ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis: Financial Economics

Low volatility factor: Evidence from Latin American Economies

Name student: Alexis Jesus Zorrilla Garcia

Student ID number: 581769

Supervisor: Onno Steenbeek

Second assessor: Jan Lemmen

Date final revision: 28/09/2023

ABSTRACT

This study delves into whether the low volatility anomaly, extensively observed in developed markets and documented by Blitz et al. (2007) over the long term and Ang et al. (2006) in the short term, extends to Latin American economies. While extensive research has explored this anomaly in developed markets, there exists a notable research gap concerning its presence in Latin American economies. To bridge this gap, this study compiles performance data from the most liquid stocks in the largest economies of this region, spanning from 2003 to 2023. These portfolios undergo testing employing both the basic CAPM model and the Fama and French 3-factor model. The objective is to uncover potential sources of excess returns among portfolios categorized by long-term, short-term volatility, and IVOL. The principal finding of this study points towards an absence of the low volatility anomaly in Latin American economies. This diverges from observations in more established markets, where low volatility has been deemed influential. Our investigation suggests that stocks with higher risk ultimately yield superior returns. Moreover, a noteworthy discovery is that portfolios constructed based on the three proposed volatility approaches outperformed the primary indexes of the region in terms of both returns and Sharpe ratios. Finally, portfolios comprising stocks from the six largest economies of the region exhibit non-normality, a factor that could potentially skew results obtained from testing using the CAPM and F&F 3-factor model.

Table of Content

1. INTRODUCTION

The foundation of portfolio theory relies on the assumption that agents maximize their utility within a single period, with the utility function based solely on expected return and variance. Consequently, investors seek to either minimize risk given a specific level of return or maximize returns given a certain level of risk. It was within this framework that the Capital Asset Pricing Model (CAPM) was developed by Sharpe and Lintner in 1972. The fundamental premise of this model asserts that expected returns are linearly correlated with their market beta, implying that stocks with higher beta should yield greater returns. However, empirical tests, beginning with Fama and MacBeth (1973), indicated that low beta stocks outperformed the predictions of the CAPM model.

Subsequently, literature has revealed that stocks with low volatility have consistently outperformed their more volatile counterparts, which challenges the conventional notion that higher risk should yield higher returns. While extensive studies have been conducted on this anomaly in developed markets, the same cannot be said for developing economies. Thus, the aim of this paper is to extract additional insights from emerging economies regarding this anomaly. Specifically, we will scrutinize Latin American countries, including Brazil, Mexico, Argentina, Colombia, Chile, and Peru. Given the availability of more data, it is pertinent to examine the behavior of this anomaly during the last 20 years.

Furthermore, given the unsatisfactory results in researching the CAPM itself – signifying that the beta derived from existing literature may not be considered reliable due to the limitations of Latin American stock exchanges and the assumptions of the CAPM – the low volatility anomaly could potentially serve as a more effective approach for asset managers in constructing portfolios within these developing economies.

During my research, I diligently explored the existing literature and resources. Regrettably, I could not find any prior thorough studies examining this anomaly for the Chilean, Peruvian, and Mexican markets. Therefore, this marks the inaugural study of the low volatility factor in these markets. Finally, a significant contribution of this study lies in the method used to construct portfolios sorted by volatility, which aligns with the approach taken by Blitz et al. (2013) for emerging markets. In this regard, it departs from the existing literature on Latin American economies, providing a novel perspective.

With these considerations in mind, this research endeavor seeks to answer the following questions:

- Has the low volatility anomaly been present over the past two decades in Latin American economies?
- Do short-term volatility metrics (daily past 1 month) yield the same results as long-term volatility (monthly past 3 years)?
- Do portfolios sorted by low volatility also exhibit low beta?
- Do low volatility portfolios outperform country benchmarks?
- Do low volatility portfolios return alphas are statistically significantly different from zero when controlling by CAPM and Fama and French 3 factor model?

This research is structured as follows: the subsequent section will provide a comprehensive review of the literature in both developed and emerging markets, followed by the hypotheses to be tested. Section 3 will detail the data and methodology applied in this paper. Section 4 will present the results of the analysis, and finally, the conclusions will be provided.

2. LITERATURE REVIEW

This chapter will commence by reviewing the literature concerning the low volatility anomaly in developed economies. Subsequently, it will delve into the general findings within developing markets, with a focused emphasis on Latin American economies. Finally, it will address the implications of applying traditional models for pricing the returns of Latin American stocks according to the existing literature.

2.1.The volatility factor in developed markets

The low volatility factor has been documented since Haugen and Heins' seminal work in 1975, where they observed that portfolios with lower variance yielded greater average returns compared to riskier portfolios. Clarke et al. (2006) further examined portfolios with minimum variance without factoring in expected returns. In this study, the focus was on identifying portfolios with the lowest possible variance without stipulating a specific level of return. Upon thorough analysis, it was discovered that these low volatility portfolios consistently outperformed their high volatility counterparts, thereby challenging the conventional notion that higher risk equates to higher returns. The dataset utilized in this study spans from January 1968 to December 2005, encompassing the largest 1000 common stocks. Returns and factor exposures were considered to calculate the sample covariance matrix, employing Bayesian shrinkage and Principal Component Analysis (PCA) to generate an estimated covariance matrix. This matrix was then utilized to derive the optimal portfolio weights.

In Ang et al. (2006), it was introduced an alternative approach on the volatility anomaly, focusing on very short-term variations by calculating volatility based on the past 1-month daily returns. They assessed idiosyncratic volatility in relation to the Fama and French 3-factor model, defining it as the volatility of the error from this model. The strategy involved a formation period of N months, a waiting period of M months, and a holding period of L months, with a primary emphasis on the 1/0/1 strategy. The key finding indicates a higher average return, in favor of the lowest volatile portfolio, which obtained a 1.06% return, while the fifth quintile showed an average return of 0.09% per month. When incorporating the FF-3 model, the disparity in alphas between quintile 5 and 1 is approximately -1.19%.

One year later, David et al. (2007) proposed a simpler approach to analyze the low volatility anomaly. In this methodology, the authors formed 10 portfolios based on the past 3-year volatility, considering monthly returns. For this purpose, they utilized the FTSE World Developed index, primarily comprised of global large-cap stocks. This choice was made because anomalies are less pronounced when the data is based on large-cap companies. The results indicate that in the US, European, and Japanese equity markets, the relationship between risk and return was negative. This negative correlation persisted even after controlling for factors such as size, value, and momentum, with an excess return of 12%. In terms of risk, employing this approach yielded volatilities that were two-thirds of that of the market, representing an improvement compared to the findings of Clarke et al. (2006). The data used for this paper spanned from 1986 to 2006.

In 2014, Blitz et al. endeavored to elucidate the volatility anomaly within the framework of CAPM assumptions. For instance, CAPM assumes an absence of leverage constraints. However, seminal studies like Black (1972) had already demonstrated that such constraints could attenuate the slope of the security market line. In 2010, Frazzini and Pederson (2010) attributed the volatility effect to these leverage restrictions. When confronted with limitations on leverage, investors are inclined to lean towards portfolios with higher beta to capitalize on the equity risk premium, akin to mutual funds. Meanwhile, less restricted investors, such as private equity funds, gravitate towards low beta stocks. Additional assumptions, like skewness preferences and behavioral biases, may contribute to elucidating the apparent flat relationship between risk and return. Stocks with a high degree of attention might prompt investors to inflate their prices, while dismissing the more stable, low-volatility stocks, potentially explaining the low volatility effect. Other behavioral biases scrutinized include Representativeness, Mental Accounting, and Overconfidence. Further studies, like Novy and Marx (2014), contend that size, rather than volatility, is the primary driver of the anomaly. After controlling for size, profitability emerges as the key driver of returns. Additionally, Liu et al. (2018) demonstrated that the beta anomaly stems from beta's positive correlation with idiosyncratic volatility (IVOL). When accounting for IVOL, the beta anomaly loses significance.

2.2. The volatility factor in emerging markets

One of the pioneering studies examining the empirical relationship between risk and return in emerging markets was conducted by Rouwenhorst (1999). He observed that beta was not significantly associated with average returns during the period from 1982 to 1997. However, there was a clear presence of size, value, and momentum factors in most emerging economies. For his analysis, he relied on the Emerging Markets Database (EMDB) provided by the International Finance Corporation (IFC). The author noted certain challenges associated with the data. In some instances, there were missing values in the time series of firm characteristics required to construct portfolios based on volatility, size, and/or book-to-market ratios.

In Blitz et al. (2013), the authors analyzed the volatility effect directly in emerging markets. In this paper the authors used the S&P/IFC Investable Emerging Markets Index, which considers the most highly liquid stocks to avoid the issue of previous papers that the negative relation between risk and return is negative due to small caps, especially from high idiosyncratic volatility companies. Besides the 3-year period, a holding period up to 5 years was performed to analyze its impact given that the relation between risk and return might be positive for longer periods based on Amenc et al. (2011) critique. The results indicated a similar pattern than in developed markets, a negative relation between risk and return. This outcome remains robust first after controlling by size, value, and momentum. Secondly, after removing the less 50% liquid stocks. However, one of the main findings is that there appears to be a low correlation between the volatility anomaly in emerging markets and developed economies, which signaled that these effects might be a different anomaly. In the case of the Latin American economies, the authors found that low volatile stocks outperformed the most volatile ones, nevertheless, based on pricing models, alphas were not statistically significantly different from zero. The data spans from 1988 to 2010, which were periods of extremely low levels of liquidity in Latin American markets.

Looking at research focused on Latin American economies, there has been relatively little attention given to the low volatility anomaly. Among these economies, Brazil, being the largest, has seen the most study in this area. For example, in a paper by Samsonescu et al. (2016), the authors used a method developed by Clarke et al. (2006) and a methodology similar to that of Blitz et al. (2007) to create portfolios with minimum variance and low volatility. They looked at data from 2003 to 2013. However, the main goal of this research was to compare the returns from these portfolios, which aimed for low volatility, against standard benchmarks like the IBOVESPA index and a portfolio with equal weighting. In their optimization process, they considered limitations on short positions and how much weight each asset could have in the optimized portfolios. One significant difference from the approach used by Blitz et al. (2013) in their study of emerging markets was the timing of rebalancing. Instead of doing it monthly, these authors suggested a 4-month holding period. This was because the benchmark they used also underwent changes in composition every four months, and to make a fair comparison, they matched the rebalancing process. The portfolios aiming for minimum variance were built based on the daily returns of the past twelve months, using a method distinct from previous research. Another noteworthy aspect of this study was that, due to limitations in the number of assets traded during the study period, the authors chose to consider only a fixed 17% of the assets available for trading in each period. This is a significant departure from the approach taken by Blitz et al. (2013) in their study of emerging markets to build up portfolios. The key finding here is that by employing various techniques to optimize and construct portfolios with minimum variance, and by sorting portfolios to target low volatility, similar to what Blitz et al. (2007) did, the returns outperformed the benchmark returns. This was true in terms of average returns and when considering risk-adjusted measures.

Another study that delved into the low volatility anomaly in the Brazilian market was conducted by Boudjoukian (2017). The dataset covers the period from January 2003 to June 2017, utilizing the IBrX 100 index, which tracks the top 100 most active stocks in the Brazilian market. Boudjoukian's approach paralleled that of Samsonescu et al. (2016), considering the preceding 252 daily returns with a quarterly rebalancing cycle. The findings of Boudjoukian's study revealed an inverse relationship between volatility and returns using this methodology. Notably, the portfolio with lower decile volatility demonstrated a superior Sharpe ratio compared to the market, particularly when contrasted with the portfolio with higher decile volatility. Another discovery was the negative impact of the volatility factor in 2009, following the financial crisis. Returns that were accrued prior to the crisis saw a substantial reduction within a single year. This discovery aligns with the research of Moskowitz and Daniel (2004), who examined the momentum factor during a prior crisis and noted extremely negative returns. Furthermore, from 2010 to 2017, the author did not find evidence of a volatility effect during this period. In the evaluation of pricing using the CAPM, portfolios sorted by volatility yielded a non-significant alpha when the data was partitioned into decile portfolios. However, adopting the portfolio formation method advocated by Fama & French, which involved categorizing data into three portfolios (the least volatile 30% of stocks in the first portfolio, the subsequent 40% in the second, and the top 30% most volatile in the third), resulted in the acquisition of noteworthy alphas. The incorporation of additional factors into the pricing model, such as momentum and the quality factor, once again led to non-significant alphas.

