DIFFERENCES IN THE INTEREST RATES OF MICROFINANCE INSTITUTIONS IN SOME MARKETS ECONOMIES: AN HLM APPROACH

DIFERENCIAS EN LAS TASAS DE INTERÉS ENTRE INSTITUCIONES FINANCIERAS DE ALGUNAS ECONOMÍAS EMERGENTES: UN ENFOQUE HLM

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Resumen: Se analizan las diferencias en las tasas de interés entre las instituciones microfinancieras (IMFs) de algunos países de Latinoamérica, África, Europa del Este y Asia. Encontramos que los gastos operativos son factores esenciales en las tasas de interés de las IMFs. Además, se encontró que dichos gastos, el tamaño promedio del préstamo, el crecimiento del PIB y la efectividad en la gobernanza son factores clave para explicar por qué las tasas de interés son más altas en unos países que en otros. Como metodología se utilizó la modelación jerárquica lineal (HLM).

Abstract: In this study, we analyzed the differences in the interest rates of microfinance institutions (MFIs) of some countries in Latin America, Africa, Eastern Europe and Asia. We found that the operating expenses are essential drivers of these interest rates. We also found that operating expenses, average loan per borrower, real growth GDP, and government effectiveness, are key factors that explain differences in interest rates. We use apply Hierarchical Linear Modeling (HLM) to analyze these differences.

Clasificación JEL/JEL Classification: G21, E43, C55

Palabras clave/keywords: instituciones microfinancieras; tasas de interés IMFs; modelación jerárquica lineal; efectividad del gobierno; economías emergentes; microfinance institutions; IMFs interest rates; hierarchical linear modeling; government effectiveness; emerging markets economies

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1. Introduction

Due to their potential impact on a society's welfare and economic growth, several studies have examined microfinance institutions (MF Is). Another reason for this interest is that MFIs represent an opportunity to achieve financial inclusion and eradicate poverty and have therefore become an essential part of one of the United Nations development goals (Patiño, 2010).

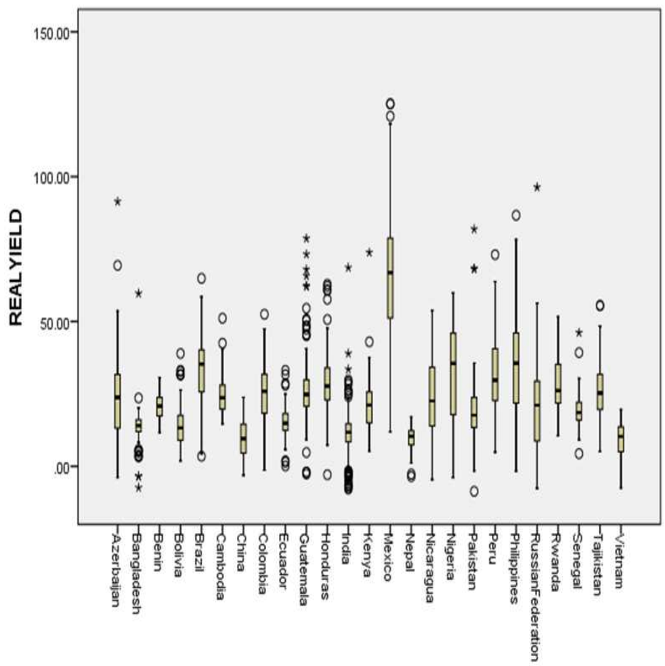
"If the interest rate increase becomes important, evidently, we will have to follow the market, funding costs for us will increase too, and evidently, we could have a scenario with higher-cost loans-", Patricio Diez, Gentera Group CFO (Juárez, 2016). The previously quote comes from an article published by a Mexican newspaper in response to the 2016 interest rate increases announced by Mexico's Central Bank, which occurred both in Mexico and other emerging market economies, caused by an increase in US interest rates. These increases were significant because some institutions, particularly MFIs, were already charging high interest rates. For instance, the Mexican MFI Gentera Group had an average interest rate of 65% in 2015.[1] One of the primary concerns about MFIs is the dramatic difference in microcredit interest rates by region and country. For instance, while there is evidence of MFI interest rates of around 20-22% in countries such as India and Bangladesh, in Mexico and some African countries interest rates have been as high as 100% (MIX Market Intelligence, 2015). The main reasons for these differences seem to be country-specific (Kneiding and Rosenberg, 2008). In graph 1, we show the mean interest rate per country and variations among interest rates to reveal the dimension of the variability within and among countries. There are many points well above and below these countries averages, and Mexico's mean is seen to be above the other countries sampled.

The significant differences in MFI interest rates among countries and regions is not new; however, as far as we know, it has not been deeply studied. In this paper, we contribute to the literature by analyzing the factors that explain these large variations. We also answer the question of whether these differences are explained by internal variables or by the external environment in which they develop. In particular, we study MFIs from Latin America, Africa, Eastern Europe and Asia. In this regard, Campbell (2010) found that microcredit interest rates were below consumer-credit interest rates in Asian countries, while in Latin America and African countries it was the opposite, with microcredits being more expensive than consumer credit.

[1] Gentera Group also has operations in Guatemala and Peru.

Graph 1

Boxplot of interest rates in MFIs per country



Source: Authors' own.

Note: circles represent outliers and asterisks represent extreme outliers.

Few studies have analyzed interest rates specifically for MFIs, and most of them do so with a single level analysis. Although their findings are quite relevant for the field, we believe that it is essential to go further and review those findings with new tools. In this case, a significant contribution of this work is the use of a multilevel approach, which allows us to understand the variations in interest rates within and among countries and regions. In this regard, Hitt, Beamish, Jackson and Mathieu (2007) found that a single-level analysis cannot wholly explain world problems, because they are complex multilevel phenomena. They argue that multilevel models are thus more useful for analyzing these kinds of issues. In this study, we use Hierarchical Linear Modeling (HLM), which is a multilevel model. This type of model considers individual- and group-level variations, among other features, when estimating group-level regression coefficients. Also, HLM allows us to relax the assumption of heteroscedasticity in error terms, which is a crucial assumption of linear models like OLS.

