Differences in interest rates in Latin American and Asian MFIs: A Hierarchical Linear Models approach

1. Introduction

Microfinance Institutions (MFI) have long been studied for their potential impact on a society´s welfare and economic growth. Because MFIs represent an opportunity to achieve financial inclusion and eradicate poverty they have become an important part of one of the United Nations development goals (Patiño, 2010).

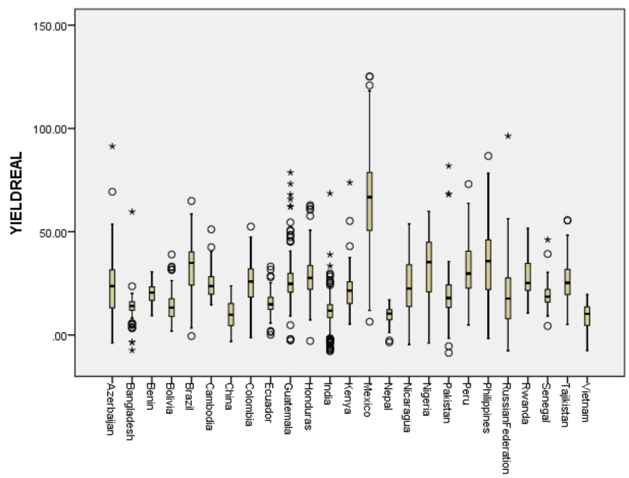
"If the interest rate increase becomes important, evidently we will have to follow the market, funding costs for us will increase too and evidently we could have a scenario with higher-cost loans"- Patricio Díez, Gentera Group CFO in El Economista (Juárez, 2016).

The above is from an article published by a Mexican newspaper in response to the 2016 interest rate increases announced by Mexico´s Central Bank which happened both in Mexico and other emerging market economies after an increase by the Federal Reserve Bank of the United States. As a result of the interest rate hike, increases were also expected in the corresponding institutions of emerging economies. This is important because some institutions, MFIs for example, were already charging high interest rates. For instance, the Mexican MFI Gentera Group, which owns Compartamos bank, the largest MFI in Mexico for example, had an average interest rate of 65% in 2015.[1] The latter is a first clue of dramatic differences in microcredit interest rates by region and country. For instance, while in countries like India and Bangladesh we found interest rates around 20-22%, in Mexico and some African countries, we found interest rates of up to 100%.[2] The main reasons for those differences seem to be country specific (Kneiding and Rosenberg, 2008). In Graph 1, we show the mean per country and variations among interest rates in order to show the dimension of the variability within and between

[1] Gentera Group also has operations in Guatemala and Peru.
[2] Data taken from MIX Market Intelligence 2015.

countries. There are many points well above and below their countries averages[3], and Mexico´s mean is seen to be above the other sampled countries.

Graph 1. Boxplot of interest rates in MFI per country



Source: Author

The significant differences in interest rates at MFIs for countries and regions is not new, however it has not been deeply studied. In this paper, we contribute to the literature by analyzing the factors that explain these large variations. Also, we answer the question: Are these differences explained by internal variables, or by the external environment in which they develop? In particular, we focus our study in Latin American, Africa, Eastern Europe and Asian MFI´s. At this regard, Campbell (2010) found that microcredit interest rate was below consumer credit interest rates in Asian countries, while in Latin America and African countries it was the opposite, and microcredits were more expensive than consumer credits.

---

[3] Circles represent outliers and asterisks represent extreme outliers.

There are few studies that analyze 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 important to prepare a deeper analysis, and revisit those findings with new tools. In this case, a multilevel approach allows us to understand the variations in interest rates within and between countries and regions. At this regard, Hitt, Beamish, Jackson, and Mathieu (2007) argue that world problems are complex multilevel phenomena, which cannot be completely understood with a single-level analysis. They propose that these kinds of problems must be analyzed with a multilevel model, as we do in this study. Specifically, we use a Hierarchical Linear Model (HLM) which importantly, takes into account individual and group level variation, among other features, when estimating group level regression coefficients. A HLM also allows the variations between individual level regression and coefficients across groups to be modeled.

Our methodology is close to that used by Sun and Im (2014), who also used a multilevel model combining MFI-level 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 to achieve a decrease in microfinance interest rates. On the other hand, our study focuses on internal and external variables that may have an effect on the difference of interest rates at MFIs.

The remainder of the paper is organized as follows. The second section presents a brief literature review. The third describes the data and methodology. The fourth section discuss estimation results. The conclusions are given in the fifth section.

2. Theoretical framework

The debate about interest rates in microfinance started in the 90´s, when *institutionalists*[4] claimed that credit demand was inelastic to changes in interest rates, and they argued that in order to abandon subsidies and achieve sustainability, MFIs should charge higher interest rates (Kar and Swain, 2014). Morduch (2000) introduced the term *microfinance schism*, which describes the conflicting objectives in MFIs: to fight for poverty reduction or to focus on profitability in order to continue serving the unbanked sector. With regard of *microfinance schism*, many studies have focused on investigating whether the it exists or not (Cotler and Rodríguez-Oreggia, 2008; Gutiérrez, 2012; Bos and Milone, 2012; Vanroose and D´Espallier, 2013; Kar, 2013; Balammal, Madhumathi, and Ganesh, 2016) while some focused on looking for 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 reach a strong conclusion that explain the variability in interest rates among countries and regions.

Prior to our study, Sun and Im (2014) took a stakeholder approach, so they tested the proportion of female borrowers, the proportion of loan executives, and the role of government in the MFI, 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 in countries with a higher degree of rule of law, interest rates tend to be lower.