One last paper on the low volatility anomaly in Brazil, authored by Brito (2017), aimed to compare the returns of low volatility and low beta portfolios with those of high volatility and high beta portfolios. The study covered the period from 2000 to 2017 and incorporated a look-back period of 60 monthly returns (equivalent to 5 years), a departure from the 3-year span utilized in prior research. To be included in the portfolio, stocks needed to have traded in at least one of the preceding 24 months, ensuring consideration of all available stocks for each period. As a rigorous test, the author conducted the study using only the top 100 most liquid stocks. Interestingly, the key finding in this scenario yielded inconclusive results, with the most volatile stocks outperforming the low volatility portfolio by a minimal margin.

In the broader economic landscape of this region, apart from the Colombian market, research on this anomaly has been scarce. Viveros (2013) paved the way in this market, concentrating on the period from 2007 to 2013, and identified a relatively subtle presence of this anomaly in Colombia. However, given the substantial progress in the Colombian market in recent years, Amorocho (2023) took on the challenge of examining the returns of portfolios characterized by minimum variance, aligning with the approach of Clarke et al. (2006), but with a specific focus on comparing them against a Colombian benchmark – in this case, the Colcap index, which monitors the top 25 most liquid companies in Colombia. The author's analysis spanned from 2008 to 2020, involving both annual and quarterly rebalancing. Consequently, the study considered 42 assets that were present from the outset of the sample period. The results echoed those of Samsonescu et al. (2016) in the Brazilian market, demonstrating that portfolios exhibiting minimum variance outperformed the Colombian benchmark.

2.3. Application of CAPM and F&F factor models in Latin America

A paper pertaining to pricing models in the Brazilian market include studies by Chague (2007) and Paiva Martins Teixeira et al. (2022), both of which examined the CAPM model in the Brazilian context. In the first paper, the author employed two methods to derive the coefficients: the Generalized Method of Moments (GMM) and Iterative Nonlinear Seemingly Unrelated Regression Estimation. The results presented a nuanced conclusion. The author focused on the Bovespa (IBOV) stock market index, as it represented the most liquid assets, with data spanning from January 1999 to August 2006. The risk-free rate considered was the Selic Interest rate. A primary finding was that this index did not exhibit a size effect; the disparity in returns between small and large companies was negligible. However, the data revealed a notable value factor, where the contrast between high and low book-to-market portfolios demonstrated a significantly positive return. In addition to the IBOV, other market portfolios examined included the Morgan Stanley Capital International for Brazil (MSCI – Brazil) and an index comprising all stocks in their database. The analysis, as determined by the GRS Test, indicated that alphas on portfolios based on book-to-market characteristics, in both the CAPM and Fama and French models, were not statistically significant. Nonetheless, the alphas exhibited an increasing trend from the lowest to the highest book-to-market portfolio, indicating the presence of a value factor in the Brazilian market.

In the second paper, the authors employed Local CAPM, Local Adjusted CAPM, and Hybrid Adjusted CAPM. As highlighted by Neto et al. (2008), "the substantial concentration of the Brazilian stock market in a few companies, along with the limited volume of common shares in market transactions, renders any attempt to work with betas obtained from the Brazilian stock exchanges invalid." Consequently, the authors opted for the models mentioned above. In these models, the CAPM was upgraded with a country risk component which enhance the results obtained.

In Machado et al. (2017), the researchers conducted a comprehensive examination of the applicability of both the CAPM and the Fama and French (2015) five-factor model to the Brazilian Stock Market. Their analysis led them to favor Keene and Peterson's (2007) five-factor model, which includes a crucial liquidity factor tailored for the Brazilian market (Machado & Medeiros, 2011). The dataset spanned from June 1997 to June 2014, as data before 1995 exhibited distortions due to high inflation and a lack of currency standardization. Their primary finding indicated that portfolios based on Value, Momentum, and liquidity, albeit to a lesser extent, displayed significance, aligning with the outcomes of Rouwenhorst (1999). Conversely, portfolios based on Size, profitability, and Investment were not found to be statistically significant. Notably, portfolios based on Book-to-Market (B/M) ratios yielded a counterintuitive result, with the highest B/M portfolio demonstrating lower returns compared to the portfolio with the lowest B/M ratio. Importantly, the five-factor model proposed by Keene and Peterson (2007) emerged as the most suitable in explaining returns, incorporating a liquidity factor while basic CAPM and Fama and French 3 factor models, were not suitable for this market.

Turning to the rest of the economies, Firacative (2015) applied the CAPM to the MILA (Mercado Integrado Latino Americano) stock exchange, which integrates the Peruvian, Chilean, and Colombian stock markets, and since 2014, also the Mexican stock exchange, becoming the largest stock exchange in Latin America. The results indicated that, much like in the case of Brazil, the CAPM model was not applicable, with reasons outlined by the author being a shallow depth of stock markets and scarce data, leading to a failure on many CAPM assumptions. The period analyzed spanned from March 2006 to November 2012. Additionally, the data obtained exhibited non-normality characteristics, which is a departure from one of the assumptions of the CAPM model, as mentioned by Sandoval et al. (2016). The MILA stock exchange has shown an increase in transactions made; however, there is still a lack of understanding about the possible negative impacts like spillovers between economies which could offset the benefits of increased investment access.

In the case of the Mexican stock exchange, Valencia-Herrera (2018) suggested that for the Mexican market, instead of using the basic CAPM model, the international capital asset pricing model (ICAPM) could be more suitable given the exposure of the Mexican economy to world indices. The recurrent periods of instability on this market, changing the sensitivity constantly of these stocks, make the basic CAPM a poor predictor of returns. In addition, the integration of the NAFTA markets, composed of the U.S., Canadian, and Mexican stock exchanges, makes the Mexican market highly susceptible to the movements in these markets, as shown by López-Herrera et al. (2014).

2.4. Hypotheses

The objective of this research is to analyze the present and performance of low volatility portfolios in Latin American markets, considering the region as one large portfolio in US dollars. As detailed previously, findings across the literature vary depending on the approach implemented, especially in Latin American economies which are quite susceptible to changes in assumptions. Given the comments made by Neto et al. (2008) about the scarcity of data points, concentration of stocks, and limited transaction volume in these markets, the data used is highly sensitive to changes. However, these studies algo gave some hints toward an absence of the low volatility anomaly as described and strongly present in developed economies. For instance, in Brito (2017), in the Brazilian market when the author considered the top 100 most liquid stocks, the results were inconclusive, in favor of the most volatile portfolio which outperform the less volatility one, even without considering a build approach as in Blitz. et al (2013) where the author formed portfolios-based stocks returns available at each specific period which could have result in an even more favored outcome for the most volatile stocks. In the case of Boudjoukian (2017), the author examined around 97 assets per period, which might be deemed excessive considering the illiquid nature of some companies available in this market for our specific considerations. This is especially relevant as, at the outset of the period, the Brazilian market had considerable fewer highly liquid stocks. Neglecting this consideration could have led to results skewed by small-cap stocks and, consequently, outcomes biased by idiosyncratic volatility, as pointed out by Bali and Cakici (2008). Moreover, the author did not address scenarios in which certain stocks did not trade in a specific month, a common occurrence in this market. An even then, during the 2010 to 2017, the author did not find evidence of a low volatility anomaly in the Brazilian market. In the Colombian case, Viveros (2013) identified a subtle, insignificant, presence of this anomaly in Colombia. Considering these results, our initial step will be to confirm the absent of the low volatility anomaly in these markets. This will be done by employing the approach of Blitz et al. (2007) with a 3-year lookback monthly period returns, and by using the approach of Ang et al. (2006) with a more short-term focus, considering the daily returns of the last month for both Total and Idiosyncratic volatility.

Hypothesis 1: Portfolios characterized by low volatility do not demonstrate superior performance compared to portfolios exhibiting the highest volatility.

Hypothesis 2: Portfolios characterized by low volatility do not demonstrate superior risk-adjusted performance compared to portfolios exhibiting the highest volatility.

Another important aspect of the low volatility anomaly, which was identified in previous studies, is the outperformance of low volatility portfolios in comparison with a country benchmark. As in Samsonescu et al. (2016), portfolios based on low volatility obtained an annualized return of 23.72% while the IBOV index an annual return of 15.10%. In the case of the Colombian market, Amorocho (2023) main conclusion is that portfolios with minimum variance constructed as in Clarke. et al (2006), outperform the Colcap index, the main benchmark in this market. However, one limitation of this paper, is its inclusion of a considerable number of highly illiquid stocks in the construction of low volatility portfolios, without detailed consideration of periods when specific stocks experienced no trading activity. These returns could have been driven by many small caps and could have been deeply offset by high transaction costs. Nevertheless, and based on these findings, it is expected that these low volatility portfolios based on the most liquid stocks of each market could have outperformed the main benchmarks in this region.

Hypothesis 3: Low volatility portfolios outperform the Bovespa, S&P BMV LPC, and S&P 500 when returns are evaluated in US dollars.

Lastly, one important feature of the Latin American stock markets is the illiquidity, scarcity of stocks, and the fact that they are under-diversified. These characteristics put the basic assumptions of the CAPM model to the test. The results from previous studies suggest that both CAPM and Fama and French models are not suitable for pricing stock returns in these markets. In Chague (2007), the analysis, as determined by the GRS Test, indicated that alphas on portfolios based on book-to-market characteristics in both the CAPM and Fama and French models were not statistically significant. In Teixeira et al. (2022), the authors had to use enhanced CAPM models to obtain better results, but still, the results were not significant. As mentioned by Neto et al. (2008), 'the substantial concentration of the Brazilian stock market in a few companies, along with the limited volume of common shares in market transactions, renders any attempt to work with betas obtained from the Brazilian stock exchanges invalid. In Firacative (2015), the results for MILA (Colombia, Chile and Peru) indicated that, much like in the case of Brazil, the CAPM model was not applicable, with possible reasons outlined by the author being a shallow depth of stock markets and scarce data, leading to a failure on many CAPM assumptions like normality. In the Mexican market, Valencia-Herrera (2018) proposed an enhanced CAPM model given the constant instability of this market. Finally, in Blitz et al. (2013), alphas for Latin American economies were not significant, which led to the belief that CAPM and F&F models are not the best option to assess and price stocks from these markets.

Hypothesis 4: Alphas derived from both 1-factor and 3-factor models for portfolios returns sorted by volatility, do not exhibit statistically significant deviations from zero.

Overview of main related papers

Author	Paper	Market	Time Period	Data	Hypothesis	Main findings
Clarke, R., De Silva, H. & Thorley, S. (2006)	Minimum-Variance Portfolios in the U.S. Equity Market	United States	1968-2005	Stock returns (1000 largest stocks).	Minimum variance portfolios add value compared to the market-capitalization weighted benchmark.	Minimum variance portfolios achieved lower volatility while delivering higher average returns than the market portfolio.
Ang, A., Hodrick, R., Xing, Y. & Zhang, X. (2006)	The cross-section of volatility and expected returns	United States and G7 markets	1963-2000	US stock returns from data providers.	Portfolios sorted on IVOL will yield no difference in average returns.	Stocks with high IVOL presented significant lower average returns, even after controlling by several factors.
Blitz, D., & Van Vliet, P. (2007)	The Volatility Effect: Lower Risk without Lower Return	United States, EU, and Japan	1986-2006	Stocks returns from FTSE World Developed index (large-cap stocks).	Low volatility portfolios yield high risk-adjusted returns.	Low volatility portfolios outperform the most volatile ones, even after controlling by size and value.
Rouwenhorst, K.G. (1999)	Local returns factors and turnover in emerging markets	Emerging Markets	1982-1997	Stocks returns from International Finance Corporation (IFC).	High beta stocks outperform low beta stocks.	Beta was not significantly associated with average returns.
Blitz, D., Pang, J., and van Vliet, P. (2013)	The volatility effect in emerging markets	Emerging Markets	1988-2010	Stocks returns from S&P/IFC Investable Emerging Markets Index.	Low volatility portfolios yield high risk-adjusted returns.	Flat or even negative relationship between risk and returns in emerging markets. 1 factor model alphas for Latin American economies were not significant.
Samsonescu, J. A. D., Morais, I. A. C., & Macêdo, G. R. (2016)	Carteiras de baixa volatilidade podem apresentar retornos elevados? Uma análise no mercado de ações brasileiro. In XLIIIEncontro Nacional de Economia.	Brazil	2003-2013	Stocks returns from Ibovespa.	Low volatility portfolios outperform the local benchmark return.	The average returns in the low volatility portfolio significantly exceed the returns of the Ibovespa index. This is achieved by considering only a fixed 17% of stocks at each period, along with a 4-month rebalancing framework.
Boudjoukian França, L. (2017)	Avaliação de ativos de baixa volatilidade no mercado brasileiro: menor risco com maiores retornos	Brazil	2003-2007	Stocks returns from IBrX which tracks the top 100 largest assets in this market.	Low volatility portfolios outperform high volatility portfolios.	By considering a fixed number of stocks (100) and the daily return volatility of the last year, the low volatility portfolio outperformed the high volatility portfolio. However, during 2010 – 2017, there was no evidence of the low volatility anomaly.
Brito, P. V. D. S. (2017)	A anomalia da baixa volatilidade no Brasil.	Brazil	2000-2017	Stocks returns from Bovespa (IBOV).	Low volatility portfolios outperform high volatility portfolios.	When considering the top 100 most liquid stocks, the most volatile stocks outperformed the low volatility portfolio by a small margin.

