Investment in Microfinance Equity:

Risk, Return, and Diversification Benefits

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Abstract

This paper takes full advantage of daily quoted prices of microfinance stocks from their issuance, and draws a global picture of worldwide microfinance equity from the viewpoint of a profit-oriented investor.We construct microfinance country equity indices and an international global microfinance index. We analyse the changes in these indices, which we assess in reference to comparable indices for the financial sector and also to national indices. Our findings show that microfinance has resumed its close correlation with the financial sector since 2001. In terms of risk exposure, estimations of the Capital Asset Pricing Model demonstrate that microfinance shares exhibit higher market beta than conventional financial institutions, and have equivalent currency exposure. We also examine whether adding microfinance to international asset portfolios improves the investor's risk-return performance. While the inclusion of microfinance equity has indeed been a major source of diversification in the 1990s, its impact has diminished in recent years. Still, optimal portfolios invested in countries where microfinance equity is available may contain up to 20% of stocks from MFIs.

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1. Introduction

The microfinance sector offers attractive opportunities to investors seeking to participate in alleviating poverty in developing countries. This paper examines whether this assertion remains true for investors who are seeking financial profitability only.[1] We therefore assess the impact of microfinance equity on globally diversified portfolios by making use of the classical tools of portfolio analysts. For that purpose we construct microfinance country indices, analyse their movements, and assess them in reference to comparable indices for the financial sector, and to national indices. International equity indices are also considered.[2]

Microfinance has dramatically changed during the last decade, moving from a universe of donor-financed NGOs towards a widely disparate industry including all sorts of institutions (Mersland, 2009), among which a growing number of commercial banks.[3] Simultaneously, socially responsible investments have gained momentum on financial markets.

At present, there are two types of publicly available investments in microfinance: Microfinance Investment Vehicles (MIVs),[4] and listed equity of Microfinance Institutions (MFIs). For reasons pertaining to data availability, this paper concentrates on MFIs. Its aim is to gauge the financial benefits of including microfinance equity in a geographically diversified portfolio. In that respect, it will also examine whether microfinance constitutes a sector by itself or should be seen as part of the mainstream financial sector.

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[1] Alternatively, financial and social returns can be combined (see Dorflteiner *et al*., 2010).
[2] J.P. Morgan has created in 2003 the Low-Income Finance Institutions (LIFIs) index including not only the listed MIFs, but also other financial institutions (see J.P. Morgan, 2009). Wall's Street Advisor Services (WSAS) has also released several benchmarks for investments in MFIs, the WSAS MFI Shareholder Value Indices, computed from book values (see http://www.wallsstreetadvisorservices.com/). In contrast, our indices are based on market prices solely.
[3] According to Dieckmann (2007), between 2004 and 2006 the international public and private-sector investors have more than doubled their investments in microfinance, reaching USD 4.4 billion in 2006.
[4] See e.g. Matthäus-Maier and von Pischke (2006).

While restricted to a relatively small number of assets, the microfinance equity has the considerable advantage over MIVs of being publicly priced on stock exchanges on a daily basis, making it more transparent and allowing for deeper financial analysis. Conversely, MIVs invest in several MFIs mainly through loans, but the content of their portfolios is often opaque,[5] making it difficult for outsiders to assess their actual level of risk.

Arguably, the microfinance equity is not representative of the whole sector. Moreover, the profitability of the microfinance sector is hotly debated.[6] Many MFIs still rely on subsidies for reaching financial sustainability (Hudon, 2010; Nawak, 2010; Hudon and Traca, forthcoming). For instance, Cull *et al*. (2009) state that: "The evidence suggests that investors seeking pure profits would have little interest in most of the institutions that are now serving poorer customers" (p. 169). Schmidt (2010) is even more pessimistic about the potential for profitable investment in microfinance: "(...) I fear that the high expectations regarding the return on an investment in MFIs, which I consider to be exaggerated, will have a negative impact on activities in the microfinance sector (...)" (p. 125).[7]

On the other hand, the microfinance sector has experienced successful Initial Public Offerings (IPOs) like the highly publicised IPO of Banco Compartamos in Mexico that occurred in 2007. Such IPOs have nevertheless been criticised by influential actors in the field, among which the Nobel-Prize laureate Muhammad Yunus who views the Compartamos IPO as a

[5] The authors - and colleagues from other universities - have tried for years to obtain data on MIVs with little success. Regarding transparency, MIVs tend to adopt an attitude comparable to that of hedge funds.
[6] Caudill *et al.* (2009) show on data from Eastern Europe and Central Asia that larger MFIs offering deposits are the most cost effective.
[7] Other opinions are more favorable. For instance, Dieckmann, (2007) says: "*Apart from poverty alleviation, microfinance offers stable financial returns over the economic cycle, low loan portfolio default rates and potentially low correlations to mainstream capital markets*" (p.19)

mission drift[8] that compromises the reputation of the sector (see Ashta and Hudon, 2009, for a detailed discussion). Leaving ethical and mission-based considerations aside, this paper starts from observable returns of publicly traded MFIs. From a portfolio perspective, these returns are to be judged not only on a case-by-case basis, but also in regard to their correlations with other assets.

Previous work has already investigated the financial properties of investment in the microfinance sector. However, due to data availability issues, authors are bound to use figures extracted from annual accounting statements provided by the Microfinance Information Exchange (MIX)[9] rather than high frequency market data. This puts strong limitations on the relevance of their results for mainstream investors. From this perspective, Krauss and Walter (2008) present evidence that, over the period 1998-2006, including microfinance in global portfolios reduces overall portfolio volatility, but show that the same result does not hold for domestic investors. Using MIX data for the period 1997-2007, Galema *et al*. (forthcoming) apply the spanning tests methodology proposed by De Roon *et al.* (2001), and confirm that investment in microfinance is profitable in terms of portfolio diversification.

In this paper, we construct microfinance country equity indices and an international Global Microfinance Index (GMI). We analyse the changes in these indices, which we assess in reference to comparable indices for the financial sector and also to national indices. Our findings show that microfinance has resumed its close correlation with the financial sector since 2001. In terms of risk exposure, estimations of the Capital Asset Pricing Model (CAPM) demonstrate that microfinance shares exhibit higher market beta than conventional financial

[8] The microfinance mission drift stems from the double bottom-line (social and financial) embodied by the MFIs. An MFI is said mission-drifted when it sacrifices its social mission (typically, poverty alleviation and/or women empowerment) for financial purposes (see, e.g., McIntosh and Wydick, 2005; Copestake, 2007; Ghosh and Van Tassel, 2008; Mersland and Strøm, 2010; Armendariz and Szafarz, forthcoming).
[9] Importantly, the MIX data are provided by the MFIs on a voluntary basis.

institutions, and have equivalent currency exposure. We then turn to mean-variance spanning tests (Basak *et al.*, 2002; Brière *et al.*, 2011) and examine whether adding microfinance to international asset portfolios improves the investor's risk-return performance. While the inclusion of microfinance equity has indeed been a major source of diversification in the 1990s, its impact has diminished in recent years. Still, optimal portfolios invested in countries where microfinance equity is available may contain up to 20% of stocks from MFIs.

The reminder of the paper is structured as follows. Section 2 describes the database and the methodology. In section 3, we study the joint movements of the finance and microfinance indices. In section 4, we estimate the CAPM including foreign exchange risk. Section 5 draws efficient frontiers and applies spanning tests. Section 6 concludes.

2. Data and Methodology

We concentrate on five countries that altogether currently have nine MFIs issuing equity: Mexico, South Africa, Indonesia, Bangladesh and Kenya. The market data (total return index and market capitalisation) come from Datastream. Table 1 presents the MFIs classified by country, with their inception date (data availability in Datastream) and market value at the end of 2010. Three MFIs are quoted in South Africa: African Bank (the oldest quoted MFI, since January 1990), Blue Financial Services (BFS), and Capitec Bank; one in Kenya: Equity Bank; two in Indonesia: Bank Danamon (also one of pioneering quoted MFI, since April 1990) and Bank Rakyat Indonesia (BRI); one in Bangladesh: BRAC Bank; and two in Mexico: Banco Compartamos and Financiera Indepencia (FI).[10]

[10] SKS, the Indian quoted MFI, is not considered here because its IPO is recent (August 2010).

