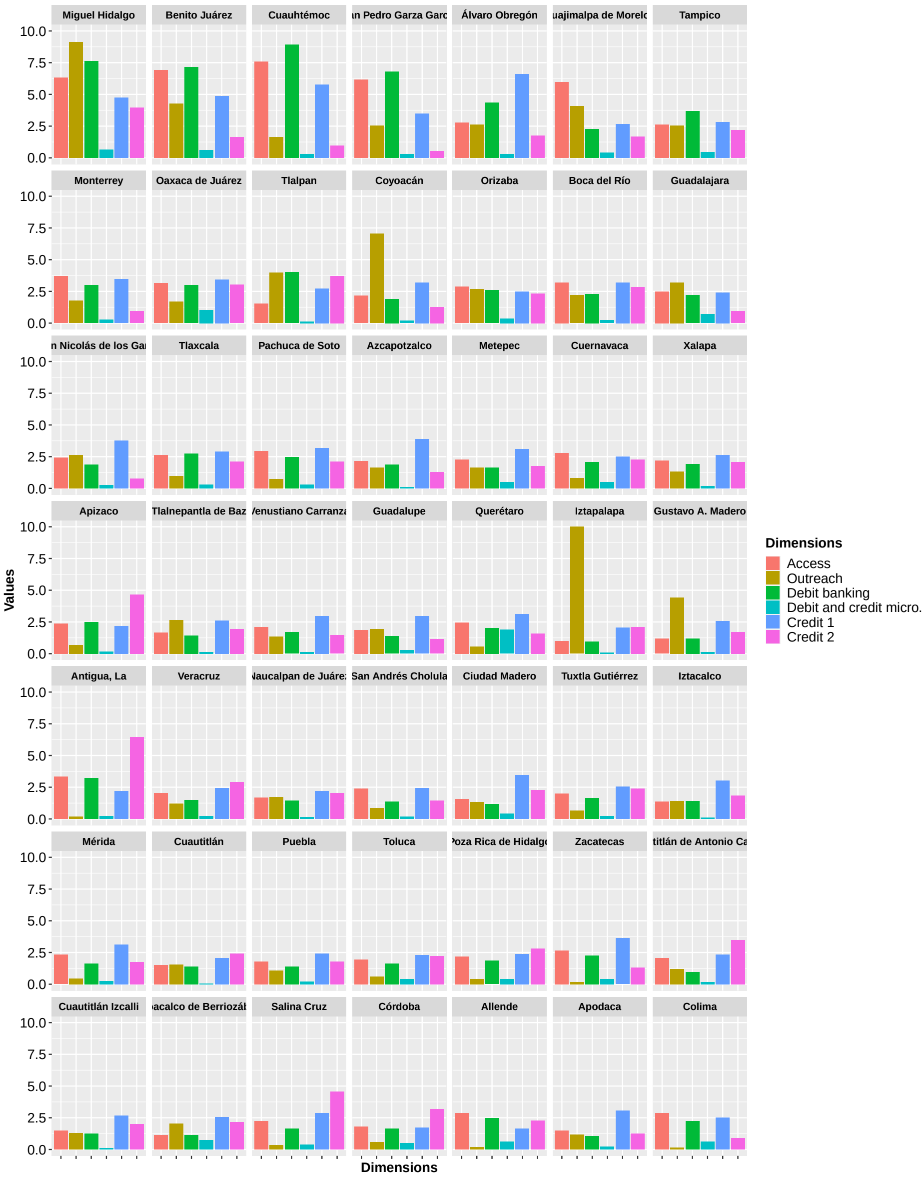
Figure 5: Kernel distribution of the FI Index 2020, by types of population



An advantage of the geometric formulation is that the importance of each dimension could be appreciated from its multiplicative components. For example, for Miguel Hidalgo in Ciudad de México, the geometric index number is the highest ranked, being 1.50. This is the result of the multiplication of the values of the different dimensions elevated by the respective weights: 1.01, 1.29, 1.04, 1.01, 1.05 and 1.05.

Each subdimension, without pondering by the weights, could also be seen as an index that ranks the municipalities by the importance each subdimension has. Recall that each subdimension is formed by indicators, previously normalized by min-max method, multiplied by ten, and then aggregated by a simple arithmetic mean. This can be appreciated in the following table and figures. They report the index with the subdimension in a simple average of min-max transformed indicators. For example, we can observe that for Miguel Hidalgo, the dimension A2 is 9.2, being of great importance, and the dimension U2 being least important being 0.64. And for a municipality as Iztapalapa all the subdimensions of inclusion are very low, but because it is very densely populated municipality in a very small geographical size demarcation, the dimension A2 is very high and this contributes to a high FI index for Iztapalapa.

Figure 6: Top 50 Municipalities of Financial Inclusion Index 2020, by min-max subdimensions



Own estimation.

Figure 7: Lowest 50 Municipalities of Financial Inclusion Index 2020, by min-max subdimensions

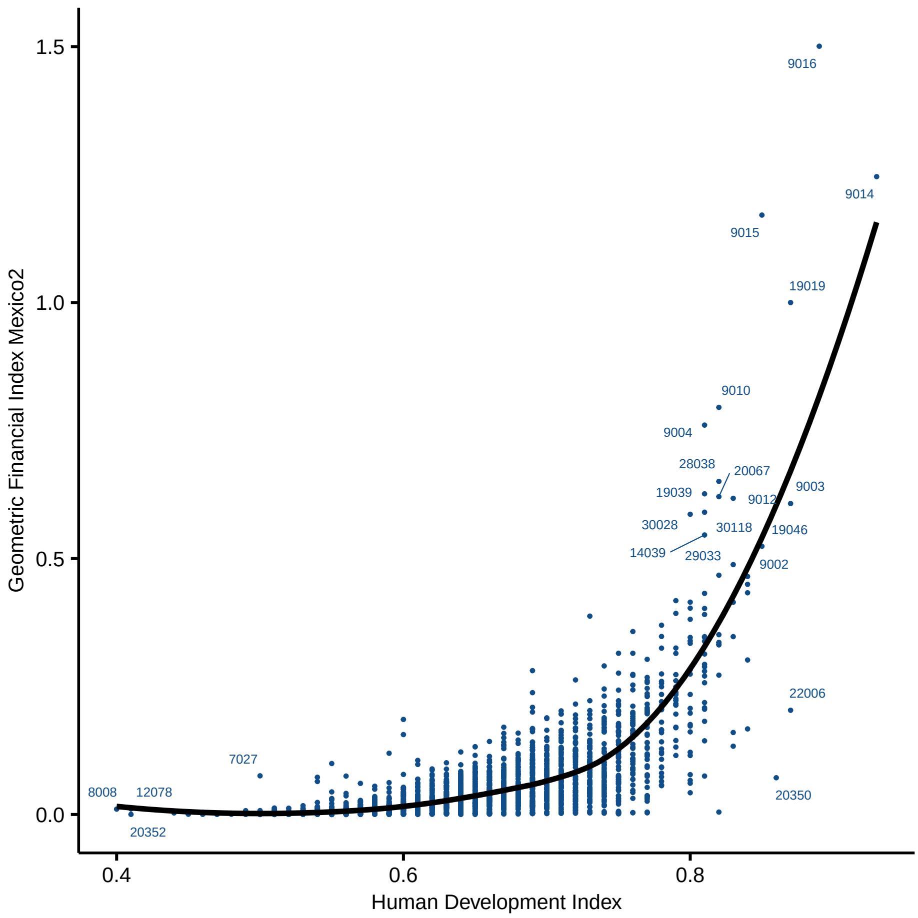
Validation of the FI Index

As a proof of the validity of the estimation of the index, Pearson correlation is considered, between the Geometric Index and the Human Development Index of Mexican municipalities (HDI), computed by the Office of the United Nations Development Programme of Mexico. The correlation is of 62 percent, statistically significant, thus validating our estimated index, as shown in the following figure. Correlation could not be higher considering that the formulation of HDI is linear versus the geometric formulation of the financial inclusion index, and of course, the different variables considered in each one.

In the figure observations are labelled with municipality code, some of them could stand out as scoring high above the correlation trend. For example 9016, Miguel Hidalgo of Ciudad de México, 9015, Cuauhtémoc of Ciudad de México, 9014 Benito Juárez of Ciudad de México, 19019, San Pedro Garza García of Nuevo León, and also 9004, 9003, 22006, 20350, 30016 and 20041. This are municipalities that are in the top of the ranking of the Geometric Financial Inclusion Index.

Figure 8: Correlation of Geometric BoD Indices 2020 and IDH

Spearman correlation is 0.75 and statistically significant.



Stratification of the FI Index for Mexico

In order for the index to give us valuable information of the degree of FI, it is necessary to divide it in stata of homogeneous groups. One way to do this is by Dalenius-Hodges stratification method. Dalenius and Hodges Jr (1959) This method is commonly used by INEGI(Instituto Nacional de Estadistica, Geografía e Informática). INEGI (2010) The Citibanamex FI Index also uses this method.

Dalenius-Hodges method consist in the formation of strata (classes) of municipalities, where the variance is minimal within them, and maximum among them, so in this way the strata are as homogeneus as it is possible.

The procedure by which the stata are obtained follows the methodology described in INEGI (2010):

1. The observations are sorted in ascending order (the $n = 2,465$ municipalities, based on the value obtained in the Geometric BoD FI Index).
2. The observations are grouped into J classes, where $J = min(h * 10, n)$. I am considering 5 strata: very high, high, medium, low, and very low. So that $J = 50$ classes will be used.
3. The upper and lower limits for each class were calculated.
4. From the limits, the frequency of cases for each class were calculated.
5. The square root of the frequency of each class is obtained.
6. The sum of the square roots of the frequencies is accumulated.
7. The last accumulated value is divided by the number of strata (5).
8. The cut-off points of each stratum are taken on the cumulative square root of the frequencies in every class.

The result were strata with the following limits, for the classification of municipalities:

- Very High: 1.5007157 to 0.210101669
- High: 0.210101669 to 0.0900445

- Medium: 0.09004455 to 0.06003027
- Low: 0.06003027 to 0.03001599
- Very low: 0.03001599 to 0.0000017

The number of observations classified in each strata are the following:

```
  Strata_D_H    n
1  Very High  107
2       High  349
3     Medium  251
4        Low  436
5   Very Low 1315
```

The classification of the municipalities are presented in the table and the maps below.

Table 12: Stratified FI Index with BoD Weights 2020. 30 highest Municipalities

State_name	Municipality_name	Type_pop	FI_Geom	Rank	Strata_D_H
Ciudad de México	Miguel Hidalgo	Semi-metrópoli	1.50	1	Very High
Ciudad de México	Benito Juárez	Semi-metrópoli	1.25	2	Very High
Ciudad de México	Cuauhtémoc	Semi-metrópoli	1.17	3	Very High
Nuevo León	San Pedro Garza García	Urbano	1.00	4	Very High
Ciudad de México	Álvaro Obregón	Semi-metrópoli	0.80	5	Very High
Ciudad de México	Cuajimalpa de Morelos	Urbano	0.76	6	Very High
Tamaulipas	Tampico	Semi-metrópoli	0.65	7	Very High
Nuevo León	Monterrey	Metrópoli	0.63	8	Very High
Oaxaca	Oaxaca de Juárez	Urbano	0.62	9	Very High
Ciudad de México	Tlalpan	Semi-metrópoli	0.62	10	Very High
Ciudad de México	Coyoacán	Semi-metrópoli	0.61	11	Very High
Veracruz	Orizaba	Urbano	0.59	12	Very High
Veracruz	Boca del Río	Urbano	0.59	13	Very High
Jalisco	Guadalajara	Metrópoli	0.55	14	Very High
Nuevo León	San Nicolás de los Garza	Semi-metrópoli	0.52	15	Very High
Tlaxcala	Tlaxcala	Urbano	0.49	16	Very High
Hidalgo	Pachuca de Soto	Urbano	0.47	17	Very High
Ciudad de México	Azcapotzalco	Semi-metrópoli	0.46	18	Very High
México	Metepec	Urbano	0.45	19	Very High
Morelos	Cuernavaca	Semi-metrópoli	0.43	20	Very High
Veracruz	Xalapa	Semi-metrópoli	0.43	21	Very High
Tlaxcala	Apizaco	Urbano	0.42	22	Very High
México	Tlalnepantla de Baz	Semi-metrópoli	0.41	23	Very High
Ciudad de México	Venustiano Carranza	Semi-metrópoli	0.41	24	Very High
Nuevo León	Guadalupe	Semi-metrópoli	0.40	25	Very High
Querétaro	Querétaro	Semi-metrópoli	0.40	26	Very High
Ciudad de México	Iztapalapa	Metrópoli	0.39	27	Very High
Ciudad de México	Gustavo A. Madero	Metrópoli	0.39	28	Very High
Veracruz	Antigua, La	Semi-urbano	0.39	29	Very High
Veracruz	Veracruz	Semi-metrópoli	0.38	30	Very High