Amorocho, A. A. (2023)	Anomalía del portafolio de mínima varianza del mercado de valores colombiano.	Colombia	2008-2020	Stocks from Colcap and Colombian stock exchange.	Minimum variance portfolios add value compared to the market-capitalization weighted benchmark.	The portfolios, constructed using the minimum variance methodology as outlined by Clarke et al. (2006) and rebalanced annually, exhibited superior performance compared to the returns of the Colcap index.
Firacative Ropero, E. F (2015)	Aplicación del modelo CAPM para la valoración de acciones en el mercado integrado latinoamericano MILA	Chile, Colombia and Perú	2006-2012	Stock returns from IGBC, IGBVL and IPSA	The CAPM model prices MILA stocks returns.	The CAPM model is deemed invalid in this context, attributed to the limited depth of these markets, scarcity of reliable information sources, and violations of certain model assumptions, such as the normality of returns.

3. DATA AND METHODOLOGY

In this section, we will first present the data utilized for this research, including essential statistical descriptive measures. Following this, we will outline the proposed portfolio construction methodology, along with detailing the regression models to be employed in subsequent stages.

3.1. Data

To conduct this research, we utilized data encompassing stock returns, market capitalizations, and equity book values from 211 companies listed on Latin American stock exchanges. These companies represent the most liquid stocks within these markets. The sample period extends from 2003 to 2023, and the data was procured from DataStream and Economatica. In the Brazilian market, we focused on stocks that comprised the Bovespa Index in June 2023, amounting to a total of 83 companies. In the Mexican market, due to its relatively high liquidity and ample availability of information, we selected the top 48 largest companies from the entirety of Mexican stock exchanges as of June 2023. For the remaining countries, we assembled the universe of stocks from the primary indexes of each respective country. This included the S&P Merval for Argentina, S&P BVL Lima 25 for Peru, MSCI Colcap index for Colombia, and S&P IPSA CLP index for Chile. This meticulous selection process culminated in the inclusion of 80 companies for our comprehensive analysis. The selection of the largest and most liquid stocks in the entire region addresses a key issue, as highlighted by Bali and Cakici (2008) and Blitz et al. (2013), concerning a potential size effect. This selection consequently helps to mitigate potential liquidity biases as well. Finally, the selected stocks have been active since the beginning of the sample period, which may introduce some survivorship bias into the results.

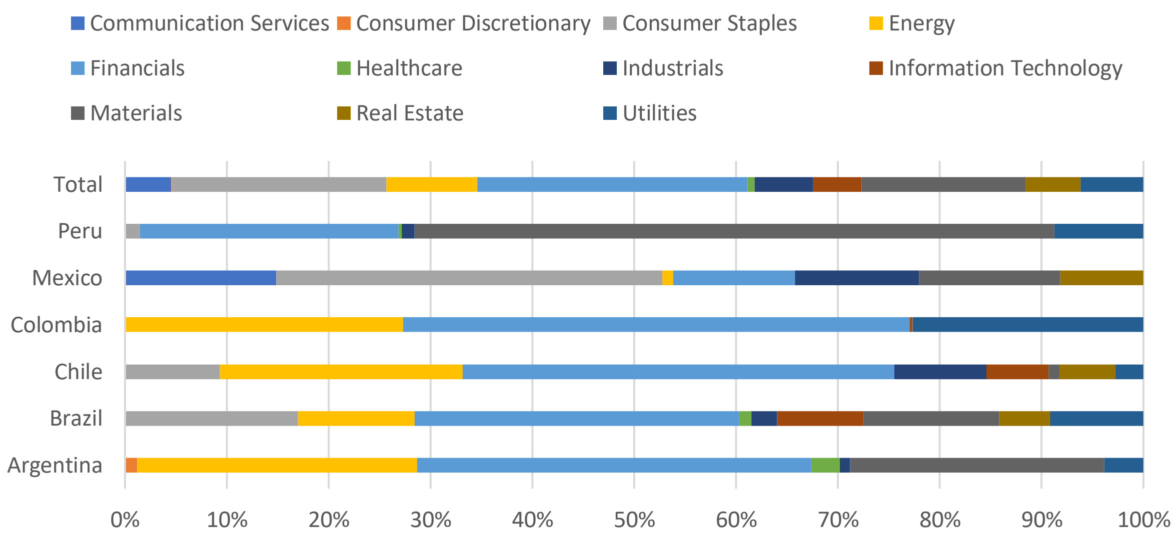
Table 1: Description of sample data by country

Country	Number of Companies	% Total	Market Cap (USD millions)	% Total	Avg. Size (USD millions)
Argentina	18	8.41%	34,755,420	2.15%	2,044,436
Brazil	83	38.79%	834,417,270	51.63%	10,053,220
Chile	24	11.21%	100,347,695	6.21%	4,181,154
Colombia	13	6.07%	37,398,697	2.31%	4,155,411
Perú	25	13.08%	114,011,248	7.05%	4,560,450
México	48	22.43%	495,255,788	30.64%	10,317,829
Total	**211**	**100.00%**	**1,616,186,119**	**100.00%**	

In Table 1, we can see that the total value of the chosen stocks for this study is about 1.6 trillion US dollars as of June 2023. The two largest economies, Brazil and Mexico, make up about 80% of the total worth. Brazil's market alone makes up nearly half of the total, with 83 carefully chosen companies. Even though we are only looking at a small number of stocks from the other countries, these stocks still represent a big part of their markets.

In Figure 1, utilizing the Global Industry Classification Standard (GICS), a comprehensive breakdown of industry exposure by both sector and country is depicted. One noteworthy insight gleaned from this illustration pertains to the three predominant industries across these markets: Consumer Staples, Financials, and Materials. The leading sector, Financials, is prominently featured in most economies, constituting a substantial percentage of companies within their respective markets. Following closely is the Consumer Staples sector, with the Mexican Market serving as a focal point and Walmart Mexico's branch emerging as the preeminent player in this domain. Lastly, the mining industry emerges as a significant player, with countries like Peru serving as a pivotal reference point and Southern Copper standing out as the foremost representative within this sector.

Figure 1: Industry sector by country



As shown in Figure 2, the number of companies in this stock exchange has increased since the beginning of our sample period. However, as of today, the market is still highly concentrated, with the top 5 companies holding 20% of the total market cap, whereas at the onset of the sample period, it was around 27%.

Figure 2: Number of companies with historical returns

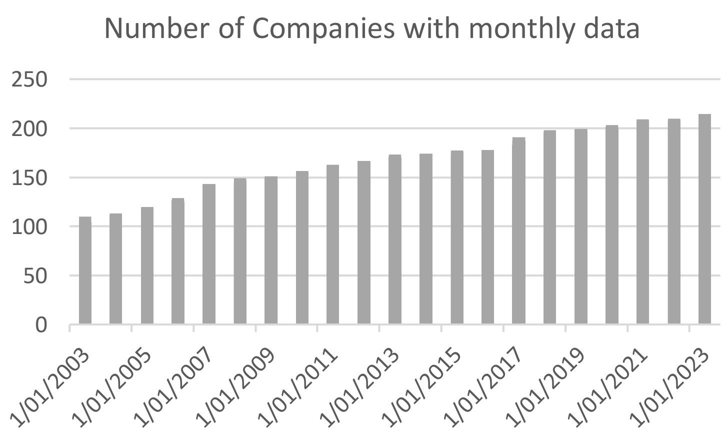


Table 2: Main statistics of Latin American Markets

Characteristic (In US dollars)	Year / Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Average Monthly Gross Returns	Argentina	5.73	(2.63)	(1.39)	4.50	4.28	3.08	2.65	5.01	(5.23)	2.79	1.17	3.20	3.02	6.35
	Brazil	1.63	(0.54)	2.20	0.24	(0.10)	(0.88)	3.71	3.09	1.47	4.01	2.51	(0.64)	(0.47)	2.76
	Chile	4.25	(1.77)	1.11	(1.54)	(1.27)	(1.33)	1.98	3.39	(1.51)	(0.74)	(0.01)	(1.34)	2.74	4.12
	Colombia	4.25	(0.76)	1.40	1.35	0.16	(0.29)	2.19	0.87	- 0.59	1.39	- 0.29	4.23	- 0.26	- 0.46
	Peru	5.23	(1.00)	1.69	- 1.63	(0.29)	(3.98)	5.21	3.00	- 0.93	0.60	0.21	1.58	1.14	1.27
	Mexico	1.89	0.54	3.23	1.33	0.62	0.53	1.28	0.76	- 0.40	0.96	1.14	2.27	1.01	1.74
Average Monthly Volatility	Argentina	11.52	10.21	11.48	17.16	14.24	16.53	10.46	8.65	15.57	23.81	20.21	12.24	12.84	14.43
	Brazil	7.70	7.88	8.64	8.09	8.92	10.63	13.01	8.27	10.29	8.86	15.00	9.43	11.09	11.18
	Chile	6.14	9.67	6.93	6.54	6.37	7.32	6.80	7.79	6.72	10.32	14.69	10.36	17.08	6.87
	Colombia	7.87	9.86	7.59	5.44	9.51	7.70	7.63	6.05	7.94	8.87	17.32	11.71	9.06	8.27
	Peru	9.68	10.26	7.50	8.80	7.36	8.48	12.94	8.08	6.73	6.99	10.63	12.26	11.77	5.81
	Mexico	7.14	6.50	6.24	6.10	5.62	6.03	6.48	5.50	6.77	6.50	11.23	7.50	8.19	6.75
Market Capitalization (In billions)	Argentina	13.00	15.00	10.00	13.00	18.00	26.00	25.00	44.00	40.00	23.00	19.00	20.00	24.00	35.00
	Brazil	1,067.00	1,133.00	978.00	918.00	856.00	554.00	613.00	806.00	841.00	947.00	676.00	810.00	779.00	834.00
	Chile	142.00	155.00	151.00	152.00	125.00	107.00	108.00	137.00	154.00	132.00	87.00	99.00	83.00	100.00
	Colombia	27.00	30.00	32.00	35.00	34.00	25.00	25.00	29.00	32.00	32.00	31.00	43.00	41.00	38.00
	Peru	90.00	97.00	104.00	93.00	85.00	71.00	72.00	96.00	109.00	101.00	91.00	100.00	102.00	114.00
	Mexico	319.00	367.00	398.00	444.00	432.00	376.00	330.00	364.00	353.00	331.00	279.00	369.00	399.00	495.00

Table 2 shows descriptive information for the 6 markets. The information displayed is from 2010 to 2023. Before this period the number of returns available per country were not significant. Average monthly gross returns and Market capitalization are in US dollars.

In Table 2, the average monthly returns per year and per country are presented. Regarding returns, most economies exhibited high rates at the close of the 2010 period. This surge was a consequence of the robust rebound in GDP growth across most Latin American economies following the 2008 financial crisis. However, over the last decade, returns have stabilized, with some even approaching zero. In recent years, there has been a significant reduction in turnover across these economies, accompanied by limited liquidity, and movements driven more by momentum or political events. This is evident in the diminished returns in the same period. In terms of volatility, the Argentine market stood out as the most volatile, attributed to the economic challenges faced by these economies, including high inflation rates. In contrast, the Mexican market boasts the most stable economic conditions. As for market capitalization, most economies have experienced an uptick, mirroring the growth in GDP within these regions.

In Figure 3, we can observe the relationship between return and risk over the past 17 years, with the Argentine market displaying the highest volatility in the last 6 years, followed by the Colombian and Chilean markets, indicating a weakness in these markets during recent years as well. On the other hand, the Mexican market has shown a more stable risk-return relationship since the beginning of the sample period, demonstrating the high liquidity in these markets compared to the rest of the countries.