The descriptive statistics for monthly and daily returns are presented in Tables 2 and 3, respectively. They cover the period for which each series is available, and end in December 2010. These statistics show great disparity in returns from MFIs. Some institutions have been exceptionally profitable from their initial public offerings, such as African Bank (annualised monthly return of 57.9% since 1990) and Capitec (71.8% since 2002) in South Africa[11] or Equity in Kenya[12] (59.3% since 2006). On the other hand, others have had disastrous performance, including BFS (-22.1% since 2006), a South African MFI. All have very high volatility (from 37.5% for Compartamos to 79.6% for BFS) and considerable extreme risks. Returns also display a phenomenon rarely found in finance: they are nearly always asymmetrical to the right, with skewness as high as 6.5 for African Bank. At the same time, African Bank has an exceptionally fat-tailed distribution, with kurtosis of 73.5, and maximum monthly and daily returns of respectively 266% for one month and 233% for one day, both occurring in February 1995. All MFI returns have been positively tested for stationarity.

To estimate the CAPM in section 3, we use country stock indices and a World index from Morgan Stanley Capital International (MSCI). More precisely, the country indices are quoted in domestic currencies and respectively encompass 21 stocks in Mexico, 45 in South Africa, 22 in Indonesia, and 7 in Kenya.[13] The World index (MSCI All Countries World Index) is quoted in USD and contains 9,000 stocks from both developed (24) and emerging (21) countries. The stock selection is based on liquidity (trade frequency and volume) and size

[11] The history of the microfinance industry in South Africa is singular (see Porteous and Hazelhurst, 2004; Napier, 2006). After having experienced full deregulation in the post-apartheid period (1992-1999) which enhanced commercial microcredit activities, the sector started to be supervised by the Microfinance Regulatory Council (MFRC) which is “entrusted with the responsibility of regulating the activities of the micro lending sector and to protect consumers against deceptive and unfair lending practices in terms of the Usury Act Exemption Notice (…) of June 1999.” (http://www.dti.gov.za/thedti/mfrc.htm).

[12] Rhyne (2009) mentions that Equity Bank boasts over a million small savers and was recognized as the best bank in Kenya by *Euromoney* in 2007.

[13] Bangladesh is excluded from the universe for CAPM estimations due to unavailability of interest rates.

(market value). The industry composition of each country index reflects the specificities of the local market.

Table 4 provides the monthly descriptive statistics over the sample period used in the CAPM estimations.[14] Annualised monthly returns for emerging equity indices range from 16.9% (South Africa since 1997) and 31.5% (Kenya since 2006). Volatility is high (from 20.5% for South Africa to 35.9% for Indonesia), but lower on average than for microfinance institutions reflecting the relatively good diversification of MSCI emerging indices, despite the low number of securities they include. Extreme risks are also lower than for MFIs (skewness is slightly negative in the majority of cases, except for Indonesia) and kurtosis ranges from 3.9 to 5.6. The MSCI World index, which mixes developed- and emerging-country equities, naturally has much less attractive performance (7.2% annualised monthly return since December 1996), but it also has lower risk (volatility of 17.2%). All MSCI returns have been positively tested for stationarity.

Data for interest rates (three-month interbank rates) in each country and exchange rates are from Datastream. Table 5 presents the descriptive statistics of these rates in our countries of interest, except Bangladesh (see footnote 12), and in the USA. Average interest rates are high in emerging countries (from 6.3% in Kenya to 12.5% in Indonesia) compared to the USA (3.5%). Some countries have experienced large swings in interest rates. For instance, Indonesian rates have varied between 5.7% and 56.0% since 1996, and South African rates have varied between 5.7% and 25.5% since 1997. Table 6 presents the descriptive statistics for the foreign exchange monthly return of the USD against emerging currencies. Average foreign exchange returns range from 3.8% in Mexico (since January 2007) to 14.4% in

[14] This period can be restricted due to unavailability of interest rates in some countries.

Indonesia (since November 1996), with volatilities lying between 11.4% and 17.3% and high extreme risks. All currencies have experienced depreciation against the USD over the sample period. Currency returns strongly depart from normality but are stationary.

In order to compare the monthly changes in microfinance and finance stocks in the five selected countries, we construct original capitalisation-weighted indices, for both the microfinance and financial sectors. We proceed in the following way. First, for each country at stake we create a local microfinance return index[15] starting when at least one MFI is quoted in that country. For the sake of comparability, the local indices are converted in USD at the current exchange rate. Second, we aggregate the local microfinance indices into the Global Microfinance Index (GMI) by weighting each stock by its market capitalisation. The GMI is defined from January 1990 on. Between January and March 1990 the GMI includes a single stock, namely the African Bank (South Africa). The subsequent inclusions of stocks take place in April 1990 (Danamon, Indonesia), February 2002 (Capitec, South Africa), and November 2003 (Bank Rakyat, Indonesia). After 2005, the acceleration of microfinance IPOs leads to more frequent adjustments of the GMI. At the end of the sample period (December 2010), the GMI is composed of nine stocks from five countries with the following geographic weights: 63% for Indonesia, 18% for South Africa, 13% for Mexico, 4% for Kenya, and 1% for Bangladesh.

Figure 1 draws the movements in the local microfinance indices (in local currency), each being normalised to 100 at its starting date. Importantly, the South African index experienced such exceptional growth over the period that a different scale is needed to represent its change (axis on the right side of Figure 1). Figure 2 draws the change in the GMI (in USD). This

[15] The index takes into account reinvested dividends.

graph should be interpreted with caution at the beginning of the sample period due to the lack of geographical diversification. Tables 7 and 8 present monthly and daily descriptive statistics for all microfinance indices, respectively. Annualised profitability of national indices ranges from 11% for Indonesia since 1990 to 58.8% for Kenya (over a short period, since 2006). Thanks to the diversification effect, national microfinance indices' present lower dispersion than the MFIs themselves. However, because the indices remain weakly diversified, their volatilities remain higher than those of traditional emerging indices (from 34.7% for Mexico to 78.1% for South Africa, compared with the equivalent MSCI emerging indices, for which volatility ranges from 20.6% for South Africa to 35.9% for Indonesia). Extreme risks are also much higher: skewness is highly positive (from 0.39 for Bangladesh to 6.59 for South Africa), as it is for individual MFIs (except for the Mexican index, where Compartamos is the only MFI to have left-skewed asymmetrical returns); kurtosis is very high (up to 74.3 for South Africa) for national microfinance indices, except for Bangladesh and Mexico (which has kurtosis of nearly 3). The GMI index has an average annualised monthly return of 20.3% and volatility of 56%, and more moderate extreme risks (skewness of 0.5 and kurtosis of 5.91).

For the finance sector, we construct local and global indices by mimicking the construction of the microfinance indices. More precisely, in each of the five countries under consideration, the local finance index is built from the financial stocks belonging to the corresponding MSCI universe, but excluding microfinance. As a consequence, at the end of the sample period the local financial indices are composed of stocks from the following numbers of banking institutions: 5 in South Africa, 3 in Kenya, 3 in Indonesia, 11 in Bangladesh, and 2 in Mexico. Table 9 lists the financial institutions included in our indices, with inception date and market capitalisation. Again, each index is weighted by market capitalisation. The number of financial institutions in Bangladesh is striking. Indeed the financial sector is particularly developed compared to others in that country (Demirguc-Kunt and Levine, 1999). Bangladesh has been subject to an important financial sector reform initiated by the World Bank at the beginning of the 1990s, and pursued by the government after 1996, which aimed at expanding and diversifying the financial sector and privatised national banks (Uddin and Hopper, 2003).

Lastly, the Global Finance Index (GFI) aggregates the five local indices. However, in order to allow rational comparisons with the GMI, the country weights in the GFI are constrained to be those of the GMI. Specifically, the weight of each country in both the GMI and GFI is dictated by the size of its microfinance sector (converted to USD). Interestingly, on the Indonesian stock market the microfinance sector (present since 1990) predates the banking sector (present since 1996). As a consequence, the GFI can only be defined for the period starting in November 1996.