Other studies that provides some clues about the variance in interest rates, are those that have been focused on mission drift and financial development. For example, Cotler et al. (2008) reported that interest rates in Mexico were almost double that of other Latin American MFIs. Although it was not their purpose to explain this variability, they argued

[4] According to Woller, Dunford, Woodworth (1999), two approaches can be recognized in 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 without successful MFIs the poorest people cannot be served.

that the high interest rates were due to the youth of Mexican MFIs at that time. In this regard, Campbell (2010) reviewed the MFI Compartamos bank. He found that its average interest rate was 73% (for that year), while the average for the entire industry was 26%. He also found that the 2.26% default rate for Compartamos was double that of Grameen Bank.

With regard to studies that justify interest rates determinants, Bogan (2012) sustained that MFIs charge high interest rates as a way to protect their investment against a lack of collateral on the customer´s side. Cotler and Almazan (2013) found that the main drivers of interest rates, and found that funding costs, loan size and efficiency level (measured by operating expenses) were crucial to determining interest rates. They used competition as a country-level variable, and proved it using simultaneous equations. This approach however, does not provide a measure of variability and does not assess the interactions between the two levels of the study. They concluded that an increase in competition leads to a reduction in lending interest rates and to a reduction 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 in spite of a more competitive environment. Dorfleitner, Leidl, Priberny and von Mosch (2013) found that operating expenses were the most important variable in determining interest rates. In addition, they found evidence that female borrowers are charged higher interest rates than male borrowers and that regulated MFIs tend to charge lower interest rates than those not regulated. Vanroose et al. (2013) found a negative relationship between financial sector development and financial performance of MFIs and conclude that competition with banks may cause one of two possible outcomes for MFIs: serving the poorer customers by increasing their costs, or reducing their interest rates in order to compete with banks.

Other studies that indirectly analyze MFI´s interest rates are for instance Cull, Demirgüç-Kunt, Morduch (2014), who exploring the impact of bank penetration in the financial development, found a negative relationship between bank penetration and the interest rates, which reinforces Vanroose et al. (2013) argument of how MFIs develop when there is a highly developed financial system. Complementing this finding, Trujillo Rodriguez-Lopez, and Muriel-Patino (2014) found that in more developed regulatory environments, especially with strong supervisory practices, MFIs' interest rates tend to be lower. Xu, Copestake and Peng (2016) analyzed the macroeconomic influence on MFIs depth of outreach, and found that the smaller the loans, the larger the interest rates.

With regard of MFI´s profitability, profit margins and interest rates, Kar et al. (2014), showed that higher interest rates actually increase the profitability of MFIs. Nwachukwu (2014), recognizing this premise, analyzed this relationship and showed that the idea is true only up to a certain point, thus there is a U-shaped relation between interest rates and profitability. She determines 76% as the inflection point. Basharat, Hudon and Nawaz (2015) found that profit increases lead MFIs to charge higher interest rates and recommended the use of technology to reduce transaction costs and interest rates. In addition, they found a positive relation between gender and interest rates. Burzynska and Berggren (2015) published a study where they included measures of social beliefs such as collectivism and trust to show whether these were related to MFIs' financial performance. One of their findings was that social beliefs, such as trust and collectivism highly impact MFIs' profitability and allows them to save money on monitoring and default costs and be able to offer lower interest rates. Finally, Cuéllar-Fernández, Fuertes-Callén, Serrano-Cinca and Gutiérrez-Nieto (2016) analyzed margins in microfinance institutions finding that the main factor that determines margins are operating expenses. They also found that MFIs operating in countries with higher financial inclusion have lower margins. They discussed the concept of poverty penalty which states that it is the poorer customers who pursue smaller loans that generate the higher margins for MFIs.

3. Data and Methodology

For the purpose of this study we used a Hierarchical Linear Model (HLM). The HLM is also known as multilevel modeling, mixed modeling, and random coefficients modeling. The use of this model is suggested when there are not entirely independent observations and, if there is a need to separate within-group and between-groups effects. According to Hitt et al. (2007), a HLM is the proper tool to analyze problems in management because it provides more accurate estimations of data due to its ability to work with different levels.

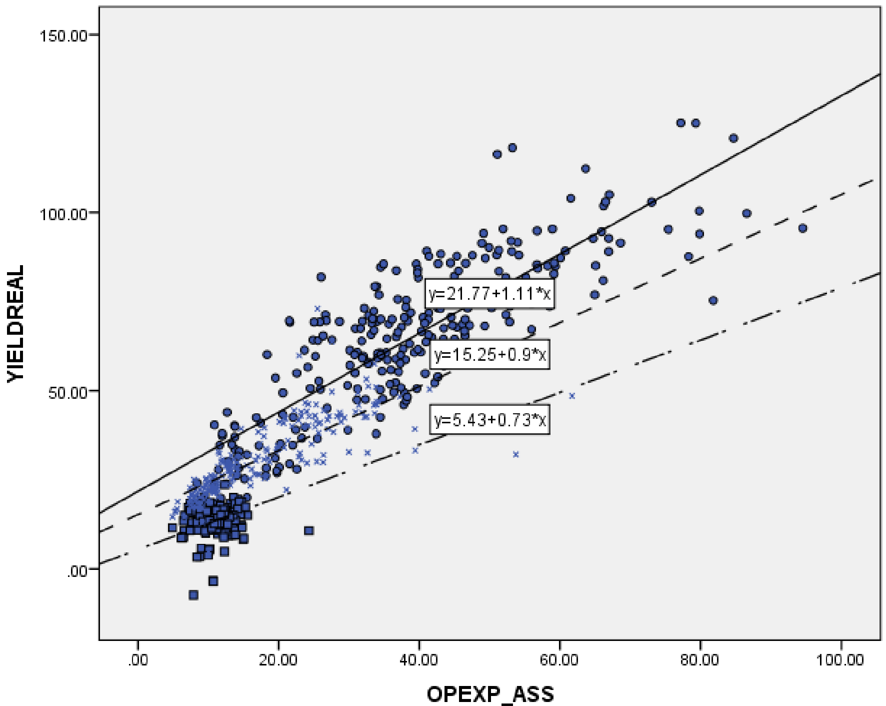
A HLM also has the following important features, which distinguish it from other methodologies: i) coefficients vary according to each group (in this article we use countries as groups); ii) coefficients present more than one variance component. According to Gelman and Hill (2007), there are three main reasons that make a HLM preferable to classical regression: i) when estimating group level regression coefficients, it takes into account individual and group level variation; ii) it allows for modeling of the variations between individual level regression and coefficients across groups and; iii) this methodology allows for estimating the regression coefficients for particular groups. In this article, we are interested in estimating variation in interest rates for countries, specifically we modeled the variations for Latin America and Asia.