Figure 3: Monthly returns and volatilities from 2006 to 2023

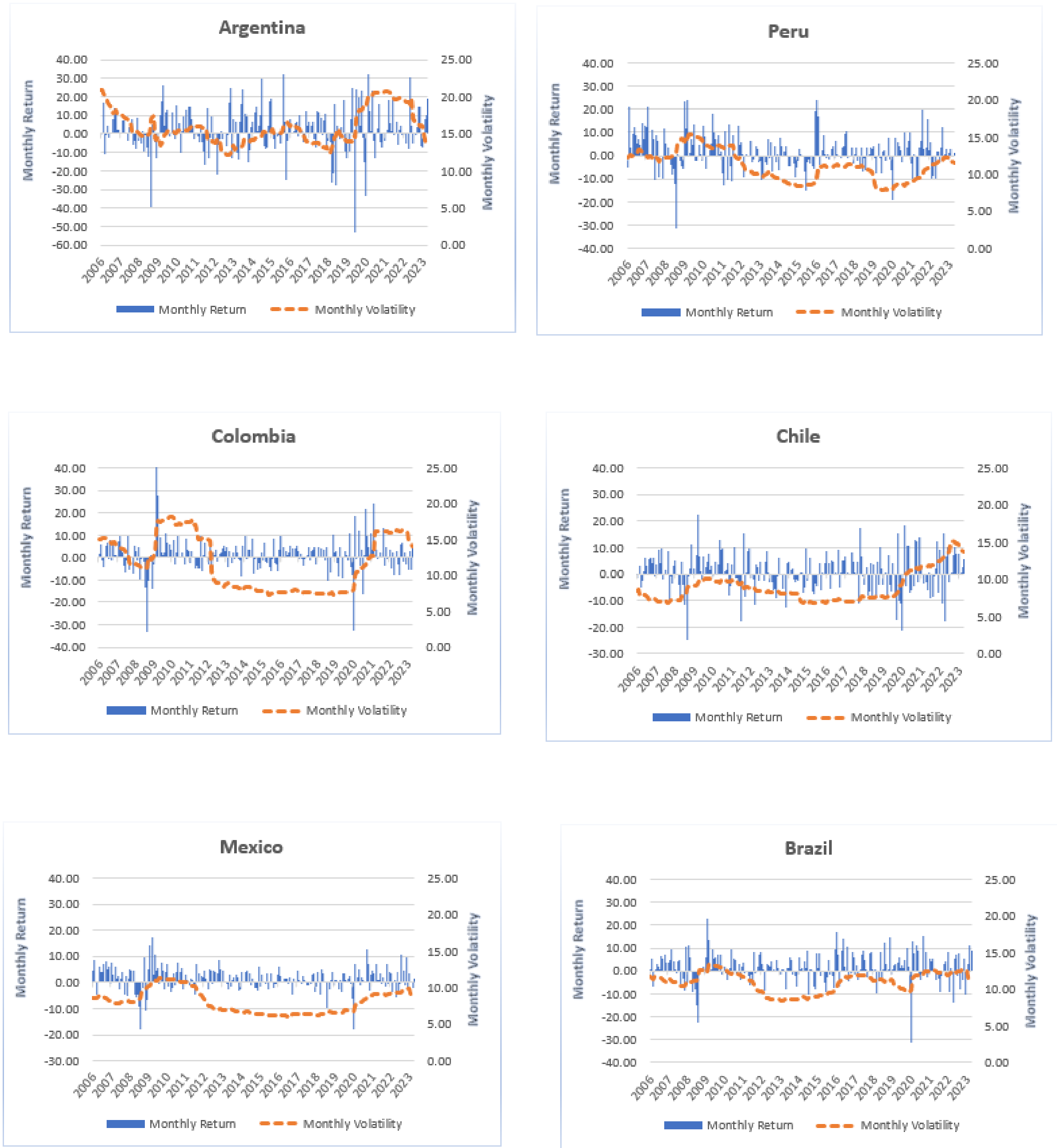
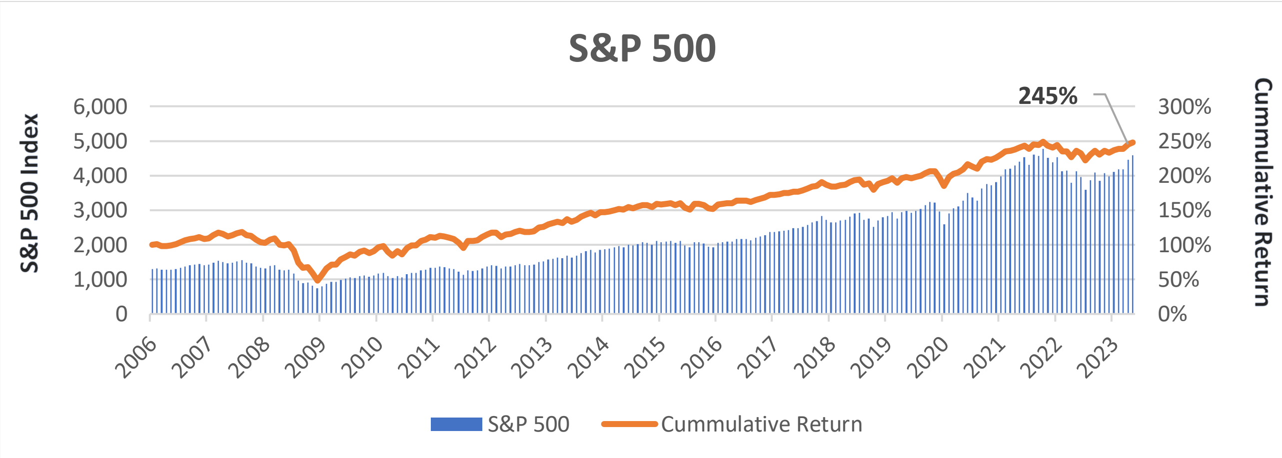
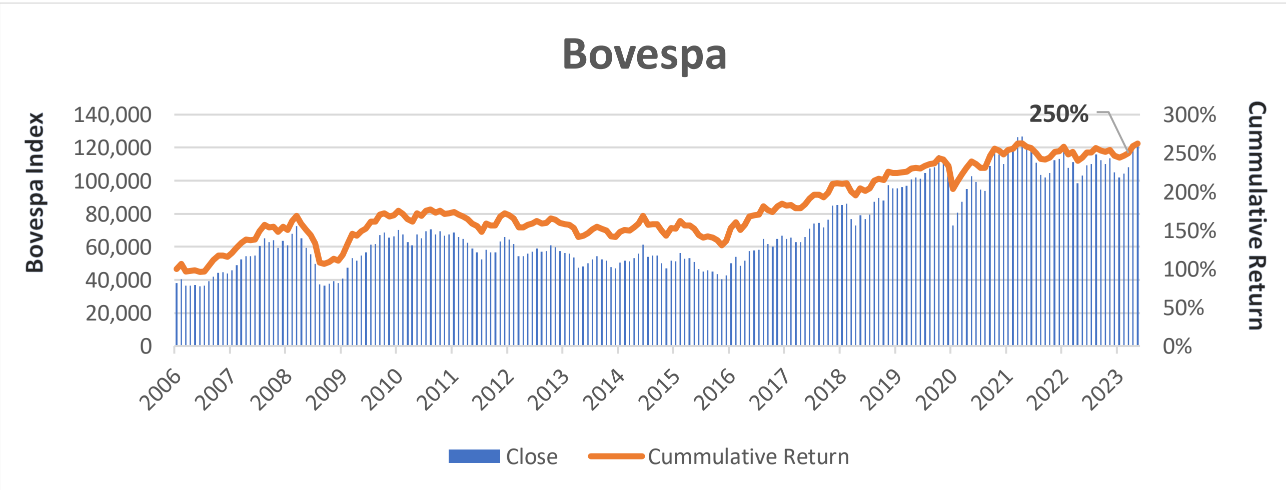


Figure 3: Plot of historical monthly returns and volatilities. The left y-axis represents the monthly return, while the right y-axis represents the monthly volatility. The sample period spans from March 2006 to June 2023.

In Figure 4, the trends in the main indexes within these markets are depicted. Firstly, we have the S&P 500, serving as the base for calculating the market factor. Additionally, we observe the Bovespa and the S&P BMV LPC representing the Brazilian and Mexican markets, respectively. Examining the cumulative returns from 2006 to 2023, the Bovespa index has shown the highest cumulative returns, boasting an impressive 250% increase over this period. In contrast, the Mexican index has displayed the lowest return, accumulating to 227%. Meanwhile, the S&P 500 has demonstrated an accumulated return of 245%.

Figure 4: Returns and cumulative returns for the main indexes from 2006 to 2023.





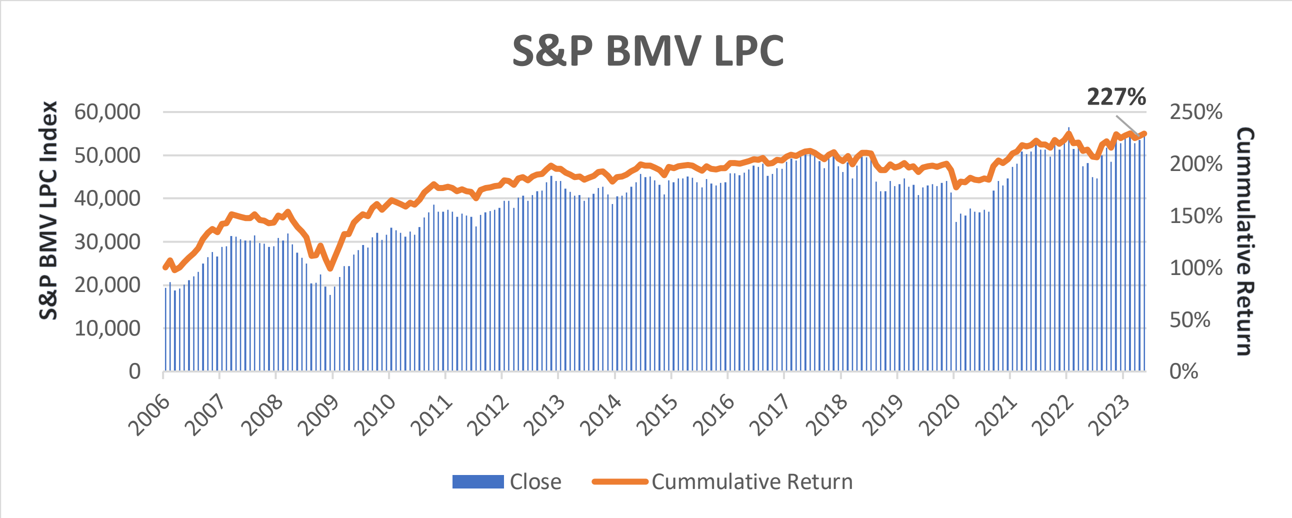


Figure 4: Plot of historical monthly returns and accumulated returns of each Index. The left y-axis represents the monthly return of each index, while the right y-axis represents the cumulative return. The sample period extends from March 2006 to June 2023.

3.2.Methodology

The long-term volatility as in Blitz et al. (2012) will be based on the monthly volatility of returns of the last 36 months (3 years) and only if the stock has traded at least in 5 months in the last 36 months. Given the limited trading of these stocks, some of them only traded in less than 5 months, and consequently they will not be considered in the sample to form part of the quintile's portfolios. For the daily volatility (short term) the analysis will be based on the daily volatility of the last month (22 working days) and in addition the approach by Ang. et al (2006), which is the idiosyncratic volatility after controlling by beta, size, and value factors. For the short-term volatility, the holding period will be one month and as in the case of the long-term volatility, it will only be considered those stocks that trade in at least 5 days of the month.

For the analysis, the S&P 500 index will be the proxy for the market factor return while the US Treasury 1 month interest rate is the risk-free rate, and all stocks will be equal weighted.

For both types of volatilities (long and short term), stocks will be grouped into five portfolios. They will be sorted from the lowest to the highest volatile stocks. Therefore, in the first quintile the less volatile stocks will be grouped while in the last quintile the most volatile ones. Even considering the most liquid stocks from each stock exchange some stocks did not trade during some months; therefore, the portfolios will be formed considering only stocks with returns as described above. For each quintile portfolio at the end of each month I will obtain the arithmetic mean return and then compare the average time series between portfolios. Average returns, standard deviations, Sharpe ratios, alphas, CAPM betas and Fama and French 3 factor model alphas will be compared.

As in the case of low volatility, size portfolios will be sorted from the smallest market cap stocks to the highest at each end of the month and then split them into quintile portfolios. The same principle will be applied to the value strategies by sorting portfolios based on Book to Market (B/M) ratios, where the first portfolio is composed of high B/M value stocks and in the last quintile those with the lowest ratio. Size and Value factors are constructed by a long position in the first quintile and a short position in the last quintile. Table 3 reveals a notable prevalence of size and value anomalies. Regarding size, quintile 1, comprised of the smallest market capitalization stocks, yielded an average monthly return of 2.38%, whereas the last quintile recorded 0.80%. A similar trend is observed with value, where the first quintile, consisting of high book-to-market ratio stocks, achieved an average monthly return of 2.03%, in contrast to the last quintile which saw 1.32% returns.