Figures 3 and 4 present the changes of the local and global indices, respectively. Tables 10 and 11 give their descriptive statistics (monthly and daily returns). Profitability of the traditional financial indices presents far lower dispersion than do the microfinance indices: average annualised monthly returns range from 22.5% for South Africa since 1990 and 33.5% for Kenya since 1991. However, financial indices' volatility (from 25.9% for South Africa to 51.6% for Indonesia) is much lower than for microfinance indices. These results also apply to the GFI index, whose average annualised monthly return (22.5%) is slightly higher than that of the GMI index, and with lower volatility (47.5% versus 56%).

3. Joint movements of the finance and microfinance global indices

To facilitate comparison of our two global indices, the GFI for finance and the GMI for microfinance, a common base of December 1996 was fixed. The graph of daily cumulative returns of the GFI and GMI (Figure 5) shows that after a period of great disparity between finance and microfinance with higher instability for microfinance, a phenomenon of convergence appeared. In fact, the correlation between the GMI and the GFI rose from 33% over the first half of the sample period (until December 2003) to 79% during the second half. Volatilities for the two series also differ by sub-period (initially 53% and then 30% for finance, and 76% and 34% for microfinance). The Engle and Sheppard (2001) test for constant conditional correlation confirms the instability of correlations at the 1% level.[16]

To describe the joint movements of the GFI and GMI indices, we adopt DCC-MVGARCH[17] modelling (Engle and Sheppard, 2001; Engle, 2002), which enables us to factor in dynamic conditional correlations. This approach was very often used to model correlation dynamics between financial series (Kearney and Poti, 2006; Brière and Signori, 2009). Consider daily returns, $r_t = (r_{1,t}, r_{2,t}, ..., r_{k,t})'$, of k assets. Let us assume that these returns are conditionally normal[18] with zero mean and conditional covariance matrix H_t:

$$r_t | I_t \sim N(0, H_t) .$$

Matrix H_t can be decomposed as follows:

$$H_t = D_t R_t D_t$$

[16] We test the null hypothesis of constant correlation. The test statistic take value 36.47 (p-value = 0).
[17] Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity
[18] Without normality the results are still valid but with a Quasi Maximum Likelihood Estimation (QMLE) interpretation.

where R_t is the conditional correlation matrix and $D_t = \left(\sqrt{h_{it}}\right)$ is a *k*k* diagonal matrix of which *i*-th element is the conditional standard deviation of the return of asset *i*.

A preliminary analysis (not reported there) has been conducted to optimally choose the orders of the univariate GARCH processes for GFI and GMI. As a result, the conditional variances are modeled using a GARCH (1,1) specification of the form:

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

Where ω_i, α_i and β_i are non-negative parameters satisfying $\alpha_i + \beta_i < 1$, and the $\left(\varepsilon_{i,t}\right)$'s are sequences of independent and identically distributed random variables, with mean 0 and variance 1.

The DCC model proposed by Engle (2002) involves two-stage estimation of the conditional covariance matrix H_t. In the first stage, univariate volatility models are fitted for each stock return and estimates of the $h_{ii,t}$'s are obtained. In the second stage, stock-return residuals are normalised: $u_{it} = \dfrac{\varepsilon_{it}}{\sqrt{h_{ii,t}}}$.

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In the DCC model, the *k*k* time-varying covariance matrix of $\left(u_t\right)$ denoted by Q_t fulfills:

$$Q_t = (1 - A - B)E(u_t u'_t) + Au_{t-1}u'_{t-1} + BQ_{t-1}$$

Where, A and B are non-negative parameters satisfying $A + B < 1$. The proper correlation matrix R_t is given by:

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}$$

We follow Engle's (2002) two-step log-likelihood estimation procedure for the DCC (results not reported here). Tables 12 and 13 display the estimates of the univariate GARCH parameters (ω_i, α_i and β_i) and the DCC parameters (*A* and *B*.) respectively. With reference to parameter significance and information criteria, the best model is unambiguously the GARCH (1,1) for both series, which is also the most frequent specification for financial returns.

The coefficients of the lagged variance and innovation terms are highly significant, which is consistent with time-varying volatility and the appropriateness of the GARCH (1,1) specification. Both GARCH (1,1) univariate processes present a high degree of persistence (long memory), signalled by $\alpha_i + \beta_i$ being close to 1, which is even higher for GMI (0.996) than for GFI (0.986). Figure 6 plots the estimated conditional volatilities of both the GMI and GFI. Figure 7 plots their conditional correlation.

Volatility of both indices has fallen significantly since 2001. The decline occurred earlier for finance (starting in 2000) than for microfinance (starting in 2002). The rise in conditional correlation between the two sectors is very pronounced over the study period. It occurred mainly between 2003 and 2006, when correlations changed from being highly variable (between -20% and 70%) to much more stable (around 80%). Although the 2000-2001 crisis had little effect on microfinance equities,[19] they were affected by the 2007-2008 crisis, confirming that microfinance is no longer a crisis-resilient sector (Visconti, 2008; Wagner, 2010).

In conclusion, the microfinance sector has been in a trend of gradual integration into mainstream finance. However, it has retained certain specific traits. Microfinance tends to

[19] Patten *et al.* (2001) also exhibit the good performances of BRI during the East Asian crisis.

develop in countries where the financial sector is relatively weak (Vanroose and D'Espallier, 2009; Maksudova, 2010),[20] such that the regional distribution of listed MFIs differs from that of the traditional financial sector. From this point, although the two sectors are converging, the potential for microfinance to provide diversification in an equity portfolio can be distinguished from the diversification potential of finance by regional bias. Section 5 examines this question in greater detail. Section 4 considers the nature of risks assumed by domestic and international investors in finance and microfinance equities.

4. Risk factors of microfinance investment

In this section, we investigate the sensitivity of both the microfinance and finance stock returns to market and foreign-exchange risks. As shown by Solnik (1974), Adler and Dumas (1983), foreign exchange risk plays a key role in international asset pricing. Moreover, Crabb (2004) underlines that foreign exchange remains an important source of risk for MFIs that are exposed to the devaluation of their funding sources.

Two perspectives are successively analyzed. First, we consider the situation of a domestic investor in a country where microfinance equity is available. Second, we consider the situation of an international investor who contemplates sector-wise investment in finance and microfinance indices.

To address the domestic investor's situation, we follow Harvey (1995) and estimate a CAPM-type model in local currency including two factors: a standard market factor and a foreign-

[20] However, Hermes *et al.* (2009) note that MFIs are more efficient in countries with more highly developed financial sectors.

exchange factor.[21] Due to the unavailability of interest rates data for Bangladesh, the following model is estimated for four countries (Indonesia, Kenya, Mexico, and South Africa):

$$(R_{MI}^k - r_f^k) = \alpha_1 + \beta_1 (R_M^k - r_f^k) + \gamma_1 R_{FX}^k \quad + \varepsilon_t \tag{1}$$

$$(R_{FI}^k - r_f^k) = \alpha_1 + \beta_1 (R_M^k - r_f^k) + \gamma_1 R_{FX}^k \quad + \varepsilon_t \tag{2}$$

where R_{MI}^k is the monthly return of the microfinance index of country *k* in domestic currency, R_{FI}^k is the return on the financial index of country *k* in domestic currency, R_M^k is the return on the domestic market (MSCI index), r_f^k is the country's risk-free rate, and R_{FX}^k is the exchange rate return (USD versus domestic currency).

To address the international investor's situation, we estimate the basic CAPM specification with a single market factor proxied by the return of the MSCI All Countries World index:

$$(R_{GMI} - r_f) = \alpha_2 + \beta_2 (R_M - r_f) + \varepsilon_t \tag{3}$$

$$(R_{GFI} - r_f) = \alpha_2 + \beta_2 (R_M - r_f) + \varepsilon_t \tag{4}$$

where R_{GMI} is the monthly return of the GMI index, R_{GFI} is the monthly return of the GFI financial index, R_M is the return of the MSCI All Countries World index, and r_f is the US risk-free rate. All returns are calculated using prices in USD.

[21] However, we use pure foreign exchange exposure against the USD rather than a trade-weighted index of currency returns, because banks and microfinance institutions primarily have liabilities in USD.