Our methodology is similar to that of Sun and Im (2015), who also used a multilevel model, combining MFI interest rates with country-level variables to analyze interest rate determinants. The difference between their study and ours is that their focus was on entrepreneurship, with a co-creation perspective. Our study focuses on internal and external variables that may affect interest rates at MFIs. Another contribution of this paper is the incorporation of variables related to the perception of government effectiveness, to explain interest rate differentials among MFIs in different countries.

We organize the remainder of this paper as follows. The second section presents a brief literature review and a theoretical framework. The third section describes the data and methodology. The fourth section discusses conclusions.

2. **Literature review theoretical framework**

2.1. *Literature review on interest rate in MFIs*

The debate on microfinance interest rates started in the 90s when institutionalists claimed that credit demand was inelastic to changes in interest rates, and they argued that subsidies could be eliminated and that MFIs should achieve sustainability,[2] by charging higher interest rates (Kar and Bali Swain, 2014). Morduch (2000) introduced the term microfinance schism, which describes the conflicting objectives in MFIs in their efforts to continue serving the unbanked sector: to fight for poverty reduction or to focus on profitability. Many studies have focused on investigating whether this schism exists or not (Cotler and Rodríguez-Oreggia, 2008; Bos and Millone, 2015; Vanroose and D'Espallier, 2012; Kar, 2013; Balammal, Madhumathi, and Ganesh, 2016), while some others have focused on finding the determinants of interest rates (Cotler and Almazan 2013; Roberts, 2013; Dorfleitner, Leidl, Priberny, von Mosch, 2013; Basharat, Hudon, and Nawaz, 2015; Guo and Jo, 2017). However, none of these studies have been able to definitively explain the variability in interest rates among countries and regions.

[2] According to Woller, Dunford, Woodworth (1999), there are two approaches in the microfinance literature: *institutionalist* and *welfarist*. While both recognize the importance of serving the unbanked sector, *welfarists* privilege depth of outreach over sustainability, while institutionalists argue that poor people are not helped by unsustainable MFIs.

Sun and Im (2015) took a stakeholder approach and assessed the proportion of female borrowers, the proportion of loan executives, and the role of governments in the MFIs, all of which were MFI-level variables, and used other country-level variables as a control. The only country-level variable used as an independent variable in their study was the measure of rule of law. They found that interest rates tend to be lower in countries with a higher degree of rule of law.

Other studies that provide some clues about the reason for the variance in interest rates have focused on mission drift and financial development. For example, Cotler and Almazan (2008) reported that interest rates in Mexico were almost double of those of other Latin American MFIs. Although it was not their purpose to explain this variability, they found that high-interest rates were a consequence of the youth of Mexican MFIs.

Regarding the studies that justify interest rate determinants, Bogan (2012) found evidence that MFIs charge high-interest rates to protect their investment from a lack of collateral to secure their loans. Cotler and Almazan (2013) studied the core drivers of interest rates. They found that funding costs, loan size and efficiency levels, measured by operating expenses, were crucial to determining interest rates. They used competition as a country-level variable and proved it using simultaneous equations. However, this approach does not provide a measure of variability. They concluded that an increase in competition leads to a reduction in interest rates and in the average loan size.

On the other hand, Roberts (2013) found that, although market competition should force MFIs to become efficient and decrease their interest rates, the behavior in for-profit MFIs was different, as they tend to impose higher effective interest rates compared to other MFIs, despite a more competitive environment. Furthermore, he found that for-profit institutions tend to have higher interest rates for their borrowers than non-profit institutions. Dorfleitner, Leidl, Priberny and von Mosch (2013) found that operating expenses were the most crucial variable in determining interest rates. They also found evidence that interest rates for female borrowers are higher than male ones, and that regulated MFIs tend to charge lower interest rates than unregulated ones. Vanroose and D'Espallier (2012) found a negative relationship between financial sector development and the financial performance of MFIs. They concluded that competition with banks might force MFIs into one of two possible outcomes: serving poorer customers (thus increasing their costs) or reducing their interest rates to compete with banks.

Other studies that indirectly analyze MFIs' interest rates include the one of Cull, Demirgüç-Kunt and Morduch (2014). They explored the impact of bank penetration in the financial development and found a negative relationship between bank penetration and the interest rates; this result reinforces the argument of Vanroose and D'Espallier (2012) concerning the increased possibility of find more developed MFIs in a more highly developed financial system. Complementing this finding, Trujillo, Rodriguez-Lopez, and Muriel-Patino (2014) found that in more developed regulatory environments, especially those with strong supervisory practices, MFIs interest rates tend to be lower. Xu, Copestake and Peng (2016) found that the smaller the loans of the MFIs, the larger the interest rates.

Regarding the profitability, profit margins and interest rates of MFIs, Kar and Bali Swain (2014) showed that higher interest rates increase the profitability of MFIs. Recognizing this premise, Nwachukwu (2014) analyzed this relationship and showed that the idea is valid only up to a certain point; thus, there is a U-shaped relation between interest rates and profitability; she found a 76% as the inflection point.

In another study, Kar and Bali Swain (2014) found that a more competitive environment will cause interest rates to increase and recommend regulatory measures to counteract the adverse effects. In that study, just like in ours, they used the Boone indicator as a measure of the degree of competition.

In 2016, Cuellar-Fernandez, Fuertes-Callen, Serrano-Cinca, and Gutierrez-Nieto analyzed margins in microfinance institutions. They found that operating expenses are the primary factor in explaining margins and that MFIs who operate in countries with higher financial inclusion have lower margins. Also, they discussed the concept of "poverty penalty", which holds that the poorer customers who pursue smaller loans generate higher margins for MFIs.

2.2. *Theoretical framework*

As we mention before, in this work we try to explain the variability in interest rates in some countries, using the real yield on the gross loan portfolio as a proxy for the interest rate. In this section, we explain the causal link between the identified explanatory variables and interest rate. Also, we explain the relevant hypotheses of this paper regarding the explanatory variables. To this end, we explain first the MFI-level variables, and then the country-level variables.

The first MFI-level explanatory variable is average loan balance per borrower, the amount of money borrowed from MFIs per borrower.