The HLM has two stages: we need to set up a regression with varying coefficients, then we set up a regression for the coefficients themselves (Gelman et al., 2007). As was proved by Gaviria (2000), the HLM is a special case of a Structural Equation Model, where the maximum likelihood estimators belong to a parameter that depends on non-observable variables. The model is solved through the *EM algorithm* proposed by Dempster et al. (1977). Also, it is important to mention that the HLM is specially designed to analyze data with complex patterns and nested sources of variability (Castro and Lizasoain, 2012). In this regard, our database (Mix Market Intelligence database) is a good candidate for HLM analysis, because it has an inherent multilevel structure with many data points per MFI. Also, we grouped MFIs into countries and countries into regions. The database contains information on 962 MFIs, grouped into 25 countries and 5 regions, for the period from 2009 to 2015. It is important to note that not all countries have the same number of observations, nor did all MFIs report data during the entire time period (see Appendix 1). For example, most MFIs reported only 3 years, however, a large number of them reported data in the period analyzed. In this sense, we have different numbers of observations per group, and the HLM has the advantage of giving more weight to groups with more observations (Huta, 2014).

The idea behind the HLM is that if an individual, a MFI in this case, belongs to one country/region, then the context in which they developed is different. In addition, the model captures if they share certain characteristics which makes them, at a certain level, homogenous within-countries/regions, and heterogeneous between-countries/regions. Thus, instead of analyzing each of their respective contexts, the HLM allows, with one single model, to differentiate the variability at each level (Castro et al., 2012).

To exemplify how the 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 (o), Bangladesh ( ) and Peru (X). In the graph, we see the three different countries where the trending line appears to have a slightly different slope and different intercepts. The latter means that the relationship between operating expenses and interest rates is not the same in all countries, and using HLM we were able to find these relationships.

Graph 2. Trending lines of the relation between operating expenses and interest rates



Source: Author

To use HLM properly, we followed the methodology proposed by Pardo, Ruiz and San Martin (2007). Per this methodology, we first need to use a null model to compare the results. Then, we analyzed the means and covariances followed by an analysis of random coefficients, which gave us an integrated model with random coefficients and slopes. After concluding this analysis, we extrapolated the model to contrast the results in three regions of interest: Latin America, East Asia and South Asia.

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 (although, an important feature of the HLM is that it does not require having balanced panel data). As a result, our sample contains 25 countries and five regions (see Appendix 1). Although the MFIs in Mix Market Intelligence's database report their information voluntarily, in order to make the data comparable, the information is reviewed and standardized according to international accounting standards (Cull Demirgüç-Kunt and Morduch, 2009). We also took some variables from the World Bank Database and the World Governance Index. Table 1 contains a brief description of the variables used.

Table 1. Definition of Variables

Variable	**Short name**	**Definition**
Real yield on gross loan portfolio	REALYIELD	Proxy of interest rates that MFIs charge to customers, calculated by MIX Market as the ratio of financial fees and revenues over gross loan portfolio minus the effect of inflation.
Voice and accountability	KKM1	Indicator published by The World Bank as part of the World Governance Index indicators which captures the population's perception of their ability to participate in selecting their government, their perception of freedom of expression and freedom of association. It includes transparency measures and effectiveness of law-making bodies.
Government effectiveness	KKM3	Indicator published by The World Bank as part of the World Governance Index indicators which captures the population's perception of the quality of public services and central public institutions. It covers the credibility of policymakers and a risk indicator of state failure.
Real growth of Gross Domestic Product	GDP_REALGROWTH	Gross Domestic Product (GDP) is the most common measure of a country´s overall economic activity. Real growth rate compares GDP growth on an

		annual basis adjusted for inflation and expressed as a percent.
Average loan per borrower as proportion of GNI per capita	LOANBORR_GNI	Average loan per borrower as proportion of gross national income per capita in order to standardize the amount and size of the loans in different countries.
Operating expenses	OPEXP_ASS	Operating expenses as a proportion of the total assets expressed as a ratio.
Portfolio at risk within 30 days	PAR30	The value of all outstanding loans that have one or more installments of principal that has been due for more than 30 days, divided by the gross loan portfolio expressed as a ratio.

Source: Author

In Appendix 2 we show a brief descriptive statistic for the variables in Table 1, where the statistic Valid N (listwise) is representative of the useful observations that matched all items, which in this case is 3182. Also, we see that on average, MFIs charge a real interest rate, our proxy of interest rate, of 23.4%, with a wide standard deviation. Another interesting statistic is the correlation between real yield and average loan per borrower (as a proportion of GNI), which is negative. This essentially means the smaller the loan, the higher the interest rate. Finally, there is a high correlation between operating expenses and interest rates, which is consistent with previous studies (Dorfleitner et al., 2013) of the main drivers of interest rates.

3.2 Null model: country as random factor

The null model allows us to verify the degree of variability that exists among groups in our case, the different countries; and gives us the Likelihood Ratio, which is used to compare the different estimated models in order to verify whether or not the new models fit the data better. The null model is the shortest multilevel model in which there are no explanatory variables, only a dependent variable on level 1, and a grouping variable. In our case, the null model is the following equation:

$$REALYIELD_{ij} = \beta_0 + u_{0j} + e_{ij}. \quad (1)$$

Where sub index *i* represents the MFI, and *j* is the country. So, $REALYIELD_{ij}$ 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 a MFI-level residual.