Table 14 presents the estimation results for the country-specific regressions given by equations (1) and (2), and the outcomes of Wald tests for equality of the beta coefficients between finance and microfinance. Except for South African microfinance, the intercepts are not significantly different from zero. The loadings on the domestic market factors are all significant, both for the microfinance and finance stocks, lying between 0.72 (Indonesia) and 1.55 (Kenya) for microfinance, and between 0.53 (Mexico) and 1.01 (Kenya) for finance. In general, market betas are higher for microfinance than for finance, signalling a higher systematic risk for MFIs than for traditional banks. However, the difference is hardly significant. The only exception is Indonesia where microfinance exhibits a smaller market beta (0.72) than finance (0.95), the difference being significant at the 10% level. For all countries, R-squared values are relatively low (between 19% for South African microfinance and 55% for Indonesian finance), which is a typical feature in estimation of market betas (Harvey, 1995).[22]

Exposure to the currency factor produces the result expected intuitively: betas are negative and significant for both finance and microfinance, except for Kenya, where betas are not significant. Banks and MFIs often fund their portfolios through debt in foreign currency, especially the USD (Crabb, 2004). When the dollar appreciates, financing becomes more expensive but the institutions' revenues (from repayment of loans contracted in local currency) remain fixed, thus penalising them. Only a few MFIs are not exposed to foreign exchange risk, either because they operate in a fully dollarised economy, or because they solely trade in local currency. Interestingly, foreign exchange betas are not significantly different for the finance and microfinance sectors, meaning that the two types of institutions share similar exposures.

[22] Indeed, CAPM is a parsimonious model, and additional local factors would likely be needed to further explain the returns of the finance and microfinance stocks.

Table 15 provides the estimation results for equations (3) and (4). We estimate the CAPM for the two global indices, GFI and GMI, firstly on the full sample period (1996-2010), and secondly on two equally split sub-samples (1996-2003 and 2003-2010) as a robustness check. The results reveal that market betas are higher than one for both microfinance and finance, likely reflecting the higher systematic risk of equity from emerging countries compared to a well-diversified world portfolio balanced between emerging- and developed-market stocks. Market betas are higher for microfinance than for finance on the full sample period (1.63 versus 1.35) as well as the two sub-samples (1.67 versus 1.31 before 2003, 1.59 versus 1.38 after 2003). Remarkably, the betas over the two sub-periods take quite similar values, conferring robustness on our results. However, the Wald test rejects the equality between the betas of the finance and microfinance sectors, on both the full and more recent periods. While this outcome might seem puzzling given the convergence observed in the previous section, it might result from differences in country effects. This intuition is corroborated by the local regressions. Indeed, the betas of the two sectors are not significantly different for South Africa and Kenya, and only borderline significantly different (at the 10% level) for Indonesia and Mexico.

Summing up, both the finance and microfinance sectors exhibit high market betas, locally and globally. Moreover, domestic investors in both sectors are significantly exposed to foreign exchange risk. Lastly, the convergence of microfinance toward mainstream finance is confirmed by the proximity of their market and foreign exchange betas in domestic markets.

5. Efficient frontiers with microfinance investment

The convergence of microfinance toward finance makes it less appealing to investors who are blind to poverty alleviation. The descriptive statistics show that microfinance remains a high-risk sector, while recent developments bring it closer to conventional finance in terms of the nature of its risks. To explore the relevance of including microfinance equity in a portfolio that is optimised by the classic mean-variance approach, this section makes use of spanning tests. This methodology will be used to test whether a given portfolio is located on the efficient frontier of the universe under consideration, i.e. whether it is optimal under the meaning of the mean-variance approach.

We apply the spanning tests to determine the efficiency of portfolios that are constrained to include a minimum percentage of microfinance equity. In practice, we first determine an unconstrained efficient frontier based on all the individual securities under consideration. We then set a minimum threshold for microfinance and determine the new efficient frontier under that constraint. The objective is to determine whether the portfolios that make up the constrained frontier stray significantly from the unconstrained frontier. However, the answer may depend on the risk level of the constrained portfolio (Drut, 2010), making it necessary to apply the test at various points along the constrained frontier. Thus, holding a given percentage of microfinance equities may worsen the risk-return trade-off for some investors but not others, based on their respective levels of risk aversion.

In the present case, the unconstrained frontier is composed of all individual securities included in an MSCI local index. However, for statistical reasons, we have restricted this frontier to securities that have been listed at least since December 1996; the estimate is in the form of monthly data for greater stability. In all, the universe includes 75 listed stocks, only two of which are MFIs (Danamon and African Bank). After establishing the efficient frontier, we consider several constrained allocations, subject to a rule that microfinance must represent a minimum weighting of 10%, then 20%, 30% and 40%. Figure 8 presents the efficient frontiers for both unconstrained portfolios and for those constrained by inclusion of increasing levels of microfinance.

The spanning test proposed by Basak *et al.* (2002) is intuitively appealing as it is based on the "horizontal distance" between any portfolio and its same-return counterpart on the efficient frontier. Unfortunately, as shown by Gerard *et al.* (2007), not all portfolios possess such a counterpart, which in turn limits the applicability of the Basak *et al.* (2002) test. To address this pitfall, Brière *et al.* (2010) introduce the "vertical test", based on the vertical distance between a portfolio and its same-variance counterpart efficient portfolio. In this paper, we use both the horizontal and vertical spanning tests to gain robustness.

Table 16 presents the empirical results. For each level of the constraint (10%, 20%, 30% and 40% microfinance equity, respectively), three portfolios are selected on the constrained efficient frontier, corresponding to volatility levels of 14%, 18%, and 22%, respectively. In that way, we end up with twelve portfolios to be checked for unconstrained efficiency. The likelihood of finding an efficient portfolio (no rejection) decreases with the level of the constraint. Moreover, as Figure 8 shows, the microfinance constraint is less binding for more risky portfolios, i.e. for portfolios chosen by investors with low risk aversion. This fact is consistent with the previous observation that microfinance equity exhibits high volatility.

According to both tests, at the 14% volatility level, corresponding to investors with high risk aversion, imposing 10% microfinance equity does not distort the efficiency of the optimal portfolio, while imposing 20% has an adverse effect according to the horizontal test. For medium risk-averse investors who tolerate 18% volatility, 20% microfinance equity remains compatible with mean-variance efficiency for both tests, and 30% microfinance is only borderline rejected by the horizontal test (p-value: 9%). Investors with low risk aversion (22% volatility level) may include as much as 30% microfinance in their portfolios without losing mean-variance efficiency.

Still, these findings need to be taken with a grain of salt for several reasons. Firstly, the universe considered in this exercise is only composed of stocks from five emerging countries with quoted MFIs as the common feature. The global capitalisation of these five countries is negligible with respect to the world market (1.6%), so that even if our results are taken at face value, the optimal proportion of microfinance equity in a geographically balanced global portfolio remains tiny. Secondly, the distributions of both test statistics have been established asymptotically under the assumption that returns are normal, which is far from being verified in our dataset. Non-normality distorts the test decision rule and leads to insufficient rejection (Beaulieu et al., 2007). However, given this evidence, we have already drawn conclusions in a conservative way.

Despite the data issues that can alter the precision of our results, the central message is unambiguous. Microfinance equity is significantly present in optimal global portfolios, and remarkably, this is true even in low-risk portfolios.

6. Conclusion

Despite the impressive development of the microfinance sector, the financial performance of microfinance equity remains poorly understood for reasons likely pertaining to data availability. Still plagued by data limitations, this paper takes full advantage of daily quoted prices of microfinance stocks from their issuance, and draws a global picture of worldwide microfinance equity from the viewpoint of a profit-oriented investor. Three main messages stand out.

Firstly, we have demonstrated that the convergence of the microfinance sector toward the mainstream financial sector was largely completed around 2003. This is consistent with the evidence that the MFIs that issue stocks are the ones that mostly behave like banks without real intend to serve the poorest of the poor also referred to as the "bottom of the pyramid" (Cull *et al.*, 2007).

Secondly, we have looked into the impacts of market and foreign-exchange risk factors on both finance and microfinance stocks, locally and globally. Although the situation is far from homogenous across countries, the picture that emerges is consistent with the convergence result. Moreover, we have confirmed the intuition that both sectors remain highly exposed to exchange rate risk, which is likely attributable to their funding sources mostly originating from international capital markets.