Figure 9: Map of FI Index 2020, stratified by D-H

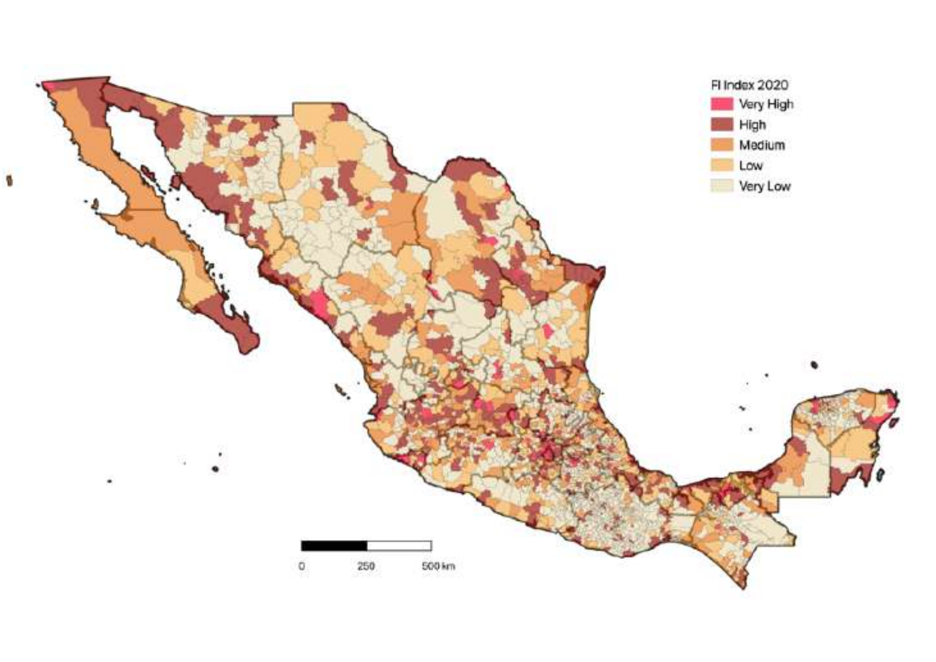
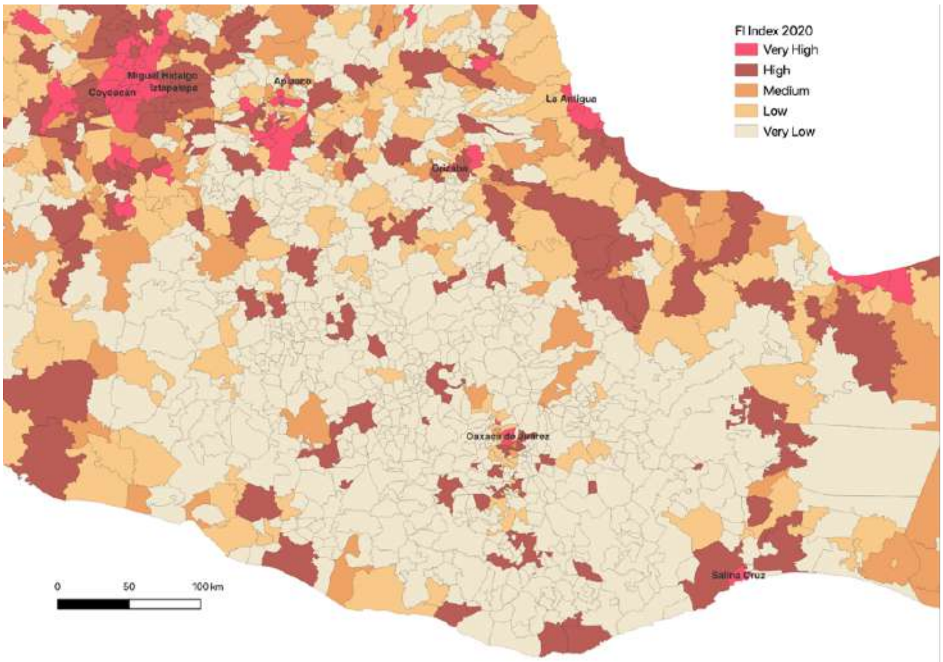


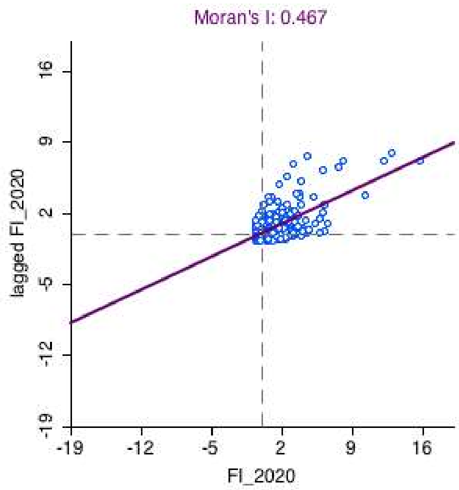
Figure 10: Map of FI Index 2020, stratified by D-H(zoom)



Exploratory spatial analysis of the FI Index 2020

Exploratory spatial analysis has been conducted to test if there is spatial autocorrelation of the FI Index 2020. Moran´s I indicates that FI Index 2020 has positive spatial autocorrelation, as shown in the figure. The null hipothesis is rejected that the FI Index is randomly distributed.

Figure 11: Univariate Moran I-FI 2020

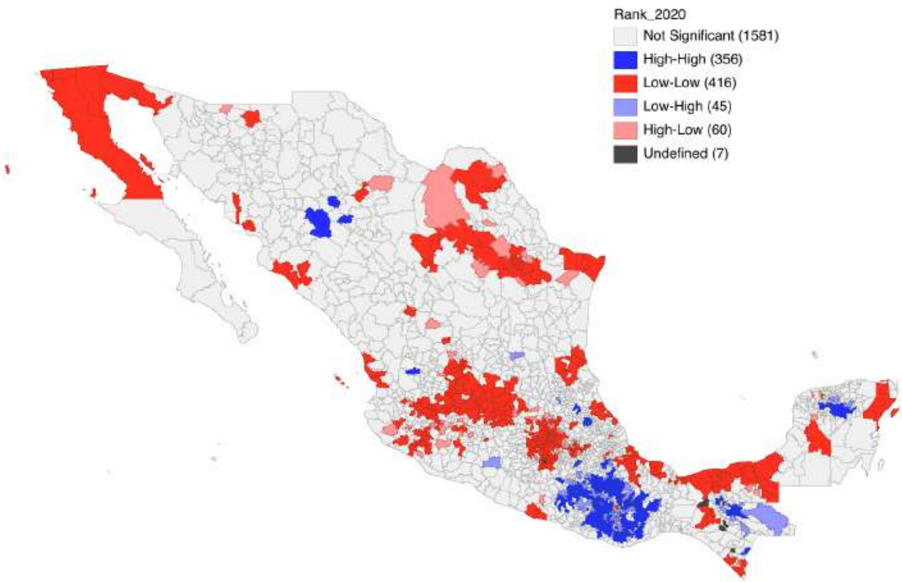


The exploratory spatial analysis was conducted in GeoDa software. Local Moran´s I has also been calculated and used for the formation of clusters. Matrices of spatial weights have been calculated, queen contiguity has been considered of order one, and of order 2. Several options of forming clusters are considered:

1. For FI Index, with queen contiguity of order one, finding 150 observations clusterized High-High and 332 clusterized Low-Low.
2. For FI Index, with queen contiguity of order two, finding 166 observations clusterized High-High and 545 clusterized Low-Low.
3. For the Rank of the FI Index, with queen contiguity of order one, finding 356 observations clusterized High-High and 416 clusterized Low-Low.
4. For the Rank of the FI Index, with queen contiguity of order one, finding 514 observations clusterized High-High and 513 clusterized Low-Low.

These types of clusterizing are shown in the maps below.

Figure 12: Map of Clusters of Ranking of FI contiguity order 1



4. FI Index for Mexican Municipalities 2013-2021 and intertemporal analysis

4.1. Measurement of intertemporal changes

Van Puyenbroeck and Rogge (2017) propose a formulation to assess the dynamic performance of a specific country. The notation extends to consider two periods of time, distinguishing from indicators and weights of period t versus those of period $t+1$. Base performance indicator also changes over time, so it will be represented as $y^B_{r,t}$ and $y^B_{r,t+1}$.

The measure of performance considered by Van Puyenbroeck and Rogge (2017) is the ratio of the transitive geometric mean quantity indices for period t and period $t+1$:

$$PC_i^i = \frac{CI_{i,t+1}^i}{CI_{i,t}^i} = \frac{\prod_{r=1}^{s} (\frac{y_{ri,t+1}}{y_{i,t+1}^B})^{\omega^*_{ri,t+1}}}{\prod_{r=1}^{m} (\frac{y_{ri,t}}{y_{r,t}^B})^{\omega^*_{ri,t}}} \tag{8}$$

The ratio PC_i^i indicates whether or not a country has advanced from period t, to $t+1$. PC values larger than 1 reflect improvement in performance, and lower than 1, decline.

Van Puyenbroeck and Rogge (2017) decompose country performance in factors, with the aim of isolate the different sources of change in performance, that could be the result of changes in: subindicator values, base performance values, and BoD weights. Doing the algebra of factor decomposition of 9, Van Puyenbroeck and Rogge (2017) arrive at the expression:

$$PC_i^i = \Delta OWN_i * \Delta BP_i * \Delta W_i \tag{9}$$

Where ΔOWN_i represents own performance change, this is the change in the subindicator values.

ΔBP_i stands for the change in the base performance indicator.

ΔW_i measures the changes in the BoD sub-indicator shares.

4.2. Intertemporal effects factor decomposition, 2019-2020

In the following table the intertemporal factor decomposition is made for 2019 and 2020. Indices are presented as ranked for 2019. In the table, PC_i^i is named "Overall Change", being the ratio of Indices of 2019 and 2020. For example, it is 1.50/1.46= 1.03 for Miguel Hidalgo municipality. In the cases where the index has risen in time, the ratio is above one. In the table ΔOWN_i is named "Change Effect"; ΔBP_i is the Benchmark Effect, in all transitive indices this effect is the same for all; and ΔW_i is named "Weight Effect".

Table 13: FI Geometric BoD Index 2019-2020 and intertemporal effects decomposition. 50 top ranked municipalities

		FI Indices and Ranks[1]				Intertemporal effects decomposition[2]			
State_name	Municipality_name	FI_2019	R_19	FI_2020	R_20	Overall_Ch.	Change_Eff.	Benchm.Eff.	Weight_Eff.
Ciudad de México	Miguel Hidalgo	1.462	1	1.501	1	1.026	0.907	1.033	1.095
Ciudad de México	Benito Juárez	1.294	2	1.246	2	0.963	0.911	1.033	1.024
Ciudad de México	Cuauhtémoc	1.259	3	1.171	3	0.930	0.946	1.033	0.952
Nuevo León	San Pedro Garza García	1.000	4	1.000	4	1.000	0.968	1.033	1.000
Ciudad de México	Cuajimalpa de Morelos	0.929	5	0.761	6	0.819	0.819	1.033	0.969
Ciudad de México	Álvaro Obregón	0.833	6	0.795	5	0.954	0.867	1.033	1.065
Nuevo León	Monterrey	0.672	7	0.626	8	0.932	0.915	1.033	0.987
Oaxaca	Oaxaca de Juárez	0.671	8	0.621	9	0.926	0.916	1.033	0.978
Veracruz	Boca del Río	0.635	9	0.586	13	0.924	0.887	1.033	1.009
Veracruz	Orizaba	0.582	10	0.590	12	1.014	0.941	1.033	1.044
Ciudad de México	Coyoacán	0.582	11	0.607	11	1.044	0.872	1.033	1.159
Tamaulipas	Tampico	0.556	12	0.651	7	1.169	1.074	1.033	1.054
Jalisco	Guadalajara	0.530	13	0.546	14	1.030	0.943	1.033	1.058
Hidalgo	Pachuca de Soto	0.522	14	0.467	17	0.895	0.928	1.033	0.935
Ciudad de México	Tlalpan	0.522	15	0.618	10	1.183	0.954	1.033	1.201
Tlaxcala	Tlaxcala	0.519	16	0.488	16	0.941	0.932	1.033	0.978
Nuevo León	San Nicolás de los Garza	0.516	17	0.524	15	1.015	0.940	1.033	1.046
Ciudad de México	Azcapotzalco	0.492	18	0.465	18	0.944	0.886	1.033	1.031
Morelos	Cuernavaca	0.489	19	0.433	20	0.885	0.922	1.033	0.930
Querétaro	Querétaro	0.486	20	0.402	26	0.828	0.905	1.033	0.886
Veracruz	Antigua, La	0.481	21	0.387	29	0.805	0.931	1.033	0.837
México	Metepec	0.464	22	0.450	19	0.970	0.942	1.033	0.997
Ciudad de México	Venustiano Carranza	0.453	23	0.415	24	0.916	0.882	1.033	1.005
Tlaxcala	Apizaco	0.442	24	0.418	22	0.945	0.953	1.033	0.960
Veracruz	Xalapa	0.441	25	0.432	21	0.980	0.937	1.033	1.013
Nuevo León	Pesquería	0.423	26	0.238	83	0.562	0.770	1.033	0.707
Zacatecas	Zacatecas	0.423	27	0.336	41	0.795	0.939	1.033	0.820
Puebla	San Andrés Cholula	0.422	28	0.357	32	0.848	0.874	1.033	0.939
Yucatán	Mérida	0.410	29	0.347	36	0.848	0.917	1.033	0.895
México	Tlalnepantla de Baz	0.406	30	0.415	23	1.021	0.909	1.033	1.088
Veracruz	Veracruz	0.406	31	0.381	30	0.940	0.917	1.033	0.993
Colima	Colima	0.402	32	0.313	50	0.780	0.945	1.033	0.799
Nuevo León	Guadalupe	0.401	33	0.403	25	1.006	0.946	1.033	1.029
Quintana Roo	Solidaridad	0.388	34	0.234	88	0.604	0.853	1.033	0.686
Veracruz	Poza Rica de Hidalgo	0.386	35	0.338	40	0.876	0.942	1.033	0.900
Quintana Roo	Benito Juárez	0.384	36	0.325	45	0.846	0.899	1.033	0.911
Oaxaca	Salina Cruz	0.384	37	0.325	46	0.847	0.952	1.033	0.862
México	Naucalpan de Juárez	0.378	38	0.370	31	0.977	0.905	1.033	1.045
Puebla	Puebla	0.372	39	0.346	38	0.930	0.905	1.033	0.995
México	Toluca	0.369	40	0.339	39	0.918	0.947	1.033	0.939
Chiapas	Tuxtla Gutiérrez	0.368	41	0.348	34	0.946	0.963	1.033	0.951
San Luis Potosí	San Luis Potosí	0.365	42	0.293	53	0.802	0.929	1.033	0.836
Ciudad de México	Iztacalco	0.360	43	0.347	35	0.965	0.888	1.033	1.052
Tamaulipas	Ciudad Madero	0.360	44	0.351	33	0.976	0.943	1.033	1.002
Nuevo León	Allende	0.359	45	0.315	48	0.877	1.058	1.033	0.802
México	Cuautitlán	0.359	46	0.346	37	0.964	0.878	1.033	1.063
Ciudad de México	Gustavo A. Madero	0.358	47	0.391	28	1.090	0.901	1.033	1.171
Nuevo León	Ciénega de Flores	0.356	48	0.263	68	0.738	0.893	1.033	0.800
Veracruz	Córdoba	0.349	49	0.315	47	0.904	0.931	1.033	0.940
Guanajuato	Guanajuato	0.348	50	0.246	78	0.708	0.948	1.033	0.722

Note:
Own elaboration.
[1] Footnote 1;
[2] Footnote 2;

4.3. Geometric BoD Indices for 2013-2021, and intertemporal analysis

In this section FI indices for the whole period of 2013-2021 are calculated, following the methology described previously, applying the calculations of equations (1) to (6). The results are presented in the following tables, with their rankings.