To do the model estimation, we use Stata *xtmixed* command with Maximum Likelihood estimation (ML). We could have used the Restricted Maximum Likelihood (REML) instead, but this does not allow for the comparison of different models using the Likelihood Ratio test (Luke, 2015). In addition, according to Snijders and Bosker (1999), in large samples the differences in the results between the two methods is negligible. Another advantage of the *xtmixed* command is that it belongs to a larger class of commands used to estimate models with longitudinal data (Albright and Marinova, 2010), as is our case.

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 can use as an estimator of the mean population. Nevertheless, the important result from the null model is the Intraclass Correlation Coefficient (ICC). This coefficient represents the percentage of observed variation of the interest variable, attributable to a specific level. In our sample, the null model ICC is 51% and represents the variation of the interest rate attributable to a country characteristic, and is calculated as follows:

$$ICC = \frac{u_{0j}}{u_{0j}+e_{ij}}. \quad (2)$$

3.3 Mean analysis

In mean analysis, we first regress one level 2 variable against our independent variable. Then, in order to verify if within and between country variation could be reduced with each of the country-level variables, we tested the relation between Real Interest Rates and the following variables: Voice Accountability (KKM1), Government Effectiveness (KKM3) and Real Growth of GDP (GDP_REALGROWTH). The results are shown in the second column of Table 2. As we can see, all variables are significant, which implies that all of them are good estimators of the independent variable.

Table 2. Results from the first two models

	Null model	Mean analysis		
	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**
Constant	23.67*** (2.27)	28.13*** (2.47)	25.1*** (2.38)	23.59*** (2.28)
KKM1		9.47*** (2.22)		
KKM3			3.096* (1.86)	
GDP_REALGROWTH				0.035* (0.02)
var (_cons)	127.97 (36.39)	125.05 (36.28)	121.8 (34.78)	128.5 (36.54)
var (Residual)	126.3 (2.95)	125.7 (2.94)	126.25 (2.95)	126.19 (2.95)
N	3693	3693	3693	3693
Years	7	7	7	7
Countries	25	25	25	25
ICC	0.51	0.5	0.49	0.5
Log Likelihood	-14235.26	-14226.21	-14233.89	-14233.71

*significant at 90%, **significant at 95%, ***significant at 99%

Source: Author

As a second step, we estimate another multilevel model, which consists of a first level model:

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

And a second level model, which interacts with one of the country-level variables:

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

Combining them we obtain:

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

Where X_j is one of the variables: KKM1, KKM3 or GDP_REALGROWTH, 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 for X_j effect over the interest rates. Now, u_{0j} represents the effect of the country after controlling the effect of the country-level variable X_j. In this model u_{0j} and e_{ij} represent the random variables of the model.

In the second column of Table 2 we show the results of Equation (5), and we can verify that the coefficients associated to the three variables are significant. In addition, if we compare the variance of these coefficients with the variance of the null model, var(_cons), for KKM1 and KKM3, they are shorter than the null model, and for GDPR_REALGROWTH it is greater than the null model. On the other hand, if we compare the variance in each country, var(Residual), again with the variance of the null model, it decreased in all three variables, which means that these three variables indeed explain a portion of the interest rate variation. The ICC remained almost the same as the null model, which indicates that intra-country variance remained equal. However, with KKM1 and KKM3 the differences observed among countries were explained in 2.28% and 4.8% respectively.[5] It is also important to note that the Likelihood Ratio actually indicates that the three variables represent good estimators for the real yield.

3.4 Covariance analysis: one random effects factor

In order to explain within-country variance, we added the MFI-level variables. It is suggested to do so one by one to test whether they reduce variability and improve the

---

[5] Percentage change between the null model *var(_cons)* and the proposed models *var(_cons)*

model fit. In this case, we add the variables: LOANBORR_GNI, OPEXP_ASS and PAR30. The model is now:

$$REALYIELD_{ij} = \beta_0 + \beta_{1j}\, OPEXP\_ASS_{ij} + e_{ij}, \qquad \text{with } \beta_{1j} = \gamma_{10}. \tag{6}$$

Where γ_{10} is the mean slope that links operating expenses to interest rates. The second level does not change:

$$\beta_0 = \gamma_{00} + \gamma_{01}\, KKM1_j + u_{0j}. \tag{7}$$

And combining them we obtain:

$$REALYIELD_{ij} = \gamma_{00} + \gamma_{01}\, KKM1_j + \gamma_{10}\, OPEXP_{ASS_{ij}} + \left(u_{0j} + e_{ij}\right). \tag{8}$$

We show the results of Equation (8) in Table 3. In this analysis, we tested the three country-level variables against each of the MFI-level variables. As we can see, the ICC is smaller for other variable combinations when we add the operating expenses. Also, the ICC remains almost constant when we add the variables LOANBORR_GNI and PAR30. With regard to the amount of variability within-countries, in all cases it is smaller than the null model, 126.3, which means that the proposed combinations of MFI-level and country-level variables are explaining a part of the within-country variability. A relevant result is that for all combinations, all the coefficients are significant, and also the Likelihood Ratio shows that for all combinations, the model fits the data better, with regard to the null model.