Lastly, an original portfolio analysis has pointed to the diversification potential of microfinance stocks. According to our exercise, the proportion of microfinance in optimal portfolios restricted to countries where microfinance equity is quoted may range between 10%

and 30% depending on the investor's degree of risk aversion. We are well aware that those numbers should not be taken at face value as mean-variance estimators are known to be time-dependent (Best and Grauer, 1991; Kan and Zhou, 2007), and the accuracy of the results relies upon normality assumptions that are far from being met in our sample. Nevertheless, our findings at least prove that microfinance may not be just disregarded by profit-oriented investors seeking new investment opportunities in developing countries. Obviously, this evidence is reinforced for investors who are (even a little) concerned by social outcomes in general, and financial access to the poor in developing countries in particular.

A seminal contribution in many respects, this paper also suffers from econometric drawbacks. The main issue likely relates to the underlying probability distributions of the returns. As the descriptive statistics have amply shown, we are dealing here with series that exhibit strong departure not only from normality, which is a common feature of most financial series, but also from the typical heavy-tail distributions that financial econometricians are used to dealing with. Moreover, CAPM-style regressions are known to miss important risk factors (Cochrane, 1999) that we failed to incorporate for at least two reasons: the lack of data on such factors for developing countries, and the limited length of the available price series. Therefore, we view our empirical results as challenging but still preliminary, and hope that they will serve as a motivation for further studies in the field. Indeed, the quoted microfinance sector is still in its infancy, and understanding of its performance drivers will likely increase with time.

Lastly, the emerging financial markets have been documented as a key source of diversification for Western portfolio holders (Bekaert and Harvey, 2003; Quisenberry and Griffith, 2010). However, the optimal composition of portfolios made of emerging-country stocks remains largely unexplored, especially with respect to their sensitivity toward global crises. In that line of thought, a promising avenue for research concerns the way sector-specific and/or country-specific investments could help in robustifying global portfolios (Brière and Szafarz, 2008; Brière *et al.*, 2010). As a prerequisite, adequate sector delineation is required. This paper has also taken steps in that direction.

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Tables

Table 1: Inception date and market capitalization of MFIs

Country	MFI	Inception date	Market capitalization*
South Africa	African Bank	01/1990	3983.3
	Capitec Bank	02/2002	1763.1
	Blue Financial Services (BFS)	10/2006	22.89
Kenya	Equity Bank	08/2006	1168.57
Indonesia	Danamon	04/1990	5995.85
	Bank Rakyat Indonesia (BRI)	11/2003	14199.43
Bangladesh	BRAC Bank	01/2007	324.05
Mexico	Compartamos Banco	04/2007	3556.38
	Financiera Independencia (FI)	11/2007	685.55

** in millions of USD at the end of sample period, 31/12/2010*

Table 2: Descriptive statistics of MFIs monthly returns, in local currency

	African Bank	Capitec	BFS	Equity	Danamon	BRI	BRAC	Compartamos	FI
Ann. Mean	57.86%	71.80%	-22.06%	59.28%	8.93%	44.80%	42.79%	25.56%	-2.52%
Median	2.07%	4.56%	-2.34%	3.67%	0.00%	3.55%	3.99%	1.16%	-1.37%
Max	266.67%	94.73%	85.61%	62.47%	100.05%	38.10%	37.39%	28.31%	29.59%
Min	-49.20%	-19.20%	-60.84%	-27.57%	-54.37%	-36.11%	-22.73%	-28.76%	-22.85%
Volatility	78.48%	47.47%	79.62%	65.59%	63.10%	40.71%	48.02%	37.57%	43.21%
Skewness	6.50	2.66	0.73	1.04	0.96	0.02	0.39	-0.01	0.46
Kurtosis	73.50	18.09	6.40	4.73	8.21	4.20	2.89	3.57	2.88
Jarque-Bera	53739.15***	1130.49***	28.62***	15.80***	318.91***	5.08*	1.24	0.60	1.34
DF	-15.27***	-12.27***	-3.18**	-9.04***	-13.55***	-9.62***	-5.25***	-4.79***	-3.94***
Start date	Jan-90	Feb-02	Oct-06	Aug-06	Apr-90	Nov-03	Jan-07	Apr-07	Nov-07
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the entire sample for which a series is available. Start and end date are given in the last two rows.
****,**,* significant at the 1%, 5% and 10% level.*

Table 3: Descriptive statistics of MFIs daily returns, in local currency

	African Bank	Capitec	BFS	Equity	Danamon	BRI	BRAC	Compartamos	FI
Ann. Mean	81.20%	85.98%	8.48%	62.65%	30.98%	57.03%	41.08%	28.08%	-10.65%
Median	0.22%	0.29%	-0.49%	0.24%	-0.51%	0.54%	-0.17%	0.01%	-0.11%
Max	233.34%	63.15%	44.48%	58.23%	50.03%	18.97%	29.99%	12.10%	21.76%
Min	-31.05%	-18.91%	-30.77%	-35.40%	-35.72%	-10.94%	-12.49%	-11.32%	-9.24%
Volatility	85.61%	56.89%	106.87%	71.58%	99.33%	51.06%	46.03%	42.43%	39.41%
Skewness	24.15	3.27	0.73	2.56	0.76	0.43	1.82	0.33	1.54
Kurtosis	1017.15	58.95	9.89	50.95	10.57	5.01	16.96	5.18	13.05
Jarque-Bera	1.47E8***	2.31E5***	1.70E3***	9.22E4***	7.70E3***	2.91E2***	8.01E3***	1.99E2***	3.49E3***
DF	-10.38***	-51.11***	-29.13***	-30.92***	-37.12***	-28.00***	-23.66***	-28.33***	-14.89***
Start date	Jan-90	Feb-02	Oct-06	Aug-06	Apr-90	Nov-03	Jan-07	Apr-07	Nov-07
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the entire sample for which a series is available. Start and end date are given in the last two rows.
****significant at the 1% level.*

Table 4: Descriptive statistics of MSCI monthly returns

	South Africa	Kenya	Indonesia	Mexico	World
Ann. Mean	16.96%	31.49%	18.15%	27.00%	7.22%
Median	1.39%	2.00%	1.53%	2.79%	1.12%
Max	16.87%	27.90%	50.67%	27.75%	12.49%
Min	-27.29%	-23.75%	-34.72%	-25.27%	-20.21%
Volatility	20.59%	28.23%	35.89%	26.71%	17.26%
Skewness	-0.57	-0.05	0.04	-0.07	-0.80
Kurtosis	5.07	5.04	5.62	3.89	4.48
Jarque-Bera	50.27***	17.85***	72.10***	8.55***	45.91***
DF	-12.11***	-6.78***	-10.55***	-4.79***	-4.58***
Start date	Apr-97	Aug-06	Nov-96	Apr-07	Dec-96
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the sample for which the CAPM has been tested. Start and end date are given in the last two rows. National indices are in local currency, MSCI World is in USD.
**** significant at the 1% level.*

Table 5: Descriptive statistics of risk-free rates

	South Africa	Kenya	Indonesia	Mexico	US
Ann. Mean	10.76%	6.30%	12.53%	6.61%	3.55%
Median	10.42%	7.20%	8.75%	7.67%	3.84%
Max	25.50%	8.40%	56.00%	8.73%	6.86%
Min	5.73%	1.20%	5.75%	4.86%	0.25%
Start date	Apr-97	Aug-06	Nov-96	Apr-07	Dec-96
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the sample for which the CAPM has been tested. Start and end date are given in the last two rows.