With regard to this variable, Kneiding and Rosenberg (2008) found that one of the primary drivers of higher interest rates is small loan sizes, and argue that reaching poorer customers, who make smaller loans, is more expensive. Other authors, such as Navajas and Tejerina (2006), Sun and Im (2015), Basharat, Hudon and Nawaz (2015), Xu, Copestake and Peng (2016), and Cuellar-Fernandez, Fuertes-Callen, Serrano-Cinca, and Gutierrez-Nieto (2016) also analyzed the relationship between average loan balances and interest rates, and found a negative correlation between these two variables as well. For Mexican MFIs, the *ProDesarrollo* (2014) annual report found a similar result. Thus, in this article, we expect to find that the smaller the amount of the loan, the higher the interest rate.

The second MFI-level variable is operating expenses as a proportion of total assets. In this work, we expect to find a positive relationship between operating expenses and interest rates because, according to Dorfleitner, Leidl, Priberny and von Mosch (2013), operating expenses are the primary drivers of interest rates, so in order to stay solvent MFIs must increase interest rates when their expenditures increase.

Our third variable is the age of the MFIs. We include this variable because some empirical studies have found that mature MFIs tend to be more efficient, and that they gain efficiency by reducing information asymmetries and taking advantage of economies of scale (Cuellar-Fernandez, Fuertes-Callen, Serrano-Cinca, and Gutierrez-Nieto, 2016). This allows them to reduce the interest rates faced by their borrowers. Other studies have found that, in order to reduce risk, younger MFIs tend to lend to wealthier customers (Xu, Copestake and Peng, 2016). Because of these arguments, we expect to find a negative relationship between the age of the MFI and the interest rate they charge. As a proxy for this variable, we use a categorical variable that indicates the longevity of the MFI, classified in one of the three groups: new (one to four years in business), young (five to nine years in business) and mature (more than nine years in business).

The fourth MFI-level variable is the portfolio at risk. This variable represents the value of all outstanding loans that have payments that been due for more than 30 days, divided by the gross loan portfolio, expressed as a ratio. For this variable, we have different arguments concerning the impact of this variable on the average interest rate charged by an MFI. On the one hand, Nwachukwu (2014) found that MFIs with higher proportions of the loan portfolio at risk tend to charge higher interest rates. On the other hand, Sun and Im (2015) claimed that it is a common practice in MFI industry to renegotiate debts, which in many cases implies lowering interest rates to promote repayment. For this article, our hypothesis for this variable is in the sense of Sun and Im (2015), the higher the portfolio at risk, the lower the interest rate the MFI charges to customers.

The last MFI-level variable is legal status of the MFIs: whether the MFI operates as a nonprofit or for-profit institution. In the literature on this subject, Cull, Demirgüç-Kunt, and Morduch (2009) found that non-profit MFIs tend to charge higher interest rates due to their higher operating costs.

We use three country-level variables: government effectiveness, degree of market competition and real *GDP*. Government effectiveness is related to the country or political risk; this risk is associated with the degree of uncertainty with respect to the stability of the political and economic system (Reilly and Brown, 2012). We expect this variable to have a positive relationship with the interest rate, since we expect that interest rates will increase when perceived risk increases. The real growth *GDP* is the most common measure of a country's overall economic activity. We expect to find a positive relationship between real growth *GDP* rates and interest rates, because according to Cull, Demirgüç-Kunt and Morduch (2014), countries with higher *GDP* growth rates tend to have a higher bank penetration, forcing MFIs to increase interest rates to attend the poorest.

Finally, we include an indicator of competition, the *BOONE* indicator, following the study proposed by Kar and Bali Swain (2018). We expect to find a positive relationship between the *BOONE* indicator and interest rates because according to those authors, MFIs located in a more competitive environment have greater incentives to increase interest rates, to obtain sufficient resources to spend on increasing their market share. In this regard, the *BOONE* indicator, also known as "profit-elasticity", is measured through the elasticity of profits to marginal costs. An increase in the *BOONE* indicator implies a weakening of financial intermediaries, which means that a competitive environment punishes inefficient institutions, including MFIs. According to these authors, there are other indicators for the degree of competition, such as the Lerner index and the H-Statistic. However, these indicators fail to measure competition in loan markets, because of interest rate regulations.

3. Data and methodology

For this study, we use Hierarchical Linear Modeling (HLM). This model allows for heteroscedastic error variance. In this regard, a critical assumption of linear methodologies like OLS is the independence of the error terms or homoscedastic error variance. However, clustering of observations within groups leads to correlated error terms, biased parameters, and standard errors. Adjusting for this variability in the error variance is a central point of HLM (Garson, 2013). Another essential feature of HLM is that the coefficients are not interpreted as fixed, as in OLS. Instead, they are considered as a variable, formed with a fixed term and an aleatory component; allowing the separation of within-group and between-group effects (Pardo, Ruiz and San Martín, 2007). Furthermore, according to Hitt, Beamish, Jackson and Mathieu (2007), HLM is the proper tool to analyze problems in management because it provides more exact estimations of data, since it can be used to work with distinct levels.

According to Gelman and Hill (2006), there are three main features that distinguish the coefficients of HLM from those of classical regressions: *i*) they can vary according to group; *ii*) they can have more than one variance component; and as a result, *iii*) they can be different depending on whether they are estimated individually or across groups. In this work, we are interested in estimating variation in interest rates for countries of Latin America and Asia.

To use HLM, we first need to set up a regression with varying coefficients, and then set up a regression for the coefficients themselves (Gelman and Hills 2006). As proven by Gaviria (2000), HLM is a particular case of a Structural Equation Model, wherein the maximum likelihood estimators belong to a parameter that depends on non-observable variables. In this work, the model is solved through the EM algorithm proposed by Dempster, Laird and Rubin (1977). HLM can also be used to analyze data with sophisticated patterns and nested sources of variability (Castro and Lizasoain, 2012). In this regard, our database (Mix Market Intelligence) is a good candidate for HLM analysis, because it has an inherent multilevel structure with many data points per MFI, and because we also grouped MFIs into countries and countries into regions.

