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The Cost of Equity beyond CAPM: Evidence from Latin American Stocks (1986-2004)*

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Abstract

In this paper we make two contributions to the empirical literature on asset pricing in emerging markets. First, we test the Fama and French three-factor model for a sample of 921 Latin American stocks over 1986-2004. Second, we elaborate a methodology to estimate the impact of firm-idiosyncratic variables on the excess returns not accounted for by CAPM. This methodology deals with potential estimator bias, non linearities and endogeneity problems usually found in the literature. Our main findings suggest that Fama and French factors (size and value premia) do not add significant explanatory power to CAPM regressions of Latin American stock (excess) returns, and that only to a limited extent are the market price-to-book value ratio, size and leverage significant determinants of these returns.

JEL codes: G12, G15.

Keywords: Stock Pricing, CAPM, Fama and French Factors, Latin America, Idiosyncratic Risk, Systematic Risk, Cost of Capital.

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1 Introduction

In a recent study on the opportunity cost of equity capital (henceforth COE) in Latin America, Grandes, Panigo and Pasquini (2006) (GPP(2006)) find that CAPM (Capital Asset Pricing Model) regressions of COE fail to explain on average 68% of their variance, i.e. the variability in individual stock excess returns.\footnote{GPP(2006) covers 921 publicly traded firms from Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela spanning monthly observations over 1986-2004. COE estimates are computed as the fitted value of GMM-48-month-rolling window regressions of an adjusted version of CAPM. See GPP (2006) for technical and other details.} This finding implies that Latin American firm’s COE is mostly driven by either idiosyncratic risk factors or other sources of systematic risk not accounted for by the domestic market portfolio. A key assumption made by CAPM is that only systematic (non-diversifiable) risk, measured by the market portfolio return in excess of the risk-free rate determines the time-series variability in the firm’s excess return and thus its COE. \footnote{Using two different measures of total variance decomposition GPP(2006) find that individual (excess) returns, and hence COE are mainly driven by idiosyncratic shocks (even in Venezuela or Argentina, the countries with the largest shares of systematic risk in total risk).} In other words, using CAPM estimates of COE for stock pricing and more generally to assess the profitability of investment projects could be misleading in a context of low probability of complete portfolio diversification.

This paper aims at identifying the risk factors that account for the average 68% of the COE variance left unexplained in GPP (2006) for the 7 Latin American countries in our sample.

There are at least two approaches to identify and econometrically test the "missing" risk factors:\footnote{A third approach would be to test the null hypothesis that global risk factors (global and currency portfolios) do not add to local market portfolio risk in explaining individual stock excess returns (and COE); GPP (2006) confirm the acceptance of the null for a large majority of firms and years.}

The first approach is based on the literature by Fama and French (FF) (see FF, 1992, 1993, 1996 and 1998). This literature points to additional sources of systematic risk that are not captured by the domestic market portfolio. Fama and French’s approach, widely known as the “Three Factor Model” (FF3FM), suggests that diversified equity portfolios sorted according to firm’s size and book-to-market value ratios, when added to a market portfolio, successfully capture the variation in the cross-section of individual stock (excess) returns (Fama and French, 1992). On the basis of these sorted portfolios, Fama and French (1993) identify two sources of systematic risk in addition to market portfolio risk, namely size and value premia: smaller firms are riskier than larger firms, hence the former should command higher returns; and so should high book-to-market value (“distressed” or "value") firms in relation to low book-to-market value (“growth”) firms. In this paper, we examine the validity of the FF3FM for our sample of Latin American stocks. We conclude that: 1)
both size and value premia are not generally statistically significant risk factors, and 2) they do not add informational power to the domestic market portfolio in the explanation of stock (excess) returns.

The second approach draws on idiosyncratic risk determinants of COE. It looks for theoretically based firm-specific variables which may be correlated to the unexplained variation in stock (excess) returns not attributable to systematic risk. In contrast with CAPM standard assumptions, this approach recognizes the possibility that there may be some idiosyncratic risk that cannot be diversified away (Levy (1978) or Merton (1987)) and therefore should be explicitly priced by way of including the appropriate variables reflecting this source of risk (see Goyal and Santa Clara (2003)). Some of the variables which have been identified in the literature on idiosyncratic risk include size, liquidity, market price-to-book value ratios, leverage, ADR issuance and the volatility of the returns on the firm’s assets. Controlling for the unobserved firm-level heterogeneity, we elaborate a two-step econometric methodology to estimate the significance and impact of these and other variables on the unexplained variation in stock (excess) returns. This is a panel regression where the dependent variable is the CAPM residual excess return estimated in GPP (2006). Overall, we find this residual is negatively and significantly correlated with the firm’s market price-to-book value ratio (as expected), size and leverage (the latter two with the wrong sign). Liquidity, ADR issuance and the volatility of the returns on the firm’s assets are generally not statistically significant determinants of that residual.

The rest of the paper is organized as follows. Section 2 surveys the Fama and French-type literature as well as the literature on the idiosyncratic determinants of stock (excess) returns. Section 3 presents the data. Section 4 presents and discusses the econometric framework. Descriptive statistics, the econometric output and a discussion on the results follow in Section 5. Finally, Section 6 concludes and raises some issues for further research.

## 2 Literature Review

### 2.1 Sources of Systematic Risk Beyond CAPM- The Three Factor Model

Over the last three decades, the Capital Asset Pricing Model (CAPM), its predictions and its empirical robustness have come under criticism. In a landmark contribution, FF (1992) called into question one of the crucial predictions of the CAPM model, the statement that only one factor, the market portfolio risk premium, should explain the variation in stock (excess) returns (Sharpe, 1964; Lintner, 1965 and Black, 1972). Their claim is supported by previous evidence documented in Basu (1977), Banz (1981), Rosenberg, Reid and Landstein (1985) and Bhandari (1988), where returns on stocks sorted according to e.g. size and
book-to-market ratios are shown to display differences not predicted by the market portfolio.\footnote{Basu (1977) showed that stocks with high earnings-price ratios had higher future returns than predicted by regular CAPM. Banz (1981) demonstrated that the same happened with those stocks with lower market capitalization. Bhandari (1988) used debt to equity ratios and found that stocks associated with relatively high debt to equity ratios yielded higher returns than those estimated using standard CAPM. This is intuitive as higher debt-to-equity ratios, ceteris paribus, mean higher leverage, hence higher (default) risk as the firm builds up debt. Finally, Statman (1980) and Rosenberg, Reid and Landstein (1985) found identical results for returns on stocks with high book-to-market equity ratios.}

FF (1992) find that when computing returns on diversified portfolios generated from a ranking of US stocks by size and book-to-market value ratios, small stock portfolios (S) outperform big stocks portfolios (B) and high book-to-market stocks (H) yield higher returns than low book-to-market stocks (L). Adopting the two-step regression approach by Fama and Macbeth (1973), where firm-specific factors are added to CAPM betas\footnote{Beta, which is obtained from the first step regression, is widely known as the coefficient of the CAPM regression that captures the sensitivity of the individual stock to the market portfolio. In terms of the CAPM assumptions, the coefficient will capture the linear response of the individual stock excess return to changes in systematic risk.} in a cross-sectional regression to account for the variation of mean excess returns, FF confirm that firms’ size and book-to-market ratios add significant information to the market portfolio in explaining these returns. Moreover, they provide evidence that the statistical significance of betas disappears when adding these factors in the regressions. In FF’s view, this result supports the rejection of the empirical validity of CAPM.

Building on their 1992 paper, FF (1993) introduce a "new" but theoretically groundless stock pricing model -broadly known as the “Three Factor Model” (FF3FM)- designed to capture the sources of common risk reported in FF (1992). Equation 1 summarizes the FF3FM: excess returns are explained by the excess return on the market portfolio (CAPM systematic risk) and two additional factors: SMB (small minus big), which is the difference between the returns on diversified portfolios of small and big stocks or simply "size premium", and HML (high minus low), which is the difference between the returns on diversified portfolios of high and low book-to-market stocks or "value premium".

\[ E(R_i) - R_f = \beta_M [E(R_M) - R_f] + \beta_{IS} [E(SMB_t)] + \beta_{IH} [E(HML_t)] \] (1)

Intuitively, the "new" betas ($\beta_{IS}$ and $\beta_{IH}$) indicate the sensitivity of asset (i) to the additional common risk that is captured by each of the two new attributes. Using the same sample of US stocks as in FF (1992), FF (1993) find that $\beta_{IS}$ and $\beta_{IH}$ are highly significant and positively correlated to $E(R_i) - R_f$, and show that their regression provides a better fit than the standard CAPM where $E(R_i) - R_f$ is regressed only against the market portfolio risk premium.
The empirical evidence on the implementation of the FF3FM is mixed. On the one hand, Kothari, Shanken and Sloan (1995) (KSL) argue that the value effect (positive and significant $\beta_{HF}$) found in the sample of US stocks is driven by selection biases in FF’s database. In particular, they claim that the main drawback of FF’s database (COMPUSTAT) is due to the survivorship bias, a typical problem of stock price databases. Furthermore, Daniel and Titman (1997), Velu and Zhou (1999), Bartholdy and Peare (2005) and Zhang (2006) reject the empirical relevance of size and book-to-market risk factors as additional covariates in standard asset pricing equations. On the one other hand, using different approaches and databases Lewellen (1999), Lam (2002), Tai (2003) find conclusive evidence in favour of the FF3FM.

In response to criticism regarding the sample characteristics, FF (1996 and 1998) state that persistent size and book-to-market premia can be observed in stock markets around the world. For instance, FF (1998) extend their findings on the existence of value and size premia to a larger sample including 13 developed and 14 emerging stock markets (the latter including some of the Latin American countries covered in our study). Their results exhibit an average value premia of 7.68 percent per year in 12 of the 13 developed markets and 16.9 percent per year in 12 of the 14 emerging markets covered, respectively.

On a similar note, Rowenhorst (1999) analyzes a sample of 22 emerging markets (including 6 of the 7 countries covered in this paper) and concludes that the factors which drive cross-sectional differences in expected (excess) returns (size and book-to-market) in emerging markets are similar to those that have been documented for developed markets. Section 5.1 reports some statistics on value and size premia taken from FF(1998) and Rowenhorst (1999) and compares them with the results from this paper.

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6 Using an alternative database (S&P’s Analyst’s Handbook), KSL find no evidence of a monotonic strong relationship between book-to-market ratios and average returns over the period 1947 to 1987. Regarding size and book-to-market effects they also state that, as these variables emerge as the winners in a sequential process of examining and eliminating many other variables (data-snooping), classical measures of statistical significance will likely overstate the true economic significance of the variables that provide the best fit. Furthermore, KSL (1995) demonstrate that market portfolio betas should not be rejected because significant compensation for beta risk is found when betas are estimated through time-series regressions of annual returns on an equally weighted market index. Other studies such as Black (1993) and Lo and MacKinlay (1995) also claim that size and value premia results in FF (1993) may be a product of sample specific results.


8 FF (1996) use the three-factor model (FF (1993)) to address the critique by Lakonishok, Shleifer and Vishny (1994) who find stock pricing anomalies. Davis (1994) also shows that there is a value premium before the starting date in the studies of FF and others.