Table 3: Portfolios sorted by Size and Value

Country	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Size	2.38	1.43	1.34	0.96	0.80

Value	2.03	1.31	1.21	1.07	1.32

Table 3 displays the average monthly returns of portfolios categorized by Size and Value. Size-based portfolios are arranged from the smallest Market Cap to the largest Market Cap, where portfolio 1 represents returns from small stocks and portfolio 5 from large stocks. In the case of sorting by Value, portfolio 1 represents stock returns with the highest B/M ratio, while portfolio 5 represents stocks with the lowest B/M ratio.

The portfolios formed by quintiles of long- and short-term volatility, as well as IVOl, will be subjected to testing using the two primary models in asset pricing: the Capital Asset Pricing Model (CAPM) and the Fama and French 3-factor model.

$$\boldsymbol{E(Ri) = Rf + B * (E(Rm) - Rf)} \tag{1}$$

$$\boldsymbol{Ri = Rf + B * (E(Rm) - Rf) + S * SMB + H * HML + e} \tag{2}$$

The GRS-test is used to test whether the intercepts in a set of linear time-series regressions are jointly equal to zero. Using the OLS estimates, one can test the null hypothesis that αi = 0 ∀ i. If the disturbances are temporally independent and jointly normal, with mean zero, Gibbons, Ross and Shanken (1989) suggest using the following statistics:

$$\boldsymbol{GRS = \left(\frac{T}{N}\right)\left(\frac{T-N-K}{T-K-1}\right)\left[(\hat{\alpha}^{I}\hat{\Sigma}^{-1}\hat{\alpha})/(1+\hat{u}_f^{1}\hat{\Sigma}_f^{-1}\hat{u}_f)\right] \sim F(N, T-N-K)} \tag{3}$$

Where:

$\hat{\alpha}$ is an N x 1 vector of constants estimated by either equation 1 or 2.

$\hat{\Sigma}$ is an N x N residual covariance matrix.

$\hat{u}_f$ is a K x 1 factor means; and

$\hat{\Sigma}_f$ is a K x K factor covariance matrix.

Due to the CAPM's demonstrated inadequacy in explaining variations in cross-sectional returns, and given the prevalent adoption of the FF-3 model in applied financial analyses, as noted by Ang et al. (2006), these researchers advocated for the incorporation of IVOL, defined as:

$$\boldsymbol{r_t^i = \alpha^i + B_{MKT}^i MKT + B_{SMB}^i SMB_t + B_{HML}^i HML_t + \varepsilon_t^i} \tag{4}$$

where $\sqrt{Var_\varepsilon}$ is the idiosyncratic volatility.

Finally, in line with Blitz et al. (2007), the Jobson and Korkie test will be employed to assess the statistically significant disparities in Sharpe ratios among portfolios. Should the z-score exceed 1.645, this test will assert, at a 5% significance level, that the Sharpe ratios are indeed distinct.

$$\boldsymbol{z = \frac{(SR_i - SR_j)}{\sqrt{V}}} \tag{5}$$

$$\boldsymbol{V = \frac{1}{T}[2\sigma_i\sigma_j - 2\sigma_i\sigma_j\sigma_{ij} - \frac{1}{2}u_i^2\sigma_j + \frac{1}{2}u_j^2\sigma_i - \frac{u_i u_j}{\sigma_i\sigma_j}\sigma_{ij}^2} \tag{6}$$

Where:

V is the variance of the Sharpe ratio difference

T is the number of returns.

σ_i and σ_j are the standard deviations of portfolio i and j.

σ_{ij} is the covariance.

u_i and u_j are the average returns of portfolio i and j.

4. EMPIRICAL RESULTS

In this section, I will present the results of sorting portfolios as previously outlined: first by long-term volatility, followed by the short-term approach, and lastly, employing the IVOL methodology. These three sets of results will be subjected to testing using the proposed models. Additionally, the returns derived from the lowest volatile portfolios will be compared against the main benchmarks of the region. Finally, the significance of the alphas obtained will be analyzed using the GRS test and the normality of the data. With these three sets of results, we will address the four hypotheses presented in the second chapter.

4.1.Long term Volatility

The long-term volatility is computed based on the preceding 36 monthly returns. As illustrated in Table 4, the portfolio with the lowest volatility achieved an average monthly excess return of 0.98%, while the last quintile yielded 2.04%. Regarding Sharpe ratios, no significant disparity was observed between quintile 1 and 5. Comparatively, when juxtaposed with the market factor (S&P 500 minus 1-month US Treasury rate), the lowest volatile portfolio not only outperformed in risk-adjusted terms but also in terms of average gross monthly returns. These results present mixed conclusions in comparison with Blitz et al. (2013), Boudjoukian (2017), and Brito (2017). In the first case, the authors found that the last quintile had the highest volatility but with a lower return. In our case, the higher the risk, the higher the return obtained. Portfolio 5, for instance, has a monthly volatility of 8.82, whereas the first quintile has a lower return of 4.38 despite its lower risk. In the case of Boudjoukian (2017) for the period 2010 and 2017, the author also did not find a low volatility anomaly despite using a fixed number of stocks returns per period which could have led to misleading results. Lastly, in Brito (2017), the author found that considering the top 100 most liquid stocks of the Brazilian market, the highest volatile portfolio outperformed the low volatile ones, which is the same result we obtained in this research.

Table 4: Portfolios based on long term volatility

Portfolios	Obs	Mean	Std. Dev.	Sharpe Ratios
Portfolio1 LT	208	0.979	4.383	0.223
Portfolio2 LT	208	1.063	5.062	0.210
Portfolio3 LT	208	1.158	6.347	0.182
Portfolio4 LT	208	1.375	7.272	0.189
Portfolio5 LT	208	2.044	8.821	0.232
Market Factor	208	0.609	4.491	0.136
J&K Test				0.02

In Table 5, Panel A presents the key findings from the 1-factor model. Across all portfolios, the alphas exhibited significant deviations from zero at the 10% significance level. Notably, the highest volatility quintile also recorded the highest beta along with the highest CAPM alpha. In this context, quintile 5 achieved an alpha of 1.33, while the first quintile attained 0.583. In Panel B, we delve into the results obtained from the 3-factor model. In this model, only the alpha for the first quintile exhibited slight significance, however just at the 10% significance level. This could potentially be attributed to the presence of a value factor or size factor inherent in these low volatility portfolios. Scherer (2010) posited that the alphas in the US market, when comparing low volatility to high volatility portfolios, are primarily influenced by a Value effect. However, Blitz et al. (2013) discovered that for low volatility portfolios, the alphas from both 1 and 3 factor models were comparable, suggesting a distinct anomaly. This previous observation differs from results of this research, where the disparity in alphas in the 1-factor model favors the most volatile portfolio (0.74), while in the 3-factor model, it leans towards the less volatile one (-0.27), with all alphas lacking statistical significance. One plausible explanation could be the limited data availability from these markets two decades ago, coupled with their highly illiquid nature, which might have influenced the findings in Blitz et al. (2013). Lastly, Table 6 presents the outcomes of the GRS test, indicating that the alphas did not exhibit a significant difference from zero.

Table 5: OLS Regressions on portfolios sorted by long term volatility

Panel A: 1 Factor model	(1)	(2)	(3)	(4)	(5)
	Portfolio1_LT	Portfolio2_LT	Portfolio3_LT	Portfolio4_LT	Portfolio5_LT
Market Factor	.651***	.779***	.92***	1.069***	1.173***
	-0.051	-0.057	-0.075	-0.085	-0.11
_cons	.583**	.589**	.598*	.724*	1.33***
	-0.229	-0.257	-0.338	-0.383	-0.496
Observations	208	208	208	208	208
R-squared	0.444	0.478	0.423	0.435	0.357

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Panel B: 3 Factor model	(1)	(2)	(3)	(4)	(5)
	Portfolio1_LT	Portfolio2_LT	Portfolio3_LT	Portfolio4_LT	Portfolio5_LT
Market Factor	.636***	.749***	.87***	1.009***	1.073***
	-0.05	-0.054	-0.068	-0.076	-0.091
Size Factor	0.063	.156***	.253***	.336***	.621***
	-0.05	-0.054	-0.068	-0.076	-0.091
Value Factor	.098*	.16***	.271***	.281***	.365***
	-0.053	-0.057	-0.072	-0.08	-0.096
_cons	.422*	0.247	0.034	0.029	0.15
	-0.236	-0.253	-0.319	-0.358	-0.426
Observations	208	208	208	208	208
R-squared	0.466	0.541	0.534	0.553	0.57

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 5, Panel A, presents the regression results for the 1-factor model. The market factor is derived from the excess return of the S&P 500 above the 1-month US Treasury rate. Portfolio1_LT comprises portfolios composed of stocks with the lowest long-term volatility, whereas Portfolio5_LT comprises portfolios with the highest long-term volatility. In Panel B, the results for the 3-factor model are displayed. The Size factor is calculated from the returns of small-cap stocks minus big-cap stocks, and the Value factor is determined from the returns of high book-to-market (b/v) stocks minus low b/m stocks returns.

Table 6: GRS Test Results LT Volatility

Variable	
Number of Obs.:	208
Number of Asset:	5
Number of Factor:	3
Results	
GRS_F-test = 1.171761	
GRS_pvalue = 0.324362	

4.2. Short term Volatility

The short-term volatility is computed based on the daily returns of the past month. As illustrated in Table 7, and consistent with the approach used for long-term volatility, the first quintile yielded a lower return compared to the last quintile, which encompasses the most volatile stocks. Portfolio 1 achieved an average monthly excess return of 1.164%, while portfolio 5 recorded 1.59%. In terms of risk-adjusted performance, Portfolio 1 outperformed Portfolio 5, but the results from Jobson and Korkie of 0.12 indicated no statistical differences in Sharpe ratios. In relation to the market factor, the less volatile portfolio exhibited superior average returns and Sharpe ratios. Notably, in this case, based on short-term volatility, the lowest volatile portfolio garnered better results compared to the long-term volatility approach both in average returns and in Sharpe ratios.

Table 7: Portfolios based on Short-term volatility

Variable	Obs	Mean	Std. Dev.	Sharpe Ratios
Portfolio1 ST	208	1.164	4.985	0.234
Portfolio2 ST	208	1.183	5.052	0.234
Portfolio3 ST	208	1.053	5.996	0.176
Portfolio4 ST	208	1.398	6.966	0.201
Portfolio5 ST	208	1.59	8.2	0.194
Market Factor	208	0.609	4.491	0.136
J&K Test				0.12

Table 8: OLS Regressions on portfolios sorted by Short-term volatility

Panel A: 1 Factor model	(1)	(2)	(3)	(4)	(5)
	Portfolio1_ST	Portfolio2_ST	Portfolio3_ST	Portfolio4_ST	Portfolio5_ST
Market Factor	.743***	.775***	.89***	1.003***	1.044***
	-0.057	-0.057	-0.069	-0.082	-0.104
_cons	.712***	.711***	0.511	.787**	.955**
	-0.26	-0.257	-0.314	-0.373	-0.472
Observations	208	208	208	208	208
R-squared	0.448	0.474	0.444	0.418	0.327

Standard errors are in parentheses

*** $p<.01$, ** $p<.05$, * $p<.1$

Panel B: 3 Factor model	(1)	(2)	(3)	(4)	(5)
	Portfolio1_ST	Portfolio2_ST	Portfolio3_ST	Portfolio4_ST	Portfolio5_ST
Market Factor	.712***	.744***	.851***	.955***	.945***
	-0.055	-0.054	-0.065	-0.076	-0.085
Size Factor	.208***	.168***	.211***	.208***	.617***
	-0.055	-0.054	-0.065	-0.076	-0.085
Value Factor	0.086	.148***	.195***	.324***	.355***
	-0.058	-0.057	-0.069	-0.08	-0.089
_cons	0.342	0.358	0.061	0.256	-0.212
	-0.257	-0.253	-0.306	-0.358	-0.398
Observations	208	208	208	208	208
R-squared	0.51	0.538	0.519	0.513	0.567

Standard errors are in parentheses

****p<.01, **p<.05, *p<.1*

Table 7, Panel A, presents the regression results for the 1-factor model. The market factor is derived from the excess return of the S&P 500 above the 1-month US Treasury rate. Portfolio1_ST comprises portfolios composed of stocks with the lowest short-term volatility, whereas Portfolio5_ST comprises portfolios with the highest song-term volatility. In Panel B, the results for the 3-factor model are displayed. The Size factor is calculated from the returns of small-cap stocks minus big-cap stocks, and the Value factor is determined from the returns of high book-to-market (b/v) stocks minus low b/m stocks returns.