Table 14: Index of Financial Inclusion- Geometric with BoD Weights, 2013-2017. Top 50 Municipalities ranked.

State_name	Municipality_name	FI_13	R_13	FI_14	R_14	FI_15	R_15	FI_16	R_16	FI_17	R_17
Ciudad de México	Miguel Hidalgo	1.502	1	1.538	1	1.530	1	1.571	1	1.595	1
Ciudad de México	Benito Juárez	1.249	2	1.284	2	1.262	2	1.256	2	1.265	2
Ciudad de México	Cuauhtémoc	1.136	3	1.142	3	1.150	3	1.082	3	1.139	3
Nuevo León	San Pedro Garza García	1.000	4	1.000	4	1.000	4	1.000	4	1.000	4
Ciudad de México	Álvaro Obregón	0.831	5	0.933	5	0.938	5	0.917	5	0.921	5
Ciudad de México	Cuajimalpa de Morelos	0.777	6	0.865	6	0.870	6	0.856	6	0.835	6
Ciudad de México	Coyoacán	0.703	8	0.813	7	0.819	7	0.738	7	0.705	7
Nuevo León	Monterrey	0.723	7	0.741	8	0.742	8	0.723	8	0.698	8
Oaxaca	Oaxaca de Juárez	0.630	11	0.657	10	0.658	10	0.690	10	0.670	9
Veracruz	Boca del Río	0.654	9	0.685	9	0.687	9	0.693	9	0.653	10
Tamaulipas	Tampico	0.632	10	0.649	12	0.649	11	0.640	11	0.605	11
Veracruz	Orizaba	0.539	15	0.563	15	0.565	15	0.590	13	0.591	12
Jalisco	Guadalajara	0.628	12	0.649	11	0.640	12	0.619	12	0.568	13
Nuevo León	San Nicolás de los Garza	0.592	14	0.607	13	0.608	13	0.589	14	0.560	14
Ciudad de México	Azcapotzalco	0.510	17	0.533	17	0.543	16	0.541	16	0.533	15
Hidalgo	Pachuca de Soto	0.496	18	0.524	19	0.529	19	0.538	17	0.517	16
Ciudad de México	Tlalpan	0.609	13	0.590	14	0.589	14	0.550	15	0.514	17
Morelos	Cuernavaca	0.493	20	0.528	18	0.533	18	0.526	18	0.507	18
México	Metepec	0.516	16	0.533	16	0.534	17	0.518	19	0.491	19
Tlaxcala	Tlaxcala	0.454	24	0.481	22	0.481	22	0.479	22	0.474	20
Veracruz	Xalapa	0.481	21	0.517	21	0.517	20	0.517	20	0.469	21
México	Tlalnepantla de Baz	0.493	19	0.519	20	0.516	21	0.486	21	0.452	22
Ciudad de México	Venustiano Carranza	0.441	26	0.468	26	0.471	25	0.451	25	0.442	23
Querétaro	Querétaro	0.409	29	0.434	31	0.436	30	0.435	29	0.434	24
Veracruz	Veracruz	0.441	27	0.454	28	0.460	28	0.477	23	0.430	25
Nuevo León	Guadalupe	0.450	25	0.461	27	0.461	27	0.447	26	0.427	26
Tlaxcala	Apizaco	0.384	36	0.400	36	0.411	33	0.427	31	0.421	27
Ciudad de México	Gustavo A. Madero	0.434	28	0.476	24	0.480	23	0.453	24	0.418	28
Quintana Roo	Benito Juárez	0.390	33	0.392	39	0.400	39	0.426	33	0.417	29
México	Naucalpan de Juárez	0.464	22	0.470	25	0.468	26	0.443	28	0.416	30
Veracruz	Antigua, La	0.334	46	0.357	46	0.369	45	0.406	38	0.416	31
Tamaulipas	Ciudad Madero	0.456	23	0.477	23	0.474	24	0.445	27	0.404	32
Ciudad de México	Iztacalco	0.385	35	0.423	32	0.430	31	0.411	36	0.400	33
Puebla	San Andrés Cholula	0.349	45	0.369	44	0.379	44	0.390	40	0.399	34
Puebla	Puebla	0.381	38	0.400	35	0.405	36	0.415	35	0.399	35
Ciudad de México	Iztapalapa	0.399	30	0.435	29	0.438	29	0.427	32	0.399	36
Chiapas	Tuxtla Gutiérrez	0.387	34	0.399	38	0.408	35	0.434	30	0.395	37
Yucatán	Mérida	0.378	39	0.403	34	0.409	34	0.408	37	0.393	38
Zacatecas	Zacatecas	0.359	44	0.379	43	0.383	42	0.381	42	0.391	39
México	Toluca	0.395	32	0.435	30	0.428	32	0.420	34	0.379	40
México	Cuautitlán	0.375	40	0.387	40	0.388	40	0.388	41	0.375	41
Veracruz	Poza Rica de Hidalgo	0.398	31	0.400	37	0.401	38	0.403	39	0.374	42
Jalisco	Zapopan	0.365	41	0.387	41	0.383	43	0.358	46	0.351	43
Tlaxcala	Apetatitlán de Antonio Carvajal	0.292	59	0.335	50	0.348	49	0.342	50	0.348	44
Colima	Colima	0.312	51	0.333	52	0.333	53	0.312	56	0.347	45
México	Cuautitlán Izcalli	0.363	42	0.382	42	0.384	41	0.365	44	0.345	46
Oaxaca	Salina Cruz	0.326	48	0.352	48	0.356	48	0.357	47	0.344	47
México	Coacalco de Berriozábal	0.382	37	0.404	33	0.403	37	0.377	43	0.343	48
Nuevo León	Apodaca	0.360	43	0.360	45	0.361	46	0.358	45	0.341	49
Veracruz	Córdoba	0.319	50	0.334	51	0.334	52	0.342	49	0.339	50

Note:
Own elaboration. The indices are ordered by the ranking of 2017 FI Index.

Table 15: Index of Financial Inclusion- Geometric with BoD Weights 2018-2021. Top 50 Municipalities ranked

State_name	Municipality_name	FI_18	R_18	FI_19	R_19	FI_20	R_20	FI_21	R_21
Ciudad de México	Miguel Hidalgo	1.546	1	1.462	1	1.501	1	1.300	1
Ciudad de México	Benito Juárez	1.259	2	1.294	2	1.246	2	1.086	2
Ciudad de México	Cuauhtémoc	1.135	3	1.259	3	1.171	3	1.072	3
Nuevo León	San Pedro Garza García	1.000	4	1.000	4	1.000	4	1.000	4
Ciudad de México	Álvaro Obregón	0.903	5	0.833	6	0.795	5	0.665	5
Ciudad de México	Cuajimalpa de Morelos	0.894	6	0.929	5	0.761	6	0.603	7
Tamaulipas	Tampico	0.582	12	0.556	12	0.651	7	0.502	14
Nuevo León	Monterrey	0.683	7	0.672	7	0.626	8	0.611	6
Oaxaca	Oaxaca de Juárez	0.672	9	0.671	8	0.621	9	0.550	9
Ciudad de México	Tlalpan	0.484	18	0.522	15	0.618	10	0.581	8
Ciudad de México	Coyoacán	0.682	8	0.582	11	0.607	11	0.520	11
Veracruz	Orizaba	0.600	11	0.582	10	0.590	12	0.541	10
Veracruz	Boca del Río	0.646	10	0.635	9	0.586	13	0.510	13
Jalisco	Guadalajara	0.566	13	0.530	13	0.546	14	0.520	12
Nuevo León	San Nicolás de los Garza	0.546	14	0.516	17	0.524	15	0.499	15
Tlaxcala	Tlaxcala	0.483	19	0.519	16	0.488	16	0.451	16
Hidalgo	Pachuca de Soto	0.506	16	0.522	14	0.467	17	0.391	22
Ciudad de México	Azcapotzalco	0.518	15	0.492	18	0.465	18	0.397	18
México	Metepec	0.477	20	0.464	22	0.450	19	0.406	17
Morelos	Cuernavaca	0.494	17	0.489	19	0.433	20	0.395	19
Veracruz	Xalapa	0.464	21	0.441	25	0.432	21	0.391	21
Tlaxcala	Apizaco	0.421	25	0.442	24	0.418	22	0.387	23
México	Tlalnepantla de Baz	0.445	23	0.406	30	0.415	23	0.374	24
Ciudad de México	Venustiano Carranza	0.440	24	0.453	23	0.415	24	0.352	26
Nuevo León	Guadalupe	0.417	26	0.401	33	0.403	25	0.392	20
Querétaro	Querétaro	0.446	22	0.486	20	0.402	26	0.337	29
Ciudad de México	Iztapalapa	0.396	32	0.319	65	0.393	27	0.334	31
Ciudad de México	Gustavo A. Madero	0.408	29	0.358	47	0.391	28	0.347	28
Veracruz	Antigua, La	0.408	30	0.481	21	0.387	29	0.334	30
Veracruz	Veracruz	0.410	27	0.406	31	0.381	30	0.327	32
México	Naucalpan de Juárez	0.410	28	0.378	38	0.370	31	0.354	25
Puebla	San Andrés Cholula	0.397	31	0.422	28	0.357	32	0.283	50
Tamaulipas	Ciudad Madero	0.392	34	0.360	44	0.351	33	0.308	37
Chiapas	Tuxtla Gutiérrez	0.377	39	0.368	41	0.348	34	0.316	35
Ciudad de México	Iztacalco	0.383	38	0.360	43	0.347	35	0.295	46
Yucatán	Mérida	0.388	36	0.410	29	0.347	36	0.301	43
México	Cuautitlán	0.367	40	0.359	46	0.346	37	0.301	42
Puebla	Puebla	0.388	35	0.372	39	0.346	38	0.299	44
México	Toluca	0.360	42	0.369	40	0.339	39	0.320	34
Veracruz	Poza Rica de Hidalgo	0.363	41	0.386	35	0.338	40	0.322	33
Zacatecas	Zacatecas	0.384	37	0.423	27	0.336	41	0.307	38
Tlaxcala	Apetatitlán de Antonio Carvajal	0.335	46	0.342	53	0.334	42	0.257	56
México	Cuautitlán Izcalli	0.334	47	0.335	54	0.333	43	0.306	39
México	Coacalco de Berriozábal	0.323	51	0.310	69	0.331	44	0.301	41
Quintana Roo	Benito Juárez	0.394	33	0.384	36	0.325	45	0.285	49
Oaxaca	Salina Cruz	0.336	45	0.384	37	0.325	46	0.297	45
Veracruz	Córdoba	0.329	49	0.349	49	0.315	47	0.288	48
Nuevo León	Allende	0.294	60	0.359	45	0.315	48	0.314	36
Nuevo León	Apodaca	0.324	50	0.315	67	0.315	49	0.290	47
Colima	Colima	0.342	44	0.402	32	0.313	50	0.305	40

Note:
Own elaboration. The indices are ordered by the ranking of 2021 FI Index.

Each of the FI indices presented in the above tables give us very important information of the particular level of financial inclusion of each municipality for each year, for this reason the results obtained are very relevant. But to evaluate changes in time of indices we use ranking correlations of the index of one year, compared to the index of the following year. We present the graphs of this ranking correlations, showing that the correlation is in all cases very high, but illustrating some changes.Because the rank goes from 1 to 2546, in the graphs, the municipalities located near zero are the top ranked, and the ones located near 2500 are the ones at the bottom of the rank. We can identify specific municipalities below the regression line, as municipalities that improve in the ranking. When we see many dots (Municipalities) below the fit line, it means that financial inclusion improved for that municipalities in the period, which is the case in 2016-2017 and 2018-2019. The graph for all the period 2013-2021 is also presented, where we can see clearly many more changes in the ranking of financial inclusion for several Municipalities.