9 For the sample of developed markets they test a two factor model including a H-L (high minus low book-to-market value) factor added to the market portfolio and find that their model provide a better fit of stock excess returns than the single-factor CAPM.
2.2 Idiosyncratic Determinants of Stock Returns

An alternative reason why part of the expected (excess) returns may remain unexplained by CAPM is firm-specific or idiosyncratic risk. All CAPM versions share the common hypothesis that only systematic risk is priced in the market because (firm or country-specific (in the case of ICAPM) idiosyncratic risk can be completely diversified away. If this assumption didn’t hold, idiosyncratic risk should be explicitly priced by means of appropriate variables reflecting this source of risk.

Indeed, a wealth of recent studies have given rise to discussions regarding the significance of idiosyncratic risk in explaining (excess) returns and ultimately COE. The main questions explored by this literature are: Why idiosyncratic risk matters? How much risk not priced in stock markets is idiosyncratic? What variables are used to proxy for this source of risk?

There are at least two theories on why idiosyncratic risk matters: 1) investors hold undiversified portfolios due to incomplete information (Merton, 1987) or transaction costs (Levy, 1978); 2) investors hold nontraded assets (for example human capital (see Mayers (1976)) which add background risk to their portfolio decisions. The early empirical implications of these models support the role of idiosyncratic risk in stock pricing and consequently in COE estimation.

In a seminal but contested paper, Goyal and Santa Clara (2003) find evidence that idiosyncratic risk is indeed priced in the market. They argue that poor diversification of investors’ portfolios makes idiosyncratic risk an important determinant of conditional excess stock market returns. Using CRSP stocks data for the US, they show how idiosyncratic risk can be captured through a measure of average stock risk and then how this measure successfully predicts the return on the market portfolio in an econometric regression. Furthermore, in order to test the robustness of these results, they use the FF3FM residuals and construct an alternative idiosyncratic variance measure. This measure is also found to forecast the return on the market portfolio.

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10Levy’s model suggests that the variance of each security is a key determinant of the security price and expected returns, especially when those securities are less held. On these grounds, Levy incorporates a variance term together with the systematic risk loading (beta) in a cross-section regression, namely: \( \hat{R}_i = \gamma_1 \beta_1 + \gamma_2 \sigma_i^2 \) to test the significance of \( \gamma_2 \). The empirical results support the model predictions and the key role of idiosyncratic risk.

11In the case of Merton’s model, the assumption of incomplete information implies that an investor will face an additional cost for not knowing a security. This cost is translated into the emergence of a new term in the pricing relation. This model can be tested using a standard security market line test (see for example Roll (1977)): \( R_i - R_F = \beta_1 [R_M - R_F] + \alpha_i \), where the null hypothesis is \( \alpha_i = 0 \) and \( i = 1 \ldots n \). Once again, as this model predicts, the rejection of the null is consistent with an inefficient market portfolio, as reported by Blume and Friend (1973), Black, Jensen and Scholes (1972), and Fama and Macbeth (1973).

12Earlier contributions of Lintner (1965), Douglas (1968) or Lehmann (1990) have already pointed out that idiosyncratic risk seems to explain some of the cross sectional variation in stock returns.

13Additional recent evidence for the U.S. market highlights the fact of little diversification.
Although there is a large quantity of studies on firm-specific factors driving the cross-sectional variation in returns on developed-market stocks (for a survey see Santa Clara and Goya, 2003), evidence for emerging markets is still scarce.

A strand of the stock pricing literature has documented some evidence supporting the claim that idiosyncratic risk is not only priced in US stock markets but also in other stock markets around the world like Shangai (see See Drew, Naughton and Veeraraghavan (2004)).

Claessens, Dasgupta and Glen (CDG) (1996) examine the cross-sectional pattern of stock returns in 19 emerging markets of which 5 are from Latin America, covering (on average) the 1986-1993 period. Resorting to the between estimator CDG find that, in addition to CAPM betas, two factors - size and trading volume - have significant explanatory power in a number of these markets. According to their research, dividend yield and the earnings-to-price ratio are also important, but in slightly fewer markets. For several of the markets studied, the relationships between all four of these variables and returns is contrary to the relationships documented for U.S. and Japanese markets. This especially holds in the case of size, which enters positively and significantly in several regressions (including Brazil and Chile).

Wong Davila (2003) studies a cross section of seven major Latin American stock markets in 1995-1999. In addition to CAPM betas, size and market price-to-book value ratios, Wong Davila also includes firms’ earnings-to-price and turnover ratios. Using a panel between estimator he finds that besides CAPM betas, the earnings-to-price and the market price-to-book value ratios are significant explanatory variables of the cross section of Latin American stock returns. Yet, the positive coefficients estimated in 4 countries in the case of the market price-to-book value ratio runs counter to former empirical evidence on the value premium hypothesis (i.e. low market price-to-book value or high book-to-market- firms should exhibit higher (excess) returns). The author concludes that adding firm’s variables to analyze the cross-sectional differences in stock returns does not appear to shed much light on the relevant factors in these Latin American markets.

3 Data

Our dataset is an unbalanced panel spanning monthly observations over the period 1986-2004 for 921 publicly traded firms from the 7 largest Latin American stock markets: Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela. The main source is Economatica. All data are expressed in current US dollars.

See Barber and Odean (2000), Goetzmann and Kumar (2001) or Benartzi and Thaler (2001). Moreover, a number of other studies (e.g., Campbell, Lettau, Malkiel, and Xu (2001); Moreck, Yeung, and Yu (2000)) demonstrate that firm-specific risk has climbed steadily since the nineties while systematic risk has remained stable.

Moreover, the fact that many intercepts turn out significant offers evidence that the model could be misspecified.
Table I presents summary statistics about the seven stock markets. Column I displays the absolute number of firms (stocks) per country reported by Economatica and Column II indicates the percentage share of these firms in the total number of companies listed in each stock market at the end of 2004 according to the World Federation of Stock Exchanges. Chile is the country with the highest representation of publicly traded stocks (88% of the listed firms are in our database), followed by Brazil (79%, but the highest absolute number of firms per country), whereas Colombia has the lowest share of listed firms covered by Economatica (44%). Columns 3 and 4 exhibit the mean and standard deviation statistics computed on the basis of monthly-average stock returns. We observe significant variation in mean returns and standard deviations across stock markets.

The last three Columns provide estimates of the median firm market capitalization (size) and median book-to-market value. In Column 5, we evidence a sizeable variability in median market capitalizations across countries. For instance, the Peruvian and Venezuelan median firms exhibit about one tenth and two tenths respectively the size of the Mexican median firm, the largest in the sample. This fact suggests that in spite of the restricted number of listed firms in each stock market, if there is any cross-sectional variation in returns associated with size we should be able to capture it. Column 6 shows a measure of market concentration, defined as the share of the equity market capitalization accumulated by the 5 largest firms. The less concentrated market is Chile (27.7%), followed by Brazil (30%). Finally, the last column displays the median book-to-market values, a proxy for relative distress, as seen above. These figures suggest that Chilean firms are the "stronger" (lowest book-to-market ratio: 0.9) while the relatively more distressed companies (highest book-to-market ratios) can be found in Brazil (1.7) and Venezuela (2.0).

\[\text{We report median instead of average values because of the huge variability across firms within each stock market. For example, the ratio between the mean market capitalizations of the 10 largest and the 10 smallest firms is 536 in Argentina, 767 in Chile, and 4818 in Brazil (these figures are not reported in the table).}\]

\[\text{See Claessens, Dasgupta and Glen (1996).}\]
Table I

All statistics except for columns 1 and 2 are computed using monthly average observations per firm/market over the period 1997-2004. As the starting date in the sample differs across countries, e.g. it is 1986 in the case of Brazil and 1993 for Colombia, we restrict the sample to the period 1997-2004 in order to work with comparable figures. This yields 96 monthly observations per firm/country.

Columns 3 and 4 are based on a “value-weighted” portfolio return. The “value weighted” portfolio return weighs each stock return by its respective market capitalization as a percentage of the total market capitalization. The table reports the time-series means and standard deviation.

<table>
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<th>Sample Coverage</th>
<th>Stock returns</th>
<th>Stock Valuation</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Number of firms in the sample</td>
<td>Coverage rate (%)</td>
<td>Mean (%)</td>
</tr>
<tr>
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<td>74</td>
<td>23.9</td>
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<tr>
<td>Brazil</td>
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<td>79</td>
<td>40.0</td>
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<tr>
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<tr>
<td>Venezuela</td>
<td>40</td>
<td>74</td>
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</tr>
</tbody>
</table>
4 Econometric Framework

4.1 Testing the Fama-French Three-Factor Model

Fama and French (1993) introduce an extended CAPM model (FF3FM, Equation 1 below), where a firm's excess return over the risk-free rate is explained by the excess return on the market portfolio (CAPM systematic risk) and two additional factors designed to capture other sources of systematic risk premia beyond market portfolio risk: SMB (small minus big), which is the difference between the returns on diversified portfolios of small and big stocks or simply "size premium", and HML (high minus low), which is the difference between the returns on diversified portfolios of high and low book-to-market stocks or "value premium". More specifically:

\[ E(R_{i,t}) - R_{f,t} = \beta_{iM} [E(R_{M,t}) - R_{f,t}] + \beta_{iS} [E(SMB_t)] + \beta_{iH} [E(HML_t)] \] (1')

with

\[ SMB_t = \sum_{j=\text{smallest}}^{\text{largest}} R_{j,t} w_{j,t}^S - \sum_{j=\text{smallest}}^{\text{largest}} R_{j,t} w_{j,t}^B \] (2)

where \( j \in [\text{smallest}, \text{largest}] \) is a firm index, \( j \) is the smallest firm (the company posting the lowest market capitalization), \( \text{largest} \) is the largest one, \( j \) is the upper bound firm of the small-size group (i.e. the 30\(^{th}\) percentile firm), \( \text{smallest} \) is the lower bound firm of the big-size group (the 70\(^{th}\) percentile firm), \( w_{j,t}^S = MKC_{j,t}/\sum_{j=\text{smallest}}^{\text{largest}} MKC_{j,t} \) and \( w_{j,t}^B = MKC_{j,t}/\sum_{j=\text{smallest}}^{\text{largest}} MKC_{j,t} \) are the market capitalization shares of firms \([\text{smallest}, \text{largest}]\) and \([\text{smallest}, \text{largest}]\), respectively (with \( MKC_{j,t} \) being the firm \( j \) Market Capitalization at \( t \)); and

\[ HML_t = \sum_{k=\text{lowest}}^{\text{highest}} R_{k,t} w_{k,t}^H - \sum_{k=\text{lowest}}^{\text{highest}} R_{k,t} w_{k,t}^L \] (3)

where \( k \in [\text{lowest}, \text{highest}] \) is another firm index, \( \text{lowest} \) is the firm displaying the lowest book-to-market ratio, \( \text{highest} \) is the firm with the highest book-to-market ratio, \( k \) is the 30\(^{th}\) percentile firm, \( \text{highest} \) is the the 70\(^{th}\) percentile firm, while \( w_{k,t}^H \) and \( w_{k,t}^L \) are defined in the same way as \( w_{j,t}^B \) and \( w_{j,t}^S \).