Table 6: Descriptive statistics of foreign exchange monthly returns

	South Africa	Kenya	Indonesia	Mexico
Ann. Mean	4.39%	5.94%	14.42%	3.84%
Median	0.29%	0.00%	0.12%	-0.12%
Max	18.06%	11.91%	81.08%	17.46%
Min	-11.56%	-7.94%	-28.97%	-6.94%
Volatility	17.27%	11.40%	34.45%	13.37%
Skewness	0.65	0.99	4.13	1.98
Kurtosis	4.18	6.30	31.89	9.97
Jarque-Bera	21.06***	25.31***	6384.62***	120.58***
DF	-11.88***	-5.44***	-9.23***	-4.61***
Start date	Apr-97	Aug-06	Nov-96	Apr-07
End date	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the sample for which the CAPM has been tested. Start and end date are given in the last two rows. We display returns of USD against emerging market currencies.
**** significant at the 1% level.*

Table 7: Descriptive statistics of microfinance national indices and GMI monthly returns

	South Africa	Kenya	Indonesia	Bangladesh	Mexico	GMI
Ann. Mean	58.80%	59.28%	10.99%	42.79%	16.12%	20.35%
Median	1.87%	3.67%	0.00%	3.99%	1.38%	-0.03%
Max	266.67%	62.47%	100.05%	37.39%	25.93%	71.08%
Min	-49.20%	-27.57%	-54.37%	-22.73%	-25.07%	-49.93%
Volatility	78.10%	65.59%	61.96%	48.02%	34.68%	55.99%
Skewness	6.59	1.04	1.03	0.39	-0.08	0.50
Kurtosis	74.83	4.73	8.65	2.89	3.03	5.91
Jarque-Bera	55774.33***	15.80***	373.78***	1.24	0.05	98.97***
DF	-15.23***	-9.04***	-13.58***	-5.25***	-4.30***	-13.75***
Start date	Jan-90	Aug-06	Apr-90	Jan-07	Apr-07	Jan-90
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the entire sample for which a series is available. Start and end date are given in the last two rows. National indices are in local currency, GMI is in USD.
****,**,* significant at the 1%, 5% and 10% level.*

Table 8: Descriptive statistics of microfinance national indices and GMI daily returns

	South Africa	Kenya	Indonesia	Bangladesh	Mexico	GMI
Ann. Mean	79.73%	64.00%	32.93%	43.45%	17.93%	18.83%
Median	0.17%	0.26%	0.01%	-0.17%	0.01%	0.01%
Max	233.34%	58.23%	50.03%	29.99%	9.23%	25.89%
Min	-31.05%	-35.40%	-35.72%	-12.49%	-7.28%	-31.42%
Volatility	83.11%	71.33%	94.85%	45.97%	35.41%	55.54%
Skewness	25.57	2.56	0.83	1.80	0.34	0.13
Kurtosis	1109.66	51.28	11.83	16.87	4.65	13.94
Jarque-Bera	1.80E8***	9.41E5***	1.11E5***	7.99E4***	124.82***	2.71E5***
DF	-9.79***	-31.03***	-13.12***	-23.79***	-28.00***	-78.81***
Start date	Jan-90	Aug-06	Apr-90	Jan-07	Apr-07	Jan-90
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the entire sample for which a series is available. Start and end date are given in the last two rows. National indices are in local currency, GMI is in USD.
****,**,* significant at the 1%, 5% and 10% level.*

Table 9: Inception date and market capitalization of Banks included in GFI

Country	Bank	Inception date	Market capitalization*
South Africa	Absa Group	07/1991	13063.36
	Firstrand	01/1990	15938.54
	Investec	01/1990	2154.29
	Nedbank Group	10/1986	9015.54
	Standard Bank Group	01/1991	22793.17
Kenya	Barclays Bank Kenya	01/1991	1033.54
	Cooperative Bank of Kenya	12/2008	821.22
	Kenya Commercial Bank	01/1991	775.90
Indonesia	Bank Central Asia	05/2000	16346.15
	Bank Mandiri	07/2003	14723.59
	Bank Negara Indonesia	11/1996	6778.92
Bangladesh	AB Bank	02/1992	661.32
	Al Arafa Bank	09/1998	237.43
	City Bank	01/1992	257.74
	Dutch Bank	03/2001	630.39
	Exim Bank	10/2004	411.99
	Islami Bank Bangladesh	01/1992	126.67
	NBL	01/1992	932.86
	Prime Bank	03/2000	585.30
	Prime Finance and Investment	10/2005	136.86
	Pubali Bank	01/1992	778.89
	United Commercial Bank	01/1992	990.02
Mexico	Gfinbur	02/1993	14513.34
	Gfnorte	10/1993	8700.07

** in thousands of USD at the end of sample period, 31/12/2010*

Table 10: Descriptive statistics of finance national indices and GFI monthly returns

	South Africa	Kenya	Indonesia	Bangladesh	Mexico	GFI
Ann. Mean	22.50%	33.47%	23.46%	31.56%	29.80%	22.52%
Median	1.43%	1.52%	0.34%	0.84%	1.73%	0.94%
Min	31.13%	76.79%	74.96%	38.77%	39.88%	78.28%
Max	-40.03%	-22.65%	-37.29%	-22.31%	-37.50%	-42.49%
Volatility	25.86%	37.79%	51.63%	30.76%	33.75%	47.53%
Skewness	-0.19	1.91	1.22	1.07	0.20	0.99
Kurtosis	6.93	12.57	7.75	5.25	5.14	8.75
Jarque-Bera	162.71***	1056.41***	201.09***	81.39***	42.27***	260.44***
DF	-15.77***	-14.47***	-12.50***	-5.87***	-14.37***	-12.15***
Start date	Jan-90	Jan-91	Nov-96	Jan-92	Feb-93	Dec 96
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the entire sample for which a series is available. Start and end date are given in the last two rows. National indices are in local currency, GMI is in USD.
****,**,* significant at the 1%, 5% and 10% level.*

Table 11: Descriptive statistics of finance national indices and GFI daily returns

	South Africa	Kenya	Indonesia	Bangladesh	Mexico	GFI
Ann. Mean	18.70%	28.03%	23.35%	36.48%	21.58%	13.75%
Median	0.06%	0.04%	0.00%	0.06%	0.03%	0.00%
Max	11.36%	80.23%	44.11%	22.38%	20.39%	26.87%
Min	-14.28%	-42.51%	-33.09%	-22.11%	-17.26%	-17.67%
Volatility	31.58%	42.79%	67.90%	30.55%	35.94%	35.61%
Skewness	0.00	8.59	0.71	0.72	0.15	0.64
Kurtosis	7.91	275.39	15.78	28.86	13.22	15.72
Jarque-Bera	5.51E3***	1.62E7***	2.53E4***	6.01E6***	2.03E4***	3.73E4***
DF	-66.38***	-48.38***	-62.88***	-47.67***	-61.19***	-71.65***
Start date	Jan-90	Jan-91	Nov-96	Jan-92	Feb-93	Dec 96
End date	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10	Dec-10

The table reports summary statistics over the entire sample for which a series is available. Start and end date are given in the last two rows. National indices are in local currency, GMI is in USD.
**** significant at the 1% level.*

Table 12: Univariate GARCH parameters estimates, December 1996 – December 2010

Index	ω	α	β	$\alpha + \beta$
GFI	1.07E-5***	0.101***	0.884***	0.986
	(1.21E-11)	(3.80E-4)	(0.00048)	
GMI	6.94E-6***	0.077***	0.92***	0.996
	(7.10E-12)	(2.25E-4)	(2.28E-4)	

Results of the univariate GARCH estimation on (1) GFI, (2) GMI, α *represents the ARCH term,* β *the GARCH term,* ω *the constant of the variance equation. Standard errors in parenthesis.*

Table 13: DCC (1,1) parameters estimates, December 1996 – December 2010

Parameters	Estimates	St.Dev.	z-stat
A	0.028***	4.52E-05	606.55
B	0.971***	5.00E-05	18789.6

Results of the second step DCC-GARCH estimation on (1) GFI, (2) GMI, Arepresents the ARCH term,B the GARCH term.

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Table 14: Results of CAPM regressions, local finance and microfinance country indices

	start date	end date	α	β_{Market}	Wald Test	β_{FX}	Wald Test	R^2	$Adj\ R^2$	SEE
South Africa microfinance	Apr-97	Dec-10	0.02*** (2.19)	0.90*** (5.80)	0.45 (0.49)	-0.36** (-1.82)	0.08 (0.78)	20.17%	19.2%	0.125
South Africa finance	Apr-97	Dec-10	0.00 (0.88)	0.81*** (11.66)		-0.39*** (-4.40)		51.7%	51.1%	0.516
Kenya microfinance	Aug-06	Dec-10	0.03* (1.59)	1.55*** (5.55)	2.57 (0.11)	0.95 (1.23)	1.06 (0.31)	39.6%	37.1%	0.150
Kenya finance	Aug-06	Dec-10	0.02 (1.26)	1.01*** (4.64)		0.01 (0.02)		34.5%	31.9%	0.117
Indonesia microfinance	Nov-96	Dec-10	-0.00 (-0.42)	0.72*** (6.40)	3.22* (0.07)	-0.39*** (-3.12)	0.49 (0.48)	24.8%	23.9%	0.160
Indonesia finance	Nov-96	Dec-10	0.00 (0.68)	0.95*** (13.46)		-0.3*** (-3.85)		55.5%	55.0%	0.100
Mexico microfinance	Apr-07	Dec-10	0.00 (0.42)	1.07*** (4.65)	3.45* (0.07)	-0.07 (-0.19)	1.00 (0.32)	50.7%	48.2%	0.072
Mexico finance	Apr-07	Dec-10	0.01* (1.34)	0.53*** (3.02)		-0.58** (-2.00)		48.9%	46.4%	0.055

****,**,* significant at the 1%, 5% and 10% level.*
For regression coefficients, we display coefficient value and t-statistics in parenthesis, for Wald test, F statistics and probability in parenthesis.