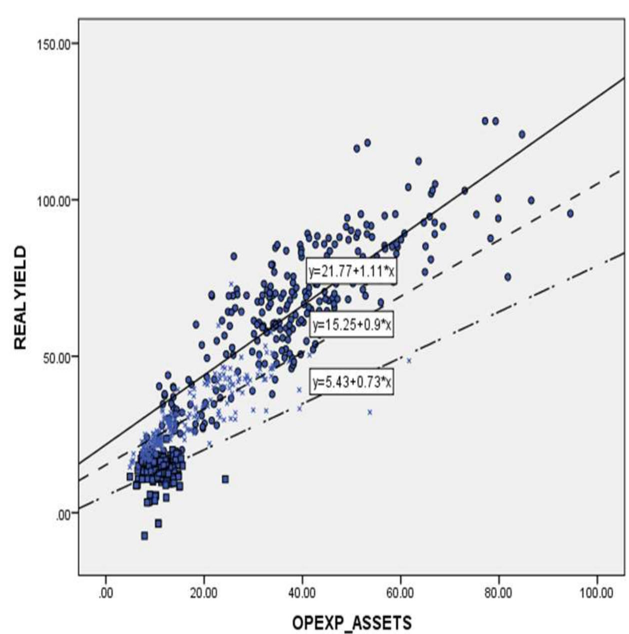
The database contains information from 962 MFIs, grouped into 25 countries and five regions, from 2009 to 2015. It is important to note that not all countries have the same number of observations, and not all MFIs reported data during the entire period (see appendix 1). For example, while most MFIs reported data for only three years, many of them did report data in the period analyzed. Thus, we have different numbers of observations per group; in this regard, HLM gives more weight to groups with more observations (Huta, 2014).

The idea behind HLM is that if an individual, an MFI in this case, belongs to one country/region, then the context in which they develop is different. The model also captures whether MFIs share specific characteristics, which at a certain level makes them homogenous within countries and heterogeneous between countries. Thus, instead of analyzing each of their respective contexts, HLM allows for differentiating the variability at each level with one single model (Castro and Lizasoain, 2012).

As an example how HLM works, see graph 2, where the scatterplot shows the trending lines for three selected countries. Each point reflects the intersection between Real Yield and Operating Expense in Mexico (○), Bangladesh (■) and Peru (x). In the graph, we see that the trending line appears to have a slightly different slope and different intercepts for each of these countries. This means that the relationship between operating expenses and interest rates is not the same in all countries; by using HLM, we were able to find these relationships.

Graph 2

Trending lines of the relation between operating expenses and interest rates



Source: Authors' own, based on information from the MIX Market Intelligence database.

In this paper, we follow the methodology proposed by Pardo Ruiz and San Martin (2007). According to this methodology, we first need to use a null model to compare the results. Then, we analyzed the means and covariance's followed by an analysis of random coefficients, which gave us an integrated model with random coefficients and slopes.

3.1. *Statistical analysis of the data*

The database was randomly selected to cover methodological requirements. We selected countries with more than 100 observations and eliminated those MFIs with significant missing information. As a result, our sample contains 25 countries and five regions (see appendix 1). Next, we standardized the data according to international accounting standards to make the data comparable (Cull Demirgüç-Kunt and Morduch, 2009). We also took some variables from the World Bank Database (World Bank, n.d.(a)) and the World Governance Index (World Bank, n.d. (b)). Table 1 contains a brief description of the variables used in this work.

Table 1
Definition of variables

Variables	*Short name*
Real yield on gross loan portfolio	$REALYIELD$
Government effectiveness+	KKM
Real growth GDP++	$GDP\_REALGROWTH$
Boone indicator as a measure of competition++	$BOONE$
Average loan per borrower, as proportion of GNI per capita	$LOANBORR\_GNI$
Operating expenses	$OPEXP\_ASSETS$
Age of the microfinance institution	AGE
Profit orientation (profit or non-profit)	$PROFITSTATUS$
Portfolio at risk within 30 days	$PAR30$

Note: +World Governance Indicators database from World Bank (n.d.(a)), ++World Development Indicators database from World Bank (n.d.(b)).

Appendix 2 contains a brief descriptive statistic for the variables in table 1, where the statistic Valid N (listwise) indicates the number of useful observations that matched all items, which in this case is 3,182. We see that on average MFIs charge an interest rate of 23.4%, with an 18.5% standard deviation. Another interesting statistic in appendix 2 is the correlation between real yield and average loan per borrower (as a proportion of GNI), which is negative. This result means that the smaller the loan, the higher the interest rate. Finally, we see a high correlation between operating expenses and interest rates, which is consistent with previous studies about the primary drivers of interest rates (Dorfleitner Leidl, Priberny and von Mosch 2013).

3.2. *Null model: Country as random factor*

In this section, we run a model called the null model. This model helps us to verify the degree of variability among the countries in our analysis. As a result, we obtain the Likelihood Ratio, which is used to compare the different estimated models. This ratio helps to verify whether the proposed models fit in multilevel analysis. In this case, this null model addresses the question: is there a level 2 country effect on the level 1 intercept of the interest rate? If there is a country effect, the linear models like OLS will suffer from correlated error, and some form of linear mixed modeling is required (Garson, 2013).

It is important to note that the null model is the shortest multilevel model. In this model, there are no explanatory variables, only the dependent variable, the first level variable, and two unobserved random effects. In our case, the null model is the following:

$$REALYIELD_{ij} = \beta_0 + u_{0j} + e_{ij} \tag{1}$$

Where sub-index i represents the MFI, and j is the country. Thus $REALYIELD_{ij}$ is the interest rate of MFI i in country j, β_0 is the overall mean of interest rates among countries, u_{0j} is the effect of the country and e_{ij} is an MFI-level residual. As in OLS, in this null model we assume that u_{0j} and e_{ij} are aleatory variables with zero mean and a constant variance.

To estimate the model, we use *Stata xtmixed* command with maximum likelihood estimation (ML). We could have used the restricted maximum likelihood (REML) instead, but this method does not allow for the comparison of different models using the likelihood ratio test. Also, according to Snijders and Bosker (1999), in large samples the differences in the results between these two methods are negligible. Another advantage of the *xtmixed* command is that it belongs to a broader class of commands used to estimate models with longitudinal data (Albright and Marinova, 2010), as in this work.