Table 3. Covariance analysis

	Covariance analysis								
	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**
Constant	29.62***	13.5***	29.04***	26.61***	11.77***	26.18***	24.79***	10.52***	24.31***
	(2.54)	(1.61)	(2.56)	(2.36)	(1.5)	(2.4)	(2.27)	(1.4)	(2.31)
KKM1	9.93***	6.09***	9.71***						
	(2.33)	(1.57)	(2.41)						
KKM3				3.74**	2.54*	3.81**			
				(1.83)	(1.39)	(1.9)			
GDP_REALGROWTH							0.039**	0.036**	0.05**
							(0.02)	(0.016)	(0.022)
LOANBORR_GNI	-0.016***			-0.016***			-0.016***		
	(0.001)			(0.001)			(0.001)		
OPEXP_ASS		0.771***			0.773***			0.773***	
		(0.01)			(0.015)			(0.015)	
PAR30			-0.055***			-0.056***			-0.055***
			(0.011)			(0.01)			(0.011)
var (_cons)	128.62	48.02	129.25	119.99	43.74	123.04	127.38	46.55	131.78
	(37.68)	(14.33)	(37.7)	(34.23)	(12.58)	(35.17)	(36.22)	(13.33)	(37.51)
var (Residual)	117.71	74.02	120.8	118.24	74.3	121.3	118.19	74.23	121.191
	(2.81)	(1.75)	(2.99)	(2.83)	(1.75)	(3.01)	(2.82)	(1.75)	(3.01)
N	3532	3625	3269	3532	3625	3269	3532	3625	3269
Years	7	7	7	7	7	7	7	7	7
Countries	25	25	25	25	25	25	25	25	25
ICC	0.52	0.39	0.52	0.5	0.37	0.5	0.52	0.39	0.52
Log Likelihood	-13492.96	-12999.74	-12533.4	-13499.99	-13005.57	-12539.45	-13500.1	-13004.58	-12538.89

*significant at 90%, **significant at 95%, ***significant at 99%

3.5 Random coefficients analysis

In the previous models, the relationship between MFI-level variables and interest rates was assumed to be homogenous among all countries, however in order to verify which part of the intra-class variance could be explained for the independent MFI-level variables, we made the regression equation for each country, and then we analyze how the intercepts and slopes vary in each country. This model is called *random coefficients model*, because it allows the slope and the intercept to vary randomly per country. The first level model is exactly the same as before:

$$REALYIELD_{ij} = \beta_0 + \beta_{1j}\, OPEXP_{ASS_{ij}} + e_{ij}. \quad (9)$$

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

$$REALYIELD_{ij} = \gamma_{00} + \gamma_{10} * OPEXP_{ASS_{ij}} + \left(u_{0j} + u_{1j}\ OPEXP_{ASS_{ij}} + e_{ij}\right). \quad (10)$$

Where γ_{00} characterizes the mean interest rate across countries, γ_{10} is the mean slope that 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 can see the results of equation (10). Again, all coefficients were significant. In this model, the Likelihood Ratio has a double meaning, now it can also be used to test random slopes.

Table 4. Random coefficients analysis

	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**
Constant	26.68*** (2.65)	11.19*** (1.04)	25.29*** (2.42)
LOANBORR_GNI	-0.095*** (0.032)		
OPEXP_ASS		0.68*** (0.067)	
PAR30			-0.18*** (0.04)
var (slope)	0.025 (0.007)	0.1025 (0.031)	0.022 (0.013)
var (intercept)	173.75 (49.5)	23.48 (7.47)	144.65 (41.29)
covar (slope, intercept)	-1.78 (0.56)	-0.32 (0.37)	-0.92 (0.51)
var (Residual)	100.23 (2.4)	63.61 (1.5)	118.54 (2.96)
N	3532	3625	3269
Years	7	7	7
Countries	25	25	25
Proportion of explained variation	21%	50%	6%
Log Likelihood	-13253.27	-12751.08	-12514.22

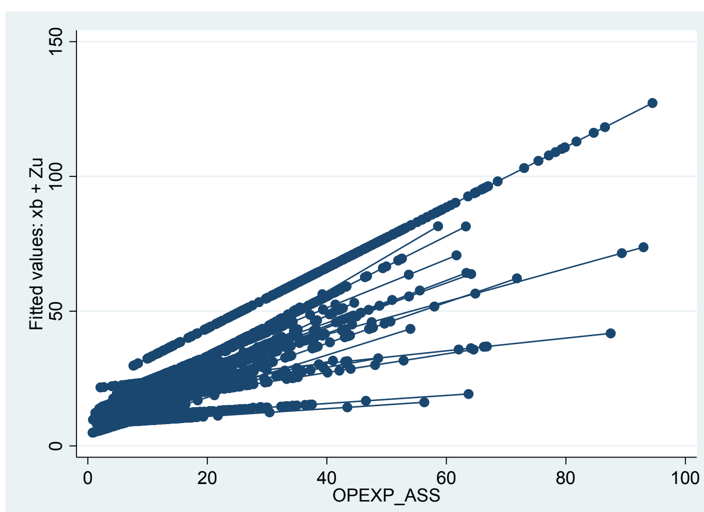
*significant at 90%, **significant at 95%, ***significant at 99%

Source: Author

Now, we review each of the variance components, because they represent the main findings in this model. First, in order to test whether the variance of the slope is significant, we need to verify if the coefficient is three times the standard error (Leckie, 2010). Results in Table 3 show that LOANBORR_GNI and OPEXP_ASS have random intercepts and random slopes. Having random slopes means that in each country, the effect of the average loan per borrower or the operating expenses on real interest rates is not the same. Thus, we have an effect as described in Graph 1.

If we look at the predicted values using the coefficients obtained with OPEXP_ASS, we would obtain the paths shown in Graph 3. Each line represents a different country and we can see how the slopes and the intercepts of each regression line are different.

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



Source: Author

In Equation (10), the covariance is an indicator of the relation between slopes and intercepts. In this case, for the variables OPEXP_ASS and PAR30, their relationship with interest rates does not seem to increase/decrease after the changes in the means, thus, there is no relationship between slopes and intercepts.

Finally, the residual variance shows the variability of each MFI around its country regression line, and it allows for the calculation of the proportion that is explained by the variation. As we expected, the variable that explains most of the variation within country, is operating expenses.

3.6 Integrated model: random coefficients and slopes

In order 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 run an integrated model. This also allows us to get MFI-level results associated to the country-level interactions. In this case we use the model with 3 MFI-level variables and 3 country-level variables. In the previous sections, we established that the six variables are significant as interest rate predictors. We also verified that this variable explains a significant proportion of the variability among MFIs and among countries. The results of this model show in Table 5 that all coefficients are significant and the model seems to fit the data well, measured by the Likelihood Ratio.