In Table 8, Panel A presents the findings from the 1-factor model. Once again, all portfolios significantly yielded alphas, mirroring the outcomes observed in the long-term scenario, apart from portfolio 3. Quintile 5 emerged with the highest alpha, boasting an excess return over the market factor of 0.95. Additionally, the highest volatility portfolio again garnered the highest beta. This outcome suggests that in these markets, higher risk is associated with higher returns. In Panel B, the results from the 3-factor model reveal that alphas are no longer significant for all portfolios. Despite focusing on the most liquid stocks from these markets, there are indications of a potential small size and/or value effect in the highly volatile portfolios, leading to an alpha lower than that of the less volatile ones. Table 9 displays the results from the GRS test applied to the 3-factor model with a p value of 0.32, showing that alphas from all portfolios were not significantly different from zero.

Table 9: GRS Test Results ST Volatility

Variable	
Number of Obs.:	208
Number of Asset:	5
Number of Factor:	3
Results	
GRS_F-test = 1.171761	
GRS_pvalue = 0.324362	

4.3. Idiosyncratic Volatility (IVOL)

As defined in equation 4, IVOL represents the volatility of the residual after controlling for the F&F 3-factor model. Table 10 displays the results from sorting portfolios by IVOL. Similar to previous scenarios, portfolio 1, comprising the lowest IVOL stocks, underperformed in returns compared to portfolio 5. In this instance, the first quintile achieved an average monthly excess return of 1.22%, while the last quintile achieved 1.58%.

In terms of risk-adjusted returns, the first quintile achieved a 0.27, whereas the last quintile of 0.14, indicating a slightly presence of IVOL in these markets. However, the Jobson and Korkie test of 0.31 indicates no differences in Sharpe ratios.

Table 10: Portfolios based on IVOL

Variable	Obs	Mean	Std. Dev.	Sharpe Ratios
Portfolio1 IVOL	208	1.219	4.508	0.270
Portfolio2 IVOL	208	1.177	5.095	0.231
Portfolio3 IVOL	208	1.185	5.921	0.200
Portfolio4 IVOL	208	1.223	6.539	0.187
Portfolio5 IVOL	208	1.581	9.25	0.171
Market Factor	208	0.609	4.491	0.136
J&K Test				0.31

A significant finding in this scenario is that among the three methodologies revisited in this research, the IVOL approach yielded the highest mean return and Sharpe ratio for Portfolios 1, as compared to long-term and short-term volatility.

In Table 11, Panel A presents the findings from the 1-factor model. All alphas were significantly different from zero, except for portfolio 5. Additionally, the alpha from portfolio 5 was marginally higher than that of portfolio 1.

In Panel B, the results from the 3-factor model are presented. Similar to the other two methodologies, the alpha from portfolio 1 outperformed that of portfolio 5. However, only the alpha from quintile 1 was marginally significant. In the case of long-term volatility, it only reached the 10% significance level. Coefficients for all portfolios regarding the size and value factor are significant, indicating a more pronounced effect for the most volatile stocks.

Table 11: OLS Regressions on portfolios sorted by IVOL

Panel A: 1 Factor model	-1	-2	-3	-4	-5
	Portfolio1_IVOL	Portfolio2_IVOL	Portfolio3_IVOL	Portfolio4_IVOL	Portfolio5_IVOL
Market Factor	.648***	.805***	.883***	.93***	1.184***
	-0.053	-0.056	-0.068	-0.078	-0.117
_cons	.824***	.687***	.648**	.657*	0.86
	-0.241	-0.252	-0.308	-0.353	-0.531
Observations	208	208	208	208	208
R-squared	0.417	0.504	0.449	0.408	0.331

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Panel B: 3 Factor model	-1	-2	-3	-4	-5
	Portfolio1_IVOL	Portfolio2_IVOL	Portfolio3_IVOL	Portfolio4_IVOL	Portfolio5_IVOL
Market Factor	.612***	.777***	.848***	.884***	1.082***
	-0.049	-0.053	-0.065	-0.073	-0.098
Size Factor	.231***	.179***	.187***	.228***	.589***
	-0.049	-0.053	-0.065	-0.072	-0.098
Value Factor	.118**	0.092	.186***	.265***	.451***
	-0.052	-0.056	-0.068	-0.077	-0.104
_cons	.397*	0.356	0.241	0.135	-0.329
	-0.23	-0.251	-0.304	-0.341	-0.462

Observations	208	208	208	208	208
R-squared	0.521	0.553	0.513	0.5	0.539

Standard errors are in parentheses

**** $p<.01$, ** $p<.05$, * $p<.1$*

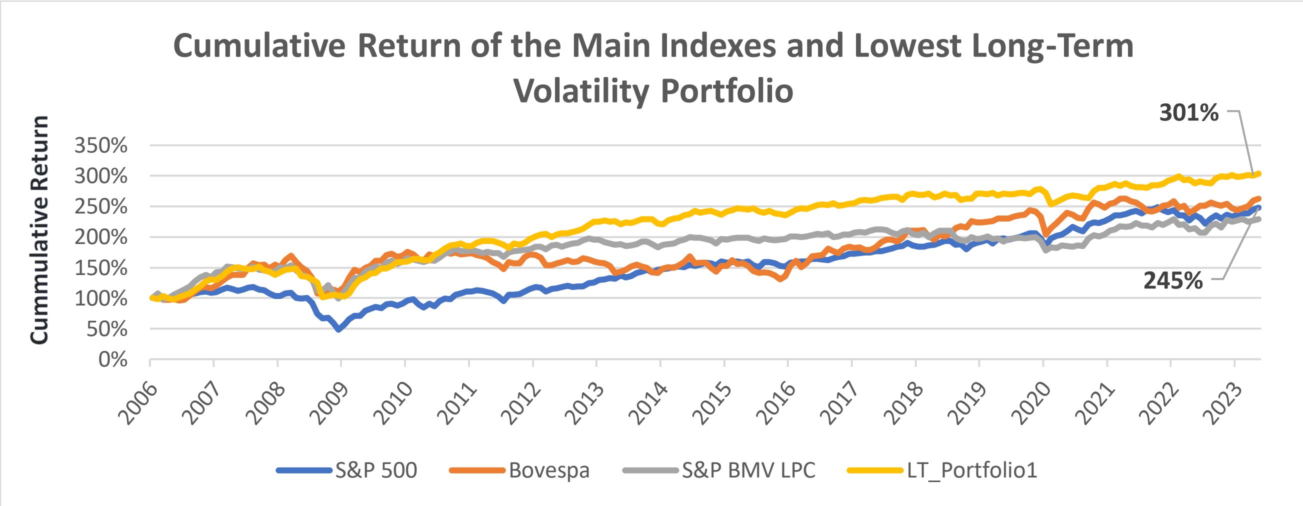
Table 9, Panel A, presents the regression results for the 1-factor model. The market factor is derived from the excess return of the S&P 500 above the 1-month US Treasury rate. Portfolio1_IVOL comprises portfolios composed of stocks with the lowest short-term volatility, whereas Portfolio5_IVOL comprises portfolios with the highest song-term volatility. In Panel B, the results for the 3-factor model are displayed. The Size factor is calculated from the returns of small-cap stocks minus big-cap stocks, and the Value factor is determined from the returns of high book-to-market (b/v) stocks minus low b/m stocks returns.

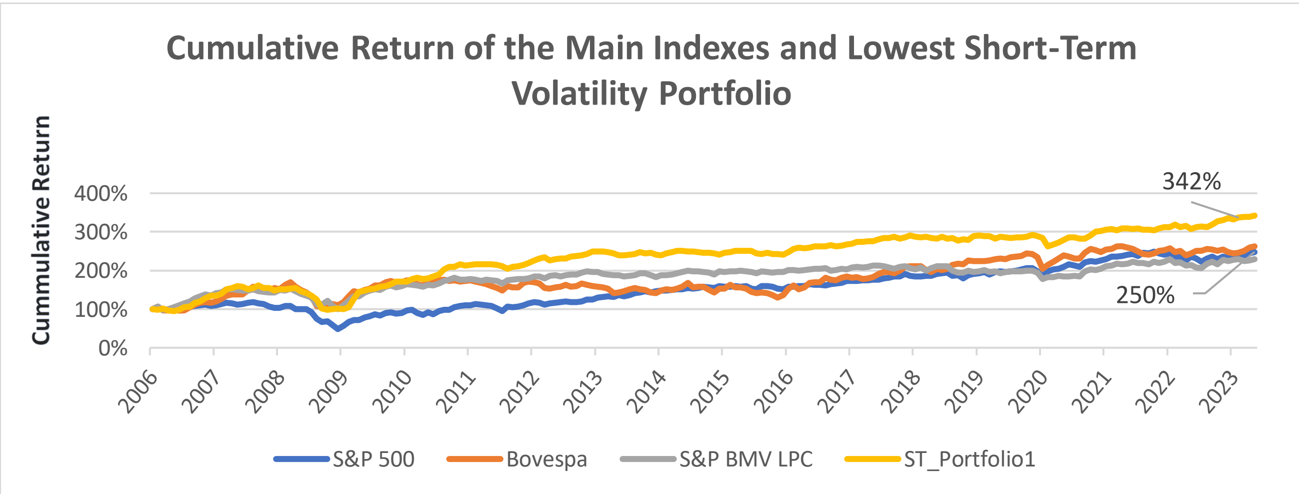
4.4.Returns against main indexes.

In line with the findings of Samsonescu et al. (2016) for the Brazilian market and Amorocho (2023) in the Colombian market, this study also yielded comparable results when applied to the broader region encompassing six countries. As depicted in Figure 5, all three approaches employed to construct the lowest volatility portfolios led to cumulative returns that outperformed the main indexes of the region.

Specifically, in the case of long-term volatility, this portfolio achieved a cumulative return of 301%, surpassing the S&P 500 which had a cumulative return of 245%. In the second scenario, the portfolio based on short-term volatility resulted in a cumulative return of 342%, while the Bovespa index had a cumulative return of 250%. Finally, the portfolio with the lowest idiosyncratic volatility culminated in a cumulative return of 353%, while the S&P BMV LPC achieved a return of 227%. Among all variants of low volatility, IVOL emerged as the most profitable in terms of cumulative returns and risk-adjusted performance.

Figure 5: Cumulative returns of low volatility portfolios and main indexes from 2006 to 2023.





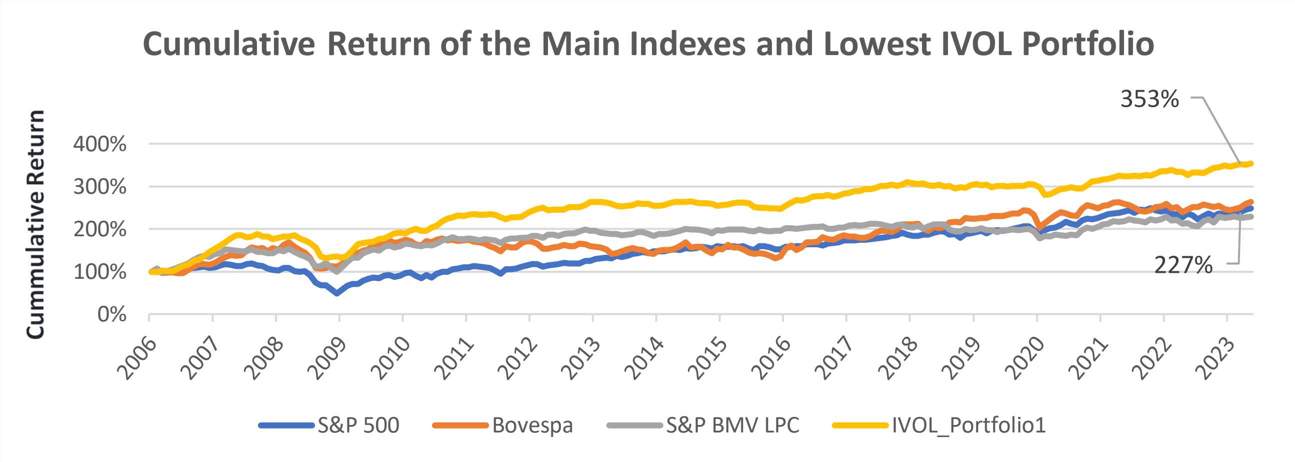


Figure 5: Plot of accumulated returns of each Index. The sample period extends from March 2006 to June 2023.

4.5.Normality of Portfolios and test statistics

Table 12 presents the skewness and kurtosis results for all portfolios considered in this research, revealing p-values under 5% for all cases except for Portfolio2_IVOl. This indicates that the hypothesis of normality can be rejected for all portfolios except Portfolio2_IVOl. Therefore, as observed in Firacative (2015) for the Peruvian, Chilean, and Colombian markets, and in Neto et al. (2008) for the Brazilian market, where both studies concluded that the Latin American markets, due to their lack of liquidity and depth in their stock exchanges, render the CAPM model invalid for practical application, the same results would apply in this research for all previous alphas obtained. Additionally, the Jobson and Korkie test encounters difficulties when portfolios do not conform to a normal distribution and exhibit fat-tailed distributions, which fosters skepticism regarding results in Latin American markets in terms of explaining differences in Sharpe ratios.