We show the results of equation (1) in the first column of table 2. As we expected, we found a mean interest rate of 23.67%, which we use as an estimator of the mean population. Nevertheless, the main result from the null model is the interclass correlation coefficient (ICC), which is estimated as follows:

$$ICC = \frac{Var\,(u_{0j})}{Var(u_{0j}) + Var\,(e_{ij})} \tag{2}$$

This coefficient means the proportion of country-level variance, $Var\,(u_{0j})$, from the total variance, where $Var\,(e_{ij})$ is the MFI-level variance. Regarding the ICC coefficient, there is a debate around whether a significant ICC validates the use of HLM since this model allows uncorrelated errors, which is an assumption that models like OLS do not allow (Roberts, Monaco, Stovall, and Foster, 2011). However, in this work, we interpret the ICC coefficient as the degree of dependence of individuals upon a higher structure to which they belong (Roberts, Monaco, Stovall, and Foster, 2011). In our sample, the ICC is 51%; in this case, this is the variation of the interest rate attributable to a country characteristic. In this regard, ICC could be evidence that using multilevel models is appropriate; whether the intercept of the null model is significant, the ICC coefficient is also significant, and HLM is appropriate (Garson, 2013), which is the case for our data (see the first column of table 2).

3.3. *Mean analysis*

Now that we have some evidence that variations in interest rates are attributable to a country characteristic, the next step is to verify whether variations within and between countries could be reduced with each of the country-level variables. The first level model is:

$$REALYIELD_{ij} = \beta_0 + e_{ij} \tag{3}$$

The second level model, which interacts with one of the country-level variables, is:

$$\beta_0 = \gamma_{00} + \gamma_{01}\ X_j + u_{0j} \tag{4}$$

Combining both we get:

$$REALYIELD_{ij} = \gamma_{00} + \gamma_{01}\ X_j + (u_{0j} + e_{ij}) \tag{5}$$

For this work, X_j is each of the following variables: KKM, $GDP\_REALGROWTH$ or $BOONE$, in each of the models. The coefficient γ_{00} is interpreted as the average interest rate for the entire population, while γ_{01} becomes the estimator of each X_j, and as usual measures the effect of each independent variable on the dependent one. Next, u_{0j} is the unobserved effect of each country after controlling for the variable X_j. In this model, u_{0j} and e_{ij} are random variables. Note that the parameter β_0 is not fixed, as in OLS; instead, it is formed with a fixed term, γ_{00}, with an aleatory component, u_{0j}, and with the term $\gamma_{01}\ X_j$. In this model, we assume that γ_{00} and u_{0j} are independent. This model is called a mean model or intercept model because β_0 is a function of the coefficients and variables of level 2 (Pardo, Ruiz and San Martin, 2007). We show the results of equation 5 in table 2 (Mean analysis).

Table 2
Results of equation 5

	Null model	*Mean analisys*		
	Coef. (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)
Constant	23.67*** (2.27)	25.1*** (2.38)	23.59*** (2.28)	24.16*** (2.27)
KKM		3.096* (1.86)		
$GDP\_REALGROWTH$			0.035* (0.02)	
$BOONE$				2.44* (1.08)

Table 2
(*continued*)

	Null model	*Mean analisys*		
	Coef. (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)
var (_*cons*)	127.97 (36.39)	121.8 (34.78)	128.5 (36.54)	132.33 (36.94)
var (Residual)	126.3 (2.95)	126.25 (2.95)	126.19 (2.95)	132.75 (2.93)
N	3693	3693	3693	3693
Years	7	7	7	7
Countries	25	25	25	25
ICC	0.51	0.49	0.50	0.50
Log Likelihood	-14235.26	-14233.89	-14233.71	-15948.82

Source: Author's own. Note: *significant at 90%, **significant at 95%, ***significant at 99%.

As we can observe in table 2, all the variables are significant, which implies that all of them are good estimators of the independent variable. Furthermore, the variance of these coefficients is smaller than the variance of the null model, var (cons). On the other hand, if we compare the variance in each country, var (Residual), against the variance of the null model, it decreases for all variables, except for the $BOONE$ indicator, which means that these three variables explain a significant portion of the interest rate variation. As a test of goodness of fit, we use the likelihood ratio: the lower the ratio, the better the goodness of fit (Pardo, Ruiz and San Martin, 2007). As can be seen in table 2, except for the $BOONE$ variable, the three variables are good estimators for the interest rate. In addition, the log likelihood associated with each variable is smaller than that of the null model, and is almost constant, which indicates that intra-country variance remains the same.

3.4. *Covariance analysis: one random effects factor*

In the last section, we analyzed variations of level 2 (country-level) variables. In this section, we add the level 1 variables, MFI level variables, to examine the differences in MFIs from the same country via a covariance analysis, which aims to explain the within-country variance. To test whether each variable reduces the variability and improves the model fit, for this model we add the MFI-level variables one by one, combined with each country-level variable. In this case, we add the variables: $LOANBORR\_GNI$, $OPEXP\_ASSETS$, AGE, $PROFITSTATUS$ and $PAR30$.

For example, for the case $OPEXP\_ASSETS$ and KKK the model is:

$$REALYIELD_{ij} = \beta_0 + \beta_{1j}\ OPEXP\_ASSETS_{ij} + e_{ij}, \text{ with } \quad (6)$$
$$\beta_{1j} = \gamma_{10}$$

Where γ_{10} is the mean slope that relates operating expenses to the interest rate. For this model, the second level does not change:

$$\beta_0 = \gamma_{00} + \gamma_{01}\ KKM_j + u_{0j} \quad (7)$$

Combining them we obtain:

$$REALYIELD_{ij} = \gamma_{00} + \gamma_{01}\ KKM_j + \gamma_{10}\ OPEXP\_ASSETS_{ij} + (u_{0j} + e_{ij}) \quad (8)$$

We show the results of equation (8) in table 3. Since the ICC is a conditional coefficient it explains the proportion of the total variance that is due to the MFI-level variables. After controlling for MFI-level variables, the proportion of the variability in interest rates due to the country features can be seen. The more the ICC decreases, compared to the null model, the more the differences observed within countries are explained by the variability in each of the MFI-level variables ($LOANBORR\_GNI$, $OPEXP\_ASSETS$, AGE, $PROFITSTATUS$). As we can see in table 3, for any combination of MFI and country variables, the ICC is smaller, especially in the case of operating expenses. The ICC coefficient remains almost constant when we add the variables $LOANBORR\_GNI$ and $PAR30$.

The degree of variability within countries is explained by the statistic var (Residual). In all cases, the statistic var (Residual) is smaller after adding level 1 variables than in the null model, which means that the combinations of MFI-level and country-level variables are explaining a significant portion of the within-country variability. Another relevant result is that for all combinations, all the coefficients are significant, except for the profit status. Furthermore, the likelihood ratio shows that for all combinations each variable is a good estimator of the interest rate; which is a goodness of fit test.