Table 15: Results of CAPM regressions, GMI and GFI

	start date	end date	α	β_{Market}	Wald Test	R^2	$Adj\ R^2$	SEE
Global microfinance	Dec-96	Dec-10	0.01 (0.87)	1.63*** (7.76)	18.96*** (0.00)	26.5%	26.1%	0.136
Global finance	Dec-96	Dec-10	0.01 (1.26)	1.35*** (7.29)		24.1%	23.7%	0.120
Global microfinance	Dec-96	Nov-03	-0.00 (-0.15)	1.67*** (4.08)	0.05 (0.82)	16.9%	15.8%	0.169
Global finance	Dec-96	Nov-03	0.01 (0.39)	1.31*** (3.64)		13.9%	12.9%	0.159
Global microfinance	Dec-03	Dec-10	0.02*** (2.73)	1.59*** (10.49)	29.67*** (0.00)	57.0%	56.5%	0.071
Global finance	Dec-03	Dec-10	0.021*** (2.36)	1.38*** (10.23)		55.8%	55.2%	0.064

****,**,* significant at the 1%, 5% and 10% level.*
For regression coefficients, we display coefficient value and t-statistics in parenthesis, for Wald test, F statistics and probability in parenthesis.

Table 16: Spanning tests results, December 1996 – December 2010

Volatility	BJS t-stat	vertical t-stat
	Microfinance weight=10%	
14%	-0.30 (0.38)	0.21 (0.39)
18%	-0.48 (0.36)	0.31 (0.38)
22%	-0.57 (0.34)	0.41 (0.37)
	Microfinance weight=20%	
14%	-0.65 (0.32)	0.50 (0.35)
18%	-0.23 (0.39)	0.16 (0.39)
22%	-0.12 (0.40)	0.09 (0.40)
	Microfinance weight=30%	
14%	-1.69* (0.09)	1.35 (0.16)
18%	-0.92* (0.26)	0.70 (0.31)
22%	-0.54 (0.34)	0.41 (0.37)
	Microfinance weight=40%	
14%	-3.07*** (0.00)	2.44** (0.02)
18%	-1.72* (0.09)	1.30 (0.17)
22%	-1.13* (0.21)	0.84 (0.28)

p values in parenthesis

****,**,* significant at the 1%, 5% and 10% level.*

Figures

Figure 1: Local microfinance indices in local currencies, monthly cumulative returns, January 1990 – December 2010

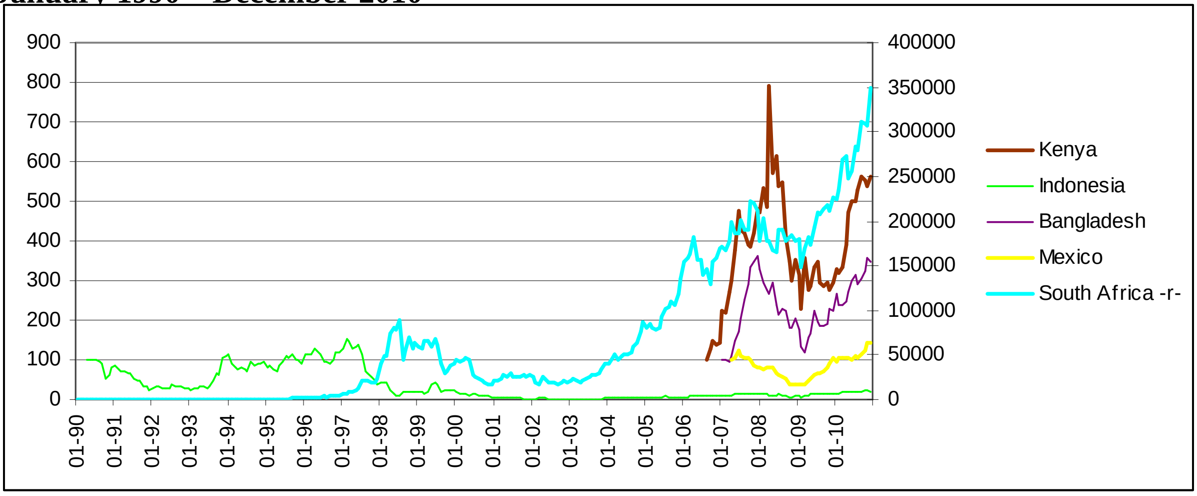

Figure 2: Global Microfinance Index (GMI) in USD, monthly cumulative returns, January 1990 – December 2010

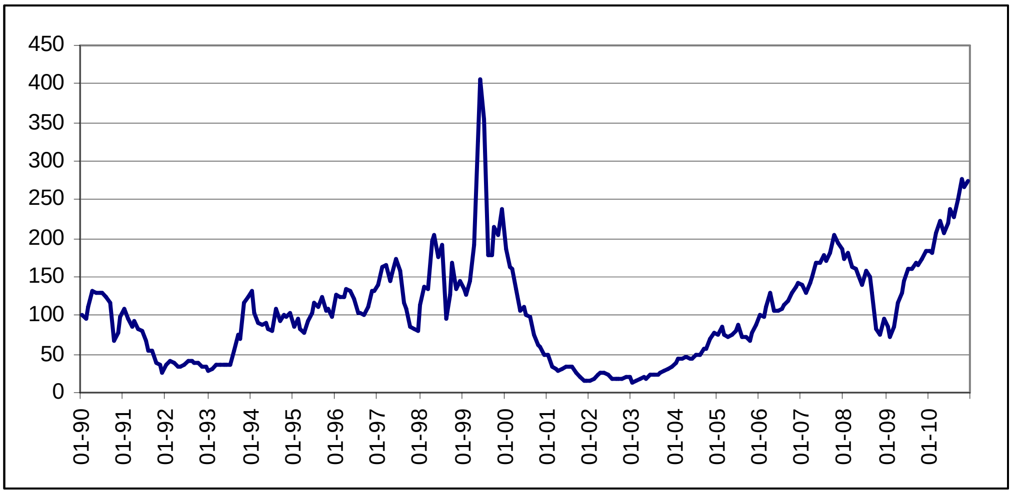

Figure 3: Local finance indices, monthly cumulative returns, December 1996– December 2010

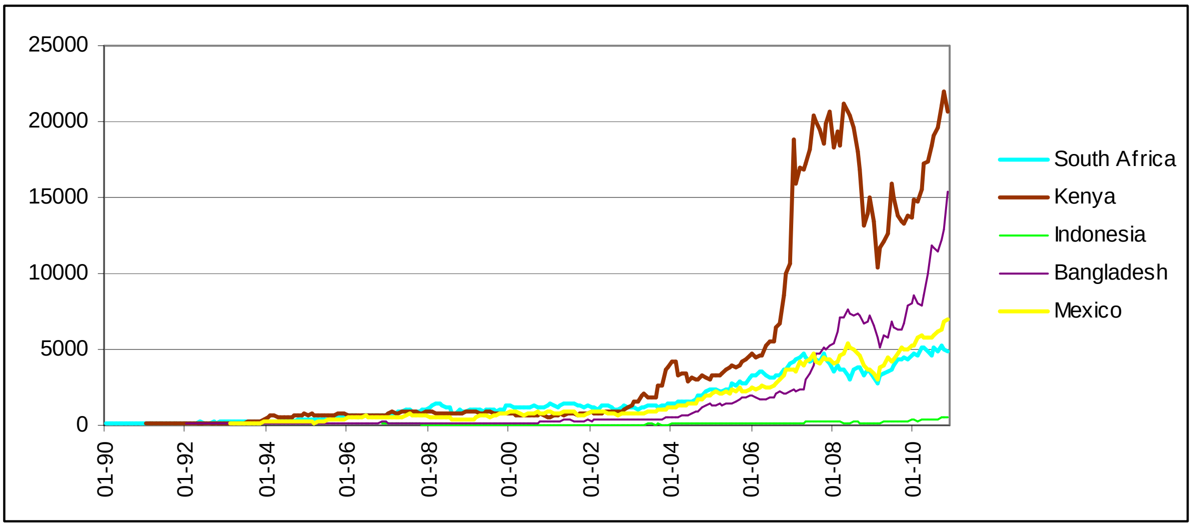

Figure 4: Global Finance Index (GFI), monthly cumulative returns, December 1996 – December 2010