For each firm/country, we test the null hypothesis \( H_0 : \beta_{iS} = \beta_{iH} = 0 \). We perform standard Wald tests on GMM estimations of \( \beta_{iS} \) and \( \beta_{iH} \) from Equation 1'. Like in GPP (2006), we run 48-month GMM rolling-window regressions.\(^{17}\)

\(^{17}\)See GPP (2006) for technical details about rolling GMM estimations.
Rejecting \( H_0 \) would imply that either SMB or HML or both are significant systematic risk factors which should not be omitted in the pricing of firm’s stocks. If so, we would expect \( \beta_{iS} > 0 \) and \( \beta_{iH} > 0 \) (see Section 2). By contrast, the non-rejection of \( H_0 \) would lead us to conclude that either SMB or HML or both do not add information to the market portfolio in the explanation of firm’s excess returns. It is worth noting, however, that rejection of \( H_0 \) might not be a sufficient condition to justify the inclusion of SMB and HML in \( 1' \). As shown in Appendix 7.1, there can be some particular cases where the rejection of \( H_0 \) is obtained by construction and yet all the risk captured by FF factors could be completely diversified away. In such a case, FF factors should not be used for pricing purposes, irrespective of the Wald test results.

4.2 Idiosyncratic Determinants of Stock Returns

In general, the "standard" econometric approach to estimating the impact and significance of firm-specific variables on individual firm’s excess returns can be summarized through the following two-step procedure:\(^{18}\)

1. Run CAPM OLS time-series regressions to obtain the systematic risk loading "\( \beta_i \)" (beta) for each firm:

\[
(R_i - R_f)_t = \beta_i (R_M - R_f)_t + \eta_{i,t}
\]

(4)

2. Compute firm average excess returns and run a cross-section (between) regression of the latter against betas from step 1 and a number of firm-idiosyncratic covariates.

\[
(R_i - R_f)_i = \gamma \beta_i + \theta' FLC_i + \epsilon_i
\]

(5)

where \( R_i, R_f, \beta_i, \gamma, R_M \) and \( \theta' \) are defined as above, \( (R_i - R_f)_i \) is the firm \( i \)'s average excess return, \( FLC_i \) stands for the firm \( i \)'s vector of K relevant idiosyncratic attributes\(^{19} \) (time series averages), \( \gamma \) captures the linear relationship between \( (R_i - R_f) \) and \( \beta_i \), and \( \theta' \) is a K-dimension vector of regression coefficients \( FLC_i \).

Notwithstanding its simplicity and empirical tractability, the "standard" two-step procedure comes with at least four shortcomings:

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\(^{19}\)\( FLC_i \) often includes variables such as earnings-to-price ratio, market price-to-book value (the inverse of the book-to-market ratio), dividend yield, market capitalization and turnover (see Claessens et al., 1996).
1. **Biased estimators.** By definition, the between estimator does not take into account the time series variation in excess returns. This tends to increase the likelihood of biased coefficients.\(^{20}\)

2. **Endogeneity.** The between estimators do not establish causal links between \((R_i - R_f)_t\) and \([\beta_i, FLC_i]_t\), resulting in a potential endogeneity bias which cannot be avoided without allowing for the time series dimension of the variables.

3. **Non-linearities.** The underlying theoretical relationship between average excess returns and beta is non-linear. Therefore, it should not be surprising to find several non-significant \(\gamma\) coefficients in previous articles (see FF (1992), CDG (1996) or Wong Davila (2003)) because when this non-linearity is not controlled for, the relevance of beta cannot be properly assessed through significance tests of \(\gamma\) in standard regressions\(^{21}\), and

4. **Collinearity.** \(\beta\) could be collinear with \(FLC\). If this is the case, the \(t\)-test value is lower than otherwise, what increases the likelihood of type II errors as we would be accepting the null hypothesis of non-significant variables when this is actually false.

The first two foregoing issues may help understand a puzzling result often found in nearly all studies on the cross-section of expected (excess) returns (see CDG (1996) and Wong Davila (2003)): the positive correlation between the latter and market-to-book value ratios. Both (excess) returns and market-to-book value ratios are chiefly driven by stock prices thereby making it difficult to disentangle the true "value" effect, that is, a change in the market-to-book ratios which exerts a significant independent impact on (excess) returns), and the feedback effect of (excess) returns on market-to-book ratios as a result of a variation in stock prices. If the feedback effect (endogenous variables) prevails, then the cross-section correlation between market-to-book value ratios and (excess) returns will forcefully be positive, what runs counter to the intuition -higher market-to-book value should be associated with lower (excess) returns.

The non-linearity and collinearity issues may be useful to understand why Fama and Macbeth (1973)-like studies are unable to find significant betas in cross-section econometric models of (excess) returns.\(^{22}\) In this literature, non-linear effects and collinearity among regressors (with a focus on CAPM beta coefficients) are completely uncontrolled for, misleadingly producing non-significant

\(^{20}\)Indeed, when individual effects are correlated with explanatory variables the between estimator is biased (see Baltagi, 1995).

\(^{21}\)An alternative methodology to assess the significance of beta in the presence of non-linearities between firm’s excess returns and betas has been developed by Pettengill, Sundaram and Mathur (1995). See appendix 7.3

\(^{22}\)See Reinganum (1981); Breeden, Gibbons and Litzenberg (1989) or Fama and French (1992) for further evidence.
betas in cross-section regressions based on unbalanced databases or in the presence of strongly correlated covariates.\textsuperscript{23}

In order to overcome these estimation and identification problems, we propose an alternative two-step econometric approach to estimating the impact of idiosyncratic risk variables on the unexplained variation of CAPM expected (excess) returns. This approach relies on three assumptions: a) systematic and idiosyncratic risk are not correlated, b) idiosyncratic risk is priced because of incomplete portfolio diversification and c) the pricing of idiosyncratic risk proceeds through a number of firm-specific variables which have been identified in the literature (see section 2.2).

This alternative methodology exploits both the time series and cross-section dimensions of the variation in (excess) returns, thus avoiding potential endogeneity and other estimator biases. Furthermore, it ensures the lack of non-linearities between beta and firm-specific variables as beta is no longer a regressor in the new econometric specification. The alternative approach is as follows:

1. The first step is similar to the standard approach: we run a time series CAPM regression for each firm. However, we use a GMM estimator.\textsuperscript{24} Our GMM estimator ensures the absence of correlation between $\beta_i$ and $\eta_{i,t}$.

$$\left(R_i - R_f\right)_t = \beta_i \left(R_M - R_f\right)_t + \eta_{i,t}$$

We compute and save the residuals $\hat{\eta}_{i,t}$ of each firm-wise CAPM regression. $\hat{\eta}_{i,t}$ is the unexplained variation in CAPM expected returns.

2. Resorting to different panel data estimators, we regress $\hat{\eta}_{i,t}$ ($UER_{it}$) against a set of firm-idiosyncratic attributes, time dummies and sector dummy variables. The firm-specific attributes are drawn from an extensive literature on the role of idiosyncratic risk in explaining the cross-section of expected (excess) returns. The variables choice is discussed below. All idiosyncratic variables but ADR (which is time-invariant) are lagged one period in order to avoid the potential endogeneity bias pointed out before.

\begin{equation}
\hat{\eta}_{i,t} = UER_{it} = \theta' DV_{i,t} + \varepsilon_{i,t} = \\
= \theta_1 M/B_{i,t-1} + \theta_2 Size_{i,t-1} + \theta_3 Pres_{i,t-1} + \theta_4 Lev_{i,t-1} + \ldots \\
+ \theta_5 (\sigma_{ROA})_{i,t-1} + \theta_6 ADR_{i,t} + \sum_{j=2}^{7} \theta_j Year_{j,t} + \ldots \\
+ \sum_{k=L}^{7} \theta_k Sector_{k,t} + \varepsilon_{i,t}
\end{equation}

\textsuperscript{23}See Appendix 7.3.

\textsuperscript{24}This is the same GMM estimator as in GPP (2006). Basically, in those regressions we corrected for illiquidity, beta instability, heteroskedasticity, serial correlation; we eliminated potential outliers and we employed different weighing techniques. For technical details see GPP (2006), Section 3.3.
where:

*IDV* is a set of idiosyncratic and dummy variables accounting for *UER<sub>it</sub>*, namely:

*M/B* is the firm’s market-to-book value ratio.<sup>25</sup> This variable is derived from the FF literature (section 2). We expect $\theta_1 < 0$ as "value" stocks (lower market price-to book value) should command higher expected (excess) returns).

*Size* is the natural logarithm of balance sheet assets. We use assets instead of equity market capitalization in order to further deal with a potential endogeneity bias. The FF literature predicts $\theta_2 < 0$ as larger firms are typically less risky, hence their stocks should yield lower expected (excess) returns. While this negative correlation has been often confirmed for developed-country stocks (see e.g., FF (1992))<sup>27</sup>, CDG (1996) and Wong Dávila (2003) find that larger firms display higher (excess) returns in emerging markets.

*Pres* is a measure of liquidity, namely the percentage of days with positive volume. We expect $\theta_3 < 0$ because more liquid stocks should be less risky and therefore drive lower expected (excess) returns. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Acharya and Pedersen (2004) and Hasbrouck (2005) all find (excess) returns decline with increased liquidity. However, this result does not hold for developing countries. Indeed, CDG (1996) and Wong Dávila (2003) find $\theta_3 > 0$.

*Lev* is the firm’s leverage ratio measured as the debt-to-asset ratio. Relatively highly leveraged firms, all else equal, are closer to bankruptcy (Merton, 1974) and its equity price should drop. To compensate for this higher risk, higher-leverage firms should offer higher expected (excess) returns. Hence, we expect $\theta_4 > 0$.

*$\sigma_{ROA}$* is the volatility of the returns on the firm’s assets, calculated as the two-year rolling standard deviation of *ROA* (returns on assets). We expect a positive relationship between $\sigma_{ROA}$ and *UER<sub>it</sub>* ($\theta_5 > 0$). If for some reasons related to the firm’s performance (independent of the business cycle or macroeconomic factors) the firm’s returns on assets are more volatile, then its stock should reflect this increased riskiness and therefore yield higher expected (excess) returns.

*ADR* is a dummy variable. ADR is equal to 1 when a firm issues an American Depositary Receipts and zero otherwise. Emerging-country firms issuing ADRs are usually more diversified, internationally-oriented, more frequently traded and less risky businesses. As a result, $\theta_6$ should be negative.

---

<sup>25</sup>Notice that market-to-book instead of the opposite ratio (book-to-market) is used for idiosyncratic regressions because of comparison purposes (as long as most applied papers focusing on idiosyncratic models uses the former expression).

<sup>26</sup>Kothari, Shanken and Sloan (1995), Claessens et al (1996), and Wong Dávila (2003) find $\theta_1 > 0$. However, they use the sort of Fama and McBeth approach discussed above.

<sup>27</sup>However, Spiegel and Wang (2006) show that holding idiosyncratic risk constant, the bigger the firm the higher the return, even in developed countries. Brennan et al (1998) reach a similar conclusion.
Year\(_j\) is a dummy variable for year \(j\) (with \(j \in [1986, ..., 2004]\)) and Sector\(_k\) is a dummy variable for Sector \(k\).\(^{28}\) Sector\(_k\) is designed to capture a differentiated sectorial impact on the expected (excess) returns on the firm, which is not due to other idiosyncratic variables (e.g. a greater exposure of IT firms to technological shocks).