Ranking Correlation 2013-2021

Figure 13: Ranking Correlation of FI Indices of 2013-2017 (Spearman), by type of population

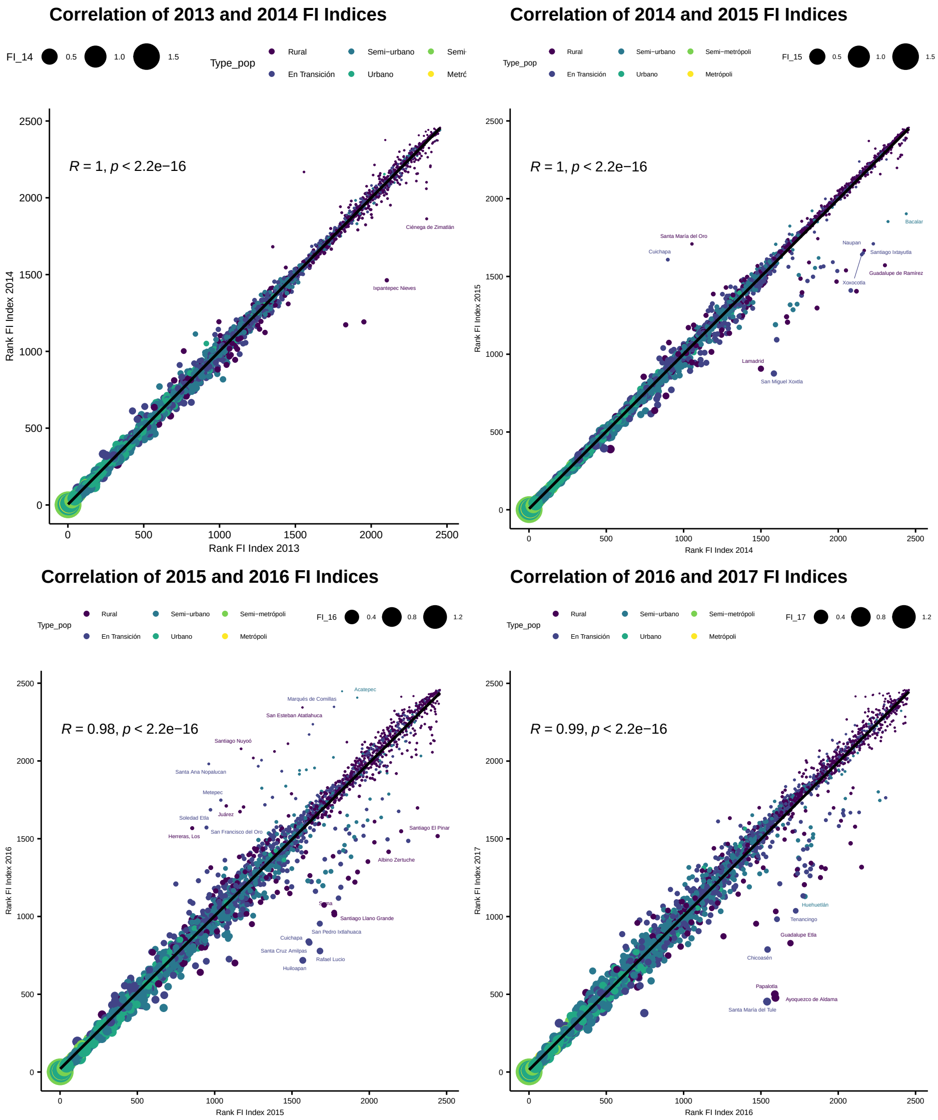


Figure 14: Ranking Correlation of FI Indices of 2017-2021 (Spearman), by type of population

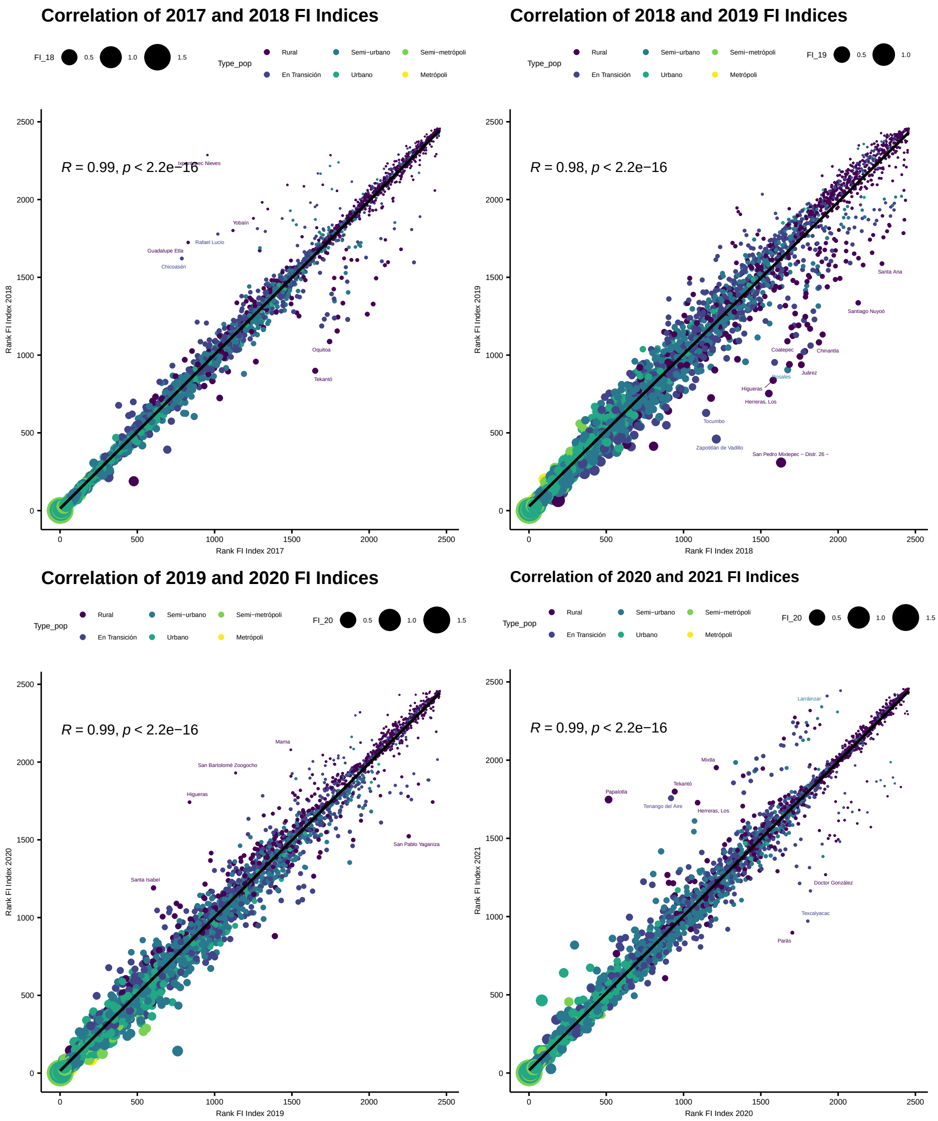
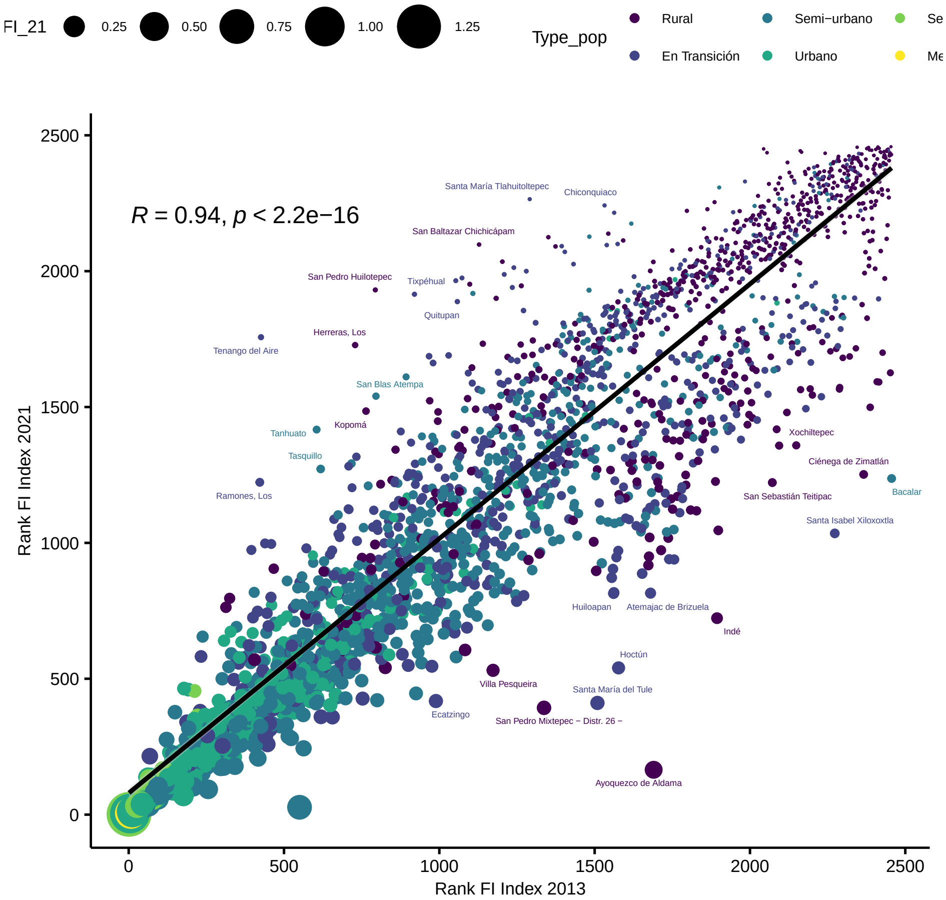


Figure 15: Ranking Correlation of FI Indices 2013 and 2021 (Spearman), by type of population



Intertemporal factor decomposition, 2013-2021

In this section intertemporal decomposition is calculated for each year for the period of 2013-2021, by the methodology explained earlier.The results are presented in the following tables.

Table 16: FI Geometric BoD Index, 2013-2015, and intertemporal effects decomposition. 45 top ranked municipalities

		FI Indices[1]			Intertemporal effects 2013-2014[2]				Intertemporal effects 2014-2015[3]			
State_name	Municipality_name	FI_13	FI_14	FI_15	O13_14	Ch13_14	B13_14	W13_14	O14_15	Ch14_15	B14_15	W14_15
Ciudad de México	Miguel Hidalgo	1.502	1.538	1.530	1.02	1.05	0.97	1.00	0.99	0.99	1	1.00
Ciudad de México	Benito Juárez	1.249	1.284	1.262	1.03	1.06	0.97	1.00	0.98	0.98	1	1.00
Ciudad de México	Cuauhtémoc	1.136	1.142	1.150	1.00	1.03	0.97	1.01	1.01	1.00	1	1.00
Nuevo León	San Pedro Garza García	1.000	1.000	1.000	1.00	1.03	0.97	1.00	1.00	1.00	1	1.00
Ciudad de México	Álvaro Obregón	0.831	0.933	0.938	1.12	1.14	0.97	1.01	1.01	1.00	1	1.00
Ciudad de México	Cuajimalpa de Morelos	0.777	0.865	0.870	1.11	1.14	0.97	1.01	1.01	1.01	1	1.00
Tamaulipas	Tampico	0.632	0.649	0.649	1.03	1.04	0.97	1.02	1.00	0.99	1	1.00
Nuevo León	Monterrey	0.723	0.741	0.742	1.02	1.03	0.97	1.02	1.00	0.99	1	1.00
Oaxaca	Oaxaca de Juárez	0.630	0.657	0.658	1.04	1.05	0.97	1.03	1.00	0.99	1	1.01
Ciudad de México	Tlalpan	0.609	0.590	0.589	0.97	0.99	0.97	1.01	1.00	1.00	1	1.00
Ciudad de México	Coyoacán	0.703	0.813	0.819	1.16	1.19	0.97	1.00	1.01	1.01	1	1.00
Veracruz	Orizaba	0.539	0.563	0.565	1.04	1.05	0.97	1.02	1.00	1.00	1	1.01
Veracruz	Boca del Río	0.654	0.685	0.687	1.05	1.06	0.97	1.02	1.00	1.00	1	1.00
Jalisco	Guadalajara	0.628	0.649	0.640	1.03	1.06	0.97	1.00	0.99	0.98	1	1.00
Nuevo León	San Nicolás de los Garza	0.592	0.607	0.608	1.03	1.05	0.97	1.01	1.00	1.00	1	1.00
Tlaxcala	Tlaxcala	0.454	0.481	0.481	1.06	1.06	0.97	1.03	1.00	0.99	1	1.01
Hidalgo	Pachuca de Soto	0.496	0.524	0.529	1.06	1.07	0.97	1.02	1.01	1.00	1	1.01
Ciudad de México	Azcapotzalco	0.510	0.533	0.543	1.04	1.07	0.97	1.01	1.02	1.02	1	1.00
México	Metepec	0.516	0.533	0.534	1.03	1.05	0.97	1.01	1.00	1.00	1	1.00
Morelos	Cuernavaca	0.493	0.528	0.533	1.07	1.08	0.97	1.02	1.01	1.00	1	1.01
Veracruz	Xalapa	0.481	0.517	0.517	1.08	1.09	0.97	1.02	1.00	0.99	1	1.01
Tlaxcala	Apizaco	0.384	0.400	0.411	1.04	1.04	0.97	1.03	1.03	1.01	1	1.01
México	Tlalnepantla de Baz	0.493	0.519	0.516	1.05	1.08	0.97	1.01	0.99	0.99	1	1.00
Ciudad de México	Venustiano Carranza	0.441	0.468	0.471	1.06	1.08	0.97	1.01	1.01	1.00	1	1.00
Nuevo León	Guadalupe	0.450	0.461	0.461	1.02	1.04	0.97	1.01	1.00	1.00	1	1.00
Querétaro	Querétaro	0.409	0.434	0.436	1.06	1.07	0.97	1.02	1.01	1.00	1	1.01
Ciudad de México	Iztapalapa	0.399	0.435	0.438	1.09	1.12	0.97	1.01	1.01	1.01	1	1.00
Ciudad de México	Gustavo A. Madero	0.434	0.476	0.480	1.09	1.12	0.97	1.01	1.01	1.01	1	1.00
Veracruz	Antigua, La	0.334	0.357	0.369	1.07	1.05	0.97	1.05	1.03	1.01	1	1.02
Veracruz	Veracruz	0.441	0.454	0.460	1.03	1.04	0.97	1.02	1.01	1.00	1	1.01
México	Naucalpan de Juárez	0.464	0.470	0.468	1.01	1.03	0.97	1.01	1.00	0.99	1	1.00
Puebla	San Andrés Cholula	0.349	0.369	0.379	1.06	1.07	0.97	1.02	1.03	1.03	1	1.00
Tamaulipas	Ciudad Madero	0.456	0.477	0.474	1.05	1.05	0.97	1.02	0.99	0.99	1	1.00
Chiapas	Tuxtla Gutiérrez	0.387	0.399	0.408	1.03	1.03	0.97	1.03	1.02	1.01	1	1.01
Ciudad de México	Iztacalco	0.385	0.423	0.430	1.10	1.11	0.97	1.02	1.02	1.01	1	1.00
Yucatán	Mérida	0.378	0.403	0.409	1.07	1.07	0.97	1.02	1.01	1.01	1	1.01
México	Cuautitlán	0.375	0.387	0.388	1.03	1.05	0.97	1.02	1.00	1.00	1	1.00
Puebla	Puebla	0.381	0.400	0.405	1.05	1.06	0.97	1.02	1.01	1.01	1	1.00
México	Toluca	0.395	0.435	0.428	1.10	1.11	0.97	1.02	0.98	0.98	1	1.01
Veracruz	Poza Rica de Hidalgo	0.398	0.400	0.401	1.00	1.00	0.97	1.03	1.00	0.99	1	1.01
Zacatecas	Zacatecas	0.359	0.379	0.383	1.06	1.06	0.97	1.03	1.01	1.00	1	1.01
Tlaxcala	Apetatitlán de Antonio Carvajal	0.292	0.335	0.348	1.15	1.15	0.97	1.02	1.04	1.03	1	1.00
México	Cuautitlán Izcalli	0.363	0.382	0.384	1.05	1.07	0.97	1.02	1.01	1.00	1	1.00
México	Coacalco de Berriozábal	0.382	0.404	0.403	1.06	1.08	0.97	1.01	1.00	1.00	1	1.00
Quintana Roo	Benito Juárez	0.390	0.392	0.400	1.00	1.01	0.97	1.02	1.02	1.01	1	1.00