Table 3

Covariance analysis

	Coef. (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)	*Coef.* (SE)
	1	2	3	4	5	6	7	8	9	10
Constant	26.61***	11.77***	30.88***	25.517***	26.18***	24.79***	10.52***	29.29***	24.06***	24.31***
	(2.36)	(1.5)	(2.48)	(2.39)	(2.4)	(2.27)	(1.4)	(2.36)	(2.29)	(2.31)
KKM	3.74**	2.54*	3.001*	2.96 NS	3.81**					
	(1.83)	(1.39)	(1.79)	(1.82)	(1.9)					
$GDP\_REALGROWTH$						0.039**	.036**	0.0278 NS	0.028 NS	0.05**
						(.02)	(0.016)	(0.019)	(0.019)	(0.022)
$BOONE$										
$LOANBORR\_GNI$	-0.016***					-0.016***				
	(0.001)					(0.001)				
$OPEXP\_ASSETS$		0.773***					0.773***			
		(0.015)					(0.015)			
AGE			-2.075***					-2.03		
			(0.333)					(0.333)		
$PROFITSTATUS$				-0.29 NS					-0.29 NS	
				(0.44)					(0.44)	
$PAR30$					-0.056***					-0.055***
					(0.01)					(.011)

Table 3
(*continued*)

var (_cons)	119.99	43.74	118.003	127.75	123.04	127.38	46.55	123.77	133.66	131.78
	(34.23)	(12.58)	(33.07)	(35.82)	(35.17)	(36.22)	(13.33)	(34.55)	(37.33)	(37.51)
var (Residual)	118.24	74.3	113.991	132.41	121.3	118.19	74.23	133.97	132.39	121.191
	(2.83)	(1.75)	(3.007)	(2.99)	(3.01)	(2.82)	(1.75)	(3.007)	(2.99)	(3.01)
N	3532	3625	3625	3625	3269	3532	3625	3625	3625	3269
Years	7	7	7	7	7	7	7	7	7	7
Countries	25	25	25	25	25	25	25	25	25	25
ICC	0.5	0.37	0.51	0.49	0.50	0.52	0.39	0.48	0.50	0.52
Log Likelihood	-13499.99	-13005.57	-15513.13	-15281.79	-12539.45	-13500.1	-13004.58	-15513.53	-15282.09	-12538.89

	Coef. (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)
	11	12	13	14	15
Constant	25.55***	11.06***	29.80***	24.37***	25.02***
	(2.28)	(1.42)	(2.39)	(2.31)	(2.32)
KKM					
$GDP\_REALGROWTH$					
$BOONE$	2.49*	2.55***	2.82*	2.27*	2.70*
	(1.06)	(0.85)	(1.10)	(1.11)	(1.10)
$LOANBORR\_GNI$	-0.016***				
	(0.001)				

Table 3
(*continued*)

$OPEXP\_ASSETS$		0.78***			
		(0.014)			
AGE			-2.08		
			(0.333)		
$PROFITSTATUS$				-0.29 NS	
				(0.411)	
$PAR30$					-0.054***
					(.011)
var (_cons)	132.97	49.81	126.26	135.94	137.59
	(37.11)	(14.01)	(35.26)	(38.00)	(38.44)
var (Residual)	123.46	78.51	133.81	132.30	125.85
	(2.8)	(1.75)	(3.00)	(2.99)	(2.98)
N	3532	3625	3625	3625	3269
Years	7	7	7	7	7
Countries	25	25	25	25	25
ICC	0.52	0.39	0.49	0.51	0.52
Log Likelihood	-15041.98	-14585.46	-15511.26	-15280.99	-13842.77

Source: Author's own. Note: *significant at 90%, **significant at 95%, ***significant at 99%.

3.5. *Random coefficients analysis*

In the previous sections, the relationship between MFI-level variables and interest rates is assumed to be homogeneous among all countries. However, to verify which part of the intra-class variance is explained for the independent MFI-level variables, we evaluated each country equation, and then examined how the intercepts and slopes vary in each country. This model is called the random coefficients model because it allows intercepts and slopes to vary randomly per country. For example, for the case $OPEX\_ASSETS$ the model is:

$$REALYIELD_{ij} = \beta_0 + \beta_{1j}\ OPEXP\_ASSETS_{ij} + e_{ij} \qquad (9)$$

Where $\beta_0 = \gamma_{00} + u_{0j}$ but β_{1j} now has a random component: $\beta_{1j} = \gamma_{10} + u_{1j}$, which means that each country has its slope. The combined model is the following:

$$REALYIELD_{ij} = \gamma_{00} + \gamma_{10} * OPEXP\_ASSETS_{ij} + \qquad (10)$$
$$(u_{0j} + u_{1j}\ \ OPEXP\_ASSETS_{ij} + e_{ij})$$

Where γ_{00} characterizes the mean interest rate across countries, γ_{10} is the mean slope which links operating expenses and interest rates, u_{0j} is the effect of each country on the means, and u_{1j} is the effect of each country on the slopes. In table 4, we show the results of equation (10). Again, all coefficients were significant. In this model, the likelihood could be used to test random slopes.

In this section, we analyze each of the variance components, since they represent the main findings in this model. First, to test whether the variance of the slope is significant, we need to verify whether the coefficient is more than three times the standard error (Leckie, 2010). The results in table 3 show that $LOANBORR\_GNI$ and $OPEXP\_ASSETS$ have random intercepts and random slopes. A significant random slope means that the effect of the average loan per borrower, or operating expenses, on the interest rate is not the same for each country, as described in graph 1. Using the predicted values obtained with $OPEXP\_ASSETS$, we obtain the lines shown in graph 3. Each line represents a different country, and we can observe how the slopes and the intercepts of each regression line are different.