In summary, we argue that a group of firm-specific attributes, namely size, market price-to-book value ratio, leverage, liquidity, profit uncertainty and issuance of ADRs\(^{29}\) should contribute to explain the residual expected (excess) returns from a CAPM or FF3FM regression. We test for the explanatory power of these variables in section 5.2.

5 Empirical results

5.1 Testing the Fama-French Three-Factor Model

5.1.1 Descriptive Statistics

In this section we look into the presence and persistence of size (\(E(SMB_t)\)) and value premia (\(E(HML_t)\)) in Latin American stock markets and we compare our results with those by FF (1998) and Rowenhorst (1999).

To compute the size and value premia we follow the procedure adopted by FF (1998). For each year in our sample, we sort stocks according to their mean market equity capitalization or to their book-to-market value and group them into three portfolios: high 33.3%, medium 33.3% and bottom 33.3%. Then, we drop the medium-characteristic portfolios, so we only keep the following portfolios: big size (B), small size (S), high book-to-market (H) and low book-to-market (L). Finally, we calculate the monthly value-weighed return on each portfolio (B, S, H and L).

Table II reports the mean, median and standard deviation of each of the portfolios returns over 1997-2004. For benchmarking purposes, we also include the local market value-weighed portfolio in the first column. If small stocks (S) persistently outperformed big stocks (B) and value stocks (H) persistently outperformed growth stocks (L), then the mean (or median) return differences S-B and H-L should be positive and statistically different from zero. Column 4 in Table II (H-L) shows positive H-L mean and median return differences in only 4 of the 7 countries. However, none of them are statistically significantly different from zero. Furthermore, in the sole case where the H-L mean return


\(^{29}\)Other variables such as dividend yield or earnings-price ratios do not come out significant in previous studies (see Claessens et al, 1996). On the contrary, Francis et al (2004) find a significant positive correlation between cash flow volatility and cross-section expected returns.
is significantly different from zero (Peru (t-value= -1.82)). H-L turns out to be negative, contrary to our expectation. Similarly, we only find positive S-B mean and median returns in two countries, Brazil and Peru, yet only Peru displays an S-B mean return significantly different from zero (t-value: 1.78).

In conclusion, there is no robust evidence of the presence and persistence of size and value premia in Latin American stocks over 1997-2004.

Table III exhibits the value (H-L) and size (S-B) premia found in FF (1998), Rowenhorst (1999) and the present study. We only report figures for the stock markets of our interest. Rowenhorst (1999) finds positive value premia in 5 of 6 countries, yet there is only one statistically significant (Brazil). FF (1998) find 3 stock markets displaying positive value premia but none is significantly different from zero. As to the size premia, the pattern is similar. Rowenhorst (1999) reports positive size premia in 5 out of 6 countries yet only two among them pass the t-test (Argentina and Mexico). FF (1998) also find positive size premia for the same markets (with the exception of Colombia), but none is statistically significant.

A caveat is in order. We regularly observe that either H-L or S-B yield opposite signs across studies or are statistically significantly different from zero in one study while not in the others. There are at least two limitations to this comparative analysis: 1) the period length and the data frequency (Table III)\textsuperscript{30}, and 2) the sample size, i.e. the number of firms covered in each study. For instance, it has been the case in Latin America that a great deal of firms delisted more remarkably during the second half of the 1990s (see GPP (2006)). Nevertheless, all three studies point to the lack of robust evidence of the presence and persistence of size and value premia in Latin American stocks throughout the period 1982-2004.

\textsuperscript{30}Our results do not change when we allow for the same data frequency as in FF (1998) or Rowenhorst (1999). These figures are available from the authors upon request.
Table II

Column I displays USD annual average statistics for the local market portfolio. Columns II through VII report USD annual average statistics for portfolios sorted by book-to-market ratios and market capitalization.

Columns II and III display statistics of high book-to-market (H) and low book-to-market (L) portfolios. Column IV is the average of the annual differences between H and L portfolio returns. Analogously, columns IV through VII report statistics for small (S) and big (B) stock portfolios and averages of annual differences between them, respectively.

For each country, the first row reports the value-weighed portfolio return. The second row displays the median return (in parentheses). The third row reports the standard deviation (in brackets) or the t-statistic corresponding to the mean difference test (in braces).

<table>
<thead>
<tr>
<th>Domestic Market</th>
<th>Book-to-Market (Value)</th>
<th>Market Capitalization (Size)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>Argentina</td>
<td>0.24</td>
<td>0.24</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(0.13)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Brazil</td>
<td>0.40</td>
<td>0.38</td>
</tr>
<tr>
<td>(0.03)</td>
<td>(0.27)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>Chile</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(0.11)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Colombia</td>
<td>0.17</td>
<td>0.17</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.14)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.21</td>
<td>0.22</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.13)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Peru</td>
<td>0.17</td>
<td>0.18</td>
</tr>
<tr>
<td>(0.00)</td>
<td>(0.15)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Venezuela</td>
<td>0.34</td>
<td>0.31</td>
</tr>
<tr>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table III
Size and Value Premia Across Three Studies

This table replicates the evidence on Latin American stock markets provided by FF (1998) and Rowenhorst (1999). H-L and S-B portfolios are formed as explained in Table II with some minor differences regarding the frequency of the sorting of portfolios: FF(1998) sort stocks using information at the end of each year, Rowenhorst (1999) uses monthly information, and this paper uses annual averages. An * (asterisk) indicates statistically significant differences between mean returns.

<table>
<thead>
<tr>
<th></th>
<th>Book-to-Market</th>
<th>Market Capitalization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H-L</td>
<td>S-B</td>
</tr>
<tr>
<td></td>
<td>Rowenhorst 1999</td>
<td>Fama and French 1998</td>
</tr>
<tr>
<td>Argentina</td>
<td>1.68</td>
<td>-0.36</td>
</tr>
<tr>
<td>Brazil</td>
<td>3.94*</td>
<td>0.73</td>
</tr>
<tr>
<td>Chile</td>
<td>1.07</td>
<td>0.15</td>
</tr>
<tr>
<td>Colombia</td>
<td>-0.36</td>
<td>-0.17</td>
</tr>
<tr>
<td>Mexico</td>
<td>1.39</td>
<td>0.00</td>
</tr>
<tr>
<td>Peru</td>
<td>Na</td>
<td>Na</td>
</tr>
<tr>
<td>Venezuela</td>
<td>1.27</td>
<td>0.57</td>
</tr>
</tbody>
</table>
5.1.2 Econometric Results

As seen in Section 2.1, there is mixed evidence of the statistical significance and economic relevance of FF systematic risk factors (value and size premia) for stock pricing. Although there is a wealth of literature on stock markets in developed countries and to a lesser extent on Asian emerging economies, to the best of our knowledge there is no previous applied research testing the FF3FM for the seven Latin American stock markets in our sample. Therefore, one of the main contributions of this paper is to test whether the FF factors are economically and statistically significant determinants of COE in these markets.

Following GPP(2006), we apply a firm-wise testing procedure. First, we run a FF3FM time-series regression (Equation 1') for each firm over a 48-month rolling window.\footnote{We estimate as many rolling window FF3FM regressions as each firm’s sample size permits, for the 921 stocks in our sample. The choice of a 48-month window is explained in GPP (2006).} We use a GMM estimator. Second, we perform individual and joint Wald tests on $\beta_{iS}$ and $\beta_{iH}$ (the joint test null hypothesis is $H_0 : \beta_{iS} = \beta_{iH} = 0$). Taking into account the potential heterogeneity of $\beta_{iS}$ and $\beta_{iH}$ across firms, we try to avoid rejecting the joint significance of FF factors when indeed they are individually significant.\footnote{In other words we minimize the probability of a type-one error.}

Table IV summarizes the percentage of Wald tests per country where the null hypothesis of insignificant FF factors is rejected at the 5% level. Overall, we conclude that FF factors do not carry significant information for stock pricing in Latin America. On average, the percentage of Wald test rejection reaches 40% in Brazil (i.e. in 40% of the regressions we reject the null $H_0 : \beta_{iS} = \beta_{iH} = 0$) whereas it is generally below 30% in the other countries. The relatively higher proportion of rejections in Brazil does not come as a surprise as 1) we observe the highest standard deviation of firm’s size in Brazil (relative to other Latin American countries), which renders size a more meaningful risk factor, and 2) the relatively low explanatory power of CAPM in this country (see GPP (2006)). Table V presents the dynamic properties of the Wald test results, where no clear-cut time trend is observed in most Latin American stock markets. Nevertheless, it must be noticed that the rejection rates of the null hypothesis (non significant FF factors) are always below the 50% excluding Brazil in 2003.
Table IV. Proportion of Wald Tests Rejecting the Null Hypothesis of Non Significant Fama-French Factors

<table>
<thead>
<tr>
<th>Country</th>
<th>S-B (size premia)</th>
<th>H-L (value premia)</th>
<th>Joint test</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>AR</td>
<td>0.07</td>
<td>0.12</td>
<td>0.15</td>
<td>0.12</td>
</tr>
<tr>
<td>BR</td>
<td>0.23</td>
<td>0.29</td>
<td>0.30</td>
<td>0.25</td>
</tr>
<tr>
<td>CL</td>
<td>0.10</td>
<td>0.15</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>CO</td>
<td>0.06</td>
<td>0.15</td>
<td>0.18</td>
<td>0.20</td>
</tr>
<tr>
<td>MX</td>
<td>0.06</td>
<td>0.13</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>PE</td>
<td>0.07</td>
<td>0.16</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>VE</td>
<td>0.10</td>
<td>0.15</td>
<td>0.24</td>
<td>0.15</td>
</tr>
<tr>
<td>Latin America</td>
<td>0.14</td>
<td>0.20</td>
<td>0.21</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Note: In Columns (1) percentages are calculated on the basis of unweighed GMM specifications while in Columns (2) they are obtained from weighted GMM models using monthly traded shares as within weights.
Table V. Proportion of Wald Tests Rejecting the Null Hypothesis of Non Significant Joint Fama-French Factors