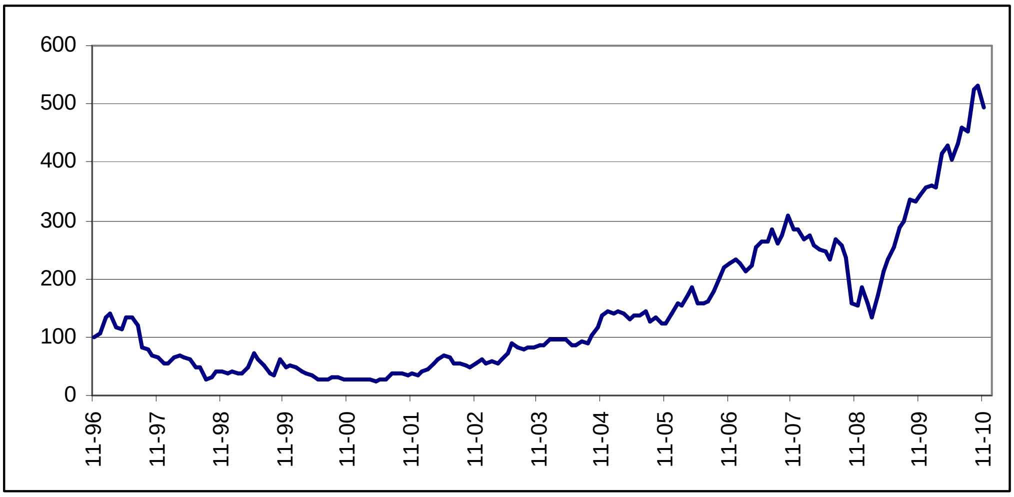

Figure 5: Global Microfinance Index and Global Financial Index, daily cumulative returns, December 1996 – December 2010

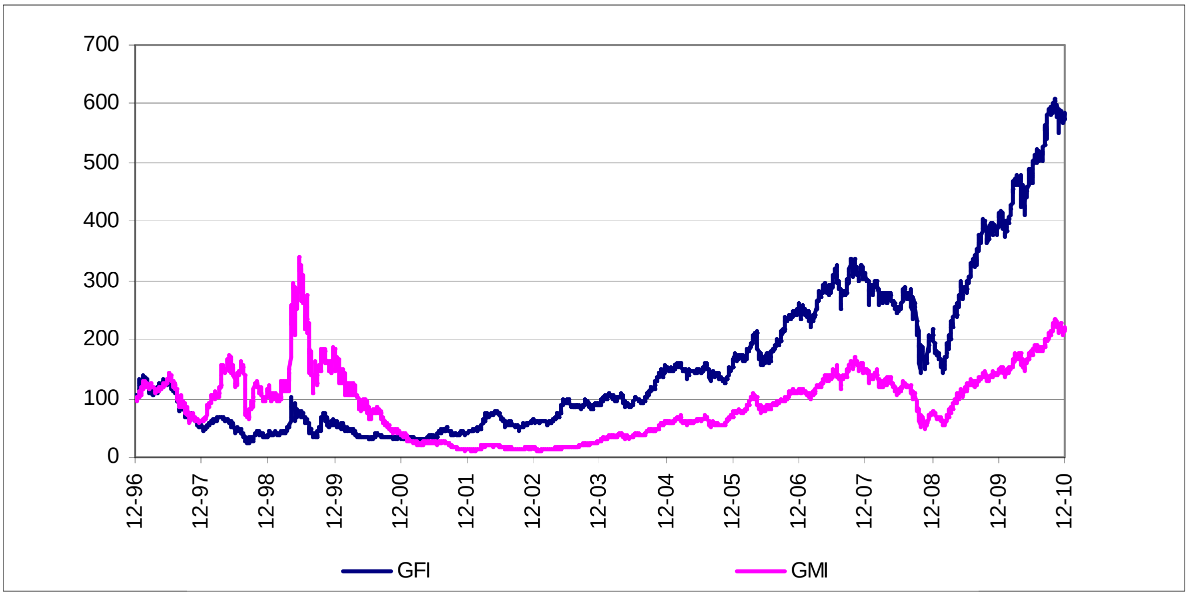

Figure 6: Conditional volatilities of GFI and GMI, December 1996 – December 2010

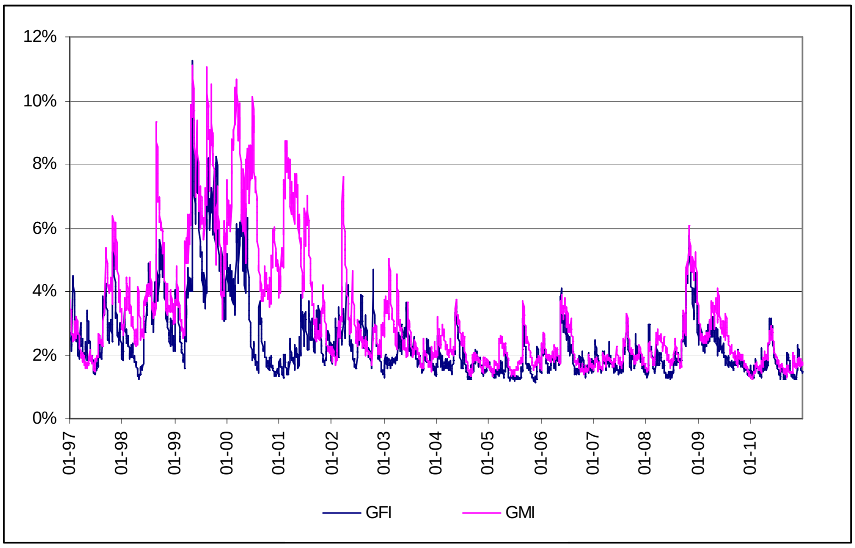

Figure 7: Conditional correlation between GFI and GMI, December 1996 – December 2010

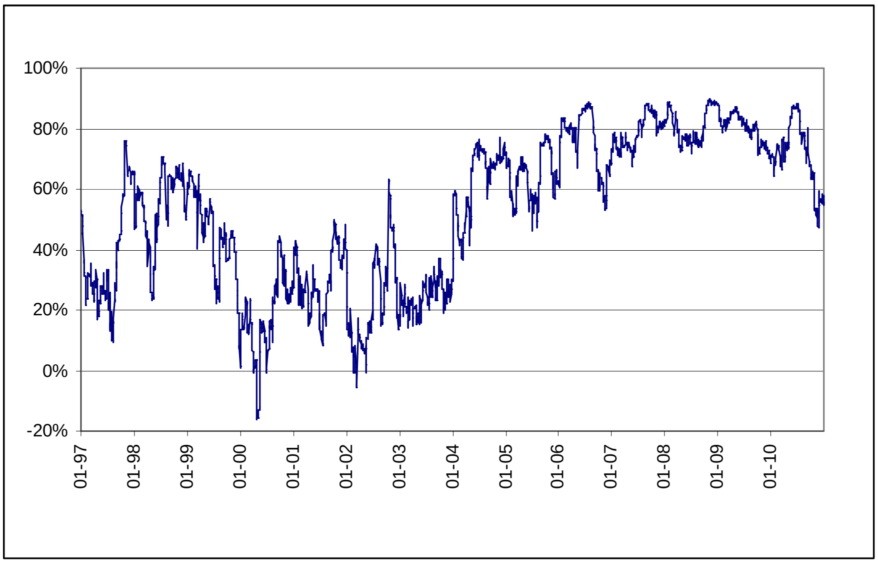

Figure 8: Efficient frontiers based on individual equities in MSCI local indices, December 1996 – December 2010