Table 12: Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob>chi2
Portfolio1_LT	208	0	0	58.24	0

Portfolio2_LT	208	0	0	37.4	0
Portfolio3_LT	208	0	0	28.21	0
Portfolio4_LT	208	0	0	37.45	0
Portfolio5_LT	208	0.025	0	16.44	0
Portfolio1_ST	208	0.001	0	35.61	0
Portfolio2_ST	208	0	0	30.93	0
Portfolio3_ST	208	0	0	41.84	0
Portfolio4_ST	208	0	0	27.08	0
Portfolio5_ST	208	0.007	0	17.46	0
Portfolio1_IVOL	208	0	0	36.66	0
Portfolio2_IVOL	208	0.334	0	22.45	0
Portfolio3_IVOL	208	0	0	44.01	0
Portfolio4_IVOL	208	0	0	34.41	0
Portfolio5_IVOL	208	0.016	0	17.66	0

4.6. Research Results

As demonstrated by Brito (2017) considering the top 100 most liquid stocks in the Brazilian market, Boudjoukian (2017) in the same market during from 2010 to 2017, and Viveros (2013) for the Colombian market, in this study and based on previous results using the three low volatility approaches, it is confirmed that low volatility is not present in these six Latin American economies. This is explained by lower returns in low-volatility portfolios, as shown in Tables 4, 7, and 10; alphas that are not statistically different from zero in the 3-factor model, as shown in Tables 5, 8, and 11 at 5% significance level as well as lower betas for these portfolios. This may imply that in these markets, a value or size effect could be the explanation for the alpha between low- versus high-volatility portfolios, as discussed in Scherer (2010). In this context, Hypothesis 1 states that 'Portfolios characterized by low volatility do not demonstrate superior performance compared to portfolios exhibiting the highest volatility.' The findings from previous results fail to reject this hypothesis, as low volatility portfolios for all methodologies did not exceed the returns of high volatility portfolios and alphas were statistically not different from zero in a 3-factor model at 5% significance level, concluding the absence of the low volatility anomaly in Latin American markets.

Secondly, in terms of risk-adjusted performance, Hypothesis 2 states that ‘Portfolios characterized by low volatility do not demonstrate superior risk-adjusted performance compared to portfolios exhibiting the highest volatility.’ The findings support this hypothesis, given that the outperformance of low volatility Sharpe ratios in the short-term volatility and IVOl, at least in statistical terms, might not be significantly different from the high volatility portfolios risk adjusted returns based on the Jobson and Korkie test, which yielded a statistic above the 5% significance level as shown in tables 4, 7, and 10. Additionally, this test results may not be reliable in non-normality scenarios, such as the ones observed in these markets, as will be discussed further, making it more challenging to draw a definitive conclusion. Therefore, the hypothesis of the absence of the low volatility anomaly in risk-adjusted returns stands.

In the case of cumulative returns, for all three types of low volatility portfolios, indeed outperformed the main indexes of this region as shown in Figure 5. This finding is consistent with the research of Samsonescu et al. (2016) for the Brazilian market, where the author compared the returns of low volatility portfolios against the Bovespa index using a four-month rebalancing framework, as well as the work of Amorocho (2023) in the Colombian market, which demonstrated that portfolios with minimum variance, as outlined in Clarke et al. (2006), outperformed the Colcap index. Hypothesis 3 posits that 'Low volatility portfolios outperform the Bovespa, S&P BMV LPC, and S&P 500 when returns are evaluated in US dollars.' Based on the results, we do not reject the hypothesis, as the performance of these portfolios, according to all three criteria of low volatility, exhibits superior returns compared to each of the benchmarks analyzed.

Lastly, in all preceding regressions, the GRS test indicates that alphas were not significantly different from zero, aligning with the findings of Blitz et al. (2013) for countries in Latin America. This could imply that either the models are not applicable to these markets, given that alphas derived from previous regressions may not hold validity due to the non-normal distribution of returns in these portfolios as shown in Table 12 or that the low volatility was indeed priced by the F&F 3-factor model as shown in tables 5, 8, and 11, and in this case, a value effect might be the explanation as stated by Scherer (2010). In this context, Hypothesis 4 posits that 'Alphas derived from both 1-factor and 3-factor models for portfolios sorted by volatility do not exhibit statistically significant deviations from zero.' Therefore, the findings fail to reject the hypothesis. This is not only because the alphas obtained were not significantly different from zero in statistical terms, implying a possible value effect, but also because these portfolios exhibited non-normal characteristics, which makes this test unreliable in this regard.

5. Conclusions

In this research, the low volatility portfolio returns for Latin American stocks, as analyzed in studies by Blitz et al. (2007) and (2013) as well as in Ang. et al (2006), were scrutinized for the period spanning from 2003 to 2023. The low volatility approach encompassed both a long-term perspective, considering the variation over the past 36 monthly returns, and a short-term view, examining the daily total volatility of returns in the last month as well as the IVOL, as defined by Ang et al. (2006). Key comparative indices included the Bovespa Index and the S&P BMV LPC, with the S&P 500 index serving as the benchmark for the market factor, and one-month US treasury rates utilized as the risk-free rate. The primary conclusion drawn is the absence of the low volatility anomaly in these markets, as the highest volatility portfolios outperform the low volatility portfolios. It is noteworthy, however, that this analysis did not factor in transaction costs or constraints on short selling for these less liquid stocks, which could potentially outweigh the advantages of investing in riskier yet more profitable ex ante cost stocks. Furthermore, in terms of risk-adjusted returns measured by Sharpe ratios, the low volatility anomaly might be present in the short-term volatility approach and IVOL. However, the disparity in risk-adjusted returns, as tested by the Jobson & Korkie (1981) test with the Memmel (2003) correction, indicated that Sharpe ratios between low and high volatility portfolios based on these two approaches were not statistically different. Additionally, the invalidity of this test given that Latin American stocks exhibited characteristics of a non-normal distribution led to the failure in rejecting the second hypothesis, and therefore, in risk-adjusted terms, the absence of the low volatility anomaly stands. In terms of cumulative returns, all three approaches outperformed the three main indexes, with IVOL emerging with the highest cumulative return, followed by the short-term approach, and lastly, the long-term approach. In this regard, hypothesis 3 was also not rejected. Finally, the non-normality characteristics of the Latin American stocks and the results from the GRS test for the three approaches, with alphas not statistically different from zero after controlling for size and value, indicating a possible value effect embedded, led us to not reject hypothesis 4 as well.

In conclusion, Hypothesis 1 and Hypothesis 2, positing the absence of the low volatility anomaly in Latin American economies based on long- and short-term volatility and IVOL, has been verified. Hypothesis 3, asserting that low volatility portfolios outperform the main indexes of the region, has also been confirmed, with IVOL proving to be the most profitable. Finally, based on the GRS test, all three approaches resulted in alphas that were not significantly different from zero. In this regard, Hypothesis 4 has also been verified. This last result, may be attributed to the scarcity of data and the non-normality exhibited by the stocks in these economies, rendering the CAPM and F&F models less suitable for pricing these stocks.

In light of the findings presented in this study, there are several avenues for future research that warrant exploration. One potential avenue involves a more comprehensive assessment of the lowest volatility approach, factoring in transaction costs such as bid-ask spreads and other associated commissions. This could provide a more nuanced view of the strategy's viability.

Considering these costs will lead to a decrease in cumulative returns, potentially resulting in the strategy being less effective compared to the main indexes studied here.

In addition, it might be pertinent to consider that in developed markets, as noted by Blitz et al. (2014), factors such as leverage constraints, skewness preferences, and behavioral biases have been identified as potential explanations for the low volatility anomaly. Given this, a similar analysis of these aspects could be of relevance in studying Latin American markets to ascertain why this anomaly is not observed in them.

Lastly, given the non-normality features observed in these markets, a promising avenue for future research could involve a comprehensive exploration of alternative techniques for assessing low volatility portfolios. Drawing inspiration from methodologies proposed by Chague (2007), Paiva Martins Teixeira et al. (2022), and Machado et al. (2017) in the Brazilian market, Firacative (2015) in the MILA market, and Valencia-Herrera (2018) in the Mexican market, a comparative analysis could be conducted to evaluate the applicability and effectiveness of these techniques in the context of Latin American economies. Such an investigation would offer valuable insights into potentially more robust approaches for managing portfolios in these markets.

6. References

Ang, A., Hodrick, R., Xing, Y. & Zhang, X. (2006). The cross-section of volatility and expected returns. Journal of Finance, 61(1), 259-299

Amenc, N., Martellini, L., Goltz, F., Sahoo, D., 2011. Is there a risk/return tradeoff across stocks? An answer from a long-horizon perspective. EDHEC-Risk Research Paper

Boudjoukian França, L. (2017). Avaliação de ativos de baixa volatilidade no mercado brasileiro: menor risco com maiores retornos (Low Volatility Asset Valuation in Brazilian Stock Market: Lower Risk with Higher Returns). Available at SSRN 3488609.

Black, F., Jensen, M.C., Scholes, M., 1972. The capital asset pricing model: some empirical tests. In: Jensen, M.C. (Ed.), Studies in the Theory of Capital Markets.

Blitz, D., & Van Vliet, P. (2007). The Volatility Effect: Lower Risk without Lower Return. Journal of Portfolio Management, 102-113. SSRN working paper no. 2270973.

Blitz, D., Falkenstein, Eric G. & Van Vliet, P. (2014). Explanations for the Volatility Effect: An Overview Based on the CAPM assumptions. Journal of Portfolio Management, 102-113.

Blitz, D., Baltussen, G., and van Vliet, P. (2019b). The Low Volatility Effect Revisited. Available online: https://ssrn.com/abstract=3442749.

Blitz, D., Pang, J., and van Vliet, P. (2013). The volatility effect in emerging markets. Emerging Markets Review, 16, 31-45.

Clarke, R., De Silva, H. & Thorley, S. (2006). Minimum-Variance Portfolios in the U.S. Equity Market. Journal of Portfolio Management, 33 (1), 10.

Fama, E. F., and French, K. R. (1992). The cross-section of expected stock returns. Journal of Finance, 47(2), 427-465.

Fama, E. F., and French, K. R. (1992). The cross-section of expected stock returns. Journal of Finance, 47(2), 427-465.

Fama, E. F., and French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22.

Haugen, R.A., Heins, A.J., 1975. Risk and the rate of return on financial assets: some old wine in new bottles. Journal of Financial and Quantitative Analysis 10 (5), 775–784.

Frazzini, A., Pedersen, L.H., 2010. Betting against beta. SSRN Working Paper, no. 1723048.

Machado, M. A. V, Faff, R. and Silva, S.C. (2017). Applicability of Investment and Profitability Effects in Asset Pricing Models. Journal of Contemporary Administration, 21(6), 851-874.

López-Herrera, F., Santillán-Salgado, R. J., & Ortiz, E. (2014). Regime switches in the tangency portfolio of NAFTA markets during the Financial Crisis. Journal of International Business and Economics, 2(3), 95-123.

Rouwenhorst, K.G. (1999). Local returns factors and turnover in emerging markets. Journal of Finance 54 (4), 1439-1464.

Sandoval, Eduardo and Soto, Macarena, Mercado Integrado Latinoamericano: Un Análisis De Cointegración (Integrated Markets of Latin American: A Cointegration Analysis) (2016). Revista Internacional Administración & Finanzas, v. 9 (1) p. 1-17, 2016,

Sharpe, W.F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. Journal of Finance, 19(3), 425-442

Scherer, B., 2010. A new look at minimum variance investing. SSRN Working Paper, no. 1681306

Valencia-Herrera, H., & López-Herrera, F. (2018). Markov Switching International Capital Asset Pricing Model, an emerging market case: Mexico. Journal of Emerging Market Finance, 17(1), 96-129.

Novy-Marx, R. (2014). Understanding defensive equity. NBER working paper no. 20591.

Liu, J., Stambaugh, R. F., and Yuan, Y. (2018). Absolving beta of volatility's effects. Journal of Financial Economics, 128(1), 1-15.

Keene, M. A., & Peterson, D. R. (2007). The importance of liquidity as a factor in asset pricing. Journal of Financial Research, 30(1), 91-109.

Chague, F. D. (2007). The CAPM and Fama-French models in Brazil: A comparative study (Doctoral dissertation).

Paiva Martins Teixeira, V., Ferreira da Cunha, M., & Renata dos Santos, T. (2022). Applicability of local CAPM, adjusted local CAPM and hybrid adjusted CAPM models to the Brazilian market.

Neto, A. A., Lima, F. G., & de Araújo, A. M. P. (2008). Uma proposta metodológica para o cálculo do custo de capital no Brasil. Revista de Administração-RAUSP, 43(1), 72-83.