<table>
<thead>
<tr>
<th>Year</th>
<th>AR</th>
<th>BR</th>
<th>CL</th>
<th>CO</th>
<th>MX</th>
<th>PE</th>
<th>VE</th>
<th>Lat. Am.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0.31</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.31</td>
</tr>
<tr>
<td>1991</td>
<td>0.35</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.35</td>
</tr>
<tr>
<td>1992</td>
<td>0.45</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.45</td>
</tr>
<tr>
<td>1993</td>
<td>0.38</td>
<td>0.19</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.31</td>
</tr>
<tr>
<td>1994</td>
<td>0.39</td>
<td>0.21</td>
<td></td>
<td>0.29</td>
<td></td>
<td></td>
<td></td>
<td>0.32</td>
</tr>
<tr>
<td>1995</td>
<td>0.36</td>
<td>0.19</td>
<td>0.38</td>
<td>0.04</td>
<td></td>
<td></td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>1996</td>
<td>0.20</td>
<td>0.28</td>
<td>0.16</td>
<td>0.22</td>
<td>0.35</td>
<td>0.24</td>
<td></td>
<td>0.24</td>
</tr>
<tr>
<td>1997</td>
<td>0.19</td>
<td>0.32</td>
<td>0.17</td>
<td>0.21</td>
<td>0.14</td>
<td>0.29</td>
<td>0.22</td>
<td>0.25</td>
</tr>
<tr>
<td>1998</td>
<td>0.20</td>
<td>0.32</td>
<td>0.18</td>
<td>0.39</td>
<td>0.13</td>
<td>0.17</td>
<td>0.21</td>
<td>0.23</td>
</tr>
<tr>
<td>1999</td>
<td>0.16</td>
<td>0.40</td>
<td>0.29</td>
<td>0.49</td>
<td>0.19</td>
<td>0.12</td>
<td>0.23</td>
<td>0.29</td>
</tr>
<tr>
<td>2000</td>
<td>0.18</td>
<td>0.42</td>
<td>0.32</td>
<td>0.35</td>
<td>0.22</td>
<td>0.15</td>
<td>0.17</td>
<td>0.30</td>
</tr>
<tr>
<td>2001</td>
<td>0.18</td>
<td>0.43</td>
<td>0.35</td>
<td>0.24</td>
<td>0.22</td>
<td>0.20</td>
<td>0.25</td>
<td>0.32</td>
</tr>
<tr>
<td>2002</td>
<td>0.15</td>
<td>0.47</td>
<td>0.32</td>
<td>0.25</td>
<td>0.25</td>
<td>0.28</td>
<td>0.33</td>
<td>0.34</td>
</tr>
<tr>
<td>2003</td>
<td>0.12</td>
<td>0.55</td>
<td>0.30</td>
<td>0.34</td>
<td>0.28</td>
<td>0.26</td>
<td>0.31</td>
<td>0.36</td>
</tr>
<tr>
<td>2004</td>
<td>0.23</td>
<td>0.48</td>
<td>0.26</td>
<td>0.25</td>
<td>0.31</td>
<td>0.21</td>
<td>0.33</td>
<td>0.34</td>
</tr>
<tr>
<td>Whole Sample</td>
<td>0.18</td>
<td>0.40</td>
<td>0.25</td>
<td>0.31</td>
<td>0.23</td>
<td>0.22</td>
<td>0.25</td>
<td>0.31</td>
</tr>
</tbody>
</table>

Note: Yearly average by country obtained from weighted GMM specifications, using monthly traded shares as within weights.

5.2 Stock pricing and Idiosyncratic Variables

5.2.1 Descriptive Statistics

This section discusses how we measure the firm-idiosyncratic determinants of the unexplained variation in CAPM (excess) returns, that is the right-hand side variables in Equation 7 above. Table VI presents summary descriptive statistics of these variables.

Size is measured as the log of the balance sheet total assets expressed in millions of US dollars. Note that mean sizes are as much as 3 to 5 times the median size. This should not be surprising as it has been well documented that the statistical distributions of size display strong right skewness. The largest firms are in Mexico (the average firm is worth USD 1597 millions), followed by Brazil (USD 1316 millions).

Market-to-Book is calculated as the ratio between the market value of equity (market price times the number of shares) and the firm’s balance sheet net worth less deferred taxes. We observe that Venezuela (0.63) and Colombia (0.72) exhibit the most relatively average "distressed" or "value" firms.

Presence is a proxy for liquidity measured as the percentage of days/year in which stocks are traded at least once. In general, Latin American publicly

33 We use the balance sheet total assets instead of the firm’s market equity capitalization, as it is standard practice in the literature, in order to avoid a potential endogeneity bias (see section 4.2).

traded firms are much less liquid than their peers in developed countries. Our figures suggest that Argentina has the most relatively liquid stocks (the average firm’s stock is traded 63.92 days a year) and Colombia the least (37.69).

Leverage is defined as the balance sheet ratio of total liabilities to total assets. The countries with the highest mean leveraged firms are Argentina and Brazil (50.6% and 58.7%, respectively).

ROA volatility is the 8-quarter rolling standard deviation of the return on assets (ROA). ROA is measured as the ratio of balance sheet total earnings to total assets. The countries with the largest average ROA volatility are Argentina and Brazil (5.34 and 4.59, respectively). This variable along with size show the highest standard deviations.

ADR is a dummy variable, as explained in Section 4.2. Table VI shows the percentage of firms who issued American Depositary Receipts. Mexico (23%) and Venezuela (36%) exhibit the largest percentages of domestic firms issuing ADR.  

35In absolute terms, there are 28 Mexican and 14 Venezuelan firms which issued ADR. Yet, these figures may underestimate the "true" absolute and relative number of firms which floated ADR. Recall from Table I that our sample covers 74% and 51% of the total listed firms in Venezuela and Mexico, respectively.
### Table VI


With the exception of the last column, the first row displays the cross-sectional mean, the second row is the median value (in parentheses), and the last is the standard deviation [in brackets].

<table>
<thead>
<tr>
<th></th>
<th>Size</th>
<th>Market to Book</th>
<th>Presence</th>
<th>Leverage</th>
<th>ROA</th>
<th>Volatility</th>
<th>ADR issuance</th>
</tr>
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<tbody>
<tr>
<td><strong>Argentina</strong></td>
<td>1225</td>
<td>0.93</td>
<td>63.92</td>
<td>50.56</td>
<td>5.34</td>
<td>0.16</td>
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<tr>
<td></td>
<td>(231.69)</td>
<td>(0.77)</td>
<td>(73.02)</td>
<td>(50.60)</td>
<td>(3.26)</td>
<td>(0.00)</td>
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<tr>
<td></td>
<td>[2380.81]</td>
<td>[0.63]</td>
<td>[34.70]</td>
<td>[22.97]</td>
<td>[5.28]</td>
<td>[0.37]</td>
<td></td>
</tr>
<tr>
<td><strong>Brazil</strong></td>
<td>1316</td>
<td>0.80</td>
<td>56.42</td>
<td>58.67</td>
<td>4.59</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(341.12)</td>
<td>(0.53)</td>
<td>(60.66)</td>
<td>(55.80)</td>
<td>(2.83)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[2984.22]</td>
<td>[0.81]</td>
<td>[38.40]</td>
<td>[38.33]</td>
<td>[7.87]</td>
<td>[0.33]</td>
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<tr>
<td><strong>Chile</strong></td>
<td>630</td>
<td>1.28</td>
<td>46.30</td>
<td>41.53</td>
<td>3.94</td>
<td>0.12</td>
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<tr>
<td></td>
<td>(175.03)</td>
<td>(1.00)</td>
<td>(40.32)</td>
<td>(42.00)</td>
<td>(2.33)</td>
<td>(0.00)</td>
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<tr>
<td></td>
<td>[1341.89]</td>
<td>[0.96]</td>
<td>[35.41]</td>
<td>[21.68]</td>
<td>[11.22]</td>
<td>[0.32]</td>
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<tr>
<td><strong>Colombia</strong></td>
<td>713</td>
<td>0.72</td>
<td>37.69</td>
<td>41.77</td>
<td>1.95</td>
<td>0.02</td>
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<tr>
<td></td>
<td>(382.31)</td>
<td>(0.63)</td>
<td>(31.97)</td>
<td>(29.80)</td>
<td>(1.61)</td>
<td>(0.00)</td>
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<td></td>
<td>[816.78]</td>
<td>[0.46]</td>
<td>[31.31]</td>
<td>[29.03]</td>
<td>[1.37]</td>
<td>[0.13]</td>
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<tr>
<td><strong>Mexico</strong></td>
<td>1597</td>
<td>1.15</td>
<td>60.33</td>
<td>49.98</td>
<td>3.02</td>
<td>0.23</td>
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<tr>
<td></td>
<td>(632.67)</td>
<td>(0.90)</td>
<td>(67.69)</td>
<td>(50.60)</td>
<td>(2.32)</td>
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<td>[19.69]</td>
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<td>Leverage</td>
<td>ROA</td>
<td>Volatility</td>
<td>ADR issuance</td>
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<td>----------</td>
<td>-----</td>
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<td></td>
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<tr>
<td>Peru</td>
<td>302</td>
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<td>37.31</td>
<td>44.20</td>
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<tr>
<td></td>
<td>(92.37)</td>
<td>(0.77)</td>
<td>(24.59)</td>
<td>(42.50)</td>
<td>(2.20)</td>
<td>(0.00)</td>
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<tr>
<td></td>
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<td>[0.96]</td>
<td>[33.39]</td>
<td>[22.81]</td>
<td>[2.52]</td>
<td>[0.16]</td>
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<tr>
<td>Venezuela</td>
<td>841</td>
<td>0.63</td>
<td>50.81</td>
<td>40.36</td>
<td>3.20</td>
<td>0.36</td>
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<tr>
<td></td>
<td>(207.59)</td>
<td>(0.43)</td>
<td>(50.82)</td>
<td>(36.40)</td>
<td>(1.87)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[1361.31]</td>
<td>[0.54]</td>
<td>[35.14]</td>
<td>[25.78]</td>
<td>[3.84]</td>
<td>[0.48]</td>
<td></td>
</tr>
</tbody>
</table>
5.2.2 Econometric Results

In this section we estimate the model of the firm-idiosyncratic determinants of stock excess returns not accounted for by CAPM and the FF3FM.

We begin by testing for stationarity of the dependent variable ($UER_t$) by means of a Fisher (1932)-like test suited for panel data. The null hypothesis is that all series are non-stationary, against the alternative that at least one series in the panel is stationary.

Then, we run several panel regressions of Equation 7 in Section 4.2, each corresponding to an alternative estimator, namely: random effects (RE), fixed effects (FE), fixed effects corrected for serial correlation (FE-AR), random effects corrected for serial correlation (RE-AR) and generalized least squares (GLS) -which remedies both serial correlation and heteroskedasticity.

In order to make a choice among these estimators, we perform a number of specification tests for each firm/country:

First, we conduct the standard Hausman (1978) tests to check whether the RE estimator is consistent. Under the Hausman’s null both FE and RE estimators are consistent but only the latter is efficient. Second, we test for time-series serial correlation applying the Wooldridge (2002) approach. Third, we perform a modified Wald test for groupwise residual heteroskedasticity (see Green (2000)). Last, we test for cross-section contemporaneous residual correlation (or cross-section error dependence) as different stocks within a country or stocks in a given industry across countries may be affected by shocks not accounted for by Equation 7.

Table VII presents the econometric output. In two parts, a discussion of

---

36 For a discussion about the optimal choice and trade-offs among these estimators we refer the reader to Kennedy (1994), Baltagi (1995) and Wooldridge (2002).

37 We must notice, however, that all these tests suffer from different shortcomings. Hausman’s test is strongly sensitive to weak instruments (or misspecification in the case of the FE model). For further details, see Staiger and Stock (1997); or Hahn and Hausman (2003). The Wooldridge’s (2002) test for serial correlation may lack of power should the first- and second-order residual autocorrelations coefficients be close in size and sign. Unfortunately, available alternative tests (such as Portmanteau-like tests) can only be applied to FE model residuals. Finally, the modified Wald test for groupwise heteroskedasticity developed by Baum (2000), can only be applied to residuals obtained from a FE estimator. Yet, its power diminishes considerably in samples where $N$ is "large", and $T" small".