Note:
Own elaboration.
[1] Footnote 1;
[2] Footnote 2
[3] Footnote 3

Table 17: FI Geometric BoD Index, 2015-2017, and intertemporal effects decomposition. 45 top ranked municipalities

		FI Indices[1]			Intertemporal effects 2015-2016[2]				Intertemporal effects 2016-2017[3]			
State_name	Municipality_name	FI_15	FI_16	FI_17	O15_16	Ch15_16	B15_16	W15_16	O16_17	Ch16_17	B_16_17	W_16_17
Ciudad de México	Miguel Hidalgo	1.530	1.571	1.595	1.03	1.04	0.99	1.00	1.02	1.00	1.03	0.99
Ciudad de México	Benito Juárez	1.262	1.256	1.265	1.00	1.01	0.99	0.99	1.01	0.98	1.03	1.00
Ciudad de México	Cuauhtémoc	1.150	1.082	1.139	0.94	0.95	0.99	0.99	1.05	1.01	1.03	1.02
Nuevo León	San Pedro Garza García	1.000	1.000	1.000	1.00	1.01	0.99	1.00	1.00	0.97	1.03	1.00
Ciudad de México	Álvaro Obregón	0.938	0.917	0.921	0.98	0.99	0.99	0.99	1.00	0.96	1.03	1.02
Ciudad de México	Cuajimalpa de Morelos	0.870	0.856	0.835	0.98	0.98	0.99	1.01	0.98	0.97	1.03	0.98
Tamaulipas	Tampico	0.649	0.640	0.605	0.99	0.97	0.99	1.02	0.95	0.94	1.03	0.98
Nuevo León	Monterrey	0.742	0.723	0.698	0.97	0.96	0.99	1.02	0.96	0.95	1.03	0.99
Oaxaca	Oaxaca de Juárez	0.658	0.690	0.670	1.05	1.04	0.99	1.02	0.97	0.95	1.03	1.00
Ciudad de México	Tlalpan	0.589	0.550	0.514	0.93	0.94	0.99	1.00	0.93	0.92	1.03	0.98
Ciudad de México	Coyoacán	0.819	0.738	0.705	0.90	0.90	0.99	1.01	0.95	0.96	1.03	0.97
Veracruz	Orizaba	0.565	0.590	0.591	1.04	1.03	0.99	1.02	1.00	0.99	1.03	0.98
Veracruz	Boca del Río	0.687	0.693	0.653	1.01	0.99	0.99	1.03	0.94	0.94	1.03	0.98
Jalisco	Guadalajara	0.640	0.619	0.568	0.97	0.96	0.99	1.02	0.92	0.92	1.03	0.97
Nuevo León	San Nicolás de los Garza	0.608	0.589	0.560	0.97	0.96	0.99	1.02	0.95	0.94	1.03	0.98
Tlaxcala	Tlaxcala	0.481	0.479	0.474	1.00	0.99	0.99	1.01	0.99	0.96	1.03	1.00
Hidalgo	Pachuca de Soto	0.529	0.538	0.517	1.02	1.01	0.99	1.01	0.96	0.93	1.03	1.01
Ciudad de México	Azcapotzalco	0.543	0.541	0.533	1.00	1.00	0.99	1.01	0.99	0.96	1.03	1.00
México	Metepec	0.534	0.518	0.491	0.97	0.96	0.99	1.02	0.95	0.94	1.03	0.98
Morelos	Cuernavaca	0.533	0.526	0.507	0.99	0.98	0.99	1.02	0.96	0.94	1.03	1.00
Veracruz	Xalapa	0.517	0.517	0.469	1.00	0.99	0.99	1.02	0.91	0.89	1.03	0.99
Tlaxcala	Apizaco	0.411	0.427	0.421	1.04	1.02	0.99	1.03	0.99	0.96	1.03	1.00
México	Tlalnepantla de Baz	0.516	0.486	0.452	0.94	0.93	0.99	1.02	0.93	0.93	1.03	0.98
Ciudad de México	Venustiano Carranza	0.471	0.451	0.442	0.96	0.96	0.99	1.01	0.98	0.96	1.03	0.99
Nuevo León	Guadalupe	0.461	0.447	0.427	0.97	0.95	0.99	1.03	0.95	0.95	1.03	0.98
Querétaro	Querétaro	0.436	0.435	0.434	1.00	0.98	0.99	1.02	1.00	0.97	1.03	1.00
Ciudad de México	Iztapalapa	0.438	0.427	0.399	0.97	0.97	0.99	1.02	0.93	0.95	1.03	0.95
Ciudad de México	Gustavo A. Madero	0.480	0.453	0.418	0.94	0.94	0.99	1.01	0.92	0.92	1.03	0.97
Veracruz	Antigua, La	0.369	0.406	0.416	1.10	1.08	0.99	1.02	1.02	0.97	1.03	1.02
Veracruz	Veracruz	0.460	0.477	0.430	1.04	1.02	0.99	1.03	0.90	0.89	1.03	0.98
México	Naucalpan de Juárez	0.468	0.443	0.416	0.95	0.94	0.99	1.02	0.94	0.93	1.03	0.98
Puebla	San Andrés Cholula	0.379	0.390	0.399	1.03	1.01	0.99	1.02	1.02	1.01	1.03	0.99
Tamaulipas	Ciudad Madero	0.474	0.445	0.404	0.94	0.92	0.99	1.03	0.91	0.90	1.03	0.98
Chiapas	Tuxtla Gutiérrez	0.408	0.434	0.395	1.06	1.05	0.99	1.02	0.91	0.89	1.03	1.00
Ciudad de México	Iztacalco	0.430	0.411	0.400	0.96	0.96	0.99	1.01	0.97	0.95	1.03	1.00
Yucatán	Mérida	0.409	0.408	0.393	1.00	0.98	0.99	1.02	0.96	0.93	1.03	1.00
México	Cuautitlán	0.388	0.388	0.375	1.00	0.99	0.99	1.02	0.97	0.95	1.03	0.99
Puebla	Puebla	0.405	0.415	0.399	1.02	1.01	0.99	1.02	0.96	0.95	1.03	0.99
México	Toluca	0.428	0.420	0.379	0.98	0.97	0.99	1.02	0.90	0.88	1.03	1.00
Veracruz	Poza Rica de Hidalgo	0.401	0.403	0.374	1.01	0.99	0.99	1.03	0.93	0.90	1.03	1.01
Zacatecas	Zacatecas	0.383	0.381	0.391	0.99	0.99	0.99	1.01	1.03	0.97	1.03	1.03
Tlaxcala	Apetatitlán de Antonio Carvajal	0.348	0.342	0.348	0.98	0.96	0.99	1.03	1.02	1.02	1.03	0.97
México	Cuautitlán Izcalli	0.384	0.365	0.345	0.95	0.94	0.99	1.02	0.95	0.93	1.03	0.99
México	Coacalco de Berriozábal	0.403	0.377	0.343	0.94	0.93	0.99	1.02	0.91	0.90	1.03	0.98
Quintana Roo	Benito Juárez	0.400	0.426	0.417	1.07	1.05	0.99	1.02	0.98	0.96	1.03	1.00

Note:
Own elaboration.
[1] Footnote 1;
[2] Footnote 2;

Table 18: FI Geometric BoD Index, 2017-2019, and intertemporal effects decomposition. 45 top ranked municipalities

		FI Indices[1]			Intertemporal effects 2017-2018[2]				Intertemporal effects 2018-2019[3]			
State_name	Municipality_name	FI_17	FI_18	FI_19	O_17_18	Ch_17_18	B_17_18	W_17_18	O_18_19	Ch_18_19	B_18_19	W_18_19
Ciudad de México	Miguel Hidalgo	1.595	1.546	1.462	0.97	0.97	1.01	1.00	0.95	0.94	1.08	0.94
Ciudad de México	Benito Juárez	1.265	1.259	1.294	0.99	0.99	1.01	1.00	1.03	0.99	1.08	0.97
Ciudad de México	Cuauhtémoc	1.139	1.135	1.259	1.00	0.99	1.01	1.00	1.11	1.00	1.08	1.03
Nuevo León	San Pedro Garza García	1.000	1.000	1.000	1.00	0.99	1.01	1.00	1.00	0.93	1.08	1.00
Ciudad de México	Álvaro Obregón	0.921	0.903	0.833	0.98	0.99	1.01	0.99	0.92	0.92	1.08	0.93
Ciudad de México	Cuajimalpa de Morelos	0.835	0.894	0.929	1.07	1.10	1.01	0.97	1.04	0.99	1.08	0.97
Tamaulipas	Tampico	0.605	0.582	0.556	0.96	0.96	1.01	1.00	0.96	0.92	1.08	0.96
Nuevo León	Monterrey	0.698	0.683	0.672	0.98	0.98	1.01	1.00	0.98	0.92	1.08	0.99
Oaxaca	Oaxaca de Juárez	0.670	0.672	0.671	1.00	0.99	1.01	1.01	1.00	0.91	1.08	1.02
Ciudad de México	Tlalpan	0.514	0.484	0.522	0.94	0.96	1.01	0.98	1.08	1.15	1.08	0.87
Ciudad de México	Coyoacán	0.705	0.682	0.582	0.97	0.98	1.01	0.98	0.85	0.93	1.08	0.85
Veracruz	Orizaba	0.591	0.600	0.582	1.02	1.00	1.01	1.01	0.97	0.93	1.08	0.97
Veracruz	Boca del Río	0.653	0.646	0.635	0.99	1.00	1.01	0.98	0.98	0.94	1.08	0.97
Jalisco	Guadalajara	0.568	0.566	0.530	1.00	0.98	1.01	1.02	0.94	0.92	1.08	0.95
Nuevo León	San Nicolás de los Garza	0.560	0.546	0.516	0.97	0.99	1.01	0.98	0.94	0.95	1.08	0.92
Tlaxcala	Tlaxcala	0.474	0.483	0.519	1.02	1.01	1.01	1.00	1.07	0.98	1.08	1.02
Hidalgo	Pachuca de Soto	0.517	0.506	0.522	0.98	0.99	1.01	0.99	1.03	0.93	1.08	1.03
Ciudad de México	Azcapotzalco	0.533	0.518	0.492	0.97	1.00	1.01	0.97	0.95	0.95	1.08	0.93
México	Metepec	0.491	0.477	0.464	0.97	0.98	1.01	0.99	0.97	0.94	1.08	0.96
Morelos	Cuernavaca	0.507	0.494	0.489	0.97	0.97	1.01	1.00	0.99	0.88	1.08	1.04
Veracruz	Xalapa	0.469	0.464	0.441	0.99	1.00	1.01	0.98	0.95	0.92	1.08	0.96
Tlaxcala	Apizaco	0.421	0.421	0.442	1.00	0.99	1.01	1.00	1.05	0.92	1.08	1.06
México	Tlalnepantla de Baz	0.452	0.445	0.406	0.98	1.00	1.01	0.98	0.91	0.94	1.08	0.90
Ciudad de México	Venustiano Carranza	0.442	0.440	0.453	1.00	1.01	1.01	0.98	1.03	0.99	1.08	0.96
Nuevo León	Guadalupe	0.427	0.417	0.401	0.98	0.98	1.01	0.99	0.96	0.95	1.08	0.94
Querétaro	Querétaro	0.434	0.446	0.486	1.03	1.02	1.01	1.00	1.09	0.93	1.08	1.09
Ciudad de México	Iztapalapa	0.399	0.396	0.319	0.99	1.01	1.01	0.97	0.81	0.95	1.08	0.79
Ciudad de México	Gustavo A. Madero	0.418	0.408	0.358	0.98	1.00	1.01	0.97	0.88	0.97	1.08	0.84
Veracruz	Antigua, La	0.416	0.408	0.481	0.98	0.99	1.01	0.99	1.18	0.94	1.08	1.17
Veracruz	Veracruz	0.430	0.410	0.406	0.95	0.96	1.01	0.98	0.99	0.94	1.08	0.98
México	Naucalpan de Juárez	0.416	0.410	0.378	0.98	1.00	1.01	0.98	0.92	0.92	1.08	0.94
Puebla	San Andrés Cholula	0.399	0.397	0.422	0.99	1.01	1.01	0.98	1.06	0.98	1.08	1.00
Tamaulipas	Ciudad Madero	0.404	0.392	0.360	0.97	0.99	1.01	0.97	0.92	0.90	1.08	0.94
Chiapas	Tuxtla Gutiérrez	0.395	0.377	0.368	0.95	0.97	1.01	0.98	0.98	0.90	1.08	1.01
Ciudad de México	Iztacalco	0.400	0.383	0.360	0.96	0.99	1.01	0.96	0.94	0.96	1.08	0.91
Yucatán	Mérida	0.393	0.388	0.410	0.99	1.00	1.01	0.98	1.06	0.93	1.08	1.06
México	Cuautitlán	0.375	0.367	0.359	0.98	0.98	1.01	0.99	0.98	0.96	1.08	0.94
Puebla	Puebla	0.399	0.388	0.372	0.97	0.98	1.01	0.99	0.96	0.92	1.08	0.97
México	Toluca	0.379	0.360	0.369	0.95	0.95	1.01	1.00	1.03	0.92	1.08	1.03
Veracruz	Poza Rica de Hidalgo	0.374	0.363	0.386	0.97	0.97	1.01	0.99	1.07	0.92	1.08	1.07
Zacatecas	Zacatecas	0.391	0.384	0.423	0.98	0.98	1.01	1.00	1.10	0.89	1.08	1.15
Tlaxcala	Apetatitlán de Antonio Carvajal	0.348	0.335	0.342	0.96	0.98	1.01	0.98	1.02	0.98	1.08	0.97
México	Cuautitlán Izcalli	0.345	0.334	0.335	0.97	0.99	1.01	0.97	1.00	1.00	1.08	0.93
México	Coacalco de Berriozábal	0.343	0.323	0.310	0.94	0.97	1.01	0.97	0.96	1.01	1.08	0.88
Quintana Roo	Benito Juárez	0.417	0.394	0.384	0.94	0.96	1.01	0.98	0.98	0.88	1.08	1.03