Table 5. Integrated model: random slopes and coefficients

	Coef. (SE)		**Coef. (SE)**
Constant	17.43*** -1.59	var (LOANBORR_GNI)	0.006 -0.002
KKM1	3.94*** -1.3	var (PAR30)	0.014 -0.008
KKM3	2.44** -1.23	var (OPEXP_ASS)	0.1093 -0.035
GDP_REALGROWTH	0.042*** -0.02	var (_cons)	41.25 -13.18

LOANBORR_GNI	-0.037** -0.016	cov (LOANBORR_GNI, PAR30)	0.002 -0.002
OPEXP_ASS	0.643*** -0.07	cov (LOANBORR_GNI, OPEXP_ASS)	0.0005 -0.005
PAR30	-0.156*** -0.033	cov (LOANBORR_GNI, _cons)	-0.336 -0.143
		cov (PAR30, OPEXP_ASS)	-0.008 -0.011
N	3182		
Years	7	cov (PAR30, _cons)	-0.147 -0.237
Countries	25	covar (OPEXP_ASS, _cons)	-0.338 -0.502
Log Likelihood	-10941.46	var (Residual)	52.21 -1.34

*significant at 90%, **significant at 95%, ***significant at 99%

Source: Author

The relevant results from this integrated model are:

1) The estimation of the interest rate mean for the population of MFIs is 17.43
2) Once we control for government effectiveness and real growth of GDP, the index of voice and accountability has a positive impact on interest rates. The same type of relationship is found when we control for the other two country-level variables, although the effect of real growth of GDP on interest rates is very small, compared with the other two variables.
3) The average loan per borrower, measured as a proportion of GNI per capita, is negatively related to the interest rates. The same is true for the portfolio at risk within 30 days. On the other hand, operating expenses as a proportion of total assets represent the highest effect on interest rates.
4) The variance of the residuals is now 52.21, which is lower than in previous models, and is an indicator that the combination of level 1 and level 2 variables reduces within-country variability. Let´s remember that initial variability among

interest rates is quite large, which is why we find such large residuals even with the variables included as estimators.

5) The variance of the means of each of the MFI-level variables is shorter, with respect to the null model, which is also an indicator that country-level variables explain the differences in countries and MFIs very well.

3.7 Regional effects

In the previous sections, we analyzed countries as a grouping variable, in this section we verify whether the relationships are similar using regions. To that end, we tested the model only in Latin America, East Asia and South Asia, in total this sample represents 78% of our total sample. Latin America is the largest region with 333 MFIs, followed by South Asia with 234 and East Asia with 185. We show the results in Table 5, where we can verify that the behavior of the variables among regions is different.

Table 6. Multilevel model: comparison between regions

	Complete sample	**East Asia**	**Latin America**	**South Asia**
	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**
Constant	17.43*** (1.59)	24.21*** (2.22)	19.85*** (1.52)	24.51*** (2.3)
KKM1	3.94*** (1.3)	9.37*** (3.03)	17.99*** (3.99)	9.39* (5.44)
KKM3	2.44** (1.23)	-0.376 *NS* (4.04)	0.0799 *NS* (2.41)	3.57 *NS* (4.26)
GDP_REALGROWTH	0.042*** (0.02)	-0.072 *NS* (0.1053)	0.015 *NS* (0.03)	0.145** (0.06)
LOANBORR_GNI	-0.037** (0.016)	-0.0002 *NS* (0.004)	-0.009*** (0.002)	-0.015 *NS* (0.02)
OPEXP_ASS	0.643*** (0.07)	0.5138** (0.227)	0.708*** (0.09)	0.393*** (0.08)
PAR30	-0.156*** (0.033)	-0.345*** (0.07)	-0.186*** (0.03)	-0.018 *NS* (0.01)

Source: Author

In these analysis, we found that average loan per borrower is not significant to explain interest rates in South Asia, nor in East Asia, but it is significant in Latin America, with a negative coefficient. The real growth of GDP is significant only in South Asia, and with a larger coefficient. The government effectiveness (KKM3) turned out not to be significant in any of the three regions.

4. Results and discussion

The use of a HLM allows us to verify the differences among countries and regions. In particular, we used it to analyze Latin America, Africa, Eastern Europe and Asian MFI´s, as well as the effect of the selected variables on the MFI´s interest rates. In general, we found that at the MFI-level, operating expenses are the main driver of interest rates, confirming the results of Dorfleitner et al. (2013) and Cuéllar-Fernández et al. (2016). However, the relationship between operating expenses and interest rates is different depending on the country. Also, the variance obtained with this coefficient allows us to measure the effect that country-level variables have on MFIs' interest rates. In addition, we tested different country-level variables, and found two significant relationships: voice and accountability on one hand and government effectiveness on the other. The positive relationship between these two variables on interest rates, means that the higher the country is graded, with regard to its voice and accountability and government effectiveness, the higher the interest rates would be.

This finding is consistent with other research. For example, Kauffman, Kray and Mastruzzi (2007) included several measures of transparency in their analysis, including freedom of association, freedom of access to internet, and institutional effectiveness because these characteristics enhance the business environment, creating more competition in the financial sector. On the other hand, Cull et al. (2014) found in their study that in countries with greater bank penetration, MFIs tend to lend to poorer customers, and as we can see in our results, the relation between average loan per borrower and interest rates is negative. Thus, the smaller the loan, the higher the interest rate. Likewise, Roberts (2013) found that even in a more competitive environment, MFIs charged high interest rates.

Another interesting finding in our analysis of regions is that the relationship between the average loan per borrower and interest rates is only significant in Latin America[6], but not in more developed microfinance markets like South Asia, where there are countries with more mature microfinance experience (Bangladesh and India), or East Asia, where China is the main player. Thus, according to Im and Sun (2015), the average loan per borrower is not relevant in Asia because it is a region with a long and popular history in microfinance, but also because countries in that region receive more support from governments, and have the chance to participate in the co-creation of new models to attend poorer customers. In South Asia, we found interesting data: more than 65% of the MFIs are large, mature and non-profit. While in Latin America, we have smaller and younger institutions with a 50%-50% proportion of for profit and non-profit MFIs.