38 Because the traditional Breusch-Pagan LM test is not valid in the context of unbalanced panels and because the alternative test developed by Pesaran (2004) is unapplicable to our sample for computational reasons -a highly unbalanced panel and relatively low sample matching across firms-, we develop an alternative but preliminary test. The reader can find the analytics and the STATA-MATA routine of this test in a complementary document named COE2_appendix 1.pdf, from the following website: http://www.cefargentina.org. With this test we reject the null of no contemporaneous residual correlation across firms in almost all Latin American stock markets. Unfortunately, there is no existing correction for such a result when the panel database is highly unbalanced. In a further research, we will present a potential solution based on the standard GLS correction for balanced panel databases.
the results follows. First, we discuss the general findings and its economic implications. Second, we go into each country panel results and analyze the robustness of the alternative estimators as well as the trade-offs facing these estimators.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) RE</td>
<td>(2) FE</td>
</tr>
<tr>
<td>$M/B_{t-1}$</td>
<td>-0.452</td>
<td>-0.528</td>
</tr>
<tr>
<td></td>
<td>(0.122)***</td>
<td>(0.157)***</td>
</tr>
<tr>
<td>Size$_{t-1}$</td>
<td>0.235</td>
<td>-0.096</td>
</tr>
<tr>
<td></td>
<td>(0.381)***</td>
<td>(0.561)***</td>
</tr>
<tr>
<td>Presence$_{t-1}$</td>
<td>0.235</td>
<td>-0.096</td>
</tr>
<tr>
<td></td>
<td>(0.381)***</td>
<td>(0.561)***</td>
</tr>
<tr>
<td>Leverage$_{t-1}$</td>
<td>-0.017</td>
<td>-0.028</td>
</tr>
<tr>
<td></td>
<td>(0.005)***</td>
<td>(0.161)**</td>
</tr>
<tr>
<td>$\sigma_{ROA_{t-1}}$</td>
<td>0.01</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.033)***</td>
<td>(0.041)***</td>
</tr>
<tr>
<td>$ADR_t$</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.004)***</td>
<td>(0.004)***</td>
</tr>
<tr>
<td>Observations</td>
<td>848</td>
<td>848</td>
</tr>
<tr>
<td>Country-specific units</td>
<td>58</td>
<td>58</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>Hausman test prob.</td>
<td>0.95</td>
<td>0.98</td>
</tr>
<tr>
<td>Wooldridge test prob.</td>
<td>0.98</td>
<td>0.00</td>
</tr>
<tr>
<td>Mod. Wald test prob.</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: The dependent variable is $UER_t$. Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. RE, FE, FE-AR, RE-AR and GLS stand for random effects, fixed effects, fixed effects with serial correlation corrections, random effects with serial correlation corrections and generalized least squares estimators, respectively. Sector and time dummy variables are not reported. All covariates but ADR are multiplied by 100 to obtain displayable coefficients.
Table VII. Idiosyncratic Determinants of CAPM Unexplained Excess Returns (cont.).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) RE (2) FE (3) FE-AR (4) RE-AR (5) GLS</td>
<td>(1) RE (2) FE (3) FE-AR (4) RE-AR (5) GLS</td>
</tr>
<tr>
<td><strong>M/B</strong>&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.026 -0.066 -0.059 -0.029 -0.051</td>
<td>-0.284 -2.165 -2.291 -0.388 -0.345</td>
</tr>
<tr>
<td></td>
<td>(0.025) (0.028)** (0.029)** (0.026) (0.029)*</td>
<td>(0.426) (0.615)*** (0.764)*** (0.456) (0.321)</td>
</tr>
<tr>
<td><strong>Size</strong>&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.096 0.126 0.405 0.106 0.057</td>
<td>0.219 0.787 0.611* 0.254 0.11</td>
</tr>
<tr>
<td></td>
<td>(0.046)** (0.276) (0.282) (0.051)** (0.036)</td>
<td>(0.256) (0.576) (0.317) (0.270) (0.187)</td>
</tr>
<tr>
<td><strong>Presence</strong>&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.002 -0.008 -0.011 -0.002 0</td>
<td>0.007 0.007 0.001 0.006 0.008</td>
</tr>
<tr>
<td></td>
<td>(0.002) (0.004)** (0.005)** (0.002) (0.002)</td>
<td>(0.006) (0.009) (0.013) (0.007) (0.004)*</td>
</tr>
<tr>
<td><strong>Leverage</strong>&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.007 -0.014 -0.018 -0.007 -0.008</td>
<td>-0.024 -0.005 -0.008 -0.023 -0.026</td>
</tr>
<tr>
<td></td>
<td>(0.003)** (0.007)** (0.008)** (0.003)** (0.002)*****</td>
<td>(0.010)** (0.012) (0.014) (0.010)** (0.007)***</td>
</tr>
<tr>
<td><strong>σ</strong>&lt;sub&gt;ROA,t-1&lt;/sub&gt;</td>
<td>-0.009 -0.014 -0.016 -0.007 0.006</td>
<td>-0.091 -0.17 -0.194 -0.068 -0.15</td>
</tr>
<tr>
<td></td>
<td>(0.016) (0.020) (0.021) (0.016) (0.016)</td>
<td>(0.197) (0.251) (0.355) (0.210) (0.132)</td>
</tr>
<tr>
<td><strong>ADR</strong>&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-0.004 -0.004 -0.002</td>
<td>-0.002 -0.002 -0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)** (0.002)*** (0.001)</td>
<td>(0.006) (0.007) (0.004)</td>
</tr>
<tr>
<td>Observations</td>
<td>2522 2522 2389 2522 2521</td>
<td>206 206 183 206 205</td>
</tr>
<tr>
<td>Country-specific. units</td>
<td>133 133 132 133 132</td>
<td>23 23 22 23 22</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.05 0.04 0.03 0.05</td>
<td>0.21 0.11 0.11 0.21</td>
</tr>
<tr>
<td>Hausman test prob.</td>
<td>N/A</td>
<td>0.00</td>
</tr>
<tr>
<td>Wooldridge test prob.</td>
<td>0.18</td>
<td>0.84</td>
</tr>
<tr>
<td>Mod. Wald test prob.</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: The dependent variable is $UER_t$. Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. RE, FE, FE-AR, RE-AR and GLS stand for random effects, fixed effects, fixed effects with serial correlation corrections, random effects with serial correlation corrections and generalized least squares estimators, respectively. Sector and time dummy variables are not reported. All covariates but ADR are multiplied by 100 to obtain displayable coefficients.
Table VII. Idiosyncratic determinants of CAPM unexplained excess returns (cont.).

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<tr>
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<tbody>
<tr>
<td></td>
<td>(1) RE</td>
<td>(2) FE</td>
<td>(3) FE-AR</td>
<td>(4) RE-AR</td>
<td>(5) GLS</td>
<td>(1) RE</td>
<td>(2) FE</td>
<td>(3) FE-AR</td>
<td>(4) RE-AR</td>
<td>(5) GLS</td>
<td>(5) GLS</td>
</tr>
<tr>
<td>$M/B_{t-1}$</td>
<td>-0.331</td>
<td>-1.134</td>
<td>-1.227</td>
<td>-0.367</td>
<td>-0.302</td>
<td>-0.501</td>
<td>-0.812</td>
<td>-1.087</td>
<td>-0.524</td>
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<tr>
<td></td>
<td>(0.106)***</td>
<td>(0.185)***</td>
<td>(0.196)***</td>
<td>(0.111)***</td>
<td>(0.081)***</td>
<td>(0.219)***</td>
<td>(0.491)***</td>
<td>(0.583)***</td>
<td>(0.234)***</td>
<td>(0.183)***</td>
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</tr>
<tr>
<td>Size$_{t-1}$</td>
<td>0.201</td>
<td>-0.225</td>
<td>-0.172</td>
<td>0.21</td>
<td>0.137</td>
<td>0.449</td>
<td>0.849</td>
<td>-0.288</td>
<td>0.448</td>
<td>0.456</td>
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<tr>
<td></td>
<td>(0.099)**</td>
<td>(0.382)</td>
<td>(0.399)</td>
<td>(0.103)**</td>
<td>(0.067)**</td>
<td>(0.262)*</td>
<td>(1.229)</td>
<td>(0.694)</td>
<td>(0.277)</td>
<td>(0.181)***</td>
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<tr>
<td>Presence$_{t-1}$</td>
<td>0.00</td>
<td>0.003</td>
<td>0.005</td>
<td>0.00</td>
<td>0.001</td>
<td>-0.03</td>
<td>-0.034</td>
<td>-0.012</td>
<td>-0.031</td>
<td>-0.029</td>
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<td></td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.015)*</td>
<td>(0.020)*</td>
<td>(0.028)</td>
<td>(0.016)**</td>
<td>(0.010)***</td>
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<tr>
<td>Leverage$_{t-1}$</td>
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<td>-0.03</td>
<td>-0.033</td>
<td>-0.012</td>
<td>-0.008</td>
<td>-0.01</td>
<td>0.011</td>
<td>-0.007</td>
<td>-0.01</td>
<td>-0.019</td>
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</tr>
<tr>
<td></td>
<td>(0.006)**</td>
<td>(0.013)**</td>
<td>(0.015)**</td>
<td>(0.006)*</td>
<td>(0.004)*</td>
<td>(0.010)</td>
<td>(0.027)</td>
<td>(0.038)</td>
<td>(0.011)</td>
<td>(0.008)**</td>
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<tr>
<td>ROA$_{t-1}$</td>
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<td>0.092</td>
<td>0.117</td>
<td>0.005</td>
<td>0.000</td>
<td>0.282</td>
<td>0.259</td>
<td>0.038</td>
<td>0.278</td>
<td>0.214</td>
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<td>(0.052)</td>
<td>(0.068)</td>
<td>(0.078)</td>
<td>(0.054)</td>
<td>(0.041)</td>
<td>(0.123)**</td>
<td>(0.193)</td>
<td>(0.220)</td>
<td>(0.130)**</td>
<td>(0.096)**</td>
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<td>0.002</td>
<td>0.00</td>
<td>0.000</td>
<td>0.00</td>
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<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.030)</td>
<td>(0.031)</td>
<td>(0.000)</td>
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<td>1497</td>
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<td>329</td>
<td>281</td>
<td>329</td>
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<td>91</td>
<td>88</td>
<td>48</td>
<td>48</td>
<td>39</td>
<td>48</td>
<td>39</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.14</td>
<td>0.06</td>
<td>0.06</td>
<td>0.14</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>Hausman test prob.</td>
<td>N/A</td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
<td>0.80</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wooldridge test prob.</td>
<td>0.00</td>
<td></td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mod. Wald test prob.</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The dependent variable is $UER_t$. Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. RE, FE, FE-AR, RE-AR and GLS stand for random effects, fixed effects, fixed effects with serial correlation corrections, random effects with serial correlation corrections and generalized least squares estimators, respectively. Sector and time dummy variables are not reported. All covariates but ADR are multiplied by 100 to obtain displayable coefficients.
Table VII. Idiosyncratic Determinants of CAPM Unexplained Excess Returns (cont.).