Note:

Own elaboration.

[1] Footnote 1;

[2] Footnote 2;

Table 19: FI Geometric BoD Index, 2019-2021, and intertemporal effects decomposition. 45 top ranked municipalities

		FI Indices[1]			Intertemporal effects 2019-2020[2]				Intertemporal effects 2020-2021[3]			
State_name	Municipality_name	FI_19	FI_20	FI_21	O_19_20	Ch_19_20	B_19_20	W_19_20	O_20_21	Ch_20_21	B_20_21	W_20_21
Ciudad de México	Miguel Hidalgo	1.462	1.501	1.300	1.03	0.91	1.03	1.09	0.87	1.01	0.88	0.97
Ciudad de México	Benito Juárez	1.294	1.246	1.086	0.96	0.91	1.03	1.02	0.87	1.00	0.88	0.99
Ciudad de México	Cuauhtémoc	1.259	1.171	1.072	0.93	0.95	1.03	0.95	0.92	1.05	0.88	0.99
Nuevo León	San Pedro Garza García	1.000	1.000	1.000	1.00	0.97	1.03	1.00	1.00	1.13	0.88	1.00
Ciudad de México	Álvaro Obregón	0.833	0.795	0.665	0.95	0.87	1.03	1.06	0.84	0.99	0.88	0.96
Ciudad de México	Cuajimalpa de Morelos	0.929	0.761	0.603	0.82	0.82	1.03	0.97	0.79	0.95	0.88	0.94
Tamaulipas	Tampico	0.556	0.651	0.502	1.17	1.07	1.03	1.05	0.77	0.91	0.88	0.96
Nuevo León	Monterrey	0.672	0.626	0.611	0.93	0.91	1.03	0.99	0.98	1.14	0.88	0.97
Oaxaca	Oaxaca de Juárez	0.671	0.621	0.550	0.93	0.92	1.03	0.98	0.89	1.05	0.88	0.96
Ciudad de México	Tlalpan	0.522	0.618	0.581	1.18	0.95	1.03	1.20	0.94	1.08	0.88	0.98
Ciudad de México	Coyoacán	0.582	0.607	0.520	1.04	0.87	1.03	1.16	0.86	1.03	0.88	0.94
Veracruz	Orizaba	0.582	0.590	0.541	1.01	0.94	1.03	1.04	0.92	1.08	0.88	0.96
Veracruz	Boca del Río	0.635	0.586	0.510	0.92	0.89	1.03	1.01	0.87	1.04	0.88	0.95
Jalisco	Guadalajara	0.530	0.546	0.520	1.03	0.94	1.03	1.06	0.95	1.13	0.88	0.96
Nuevo León	San Nicolás de los Garza	0.516	0.524	0.499	1.02	0.94	1.03	1.05	0.95	1.14	0.88	0.95
Tlaxcala	Tlaxcala	0.519	0.488	0.451	0.94	0.93	1.03	0.98	0.92	1.08	0.88	0.97
Hidalgo	Pachuca de Soto	0.522	0.467	0.391	0.90	0.93	1.03	0.93	0.84	0.99	0.88	0.96
Ciudad de México	Azcapotzalco	0.492	0.465	0.397	0.94	0.89	1.03	1.03	0.85	1.02	0.88	0.95
México	Metepec	0.464	0.450	0.406	0.97	0.94	1.03	1.00	0.90	1.09	0.88	0.94
Morelos	Cuernavaca	0.489	0.433	0.395	0.89	0.92	1.03	0.93	0.91	1.08	0.88	0.95
Veracruz	Xalapa	0.441	0.432	0.391	0.98	0.94	1.03	1.01	0.91	1.08	0.88	0.95
Tlaxcala	Apizaco	0.442	0.418	0.387	0.94	0.95	1.03	0.96	0.93	1.09	0.88	0.97
México	Tlalnepantla de Baz	0.406	0.415	0.374	1.02	0.91	1.03	1.09	0.90	1.08	0.88	0.94
Ciudad de México	Venustiano Carranza	0.453	0.415	0.352	0.92	0.88	1.03	1.01	0.85	1.02	0.88	0.95
Nuevo León	Guadalupe	0.401	0.403	0.392	1.01	0.95	1.03	1.03	0.97	1.17	0.88	0.94
Querétaro	Querétaro	0.486	0.402	0.337	0.83	0.90	1.03	0.89	0.84	1.00	0.88	0.95
Ciudad de México	Iztapalapa	0.319	0.393	0.334	1.23	0.94	1.03	1.27	0.85	1.04	0.88	0.93
Ciudad de México	Gustavo A. Madero	0.358	0.391	0.347	1.09	0.90	1.03	1.17	0.89	1.08	0.88	0.94
Veracruz	Antigua, La	0.481	0.387	0.334	0.81	0.93	1.03	0.84	0.86	1.00	0.88	0.98
Veracruz	Veracruz	0.406	0.381	0.327	0.94	0.92	1.03	0.99	0.86	1.03	0.88	0.94
México	Naucalpan de Juárez	0.378	0.370	0.354	0.98	0.90	1.03	1.05	0.96	1.15	0.88	0.95
Puebla	San Andrés Cholula	0.422	0.357	0.283	0.85	0.87	1.03	0.94	0.79	0.95	0.88	0.94
Tamaulipas	Ciudad Madero	0.360	0.351	0.308	0.98	0.94	1.03	1.00	0.88	1.07	0.88	0.93
Chiapas	Tuxtla Gutiérrez	0.368	0.348	0.316	0.95	0.96	1.03	0.95	0.91	1.08	0.88	0.95
Ciudad de México	Iztacalco	0.360	0.347	0.295	0.97	0.89	1.03	1.05	0.85	1.02	0.88	0.94
Yucatán	Mérida	0.410	0.347	0.301	0.85	0.92	1.03	0.89	0.87	1.04	0.88	0.95
México	Cuautitlán	0.359	0.346	0.301	0.96	0.88	1.03	1.06	0.87	1.04	0.88	0.95
Puebla	Puebla	0.372	0.346	0.299	0.93	0.91	1.03	0.99	0.86	1.04	0.88	0.94
México	Toluca	0.369	0.339	0.320	0.92	0.95	1.03	0.94	0.94	1.12	0.88	0.95
Veracruz	Poza Rica de Hidalgo	0.386	0.338	0.322	0.88	0.94	1.03	0.90	0.95	1.13	0.88	0.96
Zacatecas	Zacatecas	0.423	0.336	0.307	0.79	0.94	1.03	0.82	0.91	1.07	0.88	0.96
Tlaxcala	Apetatitlán de Antonio Carvajal	0.342	0.334	0.257	0.98	0.98	1.03	0.97	0.77	0.94	0.88	0.92
México	Cuautitlán Izcalli	0.335	0.333	0.306	0.99	0.93	1.03	1.03	0.92	1.11	0.88	0.94
México	Coacalco de Berriozábal	0.310	0.331	0.301	1.07	0.96	1.03	1.08	0.91	1.10	0.88	0.93
Quintana Roo	Benito Juárez	0.384	0.325	0.285	0.85	0.90	1.03	0.91	0.88	1.05	0.88	0.94

Note:
Own elaboration.
[1] Footnote 1;
[2] Footnote 2;

The information showed in the above tables give us valuable information for each municipality and each year calculated. But to interpret the results in a more general way, in the following subsections we will examine the change of weights on time, the average of the FI Index Graphs in time by subdimensions, and present some tables that summarize the increase or decrease of the indices annually.

Change of weights on time 2013-2021

The weights that were used to compute the index are reported for each year in the next table, that are the result of the BoD maximization with the benchmark municipality of San Pedro Garza García, in the State of Monterrey. The weights are pondered as the formula indicates, so that they sum one. They are reported in the following table, we observe an important change of weights that impact the index in 2019, assigning more importance to Access 1 subdimension, and diminishing the importance of subdimensions A2 and U3 for explaining financial inclusion in the Municipalities in Mexico. The benchmark Municipality, acts as an ideal of the importance of the subdimensions in explaining financial inclusion.

Table 20: Ponderated Weights of San Pedro Garza García

Weights	Dim_A1	Dim_A2	Dim_U1	Dim_U2	Dim_U3	Dim_U4
W_SPG_2012	0.3296	0.1937	0.2401	0.0015	0.2125	0.0226
W_SPG_2013	0.3334	0.2022	0.2164	0.0005	0.2383	0.0092
W_SPG_2014	0.3235	0.1962	0.2239	0.0009	0.2385	0.0170
W_SPG_2015	0.3221	0.1931	0.2311	0.0012	0.2328	0.0197
W_SPG_2016	0.3409	0.1937	0.2054	0.0027	0.2306	0.0268
W_SPG_2017	0.3201	0.1767	0.2351	0.0023	0.2418	0.0240
W_SPG_2018	0.3221	0.1798	0.2547	0.0117	0.2128	0.0189
W_SPG_2019	0.4135	0.1105	0.2429	0.0320	0.1720	0.0291
W_SPG_2020	0.2872	0.1966	0.3155	0.0129	0.1622	0.0256
W_SPG_2021	0.2778	0.1909	0.3604	0.0112	0.1409	0.0188

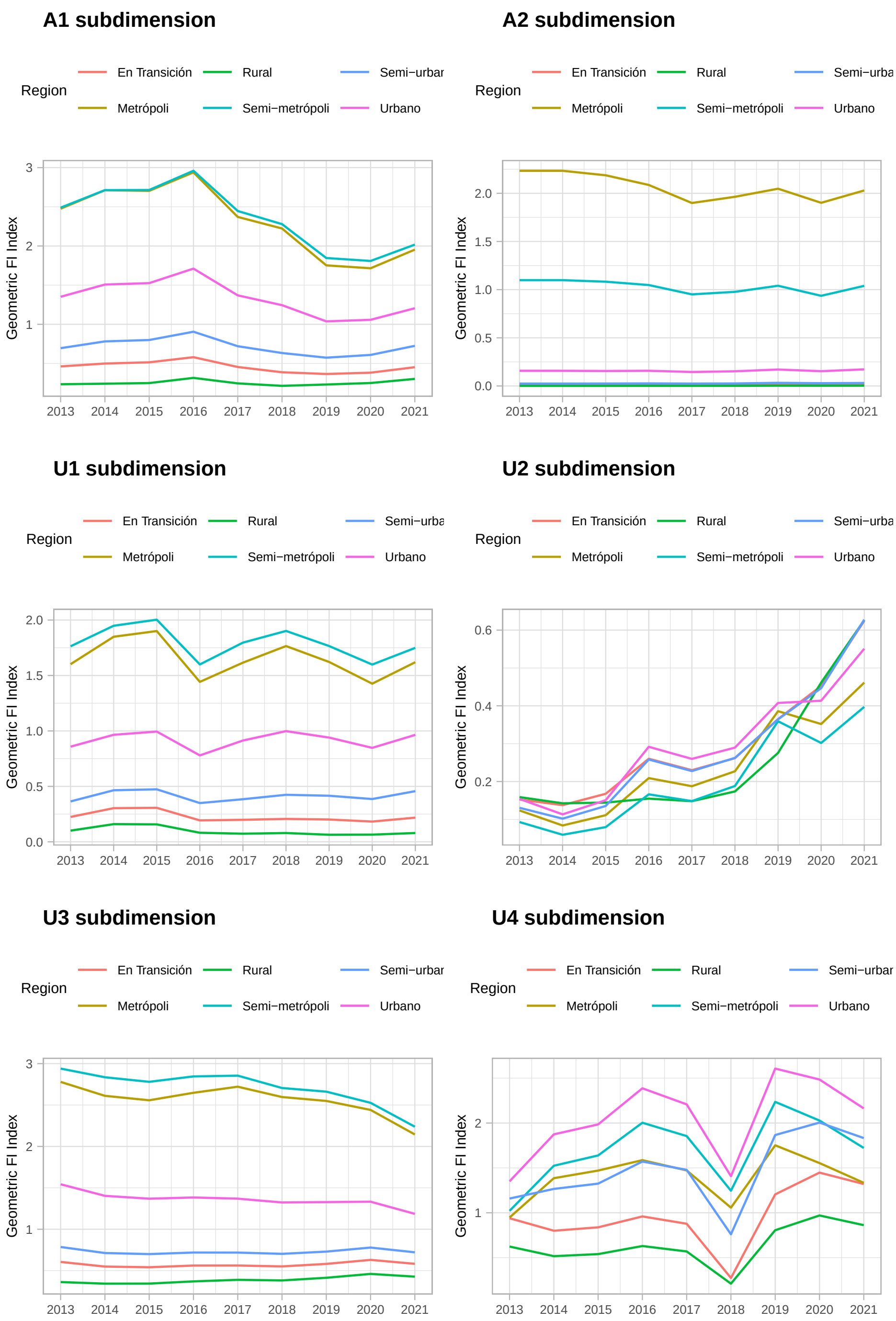
Source: Own estimation.