Firacative Ropero, E. F. (2015). Aplicación del modelo CAPM para la valoración de acciones en el mercado integrado latinoamericano MILA (Doctoral dissertation).

Valencia-Herrera, H., & López-Herrera, F. (2018). Markov Switching International Capital Asset Pricing Model, an emerging market case: Mexico. Journal of Emerging Market Finance, 17(1), 96-129.

7. APPENDIX

7.1. List of companies selected per country.

Company	Country	Industry
ALUA	Argentina	Materials
VALO	Argentina	Industrials
BMA	Argentina	Financials
BBAR	Argentina	Financials
CVH	Argentina	Information Technology
CEPU	Argentina	Energy
COME	Argentina	Energy
CRES	Argentina	Consumer Staples
EDN	Argentina	Utilities
GGAL	Argentina	Financials
SUPV	Argentina	Financials
HARG	Argentina	Materials
RICH	Argentina	Healthcare
LOMA	Argentina	Materials
MIRG	Argentina	Consumer Staples
PAMP	Argentina	Utilities
TECO2	Argentina	Information Technology

Company	Country	Industry
AENZAC1	Peru	Industrials
ALICORC1	Peru	Consumer Staples
BBVAC1	Peru	Financials
GBVLAC1	Peru	Financials
CASAGRC1	Peru	Industrials
CPACASC1	Peru	Industrials
BVN	Peru	Materials
CORAREC1	Peru	Materials
CORAREI1	Peru	Materials
BAP	Peru	Financials
SIDERC1	Peru	Materials
ENDISPC1	Peru	Utilities
ENGEPEC1	Peru	Utilities
ENGIEC1	Peru	Utilities
FERREYC1	Peru	Industrials
INRETC1	Peru	Consumer Staples
INVCENC1	Peru	Real Estate

MINSURI1	Peru	Materials
NEXAPEC1	Peru	Materials
RIMSEGC1	Peru	Healthcare
CVERDEC1	Peru	Materials
BROCALC1	Peru	Materials
SCCO	Peru	Materials
PML	Peru	Materials
IFS	Peru	Financials
UNACEMC1	Peru	Materials
BACKUAC1	Peru	Consumer Staples
VOLCABC1	Peru	Materials

Company	Country	Industry
BHI	Colombia	Financials
CEL	Colombia	Utilities
CCB	Colombia	Industrials
CIC	Colombia	Industrials
ETB	Colombia	Information Technology
GEB	Colombia	Utilities
ARG	Colombia	Industrials
GAA	Colombia	Financials
ISA	Colombia	Utilities
MAS	Colombia	Materials
TPL	Colombia	Consumer Staples
MCS	Colombia	Industrials
VAL	Colombia	Energy

Company	Country	Industry
CHILE	Chile	Financials
BSANTANDER	Chile	Financials
COPEC	Chile	Energy
CENCOSUD	Chile	Consumer Staples
ENELAM	Chile	Energy
CMPC	Chile	Industrials
FALABELLA	Chile	Financials
ENELCHILE	Chile	Information Technology
PARAUCO	Chile	Real Estate
COLBUN	Chile	Utilities
CCU	Chile	Consumer Staples
VAPORES	Chile	Industrials
QUINENCO	Chile	Industrials
CENCOSHOPP	Chile	Real Estate

LTM	Chile	Industrials
ITAUCL	Chile	Financials
CONCHATORO	Chile	Consumer Staples
ENTEL	Chile	Information Technology
CAP	Chile	Materials
MALLPLAZA	Chile	Real Estate
IAM	Chile	Utilities
SMU	Chile	Consumer Staples
RIPLEY	Chile	Consumer Staples
SONDA	Chile	Information Technology

Company	Country	Industry
ALEATIC	Mexico	Industrials
ALFAA	Mexico	Industrials
ALPEKA	Mexico	Industrials
ALSEA	Mexico	Consumer Discretionary
AMXB	Mexico	Communication Services
ASURB	Mexico	Industrials
BACHOCOB	Mexico	Consumer Staples
BBAJIOO	Mexico	Financials
BIMBOA	Mexico	Consumer Staples
CEMEXCPO	Mexico	Materials
CHDRAUIB	Mexico	Consumer Staples
KOFUBL	Mexico	Consumer Staples
CMOCTEZ	Mexico	Materials
CUERVO	Mexico	Consumer Staples
ELEKTRA	Mexico	Financials
DANHOS13	Mexico	Real Estate
EDUCA18	Mexico	Real Estate
FIBRAPL14	Mexico	Real Estate
FEMSAUBD	Mexico	Consumer Staples
FRAGUAB	Mexico	Consumer Staples
FUNO11	Mexico	Real Estate
GCARSOA1	Mexico	Industrials
GFNORTEO	Mexico	Financials
GFINBURO	Mexico	Financials
GMEXICOB	Mexico	Materials
GMXT	Mexico	Industrials
GNP	Mexico	Financials
GAPB	Mexico	Industrials
GRUMAB	Mexico	Consumer Staples
GSANBORB-1	Mexico	Financials
ICHB	Mexico	Financials

KIMBERA	Mexico	Consumer Staples
LAMOSA	Mexico	Consumer Staples
LIVEPOLC-1	Mexico	Real Estate
MEGACPO	Mexico	Communication Services
OMAB	Mexico	Industrials
SITES1A-1	Mexico	Real Estate
ORBIA	Mexico	Materials
PE&OLES	Mexico	Materials
PINFRA	Mexico	Industrials
Q	Mexico	Financials
RA	Mexico	Financials
SIMECB	Mexico	Materials
SORIANAB	Mexico	Consumer Staples
TLEVISACPO	Mexico	Communication Services
VESTA	Mexico	Real Estate
VISTAA	Mexico	Energy
WALMEX	Mexico	Consumer Staples

Company	**Country**	**Industry**
PETR3	Brazil	Energy
VALE3	Brazil	Materials
ITUB4	Brazil	Financials
ABEV3	Brazil	Consumer Staples
BBDC4	Brazil	Financials
BBDC3	Brazil	Financials
BBAS3	Brazil	Financials
ITSA4	Brazil	Financials
ELET6	Brazil	Utilities
ELET3	Brazil	Utilities
VIVT3	Brazil	Information Technology
GGBR4	Brazil	Materials
EGIE3	Brazil	Utilities
SBSP3	Brazil	Healthcare
TIMS3	Brazil	Information Technology
CMIG4	Brazil	Utilities
CCRO3	Brazil	Industrials
BRKM5	Brazil	Materials
CPLE6	Brazil	Utilities
CSNA3	Brazil	Materials
EMBR3	Brazil	Industrials
GOAU4	Brazil	Materials
USIM5	Brazil	Materials
BRAP4	Brazil	Materials

ALPA4	Brazil	Consumer Discretionary
CYRE3	Brazil	Consumer Staples
DXCO3	Brazil	Industrials
BEEF3	Brazil	Consumer Staples
IGTI11	Brazil	Real Estate
COGN3	Brazil	Consumer Staples
YDUQ3	Brazil	Consumer Staples
MRVE3	Brazil	Consumer Staples
LWSA3	Brazil	Information Technology
RAIZ4	Brazil	Energy
MRFG3	Brazil	Consumer Staples
PCAR3	Brazil	Industrials
EZTC3	Brazil	Consumer Staples
VIIA3	Brazil	Consumer Staples
GOLL4	Brazil	Industrials
PETZ3	Brazil	Consumer Staples
IRBR3	Brazil	Financials
CVCB3	Brazil	Industrials
WEGE3	Brazil	Information Technology
SANB11	Brazil	Financials
B3SA3	Brazil	Financials
RDOR3	Brazil	Healthcare
RENT3	Brazil	Industrials
SUZB3	Brazil	Industrials
BBSE3	Brazil	Financials
RADL3	Brazil	Consumer Staples
RAIL3	Brazil	Industrials
JBSS3	Brazil	Consumer Staples
CPFE3	Brazil	Utilities
EQTL3	Brazil	Utilities
CSAN3	Brazil	Energy
HAPV3	Brazil	Healthcare
PRIO3	Brazil	Energy
BPAC11	Brazil	Financials
HYPE3	Brazil	Healthcare
KLBN11	Brazil	Industrials
MGLU3	Brazil	Consumer Staples
CMIN3	Brazil	Materials
NTCO3	Brazil	Information Technology
CRFB3	Brazil	Consumer Staples
AZUL4	Brazil	Industrials
VBBR3	Brazil	Consumer Staples
ENGI3	Brazil	Utilities
UGPA3	Brazil	Energy
LREN3	Brazil	Consumer Staples

ENEV3	Brazil	Energy
TOTS3	Brazil	Information Technology
ASAI3	Brazil	Consumer Staples
MULT3	Brazil	Real Estate
ALSO3	Brazil	Real Estate
SMTO3	Brazil	Consumer Staples
TAEE11	Brazil	Utilities
CIEL3	Brazil	Financials
BRFS3	Brazil	Consumer Staples
SOMA3	Brazil	Consumer Discretionary
FLRY3	Brazil	Healthcare
ARZZ3	Brazil	Consumer Staples
SLCE3	Brazil	Consumer Staples
RRRP3	Brazil	Energy

7.2. Results per Country

Table 13: OLS Regressions on Brazilian portfolios sorted by Long Term volatility

	-1	-2	-3	-4	-5
	Portfolio1_LT_BR	Portfolio2_LT_BR	Portfolio3_LT_BR	Portfolio4_LT_BR	Portfolio5_LT_BR
MarketFactor_BR	.636***	.805***	.95***	1.005***	1.207***
	-0.039	-0.027	-0.032	-0.037	-0.049
SizeFactor_BR	.161***	.064**	.225***	.369***	.481***
	-0.039	-0.026	-0.032	-0.036	-0.048
ValueFactor_BR	-.129***	-.053*	-.095***	-0.042	.143***
	-0.041	-0.028	-0.034	-0.039	-0.051
_cons	0.385	.547***	.464**	0.239	0.044
	-0.249	-0.171	-0.204	-0.233	-0.309
Observations	208	208	208	208	208
R-squared	0.608	0.833	0.841	0.838	0.828

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 14: OLS Regressions on Mexican portfolios sorted by Long Term volatility

	-1	-2	-3	-4	-5
	Portfolio1_LT_MX	Portfolio2_LT_MX	Portfolio3_LT_MX	Portfolio4_LT_MX	Portfolio5_LT_MX
Market Factor_MX	.629***	.788***	.943***	1.161***	1.055***
	-0.037	-0.036	-0.042	-0.05	-0.064
Size Factor_MX	.17***	.149***	.249***	.376***	.257***
	-0.043	-0.042	-0.048	-0.057	-0.074
Value Factor_MX	-0.043	-0.007	.133***	.132***	.108*
	-0.036	-0.035	-0.04	-0.049	-0.062
_cons	.416**	.332*	0.201	0.204	1.044***
	-0.184	-0.178	-0.204	-0.246	-0.316
Observations	208	208	208	208	208
R-squared	0.589	0.71	0.749	0.755	0.601

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 15: OLS Regressions on Peru, Chile, Colombia and Argentina portfolios sorted by Long Term volatility

	-1	-2	-3	-4	-5
	Portfolio1_LT_OT	Portfolio2_LT_OT	Portfolio3_LT_OT	Portfolio4_LT_OT	Portfolio5_LT_OT
Market Factor	.567***	.777***	.875***	.953***	1.185***
	-0.062	-0.067	-0.068	-0.092	-0.115
Size Factor	.173***	.268***	.482***	.774***	1.037***
	-0.062	-0.067	-0.068	-0.092	-0.115
Value Factor	.172***	.29***	.338***	.416***	0.156
	-0.066	-0.071	-0.072	-0.097	-0.121
_cons	-0.025	-0.187	-.705**	-0.494	-0.449
	-0.292	-0.316	-0.321	-0.431	-0.541
Observations	208	208	208	208	208
R-squared	0.369	0.508	0.611	0.583	0.546

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 16: Means Returns and Sharpe Ratios per Country

Variable	Obs	Mean	Std. Dev.	Sharpe Ratio
Portfolio1 LT BR	208	0.484	5.504	0.087936047
Portfolio5 LT BR	208	0.842	10.309	0.081676205
MarketFactor BR	208	-0.03	6.547	-0.004582251
Portfolio1 LT MX	208	0.756	3.873	0.195197521
Portfolio5 LT MX	208	1.656	6.74	0.245697329
MarketFactor MX	208	0.165	4.832	0.034147351
Portfolio1 LT OT	208	0.716	4.992	0.143429487
Portfolio5 LT OT	208	2.018	10.893	0.185256587
MarketFactor S&P	208	0.609	4.491	0.135604542

Table 14: OT includes Argentina, Chile, Colombia and Peru. The table considered only portfolios 1 and 5 per country