<table>
<thead>
<tr>
<th>Ind. Variable</th>
<th>Venezuela (1989-2004)</th>
<th>(1) RE</th>
<th>(2) FE</th>
<th>(3) FE-AR</th>
<th>(4) RE-AR</th>
<th>(5) GLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M/B_{t-1} )</td>
<td>-0.935</td>
<td>(-0.643)</td>
<td>-1.91</td>
<td>-2.631</td>
<td>-1.019</td>
<td>-0.893</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.892)**</td>
<td>(0.991)**</td>
<td>(0.692)***</td>
<td>(0.348)**</td>
<td></td>
</tr>
<tr>
<td>( \text{Size}_{t-1} )</td>
<td>0.207</td>
<td>0.739</td>
<td>-1.208</td>
<td>0.282</td>
<td>0.153</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.105)</td>
<td>(0.751)</td>
<td>(0.315)</td>
<td>(0.190)</td>
<td></td>
</tr>
<tr>
<td>( \text{Presence}_{t-1} )</td>
<td>0.01</td>
<td>0.011</td>
<td>0.01</td>
<td>0.00</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.009)</td>
<td>(0.017)</td>
<td>(0.018)</td>
<td>(0.010)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>( \text{Leverage}_{t-1} )</td>
<td>-0.011</td>
<td>-0.033</td>
<td>-0.036</td>
<td>-0.013</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)</td>
<td>(0.035)</td>
<td>(0.038)</td>
<td>(0.014)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>( \sigma_{\text{ROA},t-1} )</td>
<td>0.018</td>
<td>0.2</td>
<td>0.151</td>
<td>0.029</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.085)</td>
<td>(0.137)</td>
<td>(0.135)</td>
<td>(0.091)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>( ADR_{t} )</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.007)</td>
<td>(0.004)**</td>
</tr>
</tbody>
</table>

Observations: 333 333 305 333 332
Country-specific units: 28 28 27 28 27
R-squared: 0.08 0.06 0.07 0.08
Hausman test prob.: 0.49
Wooldridge test prob.: 0.70
Mod. Wald test prob.: 0.00

Note: The dependent variable is \( UER_{t} \). Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. RE, FE, FE-AR, RE-AR and GLS stand for random effects, fixed effects, fixed effects with serial correlation corrections, random effects with serial correlation corrections and generalized least squares estimators, respectively. Sector and time dummy variables are not reported.

All covariates but ADR are multiplied by 100 to obtain displayable coefficients.

General Findings

1. For each panel (without exceptions) in our sample, we reject the non-stationarity hypothesis of CAPM unexplained excess returns (the dependent variable) at 1% significance level. This unambiguous result allows us to estimate the model without any transformation.

2. In terms of the goodness of fit, the firm-idiosyncratic variables included in our econometric model account for an average between 5% and 11% of the variation in CAPM unexplained excess returns \( UER_{t} \), depending on the estimator/country.

3. \( M/B \) (Market price-to-book value ratio) is the only firm-specific variable which always comes out significant and with the expected negative sign. We show that unlike in previous studies on emerging market stocks (CDG (1996) or Wong Dávila (2003), the positive artificial correlation between \( M/B \) and excess returns vanishes (though our dependent variable is different: \( UER_{t} \)). This happens because we control for endogeneity, i.e. we
use a panel instead of the between estimator and we lag all covariates one period.

4. Presence (our measure of liquidity), $\sigma_{ROA}$ and ADR are not significantly different from zero in most cases, and when they are their expected signs are in line with the theoretical predictions.\textsuperscript{39}

5. Depending on the market and the alternative estimator, and to a lesser extent than $M/B$, Size and Lev (leverage) are statistically significant determinants of the CAPM unexplained excess returns $UER_t$. However, when they enter significantly in the regression, the associated coefficient yields the sign opposite to our expectation: an increase in Size increases $UER_t$ and a positive variation in Lev indeed reduces $UER_t$. We offer two plausible explanations of these puzzling signs:

As to Lev (leverage), in the context of credit-rationing (not infrequent in Latin America), a higher degree of leverage might not be necessarily viewed as an indicator of increasing default risk but as an indicator of credit market access that enables the firms to carry on their investment plans or roll over the outstanding obligations. All else equal, weaker firms with high default risk will have their access to debt markets cut off and therefore will post relatively lower leverage ratios while healthier firms with low default risk will be able to continue to lever resources in credit markets. We argue that the positive impact of Lev on $UER_t$ could be driven by a predominance of the second type of firms in our sample of Latin American stocks.

CDG (1996) explain the puzzling positive sign of Size (larger firms command higher excess returns) they find on account of foreign investors’ preferences for emerging market big stocks ensuing capital account opening episodes.\textsuperscript{40} This preference tends to push up large stock excess returns relative to smaller stocks. Instead, we put forward an alternative theoretical (but non exclusive) explanation. Assume that small stocks are more volatile than big stocks, i.e. the variance of small stock returns is higher than the variance of big stock returns. If the underlying version of CAPM is the one proposed by Black (1972), then for a given mean return and a given correlation between the local market portfolio and individual stock returns, the smaller the firm size the higher the individual stock return volatility, the higher the estimated CAPM beta, the higher the CAPM expected (excess) return\textsuperscript{41} and the lower the CAPM unexplained excess returns (our dependent variable $UER_t$). In a second stage, when $UER_t$ are regressed against different firm-level variables, the factor loadings on the firm’s size may turn out to be positive if the downward bias attributable to the

\textsuperscript{39}Except in Venezuela for ADR and in Colombia for Presence.

\textsuperscript{40}Several Latin American countries liberalized their capital accounts and deregulated their financial markets, with nuances, in the late 1980s and early 1990s.

\textsuperscript{41}It must be noticed that CAPM-Sharpe expected returns are not affected by individual return volatility.
link between betas and stocks volatility counterweights the standard "small-size premium" effect, i.e a negative factor loading on the firm’s size.  

Country-specific findings

1. Idiosyncratic models provide a better fit in the smallest (by number of listed firms and capitalization) stock markets: Colombia, Peru and Venezuela. In these countries, the average R-squared is 0.11, whereas it is just about 0.05 in the largest. This is not surprising because smaller stock markets offer less diversification opportunities. Of course, this may not be necessarily true when these markets are globally integrated (in the sense of real market integration). However, GPP(2006) show that Latin American stock markets systematically display a significant "home bias".

2. Because heteroskedasticity is omnipresent in this sample (see the "Mod. Wald test prob." row in Table VII), country specific findings will be entirely analyzed by examining GLS results of Table VII.

3. Despite reporting the highest R-squared of all countries in our sample, only two firm-level attributes come out significant in the equation for Colombian stocks, namely Presence and Leverage. Yet, they display the wrong sign. Our proxy variable for asset liquidity is strikingly positively correlated with UER. Why we should ask for higher excess returns on liquid instead of illiquid assets in Colombia is far to be clear and exceeds the scope of this paper. Finally, Leverage enters with the counter-intuitive sign. We have offered a plausible explanation of this sign above (see general findings).

4. In the case of Peru, we find that all firm-specific variables but ADR issuance are statistically significant. Moreover, the signs of all coefficients with the exception of those associated with Size and Leverage are in line with theoretical predictions. Indeed, UER increases with ROA volatility (\(\sigma_{ROA}\)) and decreases with the Market-to-Book ratio (\(M/B\)) and liquidity (Presence).

42 A technical discussion about this methodological bias (named COE2_appendix 2.pdf) can be obtained from the following website: http://www.cefargentina.org, going to the "Publications" tab and, therein, to the "Working paper" link.

43 It is worth noting, however, that Colombian and Venezuelan results should be carefully analyzed. For these stock markets, the Modified Wald test could be misleading because such a test is only valid under FE (and we can see from Table VII that RE instead of FE estimators are preferable -e.g. more efficient- for Colombia and Brazil). However, the Hausman test (used to make the choice between FE and RE) is not robust under different circumstances (as we have already point out). Moreover, the FE-AR estimator results for Colombia and Brazil do not significantly differ from those derived from the GLS estimator. Therefore, we finally focus on the latter because it jointly address the problems of serial correlation and heteroskedasticity.
5. As for Venezuela, only $M/B$ and the issuance of $ADR$ have a statistically significant impact on $UER$. Notwithstanding, the sign of the $ADR$ coefficient is the opposite to that derived from the theory (Section 4.2). Going international does not appear to reduce required excess returns. On the contrary, Venezuelan internationalized firms display higher required returns than those without $ADR$ issuance all else equal.

6. Turning to the largest Latin American stock markets, we find that firm-idiosyncratic variables do not generally add explanatory power to CAPM unaccounted excess returns. This is what we could expect for reasons discussed in point 1 above, i.e. that firm-idiosyncratic characteristics are less relevant for stock pricing in large and more integrated markets. Indeed, only $M/B$ is statistically significant though its associated coefficient is the lowest amongst the 7 Latin American stock markets covered in this study.

7. We also find a significant but relatively small $M/B$ impact on $UER$ in Chile. In addition, we report a negative and statistically significant coefficient for $Leverage$. Above, (see general findings) we have offered an explanation of this counterintuitive effect of $Leverage$ on $UER$.

8. Finally, the panel regressions for Argentina and Mexico yield quite similar results regarding the coefficient signs and their significance levels. In both stock markets, we find a significant negative impact of $M/B$ on $UER$, we confirm the "big size puzzle", and once again we get the seemingly counter-intuitive (negative) sign for $Leverage$.

As we can see from the econometric results, we figure out, on the one hand some "country specificity" in the idiosyncratic models of the residual CAPM excess returns $UER$, but on the other we come up with some empirical regularities concerning the way Market- to-Book ratios, Size and Leverage affect the dependent variable.

6 Conclusions

The goal of this paper is to identify the determinants of the Latin American stock excess returns not accounted for by CAPM systematic risk, using a panel of 921 publicly traded firms over 1986-2004. We draw two main conclusions:

First, there is no general robust evidence of the presence and persistence of size and value premia (FF factors) in Latin American stocks. This confirms previous findings by FF (1998) and Rowenhorst (1999). Furthermore, when we estimate the FF3FM we conclude that FF factors do not add any significant information to CAPM. These findings are robust across countries and stable over time.
Second, even controlling for potential estimator bias, non linealities and endogeneity, the firm-idiosyncratic variables included in our econometric model account for an average of 5% to 11% of the variation in CAPM unexplained excess returns. Only to a limited extent the market price-to-book ratio, leverage and size are significant determinants of these returns. We find that market price-to-book value ratios have a positive impact on the dependent variable (unlike Wong Davila, 2003), what might suggest that value effects would only be observable as idiosyncratic instead of a common source of risk (e.g. value effects are relevant across firms with similar characteristics like leverage or liquidity, and not at the aggregate level as suggested by FF, 1993 or FF, 1998). Leverage and size, however, enter the regressions with the wrong sign. We offer an explanation of these results in the context of emerging markets: a) high default risk firms (associated with higher excess returns) are more likely to be credit rationed, thus their leverage ratios will be lower all else equal, and b) small stocks may drive lower CAPM unexplained excess returns under certain conditions (i.e. if their returns are more volatile than large stock returns and the valid underlying model is the Black’s CAPM). Notwithstanding, these "theoretical" puzzles (as well as the low predictive power of idiosyncratic models) could also be explained by firm-level attributes not taken into account in this paper. Therefore, further refinements concerning model specifications are needed to be sure about the actual relevance of the indiosyncratic approach.