Notes: These weights are used as benchmark for each year estimation of the FI Index.

Average of the FI Index Graphs, by dimensions

In the following figure we present graphs of the average of each one of the subdimensions (min-max) of financial inclusion indices. We can see that the indices for A1, A2, U1 and U3 for "Metrópoli" and "Semi-metrópoli" are very high above the indices for the rest of the types of population. We can see an important increase in 2016 in A1 subdimension, reflecting mainly the entrance of the big retailer Oxxo as a correspondent offering financial services. Another important tendency showed by the graphs is the increase of the U2 subdimension (the services provided by the microcredit institutions) in the period, for all types of Municipalities.

Figure 16: Average of the FI Indices on time by type of population. Access and Usage subdimensions



Summary of intertemporal changes in financial inclusion from the indices 2013-2021

One advantage of the methodology adopted is the possibility of isolating the intertemporal effects of changes. Other formulations have to fix weights, and this sometimes is a source of criticism, because the weights of one year have to be chosen by the investigator and applied to all the years, and this could be seen as arbitrary, and could not show the changing importance of dimensions of inclusion in the total index.

In a previous section changes in weights are examined, in this, the focus is only on "change effects" that reflect changes in the indicators that conform the index. The "change effects" are summarized in the following tables. As explained previously, the changes are expressed as ratios of the indices of two years. The "change effects" is a ratio of the subyacent indicators that conform the index. When this ratio is bigger than one, we can say that financial inclusion has risen between one year and another; when it is below one, that financial inclusion has fallen.

The change effect decomposition summarized in Table 21 for types of population, Table 22 for regions, and Table 23 for States, show us that there are some years in which financial inclusion clearly increased in some periods, while decreased in others. In some periods the index increase in half of the municipalities, and decrease in the other half.

Increase in financial inclusion

The tables show that there is an increase of financial inclusion for 2013-2014 in 90.2% of the Municipalities; for 2019-2020 in 66.9% of them, and for 2020-2021 in 87.8% of them. When examining the changes by type of population, it can be seen that the biggest part of the increase was in semi-urban, transition and rural municipalities; especially in semi-urban Municipalities, that represent the 27.4% of the change of all Municipalities in 2013-2014, the 18.8% of them for 2019-2020, and the 25.1% in 2020-2021.

When examining by regions, the increase was mainly in the "Centro Sur y Oriente" region (center south and east), and in the "Sur" region (south). The Municipalities of the "Centro Sur y Oriente" region, represent the 27.9% of all the Municipalities that increased in financial inclusion index in 2013-2014, the 18.6% in 2019-2020, and the 25.4% in 2020-2021. In the "Sur" region, financial inclusion increased in 33.5% of the Municipalities in

2013-2014, 28.6% in 2019-2020, and 32.2% of them in 2020-2021.

When we look at the States, the increase was more important in the Municipalities of the State of Oaxaca, followed by the Municipalities of the State of Puebla and Veracruz. The Municipalities of Oaxaca in which financial inclusion increased, represented the 20.7% of all the Mexican Municipalities in 2013-2014, the 18.5% in 2019-2020, and the 20.4% in 2020-2021. The Municipalities of Puebla in which financial inclusion increased, represented the 8.2% in 2013-2014, 6% in 2019-2020, and 7.1% in 2020-2021. The Municipalities of Veracruz in which financial inclusion increased, represented the 8.2% in 2013-2014, 5.2% in 2019-2020, and 7.5% in 2020-2021.

Decrease in financial inclusion

The tables show that there is a decrease of financial inclusion for 2016-2017 in 81.8% of the Municipalities; and for 2017-2018 in 68.2% of them. When examining the changes by type of population, it can be seen that the biggest part of the decrease was also in the semi-urban, transition and rural municipalities; especially in semi-urban Municipalities, that represent the 22.5% of the change of all Municipalities in 2016-2017, and the 19.9% of them for 2017-2018.

When examining by regions, the decrease was mainly in the "Centro Sur y Oriente" region (center south and east), and in the "Sur" region (south).

When we look at the States, the decrease was more important in the Municipalities of the State of Oaxaca, followed by the Municipalities of the State of Puebla and Veracruz.

Table 21: FI Geometric BoD Index, 2013-2021, Change Effect decomposition
Percentage of municipalities by type of population

	Change Eff.2013-14		Change Eff.2014-15		Change Eff.2015-16		Change Eff.2016-17	
Type_pop	Decr_13_14	Incr_13_14	Dec_14_15	Inc_14_15	Dec_15_16	Inc_15_16	Dec_16_17	Inc_16_17
Metropolis	0.1	0.5	0.4	0.2	0.5	0.1	0.6	0.0
Semi-metropolis	0.2	2.6	1.3	1.6	2.1	0.8	2.7	0.1
Urban	1.5	13.2	5.9	8.8	8.4	6.3	13.5	1.2
Semi-urban	1.8	27.4	12.6	16.7	16.7	12.6	22.5	6.8
In transition	2.8	22.4	12.2	13.0	15.7	9.6	19.1	6.2
Rural	3.3	24.1	15.5	11.9	14.4	13.0	23.4	4.0
Total	**9.7**	**90.2**	**47.9**	**52.2**	**57.8**	**42.4**	**81.8**	**18.3**

Note:
Own estimation.

	Change Eff.2017-18		Change Eff.2018-19		Change Eff.2019-20		Change Eff.2020-21	
Type_pop	Dec_17_18	Inc_17_18	Dec_18_19	Inc_18_19	Dec_19_20	Inc_19_20	Dec_20_21	Inc_20_21
Metropolis	0.4	0.2	0.6	0.0	0.6	0.0	0.0	0.5
Semi-metropolis	2.3	0.6	2.6	0.3	2.7	0.2	0.2	2.6
Urban	10.7	4.0	10.7	4.0	9.5	5.2	1.1	13.6
Semi-urban	19.9	9.4	11.4	17.8	10.4	18.8	4.2	25.1
In transition	18.0	7.3	12.5	12.8	6.7	18.6	4.2	21.1
Rural	16.9	10.5	12.2	15.2	3.3	24.1	2.5	24.9
Total	**68.2**	**32.0**	**50.0**	**50.1**	**33.2**	**66.9**	**12.2**	**87.8**

Note:
Own estimation.

Table 22: FI Geometric BoD Index, 2013-2021.
Change Effect decomposition by regions

	Change Eff.2013-14		Change Eff.2014-15		Change Eff.2015-16		Change Eff.2016-17	
Region	Decr_13_14	Incr_13_14	Decr_14_15	Incr_14_15	Decr_15_16	Incr_15_16	Decr_16_17	Incr_16_17
Centro Sur y Oriente	1.9	27.9	11.2	18.5	16.7	13.0	25.3	4.4
Ciudad de México	0.0	0.6	0.2	0.4	0.5	0.1	0.6	0.0
Noreste	1.3	6.5	3.8	3.9	5.1	2.6	6.0	1.8
Noroeste	1.3	7.1	3.2	5.2	5.0	3.4	6.6	1.8
Occidente y Bajío	1.6	14.7	11.2	5.2	12.2	4.1	13.3	3.1
Sur	3.7	33.5	18.2	19.0	18.2	18.9	30.0	7.1
Total	**9.8**	**90.3**	**47.8**	**52.2**	**57.7**	**42.1**	**81.8**	**18.2**

Note:
Own estimation.

	Change Eff.2017-18		Change Eff.2018-19		Change Eff.2019-20		Change Eff.2020-21	
Region	Decr_17_18	Incr_17_18	Decr_18_19	Incr_18_19	Decr_19_20	Incr_19_20	Decr_20_21	Incr_20_21
Centro Sur y Oriente	20.6	9.1	15.5	14.3	11.2	18.6	4.4	25.4
Ciudad de México	0.4	0.3	0.5	0.1	0.7	0.0	0.1	0.5
Noreste	5.8	1.9	3.8	3.9	3.6	4.2	0.7	7.0
Noroeste	5.1	3.3	5.7	2.7	2.7	5.7	0.4	8.0
Occidente y Bajío	11.9	4.4	7.3	9.0	6.5	9.8	1.6	14.7
Sur	24.2	12.9	17.1	20.0	8.6	28.6	4.9	32.2
Total	**68.0**	**31.9**	**49.9**	**50.0**	**33.3**	**66.9**	**12.1**	**87.8**

Note:
Own estimation.

Table 23: FI Geometric BoD Index, 2013-2017.
Change Effect decomposition by States

	Change Eff.2013-14		Change Eff.2014-15		Change Eff.2015-16		Change Eff.2016-17	
State_name	Decr_13_14	Incr_13_14	Decr_14_15	Incr_14_15	Decr_15_16	Incr_15_16	Decr_16_17	Incr_16_17
Aguascalientes	0.1	0.4	0.2	0.2	0.2	0.2	0.4	0.1
Baja California	0.1	0.1	0.1	0.1	0.2	0.0	0.2	0.0
Baja California Sur	0.1	0.1	0.1	0.1	0.2	0.0	0.2	0.0
Campeche	0.0	0.4	0.0	0.4	0.0	0.4	0.3	0.1
Chiapas	0.4	4.4	1.3	3.5	1.6	3.2	4.1	0.7
Chihuahua	0.2	2.5	1.3	1.4	2.1	0.7	2.0	0.7
Ciudad de México	0.0	0.6	0.2	0.4	0.5	0.1	0.6	0.0
Coahuila	0.4	1.2	0.7	0.9	1.2	0.3	1.4	0.2
Colima	0.0	0.4	0.3	0.1	0.3	0.1	0.1	0.3
Durango	0.3	1.3	0.7	0.9	1.0	0.6	1.0	0.6
Guanajuato	0.1	1.8	1.4	0.5	1.6	0.3	1.7	0.2
Guerrero	0.1	3.2	2.1	1.2	1.9	1.4	2.1	1.2
Hidalgo	0.2	3.2	2.0	1.4	2.2	1.2	2.6	0.8
Jalisco	0.4	4.6	4.4	0.7	4.2	0.9	4.8	0.2
México	0.4	4.7	3.1	2.0	4.0	1.1	4.7	0.4
Michoacán	0.6	4.0	2.8	1.8	3.3	1.3	3.1	1.5
Morelos	0.0	1.3	0.8	0.5	0.9	0.4	1.2	0.2
Nayarit	0.0	0.8	0.4	0.4	0.7	0.1	0.5	0.3
Nuevo León	0.4	1.7	0.7	1.3	1.3	0.7	1.8	0.3
Oaxaca	2.5	20.7	13.2	10.1	12.6	10.6	19.4	3.8
Puebla	0.6	8.2	2.2	6.6	4.5	4.4	7.1	1.8
Querétaro	0.2	0.6	0.4	0.4	0.5	0.2	0.6	0.2
Quintana Roo	0.2	0.2	0.1	0.3	0.2	0.2	0.3	0.1
San Luis Potosí	0.3	2.1	1.5	0.8	1.1	1.2	1.6	0.8
Sinaloa	0.1	0.7	0.1	0.7	0.2	0.5	0.6	0.1
Sonora	0.5	2.4	0.9	2.0	1.3	1.6	2.5	0.4
Tabasco	0.2	0.5	0.1	0.6	0.3	0.4	0.6	0.1
Tamaulipas	0.2	1.5	0.9	0.9	1.4	0.4	1.3	0.5
Tlaxcala	0.2	2.2	0.7	1.7	1.3	1.1	2.2	0.3
Veracruz	0.4	8.2	2.4	6.3	3.9	4.8	7.6	1.1
Yucatán	0.3	4.0	1.4	2.9	1.5	2.8	3.3	1.1
Zacatecas	0.2	2.2	1.3	1.1	1.4	0.9	2.1	0.3
Total	**9.7**	**90.2**	**47.8**	**52.2**	**57.6**	**42.1**	**82.0**	**18.4**

Note:
Own estimation.