Table 4
Random coefficients analysis

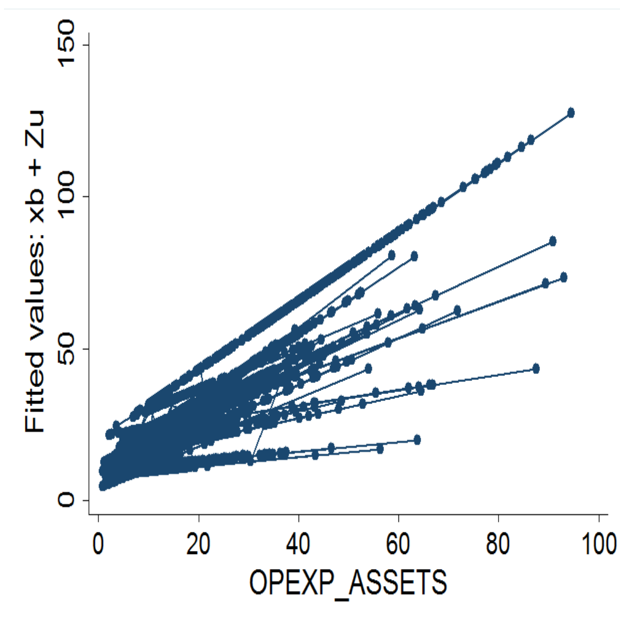
	Coef. (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)	*Coef.* (*SE*)
Constant	26.68***	11.19***	29.44***	23.16***	25.29***
	(2.65)	(1.04)	(3.14)	(2.10)	(2.42)
$LOANBORR\_GNI$	-0.095***				
	(0.032)				
$OPEXP\_ASSETS$		0.68***			
		(0.067)			
AGE			-2.01***		
			(0.77)		
$PROFITSTATUS$				1.88 NS	
				(2.15)	
$PAR30$					-0.18***
					(0.04)
var (slope)	0.025	0.1025	9.91	100.15	0.022
	(0.007)	(0.031)	(4.86)	(34.65)	(0.013)
var (intercept)	173.75	23.48	214.37	108.90	144.65
	(49.5)	(7.47)	(69.69)	(31.39)	(41.29)
covar	-1.78	-0.32	-30.04	-11.53	-0.92
(slope, intercept)	(0.56)	(0.37)	(15.72)	(22.61)	(0.51)
var (Residual)	100.23	63.61	132.32	123.45	118.54
	(2.4)	(1.5)	(2.98)	(2.80)	(2.96)
N	3532	3625	3625	3625	3269
Years	7	7	7	7	7
Countries	25	25	25	25	25
Proportion of explained variation	21%	50%	0.5%	7.1%	6%
Log Likelihood	-13253.27	-12751.08	-15504.894	-15175.955	-12514.22

Source: Author's own. Note: *significant at 90%, **significant at 95%, ***significant at 99%.

In equation (10), the covariance is an indicator of the relation between slopes and intercepts. In the case of the variables $OPEXP\_ASSETS$ and $PAR30$ the relationship with interest rates keeps on after the changes in the means; this indicates that in this case, there is no statistical evidence of a link between slopes and intercepts.

Finally, the residual variance shows the variability of each MFI around its country regression line, and it allows us to assess the variable that explains most of the variation within a country; in this case, the variable operating expenses has the greatest variation.

Graph 3
Predicted values for $REALYIELD_{ij} = 11.19 + 0.68 * OPEXP\_ASSETS_{ij} + (u_{0j} + u_{1j} * OPEXP\_ASSETS_{ij})$



Source: Authors' own, based on information from the MIX Market Intelligence database.

3.6. *Integrated model: random coefficients and slopes*

In the previous sections, we established that the eight out of the nine variables tested were significant interest rate predictors; we could not find statistical significance for the variable profit status. We also verified that these variables explain a significant proportion of the variability among MFIs and countries. Now, to evaluate why real interest rates are higher in some countries than in others and why the relation between MFI-level variables and interest rates is different in each country, we need to estimate an integrated model. This also allows us to obtain MFI-level results associated with country-level interactions. In this case, we use the model with 5 MFI-level variables and three country-level variables. The results of this model are presented in table 5. Except for the coefficients associated with $BOONE$, AGE, and $PROFITSTATUS$, the other coefficients are significant, and the model seems to fit the data well, according to the Likelihood Ratio.

Table 5

Integrated model: random slopes and coefficients

	Coef. (*SE*)
Constant	14.65***
	(1.79)
KKM	2.27**
	(1.17)
$GDP\_REALGROWTH$	.050***
	(.014)
$BOONE$	.912 NS
	(.78)
$LOANBORR\_GNI$	-.029**
	(.013)
$OPEXP\_ASS$	.675***
	(.067)
AGE	-.082 NS
	(.25)
$PROFITSTATUS$	1.55 NS
	(.99)
$PAR30$	-.142***
	(.035)
N	3182
Years	7
Countries	25
Log Likelihood	-11542.604

Table 5
(*continued*)

	Coef. (*SE*)
var ($LOANBORR\_GNI$	.004
	(0.001)
var ($OPEXP\_ASS$)	.099
	(.031)
var ($PAR30$)	.017
	(.009)
var ($PROFITSTATUS$)	18.35
	(7.67)
var (_cons)	49.63
	(15.66)
cov ($LOANBORR\_GNI, OPEXP\_ASSETS$)	.002
	(.004)
cov ($LOANBORR\_GNI, PROFITSTATUS$)	-.027
	(.064)
cov ($LOANBORR\_GNI, PAR30$)	.022
	(.002)
cov ($LOANBORR\_GNI$, _cons)	.3424
	(.124)
cov ($OPEXP\_ASSETS$, $PAR30$)	-.0001
	(.012)
cov ($OPEXP\_ASSETS$, $PROFITSTATUS$)	.14
	(.312)
cov ($OPEXP\_ASSETS$, _cons)	-.887
	(.562)
cov ($PAR30, PROFITSTATUS$)	-.226
	(.159)
cov ($PROFITSTATUS$, _cons)	.272
	(7.23)

Table 5
(*continued*)

	Coef. (*SE*)
cov ($PAR30$, _cons)	-.248 (.208)
var (residual)	51.719 (1.29)

Source: Author's own. Note: *significant at 90%, **significant at 95%, ***significant at 99%.

In table 5, we show that interest rate mean for the sample is 14.65. In addition, we found that once we controlled for the $BOONE$ indicator and real growth of GDP, the index of government effectiveness had a positive impact on interest rates. Real growth of GDP had a similar effect, although in lower intensity. The $BOONE$ indicator was not significant once we controlled for the other variables. Another remarkable result is the average loan per borrower, measured as a proportion of GNI per capita, which is negatively related to the interest rates. The same is true for the portfolio at risk within 30 days. On the other hand, the highest effect on interest rates is from operating expenses.