The lack of relationship between average loan per borrower and interest rates, for East Asia, can be explained by the following: i) for microfinance, China is the most developed country; ii) China has had, for many years, strict regulations on interest rate caps. Consequently, it discourages serving the poorest customers, as the loans they usually grant are large and less risky (Basharat et al., 2015). However, since 2013, China has been

[6] Let´s remember that in the covariance analysis we also found that the country equations relating average loan per borrower with interest rates have random slopes and random coefficients. That means, this relationship is different in each country.

working on reforming their regulatory environment to improve financial inclusion which has allowed MFIs to flourish and explore new innovative and more technology-based models (Global Microscope 2015). Thus, according to Mendoza and Vick (2010), proper regulation (i.e. in the adequate measure and direction) will allow MFIs to expand their services and capabilities to the benefit of their customers.

For MFI-level variables, we found that the portfolio at risk within 30 days, as a measure of the quality of the portfolio, is significant in all regions except in South Asia. This is explained by Nwachukwu (2014), who found that MFIs with higher proportions of loan portfolio at risk of default, are expected to charge higher interest rates. In the same line of research, according to Sun and Im (2014), it is common practice in the microfinance industry to renegotiate debts, which in many cases implies the lowering of rates to promote repayment, since microloans don´t have collateral to guarantee the payment. Our results support this notion, in fact we found that the higher the portfolio at risk within 30 days, the lower the interest rate the MFI charges to customers.

Finally, we found that GDP real growth is only relevant for South Asia, which is an indicator that interest rates in South Asia respond to macroeconomic growth and country risk factors. In East Asia, however we found that high GDP growth rates don´t translate into higher interest rates, because regulation in the microfinance sector is highly developed. In Latin America, the reasons for the non-significant relationship between GDP growth and MFIs' interest rates are still inconclusive, which could be the subject of further research.

5. Conclusions

In this paper, we use a HLM to analyze the differences in interest rates between countries and regions, and within countries and regions. In particular, we analyzed Latin America, Africa, Eastern Europe and Asian MFI´s. In our study, we conclude that there are several specific country and regional factors that moderate the relationship between MFI-level variables, which determine the differences in interest rates. In particular, we found that operating expenses are an important driver of interest rates. Also, we found that only in Latin America is there a significant relationship, negative in this case, between the loan per borrower and the interest rate. As we know, this is consistent with the concept of mission drift, which states that MFIs are providing small loans, at high interest rates to the poorest of the population. We also found that the higher the portfolio at risk within 30 days, as a proxy of past due portfolio, the lower the interest rate the MFI charges to customers. Finally, we did not find an effect of the macro interest rates on interest rate in South Asia, which is probably explained by the lack of regulation of MFIs.

Our study could suggest that in order to create better microcredit conditions with affordable interest rates and to improve financial inclusion in a country, regulating authorities, policy makers, and microfinance managers need to carefully analyze country-level variables; variables such as an adequate business environment and government effectiveness.

References

Albright, J., and Marinova, D. M. (2010). Estimating Multilevel Models using SPSS, Stata, SAS and R. Indiana University, 22(Ferron 1997), 1–35.

Balammal, A., Madhumathi, R., and Ganesh, M. P. (2016). Pentagon Performance Model of Indian MFIs, *Paradigm*, 20(1): 1–13.

Basharat, B., Hudon, M., and Nawaz, A. (2015). Does Efficiency Lead to Lower Prices? A New Perspective from Microfinance Interest Rates, *Strategic Change*, 24(3): 49–66.

Bogan, V. L. (2012). Capital structure and sustainability: an empirical study of microfinance institutions, *Review of Economics and Statistics*, 94(4): 1045–1058.

Bos, J. W. B., and Millone, M. (2012). Practice what you preach : Microfinance business models and operational efficiency, *World Development*, 70: 1–19.

Burzynska, K., and Berggren, O. (2015). The Impact of Social Beliefs on Microfinance Performance, *Journal of International Development*, 27(7): 1074–1097.

Campbell, G. (2010). Microfinancing the Developing World: how small loans empower local economies and catalyse neoliberalism's endgame, *Third World Quarterly*, 31(7): 1081–1090.

Castro, M., and Lizasoain, L. (2012). Las técnicas de modelización estadística en la investigación educativa: Minería de datos, modelos de ecuaciones estructurales y modelos jerárquicos lineales, *Revista Espanola de Pedagogia*, 70(251): 131–148.

Cotler, P., and Almazan, D. (2013). The Lending Interest Rates in the Microfinance Sector: Searching for its Determinants, *Journal of CENTRUM Cathedra*, 6(1): 69–81.

Cotler, P., and Rodríguez-Oreggia, E. (2008). Rentabilidad y tamaño de préstamo de las microfinanzas en México, *Economía Mexicana*, 17(2): 149–169.

Cuéllar-Fernández, B., Fuertes-Callén, Y., Serrano-Cinca, C., and Gutiérrez-Nieto, B. (2016). Determinants of margin in microfinance institutions, *Applied Economics*, 48(4): 300–311.

Cull, R., Demirgüç-Kunt, A., and Morduch, J. (2009). Microfinance Meets the Market, *Journal of Economic Perspectives*, 23(1): 167–192.

Cull, R., Demirgüç-Kunt, A., and Morduch, J. (2014). Banks and Microbanks, *Journal of Financial Services Research*, 46(1): 1–53.

Dempster, A.; Laird, N. and Rubin, D. (1977) Maximum Likelihood from incomplete data via the EM algorithm, *Journal of the Royal Statistical Society*, 39: 1-38

Dorfleitner, G., Leidl, M., Priberny, C., and von Mosch, J. (2013). What determines microcredit interest rates? *Applied Financial Economics*, 23(20): 1579–1597.