Table 24: FI Geometric BoD Index, 2017-2021.
Change Effect decomposition by States

	Change Eff.2017-18		Change Eff.2018-19		Change Eff.2019-20		Change Eff.2020-21	
State_name	Decr_17_18	Incr_17_18	Decr_18_19	Incr_18_19	Decr_19_20	Incr_19_20	Decr_20_21	Incr_20_21
Aguascalientes	0.2	0.2	0.0	0.4	0.2	0.3	0.1	0.4
Baja California	0.2	0.0	0.2	0.0	0.2	0.0	0.0	0.2
Baja California Sur	0.1	0.1	0.2	0.0	0.2	0.0	0.0	0.2
Campeche	0.3	0.1	0.2	0.2	0.2	0.2	0.0	0.4
Chiapas	3.9	0.9	2.9	1.9	0.8	4.0	1.0	3.8
Chihuahua	1.3	1.4	1.5	1.2	0.9	1.8	0.2	2.5
Ciudad de México	0.4	0.3	0.5	0.1	0.7	0.0	0.1	0.5
Coahuila	1.2	0.4	0.9	0.6	1.1	0.5	0.0	1.5
Colima	0.2	0.2	0.3	0.1	0.2	0.2	0.0	0.4
Durango	0.9	0.7	0.8	0.8	0.4	1.2	0.1	1.5
Guanajuato	1.5	0.4	0.9	0.9	1.2	0.7	0.2	1.7
Guerrero	2.2	1.1	1.2	2.1	0.9	2.4	0.2	3.1
Hidalgo	2.3	1.1	1.4	2.0	1.5	1.9	0.4	3.0
Jalisco	3.9	1.2	2.4	2.7	1.8	3.3	0.3	4.8
México	3.7	1.3	2.7	2.4	1.9	3.2	0.5	4.6
Michoacán	3.2	1.4	2.0	2.6	1.6	3.0	0.7	3.9
Morelos	0.8	0.6	0.7	0.6	0.6	0.7	0.1	1.2
Nayarit	0.6	0.2	0.3	0.5	0.2	0.6	0.0	0.8
Nuevo León	1.5	0.5	1.0	1.1	1.3	0.8	0.5	1.6
Oaxaca	13.8	9.4	9.2	14.0	4.7	18.5	2.9	20.4
Puebla	5.9	3.0	4.3	4.5	2.8	6.0	1.8	7.1
Querétaro	0.4	0.3	0.3	0.4	0.4	0.4	0.1	0.7
Quintana Roo	0.3	0.1	0.3	0.1	0.3	0.1	0.0	0.4
San Luis Potosí	1.9	0.4	1.0	1.4	0.6	1.8	0.1	2.3
Sinaloa	0.4	0.3	0.6	0.1	0.4	0.4	0.0	0.7
Sonora	2.1	0.8	2.3	0.6	0.7	2.2	0.0	2.9
Tabasco	0.6	0.1	0.6	0.1	0.4	0.2	0.0	0.7
Tamaulipas	1.2	0.6	0.9	0.9	0.7	1.1	0.1	1.6
Tlaxcala	1.4	1.0	1.3	1.1	0.9	1.5	0.4	2.0
Veracruz	6.5	2.1	5.0	3.6	3.4	5.2	1.2	7.5
Yucatán	3.1	1.2	2.7	1.6	1.2	3.1	0.8	3.5
Zacatecas	1.8	0.5	1.1	1.3	0.9	1.4	0.2	2.2
Total	**67.8**	**31.9**	**49.7**	**49.9**	**33.3**	**66.7**	**12.0**	**88.1**

Note:
Own estimation.

Figure 17: Map Geometric FI 2015

Figure 18: Map Geometric FI 2015-1

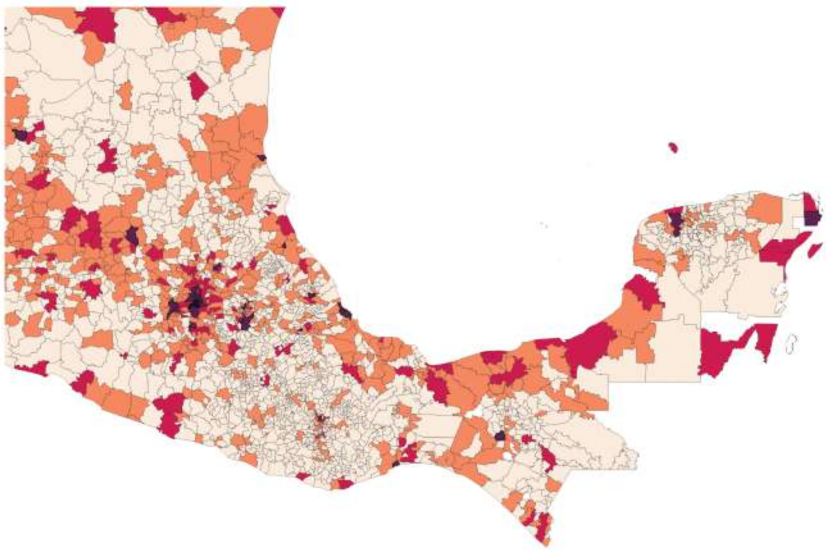


Figure 19: Map Geometric FI 2019

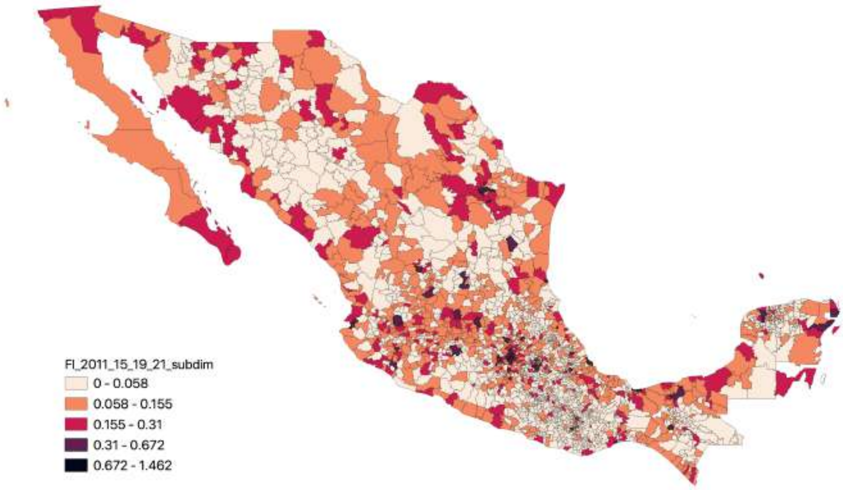


Figure 20: Map Geometric FI 2019-1

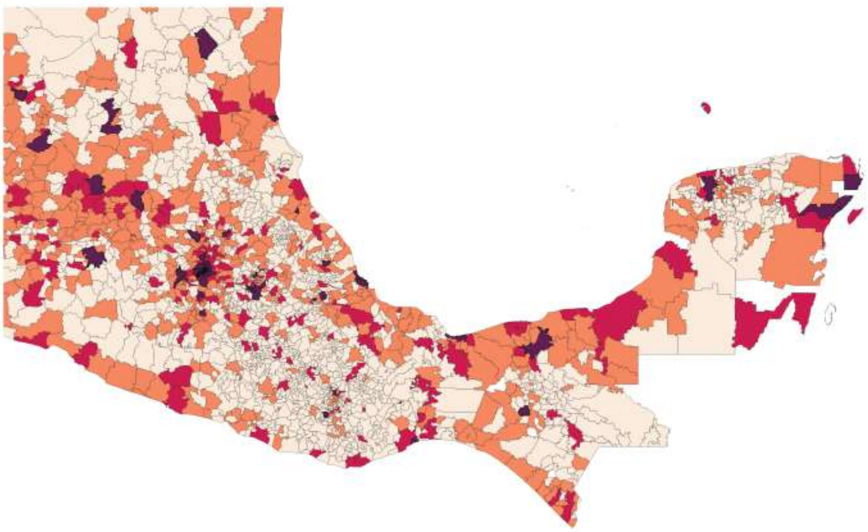


Figure 21: Map Geometric FI 2021

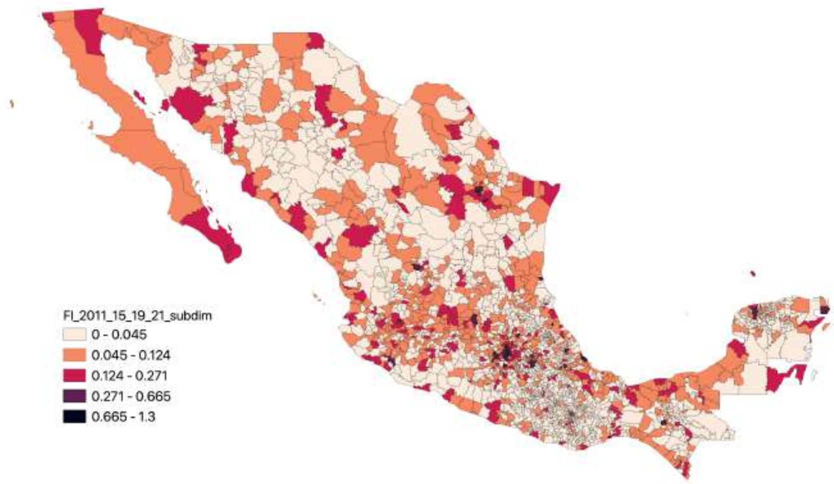
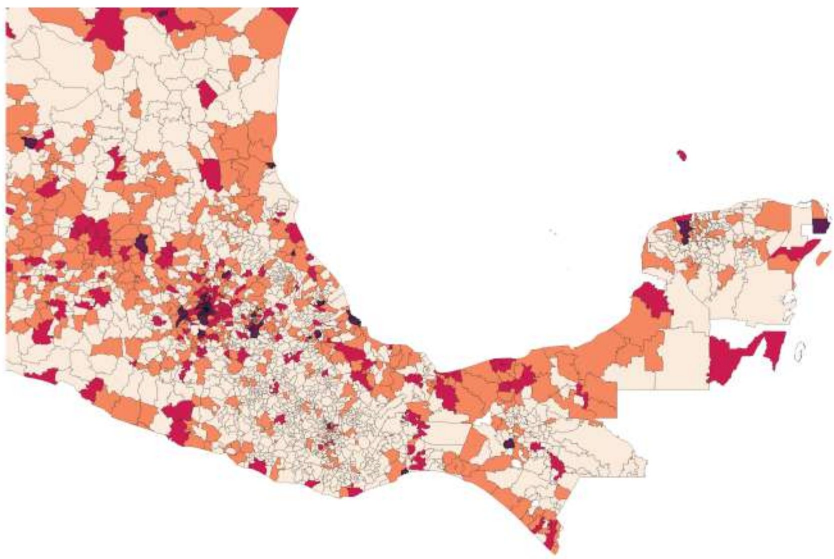


Figure 22: Map Geometric FI 2021-1



5. Conclusions

It has been recognized previously that unfortunately there is an important lack of access to infrastructure in many small municipalities in Mexico, mainly "Rural" and "En transición". Progress has been made, and other forms of access different of more traditional branches or ATMS, have advanced importantly in recent years, like correspondents or mobile banking. Nevertheless, infrastructure continues to be relevant because the proximity is important for many financial services, mainly those of retail banking. An article that presents and empirical analysis of the variables that influence in this lack of access is Cruz-García, Dircio Palacios Macedo, and Tortosa-Ausina (2021). In that case we use a logit model, exploring the variables of population, population density, and HDI that explain inclusion or exclusion.

But even determinants of infrastructure are very important to study, we have to recognise and measure financial inclusion as a multidimensional phenomenon, with many variables of access and usage interacting, substituting and complementing their impact in each other. Because of the nature of financial inclusion, a multivariate index is very appropriate. To estimate a complete and accurate index of financial inclusion has been the aim of the present research. Following the literature of financial inclusion indices, variables considered are access and usage variables divided by adult population, and geographical variables, divided by km^2 to make municipalities comparable.

For the estimation of the index, we conduct a formal methodology, as suggested by European Commission and OECD (2008), Nardo et al. (2005), Greco et al. (2019), and this is a strength of the analysis. It is considered very important that the index and the estimations have dimensions of financial inclusion. Researchers have considered theoretical background for these dimensions. But in addition, we consider that it is important that the data "speaks" for the relevant dimensions to study in the particular case of Mexican municipalities. To this aim, exploratory factor analysis was conducted, showing us that two factors, that is two combination of variables explain the variance of access data. And that four factors of usage are relevant, that is four dimensions to study for usage in Mexican municipalities.

For the construction of indices a formulation of geometric mean index, with Benefit of the Doubt weights is used, following Van Puyenbroeck and Rogge (2017). DEA Benefit of the Doubt is a data driven methodology that has been increasingly used for constructing indices. In this way the researcher does not discretionally imposes weights, that has been a critic to composite indices. Also a geometric formulation has been considered as a superior form of aggregation than a linear one, because it reflects substitution rates among indicators, which is more characteristic of variables of financial inclusion. DEA BoD do not provide transitive indices because weights calculated by BoD algorithm are specific of each observation.To make the indices transitive we calculate weights based on a benchmark, as suggested by Van Puyenbroeck and Rogge (2017). Robustness analysis was also conducted, exploring if different choices of normalisation, aggregation and weighting influence the results of the indices. The indices are robust in this sense. Validity of the indices were also proved by studying correlations with municipal HDI.

The results are presented in tables that summarise the first municipalities in the rank, for all Mexican municipalities, and top 10 for each State. Kernel distributions shows that indices vary by types of population and regions in Mexico. It is also demonstrated that each dimension of financial inclusion gives us very different ranking of the municipalities. This implies that financial inclusion, in the case of Mexico means very different things for varying types of municipalities. For some municipalities, financial inclusion is explained more because of the proximity of infrastructure. For other municipalities, usage appears to be important even banking infrastructure is not near. For some others, credits or micro-financial entities , or group and durable goods credits are more important than banking credits. It is very relevant that the indices show this variations among dimensions of financial inclusion, and different types of Mexican municipalities. Further, for more detailed analysis of financial inclusion, the indices we are presenting could be very relevant, and for specific policy proposals. It is important for further analysis why some localities rank high or low in the indices. The reasons for high ranking could be that geographically is small, with high population density, other reasons could be economic or turistic importance of the municipality. In other cases, it could be no a priori explanation, and it could motivate a detail study of success cases of financial inclusion, that should be replicated for more municipalities.

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