Taken altogether, the econometric results derived from idiosyncratic models (Equation 7) are not sufficiently robust so as to recommend moving away from standard CAPM in order to price stocks and calculate the implicit COE in Latin America. Even when more that 60% of the variance of CAPM excess returns remains unexplained (see GPP (2006)), there is no clear, conclusive evidence that the inclusion of firm-idiosyncratic information brings about a significant improvement in the explanation of stock excess returns.
References


7 Appendix

7.1 The Fama-French Theoretical Puzzle

In spite of the lack of conclusive empirical support (see Section 2 -Literature review), FF theoretical insights are also controversial.

Existing critics on FF additional factors rely on the atheoretical nature of the model. In fact, it could be as much additional "systemic" portfolios as balance sheet or market based variables exist.

Moreover, the three factor model does present another major drawback. In this section we show that FF additional factors could be relevant by construction even when all the FF-portfolio underlying risk is completely diversifiable (and should not be priced). In such a case, empirical support for FF-three factor model does not imply that CAPM should be modified. On the contrary, our example is useful to show that FF additional factors do not add significant information for pricing purposes even if they are significantly different from 0 in standard regression results.

Assume that an efficient "experimental" market is characterized by three different groups: Small firm stocks, Medium size stocks and Big firm stocks.

Let A be the between-group variance-covariance matrix of returns:

\[
A = \begin{bmatrix}
1 & 0 & -1 \\
0 & 1 & 0 \\
-1 & 0 & 1
\end{bmatrix}
\]  

(8)

where \(A_{12} = 0\) is the covariance of returns between Small and Medium size firms, \(A_{31} = -1\) is the covariance of returns between Small and Big firms and so on.

Accordingly, let \(B_1\), \(B_2\) and \(B_3\) be the within-group variance-covariance matrices for Small, Medium and Big firms, respectively. For the sake of simplicity, assume that all these matrices have characteristic elements equal to 1 (within group covariance is 1)\(^{44}\).

In other words, stock returns are assumed to be different across-groups (with Small firm returns being the mirror of Big firm returns -both of them without correlation with Medium size firm returns) but exactly the same within-group.

In order to obtain the "experimental" database with need additional information concerning stock return data generation processes for each group:

\[
R_s \sim N(0,1) \\
R_b = -R_s \\
R_m \sim N(0,1)
\]  

(9) (10) (11)

\(^{44}\)If all characteristic elements are equal to 1 not only covariances but also variances are equal to 1 within-group.
where $E(R_b R_m) = E(R_s R_m) = 0$ and $E(R_s R_b) = -1$.

From 9, 10 and 11, and assuming that small, big and medium size firms have sample weights $w_s, w_b$ and $w_m$ (respectively), we obtain the following (weighted average) portfolio returns:

$$R_{M,t} = w_s R_{s,t} + w_b R_{b,t} + w_m R_{m,t}$$

(12)

$$SMB = R_{s,t} - R_{b,t}$$

(13)

Let assume by simplicity that $w_s = w_b$. Because of 10, Equation 12 is reduced to:

$$R_{M,t} = w_m R_{m,t}$$

(14)

In Figure 2, we show a scatterplot matrix to analyze existing relationships between $R_s, R_b, R_m, R_M$ and $SMB$.

In a two factor version of the Fama-French model:

$$E(R_{i,t}) - R_{f,t} = \beta_{iM} [E(R_{M,t}) - R_{f,t}] + \beta_{iS} [E(SMB_t)]$$

(15)

underlying relationships displayed in Figure 1 entail that $\beta_{iM}$ will only be significant for Medium size firms while $\beta_{iS}$ will only be relevant for small (with a positive sign) and big (with a negative sign) firms.
In this example, the higher the share of big and small firms relative to medium size firm, the higher the Wald test rejection rate (number of rejections divided by the number of firms) of the null hypothesis of non-significant FF factors ($H_0: \beta_{S} = 0$).

As long as rejection rate increases, FF additional factor appears to be more and more significant for pricing purposes. However, one simple question arises: Why should SMB sensitivity be priced if all the underlying risk is completely diversifiable across groups (remember that $R_b = -R_s$ and $w_s = w_b$)? Why should we accept that all swans are white when we find at least one swan that is actually black?

Our black swan in this example is useful to notice that significant FF coefficients (in an extended CAPM model or three factor equation) should not be accepted as unambiguous evidence supporting the relevance of FF additional factors to improve stock pricing in practice. We are not looking for higher $R^2$ (the standard result of using the three factor model instead of the Sharpe-Litterman-Black model) but for pricing equations appropriately reflecting undiversifiable risk.

In this example, small and big firm undiversifiable risk is always 0\(^4\) (something that the FF approach is unable to reproduce -even with a higher $R^2$). The Sharpe-Litterman-Black model has a low explanation power but it is the only one deriving appropriate expected returns from a systematic risk point of view.

\(^4\)Because of a perfectly negative covariance between small and big firm returns.
7.2 Kernel Densities of Wald tests for the Fama-French Three Factor Model

Figure 3: Gaussian Kernel Densities of Wald test p-values of the null: Fama-French factors do not explain individual stock (excess) returns: 1997-2004.
7.3 Testing the Significance of CAPM Beta with Cross-Section Regressions

Since the Fama-Macbeth (1973) article was published, a wealth of applied research has followed running cross-section regressions of individual returns on CAPM Beta coefficients and other "ad-hoc" relevant variables.

However, an emerging literature based on Pettengill, Sundaram and Mathur (1995) suggests that cross-section individual returns are only "conditionally" correlated with CAPM Beta coefficients. Among these studies, Jagannathan and Wang (1996) and Howton and Peterson (1998) emphasize that allowing for beta instability and upmarket versus downmarket environments is a sufficient condition to revert the Fama and French (1992, 1996) controversial results implying non-significant CAPM Beta coefficients in cross-section regressions of individual stock returns.

The alternative methodology to Fama and Macbeth (1973) proposed by Pettengill, Sundaram and Mathur (1995) consists in a simple "conditional 'bull-bear'" beta approach to test how well CAPM fits the cross-section of returns, namely:

\[ R_i - R_f = \gamma_1 \delta \beta_i + \gamma_2 (1 - \delta) \beta_i + \epsilon_i \]  

(16)

where \( \delta \) is a dummy variable with \( \delta = 1 \) if \( R_{M,t} - R_{f,t} \geq 0 \) and \( \delta = 0 \) if \( R_{M,t} - R_{f,t} < 0 \), while \( \gamma_1 \) and \( \gamma_2 \) are estimated coefficients for "bull" and "bear" betas, respectively. Thus, we would expect \( \gamma_1 > 0 \) and \( \gamma_2 < 0 \).

Equation 16 serves to test whether the standard CAPM is the relevant stock pricing model. This can be done by means of a joint Wald-test on \( \gamma_1 \) and \( \gamma_2 \) (with \( H_0 : \gamma_1 = \gamma_2 = 0 \)). The existing empirical evidence bears out the theoretical claim that moving from "unconditional" to "conditional 'bull-bear'" beta approaches can dramatically alter the econometric results. Contrary to unconditional specifications, "conditional" models almost always reject the null hypothesis of non-significant CAPM beta coefficients because they do capture the non-linear nature of the underlying relationship between the estimated betas and cross-sectional individual returns.\(^{48}\)

Notice that when \( \gamma_1 = \gamma_2 = \gamma \) and \( \beta_i \geq 0 \), Equation 16 can be written as:

\[ |R_i - R_f| = \gamma \beta_i + \epsilon_i \]  

(17)

In a more general panel data setting,

\(^{46}\)There is a positive relationship between beta and returns when \( R_{M,t} > R_{f,t} \) (i.e. during expansions) and a negative relationship when \( R_{M,t} < R_{f,t} \) (i.e. during recessions). See panel (a) of figure 7.3.

\(^{47}\)See Fabozzi and Francis (1979) to obtain a detailed analysis of bull and bear market betas.

\(^{48}\)Crombez and Vander Vennet (2000), observed that the beta factor is a strong and consistent indicator of both upward potential in bull markets and downside risk in bear markets. They found the results to be robust for various definitions of beta and different specifications of bull and bear markets.
\[ |R_{i,t} - R_{f,t}| = |\beta_i (R_{M,t} - R_{f,t}) + \varepsilon_{i,t}| \]  
(18)

because \((R_{i,t} - R_{f,t}) = \beta_i (R_{M,t} - R_{f,t}) + \varepsilon_{i,t}\), and then

\[ \frac{\partial |R_{i,t} - R_{f,t}|}{\partial \beta_i} = \text{signum} [\beta_i (R_{M,t} - R_{f,t})] (R_{M,t} - R_{f,t}) \]  
(19)

When \(\beta_i \geq 0\) (the representative case for most Latin American stocks), Equation 19 is always positive, while \(\frac{\partial |R_{M,t} - R_{f,t}|}{\partial \beta_i} \geq 0\) depending on \((R_{M,t} - R_{f,t})\). A visual comparative inspection of panels (a) and (b) in Figure 4 can help us grasp the non-linear relationship between beta coefficients and individual returns. In cross-section linear specifications (panel a), partial derivatives of \(R_i\) on \(\beta_i\) can be either positive or negative. On the other hand, the absolute value specifications (panel b) always display a positive partial derivative proving that \(\beta_i \geq 0\).

It is worth noting that if we assume \(\beta_i \geq 0\), the higher the \(\beta_i\) the higher the \(|R_{i,t}|\) (but this correlation does not hold between \(\beta_i\) and \(R_{i,t}\)). For this reason, the cross-section relationship between CAPM betas and individual stock returns should not be estimated by means of linear models. Instead, "conditional "bull-bear"" or absolute value specifications must be used to take into account the non-linear relationship between \(\beta_i\) and \(R_{i,t}\).

However, there is a second problem affecting all these alternative methodologies to Fama and MacBeth (1973). Unconditional, conditional and absolute value cross-section regressions of \(R_{i,t}\) on \(\beta_i\) suffer from collinearity problems when the firm level covariates are included in the model (because beta coefficients depend on these additional regressors). Then, it is should not be surprising that t-test statistics of CAPM beta coefficients strongly decrease (yielding non significant factor loadings for this variable) when idiosyncratic fundamentals are introduced. However, such a result is not informative to examine the relevance of the CAPM model. Small t-test statistics are a by-product of collinearity and not an evidence of CAPM failure.

To avoid this collinearity problem, we use the two-step methodology presented in Section 4.2.

\(^{49}\)In CAPM specifications, \((R_{i,t} - R_{f,t}) = \beta_i (R_{M,t} - R_{f,t}) + \varepsilon_{i,t}\). Therefore, \(\frac{\partial R_{i,t}}{\partial \beta_i} = (R_{M,t} - R_{f,t})\), with \((R_{M,t} - R_{f,t}) \geq 0\).

\(^{50}\)For the sake of simplicity, we assume \(R_{f,t} = 0\) (for all \(t = 1, \ldots, T\)) in figure 7.3.

\(^{51}\)Such as \(|(R_i - R_f)| = \gamma \beta_i + \varepsilon_i\), proving that most \(\beta_i \geq 0\) for all \(i = 1, \ldots, N\).
Figure 4: Non linear relationship between returns and Beta coefficients

(a) R in levels
(b) R in absolute values