Economist, T., and Unit, I. (2015). Global Microscope 2015 The enabling environment for financial inclusion report.

Gaviria, J.L. (2000) Cambios en las técnicas cuantitativas de investigación socioeducativa, *Actas del XII Congreso Nacional y II Iberoamericano de Pedagogía*, Madrid: 39-45

Gelman, A., and Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. New York: Cambridge University Press.

Guo, L., and Jo, H. (2017). Microfinance Interest Rate Puzzle: Price Rationing or Panic Pricing? *Asia-Pacific Journal of Financial Studies*, 46(2): 185–220.

Gutiérrez, J. G. (2012). Las microfinanzas en el marco de la financiación del desarrollo: compatibilidad y/o conflicto entre objetivos sociales y financieros. *Tesis doctoral*. Universidad del País Vasco.

Hitt, M. A., Beamish, P. W., Jackson, S. E., and Mathieu, J. E. (2007). Building theoretical and empirical bridges across levels: Multilevel research in management, *Academy of Management Journal*, 50(6): 1385–1399.

Huta, V. (2014). When to use hierarchical linear modeling, *Tutorials in Quantitative Methods for Psychology*, 10(1): 13–28.

Im, J. and Sun, S. L. (2015). Profits and outreach to the poor: The institutional logics of microfinance institutions, *Asian Pacific Journal Management*, 32: 95–117

Juárez, E. (2016). Microcréditos podrían encarecerse por alza de tasas: Gentera. El Economista, retrieved on September 29, 2017, from: http://eleconomista.com.mx/sistema-financiero/2016/11/01/microcreditos-podrian-encarecerse-alza-tasas-gentera

Kar, A. K. (2013). Mission drift in microfinance: are the concerns really worrying? Recent cross-country results, *International Review of Applied Economics*, 27(1): 1–17.

Kar, A. K., and Swain, R. B. (2014). Interest Rates and Financial Performance of Microfinance Institutions: Recent Global Evidence, *The European Journal of Development Research*, 26(1): 87–106.

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2007). Governance Matters VI: Governance Indicators of 1996–2006. *World Bank Policy Research Working Paper 4280*. Washington, DC.

Kneiding, C., and Rosenberg, R. (2008). *Variations in Microcredit Interest Rates*. BRIEF. CGAP.

Leckie, G. (2010). Module 5: Introduction to Multilevel Modelling. *In LEMMA VLE, Centre for multilevel modelling*: 1–5.

Luke, A. D. (2015). *Multilevel Modeling Tutorial*. Statistical Consulting, (March).

Mendoza, R. U., and Vick, B. C. (2010). From Revolution to Evolution: Charting the Main Features of Microfinance 2.0, *Perspectives on Global Development and Technology*, 9(3): 545–580.

Morduch, J. (2000). The Microfinance Schism, *World Development*, 28(4): 617–629.

Nwachukwu, J. (2014). Interest Rates, Target Markets and Sustainability in Microfinance, *Oxford Development Studies*, 42: 86–110.

Pardo, A., Ruiz, M. Á., and Martín, R. S. (2007). Como ajustar e interpretar modelos multinivel con SPSS. *Psicothema*, 19(2): 308–321.

Patiño, A. O. (2010). El modelo MIFE como instrumento para la formalización del empresariado. Una aplicación para las microempresas informales de Bogotá D.C. Doctoral Thesis. Universidad Antonio de Nebrija.

Roberts, P. W. (2013). The Profit Orientation of Microfinance Institutions and Effective Interest Rates, *World Development*, 41(1): 120–131.

Snijders, T. a B., and Bosker, R. J. (1999). Multilevel Analysis: An introduction to basic and advanced multilevel modeling (2nd. Ed.). Thousand Oaks: CA SAGE.

Sun, S. L., and Im, J. (2014). Cutting Microfinance Interest Rates: An Opportunity Co-Creation Perspective, *Entrepreneurship: Theory and Practice*, (816): 101–128.

Trujillo, V., Rodriguez-Lopez, F., and Muriel-Patino, V. (2014). Microfinance Regulation and Market Development in Latin America. B.E, *Journal of Economic Analysis and Policy*, 14(4): 1615-1644.

Vanroose, A., and D'Espallier, B. (2013). Do microfinance institutions accomplish their mission? Evidence from the relationship between traditional financial sector development and microfinance institutions' outreach and performance, *Applied Economics*: 45(15).

Woller, G. M., Dunford, C., and Woodworth, W. (1999). Where to microfinance? *International Journal of Economic Development*, 1(1): 29–64.

Xu, S., Copestake, Ja., and Peng, X. (2016). Microfinance institution´s mission drift in macroeconomic context, *Journal of International Development*, 28(1): 1123–1137.

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	

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	

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

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

Appendix 2. Descriptive Statistics

	N	Mean	Std. Deviation
YIELDREAL	3693	23.42	18.15
KKM1	4491	-0.32	0.62
KKM3	4491	-0.37	0.40
GDP_REALGROWTH	4491	2.41	12.39
LOANBORR_GNI	4119	54.39	138.65
OPEXP_ASS	3661	16.67	12.14
PAR30	3528	6.73	17.63
Valid N (listwise)	3182		

Correlation coefficients

	YIELDREAL	KKM1	KKM3	GDP_REALGROWTH	LOANBORR_GNI	OPEXP_ASS	PAR30
YIELDREAL	1						
KKM1	.133**	1					
KKM3	.291**	.366**	1				
GDP_REALGROWTH	-.033*	-.131**	-.048**	1			
LOANBORR_GNI	-.152**	-.192**	-.145**	.052**	1		
OPEXP_ASS	.793**	.116**	.229**	-.050**	-.173**	1	
PAR30	-0.024	.035*	0	-.047**	-0.009	0.008	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).