With regard to the variance of the residuals, in table 5 we observe that it is 51.72, which is significantly lower than in the previous models, and is an indicator that the combination of level 1 and level 2 variables reduces within-country variability. Furthermore, the variance among the means of each of the MFI-level variables was shorter, in comparison to the null model, which is also an indicator that country-level variables explain the differences among countries and MFIs very well. At a country level, we did not find statistical evidence that the level of competition, measured with the Boone indicator, is related to the interest rates. Neither did we find statistical proof that the age or the profit orientation has a relationship with the real interest rate.

Finally, as an indicator of robustness check, we made the same analysis presented in table 1 to table 5, but this time we divide the sample by regions: Latin America, East Asia, and South Asia. In this analysis we found that the variable for real growth of GDP was not significant for the East and South Asia regions, while the variable representing government effectiveness was not significant for Latin America and South Asia. Finally, we found that the variable for average loan per borrower was not significant in South Asia.

4. Conclusions

In this paper, we analyze the differences in interest rates between and within Latin America, Africa, Eastern Europe, and Asian IMF's. In our study, we first found that there are several specific countries and regional factors that explain differences in MFIs interest rates. We also found statistical evidence that, for our sample, hierarchical linear modeling is the appropriate methodology.

In the first stage of the methodology, we assumed that the relationships between the MFI-level variables and interest rates are homogeneous among all countries. As we expected, we found that operating expenses were a significant driver of MFI interest rates and that there was a positive relationship between these two variables. We also found a negative relation between average loan per borrower and interest rates. Together, these two results contribute to the statistical outcomes that argue that reaching poor IMF customers is expensive and that this cost is transferred to the interest rate through operating expenses. Another relevant result was that the higher the past due to a portfolio, the lower the interest rate. Concerning government effectiveness, which is an indicator of perception of significant changes in the political environment of a country, we found a positive relationship between this variable and interest rates.

To verify whether intercepts and slopes vary in each country, in a second stage of the methodology we used a random coefficients model. In our sample, we found that average loan per borrower and operating expenses were the only variables with random intercepts and random slopes, which implies that the effect of these two variables on real interest rates was different for each country. Also, in this analysis, we found that the variable operating expenses explained most of the variation within a country.

In the final stage, the integrated model, we found that government effectiveness and real growth of GDP explained why interest rates are higher in some countries than in others and why the relation between MFI-level variables and interest rates is different in each country. Finally, we did not find evidence that the level of competition, measured with the Boone indicator, or the age or the profit orientation of the IMF explained why interest rates are different in each country.

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Appendix 1. Frequency tables and database information

Observations per year

Year	*Freq.*	*Percent*	*Cum.*
2009	748	16.67	16.67
2010	793	17.67	34.34
2011	805	17.94	52.27
2012	657	14.64	66.91
2013	533	11.88	78.79
2014	550	12.25	91.04
2015	402	8.96	100
Total	4,488	100	

Source: Author's own, based on information from the MIX Market Intelligence database.

Frequency of number of years reported per MFI

numYear	*Freq.*	*Percent*	*Cum.*
1	36	3.74	3.74
2	60	6.24	9.98
3	238	24.74	34.72
4	129	13.41	48.13
5	113	11.75	59.88
6	165	17.15	77.03
7	221	22.97	100
Total	962	100	

Source: Author's own, based on information from the MIX Market Intelligence database.

Number of MFIs per region

Region	*Number of MFIs*
Africa	583
East Asia and The Pacific	669
Eastern Europe and Central Asia	372
Latin America and The Caribbean	1677
South Asia	1187

Source: Author's own, based on information from the MIX Market Intelligence database.

Number of MFIs per country

Country	*Number of MFIs*
Azerbaijan	131
Bangladesh	217
Benin	117
Bolivia	139
Brazil	138
Cambodia	109
China	167
Colombia	161
Ecuador	313
Guatemala	108
Honduras	139
India	656
Kenya	106
Mexico	344
Nepal	150
Nicaragua	135
Nigeria	141
Pakistan	164
Peru	200
Philippines	241
Russian Federation	112
Rwanda	100
Senegal	119
Tajikistan	129
Vietnam	152

Source: Author's own, based on information from the MIX Market Intelligence database.

Appendix 2

Descriptive statistics

	N	$Mean$	$Std.\ Deviation$
$REALYIELD$	3693	23.42	18.15
KKM	4491	-0.37	0.40
$GDP\_REALGROWTH$	4491	2.41	12.39
$BOONE$	5034	-0.12	0.38
$LOANBORR\_GNI$	4119	54.39	138.65
$OPEXP\_ASSETS$	3661	16.67	12.14
AGE	4796	2.61	0.68
$PROFITSTATUS$	4665	NA	NA
$PAR30$	3528	6.73	17.63
Valid N (listwise)	3182		

Source: Author's own, based on information from the MIX Market Intelligence database.

Correlation coefficients

	$REALYIELD$	KKM	GDP_REAL $GROWTH$	$BOONE$	$LOAN$ $BORR\_GNI$	$OPEXP\_$ $ASSETS$	AGE	$PROFIT$ $STATUS$	$PAR30$
$REALYIELD$	1	.276**	-0.029	-.059**	-.157**	.784**	-.085**	.189**	-0.017
KKM	.276**	1	-.056**	.239**	-.120**	.217**	0.001	.055**	0.000
$GDP\_REALGROWTH$	-0.029	-.056**	1	.071**	.053**	-.052**	-.081**	-0.015	-.046**
$BOONE$	-.059**	.239**	.071**	1	-.005	-.060**	.286**	-.176**	-.135**
$LOANBORR\_GNI$	-.157**	-.120**	.053**	-.005	1	-.167**	-.019	.114**	-.017
$OPEXP\_ASSETS$	.784**	.217**	-.052**	-.060**	-.167**	1	-.149**	.114**	.015
AGE	-.085**	0.001	-.081**	.286**	-0.019	-.149**	1	-.305**	.003
$PROFIT\ \ STATUS$	.189**	.055**	-0.015	-.176**	.114**	.114**	-.305**	1	.033*
$PAR30$	-.017	.000	-.046**	-.135**	-.017	.015	.003	.033*	1

Source: Author's own, based on information from the MIX Market Intelligence database.